Complex Adaptive Food Supply Systems

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Abstract

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The long-term sustainability of food supply chains (FSCs) is critical to human and environmental health. While the modern industrial FSC is capable of the production and global distribution of enormous quantities of food, it also faces serious long-term environmental, social, and economic sustainability challenges. In particular, consolidation and centralization within the modern industrial FSC have led to efficiency gains due to economies of scale, but the associated reduction in FSC structural complexity is thought to have been detrimental to its sustainability and resilience. Existing mathematical models that have been developed to study FSC sustainability have not investigated FSC structure, partly because the most commonly-used modeling methods are incapable of capturing the nonlinear and adaptive behaviors within the FSC that lead to emergent structures. These existing models are typically static and deterministic and are focused on guiding operational on-farm

decision-making. While individual on-farm decisions are important to FSC sustainability outcomes, coordination decisions among FSC actors, which affect the development of overall FSC structural characteristics, are also believed to significantly influence long-term system sustainability. Therefore, the development of a modeling methodology that can be used to study interactions and coordination among FSC actors and the resulting impacts on FSC structure and sustainability is critical. Recent research suggests that agent-based modeling (ABM) is an effective method of capturing complex behaviors in supply chains, particularly the interactions (e.g., coordination and cooperation) that occur among autonomous supply chain actors and the nonlinear emergent system behavior and structures that result. This research develops an ABM methodology that enables an analysis of the impacts of individual attributes, behaviors, decisions, interactions, and adaptations on the structural development of FSCs over time, and the implications of these developments for long-term sustainability. This new methodology involves the development of a multi-agent simulation model of a theoretical FSC that is used to test the impacts of a variety of system parameters on the extent and structure of coordination among FSC agents, and to explore the relationships among resultant FSC structures and long-term environmental, social, and economic sustainability. Results provide insight into these relationships and suggest avenues for improving long-term FSC sustainability.

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Chapter 1 : Introduction

1.1 Motivation

The modern industrial food system feeds six billion people, an accomplishment that is mainly a consequence of the increased yields resulting from inputs of synthetic fertilizers, irrigation, pesticides, new crop strains, and other technologies (Tilman et al. 2002). These increased yields have provided food for millions of people whose lives would have otherwise been diminished and likely shortened by malnutrition. However, this incredible productivity has not come without costs. There are many negative externalities associated with the industrial food supply chain (FSC), including toxic outputs to the environment, such as the release of greenhouse gases and pollution due to pesticide and nutrient run-off, as well as an unsustainable rate of energy and water consumption (Godfray et al. 2010). These problems severely stress the very inputs to the FSC that enable its productivity, raising concerns about the danger of relying on such a system in the long term. Of even greater concern are predictions of rapid demand growth. By 2050 the global population is projected to increase by as much as 50%, and recent studies suggest that at that time, the world will need 70% more food than is currently produced (United Nations 2010, FAO 2009). Increasing and sustaining food production at this level without compromising environmental and public health are major challenges, which are influenced by numerous physical, political, social, and economic factors.

1.1.1 The modern industrial food supply chain

FSCs in industrialized regions have changed dramatically over the past 50 years. Traditionally, individual farms produced a wide variety of food, recycled inputs for self-sufficiency, and relied upon human and animal labor as their primary energy inputs. Now,

farms are typically highly specialized and mechanized, using externally-produced synthetic inputs. Small, independent farms are being increasingly consolidated and controlled by multi-national agricultural corporations, leading to severe implications for rural social sustainability (see Hoffman (2007) and Lyson (2007) for a historical perspective on this transition). The farms that remain capture a decreasing proportion of total FSC value, as other actors (input suppliers, processors, distributors and retailers) have consolidated and become the main drivers of the FSC (Renting et al. 2003, Lang and Heasman 2004). For example, in the U.S., only two firms sell two-thirds of all corn and soybean seeds, while the four largest companies in each industry process over two-thirds of the meat, manufacture about half the milk, and sell half the groceries (Hendrickson and Heffernan 2007). In addition to consolidation, standardization, and centralization of control, industrial FSC structures are characterized by long-distance transport. On average, food in the U.S. travels 1500 miles from producer to consumer, and in the U.K., trucks moving food now account for nearly 40 percent of all road freight (Halweil 2002).

Modern food production technologies, particularly synthetic fertilizers, pesticides, and irrigation, have allowed the production of enormous quantities of food, irrespective of seasons or locale. Long-distance FSCs also enable some efficiencies, by allowing regional specialization in the production of locally appropriate foods, offering local food producers access to larger markets and capital for investment, and providing insurance against regional shocks on production such as conflict, epidemics, droughts, or floods, which are likely to increase in frequency as climate change occurs (Godfray et al. 2010). However, these efficiencies are outweighed by long-term environmental and social costs,

particularly from energy expenditure. This heavy reliance on fossil fuels indicates that, without significant changes in the quantities and types of energy inputs, significant increases in energy prices will have a dramatic effect, since these price increases will propagate throughout the entire supply chain's input, output, processing, distribution, marketing and waste streams (Dahlberg 2008). Modern FSCs are also vulnerable to a range of other economic and social disruptions, including the loss of commodity and export subsidies, increased pressures from large food processors and retailers to cut cost, and major calamities such as climate change, major accidents and/or terrorist attacks (Dahlberg 2008).

1.1.2 The future

Faced with these challenges, it is critical that modern FSCs transition toward greater sustainability and resilience. Such a transition will require changes to management practices and production systems within individual farms, as well as development of FSC infrastructure and networks that link farms to consumers (Sassenrath et al. 2010). Of particular focus is the local food movement, also known as a civically-based FSC, in which consumers favor locally-grown food over food that comes from industrial growers or retail giants, hoping to support local economies and reduce environmental impacts (Hopkins 2003, Flint 2004). Localized food systems, with their shorter FSCs, reduce the number of intermediaries and spatial distance between producers and consumers, potentially reducing the energy and ecological costs of long-distance transportation and redistributing value along the FSC (Bloom and Hinrichs 2010). Such systems may also enable consumers to demand greater producer accountability for ecological degradation (Iles 2005). Localized FSCs may also contribute to food security through decentralization

and diversity, because their lower resource intensity makes them inherently more stable and resilient (Dahlberg 2008). However, some argue that localized FSCs are not inherently sustainable, since the FSC structure does not require that the practices of individual FSC agents be sustainable (Born and Purcell 2006). Additionally, there are concerns that localized FSCs will not produce sufficient output, although it may be possible to maintain the high productivity of the current industrial FSC structure in parallel with a localized, low-input FSC structure in a type of hybrid system (Krejci and Beamon 2010). It is therefore unclear what sort of macro-level FSC structures would best provide long-term sustainability, although the underlying micro-level actor behaviors that are likely to contribute to sustainability in both resource consumption and productivity are well-known (Pretty 2008).

1.2 Problem statement and research questions

The most critical tasks in overcoming these challenges are the sustainable management of resources, successful strategies for adaptation to system variability, and the development of system resilience through sufficient structural complexity.

1.2.1 Resource use

Food production is the fourth-largest consumer of energy in the U.S., accounting for 16 percent of total energy consumption, nearly all of which is fossil-fuel-based (Pimentel and Pimentel 2008). Because industrial FSCs rely heavily on agrochemicals, mechanization, and long-distance transport, petroleum scarcity could seriously compromise food production and increase food insecurity, particularly among those with fewer resources (Frumkin et al. 2009). Additionally, with agriculture accounting for 70% of withdrawals from water resources globally and 80–90% of total freshwater used by

humans, water supplies for agriculture are rapidly dwindling, with crop production in many parts of the world already seriously limited by lack of water (Morison et al. 2008). In response to these challenges, individual FSC actors will be forced to adapt their practices to conserve energy and water, while simultaneously increasing output to meet the needs of a growing population. These micro-level adaptations, along with interactions and coordination among actors, will shape the structure of a new emergent macro-level FSC. It is critical to understand what will influence FSC actors to behave in such a way that leads to the emergence of overall system sustainability. This research seeks to address:

RQ0: What factors (controls/incentives) lead to the emergence of a FSC that exhibits sustainable resource use and sufficient outputs in the long term?

1.2.2 Variability

Environmental variability is another major concern for the future of food production and distribution. Compounding the problem of resource overconsumption, climate-change-induced precipitation and temperature variability are predicted to further stress the agricultural water supply in many parts of the world, and changes in the frequency and severity of extreme climate events are projected to pose significant challenges to food production and food insecurity (IFPRI 2009, Parry et al. 2007). Individual FSC actor adaptations to environmental variability and resource scarcity will also vary and will depend on the unique characteristics of each actor. Actor characteristics include objectives, knowledge, skills and abilities, decision-making methods, and risk tolerance. The combination of an unpredictable environment and variable actor responses to that

environment has implications for the emergent FSC macrostructure over time. Specifically, this research will determine:

RQ1: How do variable actor characteristics and external forces influence the emergence of an FSC's structure over time?

The FSC structure refers to the number and strength of connections among actors, including the physical structure (e.g., number of actors, transport distances), the decision-making/control structure, and information-sharing structure. This research seeks to understand the effects of actor and environmental variability on long-term FSC sustainability. For example, given the increased likelihood of extreme climate events brought on by climate change, how resilient is the emergent FSC against short-term disruptions (e.g.,, weather-based crop destruction, contamination, fuel or transport disruptions), and under what conditions do short-term disruptions damage prospects for long-term sustainability? Finally, what specific actions can be taken to improve resilience to future disruptions?

1.2.3 Complexity

The structure of the modern industrial food system is very lean, with significant horizontal and vertical integration throughout. For example, two large food manufacturers (ADM and Cargill) dominate the corn and soybean supply chains, acting as the primary customers of a relatively few large-scale growers, and controlling the supply of processed products to food manufacturers. From the standpoint of these processors, FSC consolidation is efficient, streamlining operations, reducing risk, and externalizing cost. However, such a centralized and homogeneous food system has also been criticized as inflexible and vulnerable to supply disruptions, particularly when faced

with variability (United Nations 2006, Dahlberg 2008, Clancy and Ruhf 2010). An example of the risks posed by concentration in a supply chain for vital products is the flu vaccine supply chain. In 2004, one of the two manufacturers of flu vaccine for the U.S. market was unable to deliver, creating a supply shortage. In contrast, a highly complex, decentralized structure allows risk to be spread among a large number of diverse actors, as well as increasing regional/local self-reliance, which may help to mitigate the negative effects of a disruption. As FSC actors adapt to resource scarcity and increasing environmental variability, a new FSC structure will emerge over time. This research seeks to explore the implications for FSC structural complexity throughout this transition, as well as the ramifications for long-term system sustainability:

> **RQ2**: What do the intermediate/transitional stages of FSC structural emergence look like, in terms of FSC metrics, the rate of change, and the potential for a steady-state structure?
>
> **RQ3**: What is the impact of initial, transitional and emergent FSC structure on long-term sustainable resource use and outputs?

A complex adaptive system is a system of interconnected autonomous entities that make choices to survive and, as a collective, the system evolves and self-organizes over time (Pathak et al. 2007). The FSC is a complex adaptive system with emergent behavior and is therefore amenable to modeling with multi-agent simulation. By addressing these questions, the proposed research seeks to address limitations of existing studies by developing a dynamic, agent-based modeling approach to FSC security and long-term sustainability.

Chapter 2 : Background and Literature Review

2.1 Modeling the FSC for sustainability

One option for exploring the sustainability of FSCs is through the use of modeling. In particular, mathematical modeling, in which real-world systems are represented through mathematical statements and/or computer code, is a method that can be used to capture the essential elements of a system, which can then be used to create a "virtual" version of that system for experimentation and analysis. Models typically include objective functions, constraints, and/or rules that are based on empirically-observed relationships (e.g., from case study and/or farm test plot data). Modeling provides a systematic and efficient platform for predicting future system behavior, identifying conditions for optimality, performing sensitivity/what-if analyses, and studying the mechanisms that underlie system behavior. Because a model is by definition an abstract representation of a real system, there is an inherent danger that critical system details will be unintentionally omitted from the model, leading to inaccurate conclusions. On the other hand, excessive details can increase computational complexity and data requirements, resulting in an inflexible and cumbersome model. Additionally, models often can only provide information about the performance of a very specific type of system under certain conditions, and conclusions can be very difficult to generalize and extend to other systems. Despite these challenges and limitations, mathematical models can be very useful for experimentation and analysis, and they have been used extensively to study individual FSC stages, particularly farm operations.

Existing literature in the area of agricultural mathematical modeling falls into two broad categories: optimization models and computer simulation models. Optimization has been used for decades to model food systems. Many existing agricultural optimization models are

static, deterministic linear programming (LP) models with a single objective of maximizing short-term farm income or profit, subject to constraints of farm input costs or availability. The literature also contains some dynamic and stochastic optimization models, which explicitly capture random system elements and multiple time periods. Other models use multi-criteria decision-making to model multiple different (and often conflicting) objectives.

Food systems have also been modeled using computer simulation, which can explicitly model time dynamics and stochastic behavior. Some existing simulation models are discrete-event and simulate on-farm operations (de Toro & Hansson 2004, Semenzato et al. 1995) or entire FSCs (van der Vorst et al. 2000); these models are focused on improving short-term productive efficiencies and are not concerned with long-term sustainability. Most existing computer simulation models are ecological simulators, which model the impacts of varying inputs on yields and/or environmental impacts of farming practices. Table 2.1 lists examples of ecological computer simulation models. Such modeling tools are commonly used to generate data for environmental resource conservation efforts in agriculture.

In addition to ecological simulators, recent research has used multi-agent simulation to model different aspects of food systems. Multi-agent simulation (MAS) is a modeling tool that can effectively model heterogeneous, autonomous, intelligent, and interacting actors. Such actors are known as agents. The agents in an MAS are intelligent (i.e., they have internal logic) and are capable of making complex decisions while engaging in complex interactions with other agents and objects within their environment. Agents are affected by their environment and can also act in ways that affect their environment. Collectively, the agents make up a complete system, wherein some agents may be more influential than others, but none completely controls the behavior of the system (North and Macal 2007).

One of the advantages of MAS is its ability to represent a food-producing region spatially (Balmann 1997). Another benefit of MAS is its ability to model individual farms as heterogeneous and autonomous agents, which more accurately represents the diversity and independent behavior of real-world farms (Freeman et al. 2009). MAS also allows the farms themselves to be modeled as intelligent agents; that is, farming operations have the capacity to "learn" from their environment over time and adapt their behaviors accordingly to meet their design objectives under dynamic conditions (Wooldridge 2002). Finally, with MAS, autonomous farms can interact with one another across the simulated region, which enables modeling of resource and innovation exchanges among farms (Berger 2001).

Ecological Simulator	**Source**	**Environmental Sustainability Element**				
		Soil Erosion	**Nutrient/Pesticide Leaching**	**Water Conservation**	**Crop Rotation**	**Carbon Sequestration**
SWAT	Arnold et al. (1998)	x	x			
AnnAGNPS	Bosch et al. (1998)	x	x			
CEEPES	Bouzaher et al. (1995)		x			
APSIM	Keating et al. (2003)	x	x	x	x	
CREAMS	Knisel (1980)	x	x			
GLEAMS	Leonard et al. (1987)		x			
WEPP	Nearing et al. (1989)	x				
CENTURY	Parton et al. (1988)	x	x			
SUNDIAL	Smith et al. (1996)		x			
EPIC	Williams et al. (1989)	x				
AGNPS	Young et al. (1989)	x	x			
Crop-DNDC	Zhang et al. (2002)		x			x

Table 2.1. List of commonly-used ecological simulators for assessment of environmental agricultural sustainability.

Mathematical food systems modeling is a well-established area of research, which has given rise to several reviews of food system models. Most of these reviews cover on-farm or regional bio-economic optimization and computer simulation models (Ahumada and Villalobos 2009, Hayashi 2000, Janssen and van Ittersum 2007, Lucas and Chhajed 2004, Malezieux et al. 2009, Payraudeau and van der Werf 2005, Weintraub and Romero 2006), while some discuss models with a global reach (Reilly and Willenbockel , Tongeren et al. 2001). Some reviews of multi-agent models also exist (Higgins et al. 2010, Matthews et al. 2007, Parker et al. 2003).

Nearly all existing mathematical food systems models include economic sustainability as an objective or constraint. In particular, the primary or only objective of most models is to maximize farmers' incomes, typically subject to resource constraints. While the economic sustainability of a farm is a critical component of overall sustainability, it is generally not a sufficient proxy for sustainability as a whole. Therefore, this review will focus specifically on mathematical models of agricultural systems that address issues of environmental and/or social sustainability, in addition to economic sustainability.

For the purposes of this discussion, elements of environmental sustainability are those that refer to agricultural practices that enhance an agro-ecosystem's long-term productivity while minimizing damage to the surrounding ecosystem. Mathematical food systems models in the literature typically address practices that fall into one or more of seven major categories: minimizing soil erosion, minimizing nutrient leaching, avoiding harmful pesticide impacts to surrounding ecosystems, conserving limited water resources, using energy efficiently, improving ecosystem biodiversity, and optimizing the positive impacts of multispecies cropping systems. In many cases, optimizing these environmentally-beneficial

practices is also associated with improving economic sustainability. For example, reducing the use of costly agrochemical inputs might mitigate harmful environmental impacts of a system, while simultaneously increasing farmers' profits for a given yield.

Social sustainability can be assessed in a number of ways; for example, affordability and equity in food availability are necessary components of a socially sustainable food system. However, only two elements of social sustainability are featured prominently in the FSC modeling literature: employment and nutrition. Therefore, this review focuses on socially sustainable practices that improve the quality of life in rural communities through increased on-farm employment, and/or those that provide sufficient nutritional security for a community. While nutritional security is by no means determined solely by calories, other system characteristics, such as vitamin and mineral sufficiency and diet diversity, are not typically considered explicitly in food systems models in the literature.

Other techniques for analyzing sustainability in food systems exist in the literature. However, the predominant tools for modeling sustainable food systems are quantitative, and these are the focus of this review. Livestock farming is not considered explicitly here, nor is modeling of sustainable forestry or fisheries management. Empirical models that use statistical analysis to draw conclusions about farm data (such as test plot analyses) are useful and are often included within larger mathematical models of food systems. However, stand-alone data analyses of empirical experiments will not be covered here. Also, while modeling methods such as life-cycle analysis, environmental risk mapping, environmental impact assessment, or agro-environmental indicators provide valuable insights to sustainability issues in food systems (Payraudeau and van der Werf 2005), they fall outside the scope of this review.

The articles are grouped by the primary type of environmentally sustainable practices considered in each paper. Most of the literature has a predominant focus; however, some work addresses multiple practices with equal emphasis, and these articles fall under the "Multiple Elements" heading.

2.1.1 Soil quality and erosion

Soil health is fundamental for agricultural sustainability, but many farming practices degrade it, making the soil vulnerable to wind and water erosion. The models of soil erosion in the literature focus primarily on optimizing land use to minimize soil degradation while maintaining economic viability. Stephenne and Lambin (2001) develop an ecological computer simulation (SALU) to model the impact of different land uses (forest, crops, fallow and pasture) on soil erosion. Other models are in the form of linear programs (LPs), which are developed using historical input data from databases such as FAOSTAT, or from locally-created databases. Segarra et al. (1985) develop an LP that determines optimal crop choices to maximize farm revenues, subject to stochastic soil loss constraints. Veeneklaas et al. (1991) develop an LP that optimally allocates land use, with the goal of either maximizing crop revenues or minimizing risk, subject to land and labor constraints, yield targets, nutritional requirements and soil maintenance costs. Similarly, the multi-objective LP models of Agrell et al. (2004) and Sadeghi et al. (2009) also seek to optimize land allocation; however, these models explicitly include the minimization of soil erosion as one of their objectives, and the multiple objectives are optimized simultaneously.

Several MAS models that focus on soil erosion also exist. In contrast with the LP models that study soil erosion, these MAS models take advantage of the ability to create heterogeneous agents that can interact and autonomously pursue their individual objectives to

capture the impact of human interactions and decisions on soil erosion outcomes. Belem et al. (2011) model management and allocation of soil carbon and other organic inputs (e.g.,,, wood and livestock fodder) among a farming community, embedding the CENTURY carbon cycling simulator in their MAS to determine the sustainability of certain land uses and farming practices over time. Sengupta et al. (2005) study the effect of government policy on environmental outcomes by modeling the impact of subsidies on farmer agents' decision to fallow highly-erodible land. Using information gathered from farmer surveys, they develop a model of heterogeneous farmer agents to predict the influence of the government program on farmer behavior and thus regional land use. They use an LP to model farmer crop decisions, where farmers select a mix of crops (and crop prices) that will maximize their profits, constrained by the type and quality of soil on their farms. Lynam (2002) includes detailed models of biological processes in his MAS model of food production, using a geographic information system (GIS) in combination with crop yield equations and soil erosion models, with the objective of determining the agro-ecosystem components that most contributed to a farming household's survival.

Although farms in both industrialized and developing countries suffer from soil erosion, most of the applications in the literature focus on farming regions in the developing world. This may be because farmers in wealthy countries have access to abundant resources to either avoid soil erosion, or at least can mask its negative effects through the use of chemical fertilizers (Bakker et al. 1998). For example, Veeneklaas et al. (1991) and Agrell et al. (2004) include nutritional security as an objective in their models, which is of critical importance in many developing nations.

2.1.2 Nutrient leaching

Nutrient leaching occurs when fertilizers that have been applied to fields run off via rainfall or irrigation water and join the neighboring ecosystem's waterways. This runoff fertilizer acts as a pollutant, causing severe environmental problems downstream. In addition to the negative impacts of nutrient leaching on the environment, it is also economically wasteful for the farmers who purchase costly nitrogen inputs. Therefore, optimizing farming practices to minimize leaching while maximizing yields/revenues is an important objective for both farmers and environmentalists.

There are several widely-used ecological/crop simulators that estimate nitrate leaching. David et al. (2009) review six of these simulators to assess their accuracy, determining that although there was considerable variability among different models' results, in general, the models predicted crop yields and nitrate flux fairly accurately. Alocilja and Ritchie (1993) use a crop simulator (CERES-Maize) to estimate values for corn yields and leached nitrogen quantities, given environmental conditions and the quantity and timing of fertilizer application. They then Pareto-optimize the results to determine a fertilization schedule for maximum profit and minimum nitrate leaching. Irrigation scheduling is also critical to managing nutrient leaching. Johnson et al. (1991) use CERES, dynamic optimization, and LP to assess the impact of different crop rotations and irrigation schedules on optimal fertilizer management for reduced nitrate leaching. They find that optimizing an irrigation schedule can simultaneously conserve water and reduce nitrate leaching, without significant economic investment. Knapp and Schwabe (2008) also address irrigation in their model, allowing for field-level spatial heterogeneity in the soil and irrigation parameters of their dynamic optimization model. They conclude that irrigation scheduling is as important to

nitrate leaching as fertilizer application management. Yiridoe et al. (1997) use the CENTURY simulator to assess the impacts of other farm practices on nitrate leaching, including tillage, crop choice and crop rotation.

Happe et al. (2011) attach the FARM-N fertilizer management model to their MAS of a farming region to assess the relationship between environmental impact and different regional structures and farming practices over time. Given a farming scenario, this model is able to predict very specifically the quantity of resultant polluting outputs. Matthews (2006) and Schreinemachers et al. (2007) also embed crop simulators within their MAS models to achieve a high level of biological realism to capture soil fertility dynamics. In contrast, Janssen's (2001) MAS model does not use include a crop simulator but instead focuses on the impact of farmer attributes on farmer decisions to use conservative or intensive fertilizer applications. This model includes a "tax payment" parameter with a value that depends on the intensity of a farmer's fertilizer use. The tax value can be varied in different simulated scenarios to study its impact on farmer pollution and subsequent eutrophication in a neighboring lake.

All of these models are intended for application to industrialized farming systems, which have access to abundant supplies of synthetic nitrogen fertilizer and are more likely to use irrigation than systems in developing regions. It should be noted that none of these models suggest that the use of chemical fertilizer be entirely eliminated to increase environmental sustainability. Social sustainability measures are not explicitly included in any of these models.

2.1.3 Pesticide impacts

Many farmers, particularly in industrialized food production systems, depend on synthetic pesticides to control pests, weeds and diseases. However, while synthetic pesticides can destroy targeted pests and save farmers' yields, harmless and/or beneficial plants and animals in the surrounding ecosystem can become collateral damage. As with nutrient leaching, excessive or incorrectly applied pesticides can also leach into groundwater, which is a potential risk to human health. Additionally, weeds have been known to develop resistance to over-applied herbicides, forcing farmers to resort to increasingly stronger chemicals to achieve the same results.

Farmers who use synthetic pesticides must therefore balance their pesticide use, which has both monetary and environmental costs, with the yields lost to pests as a result of reductions in pesticide application. Future cropping seasons must also be considered, since pest-control decisions will affect the following years' weed populations and thus future cropping potential and profit. To capture this time element, Sells (1995) and Benjamin et al. (2009) develop stochastic dynamic programming models of herbicide application, with a single objective of minimizing operational costs. They use their models to determine optimal long-term strategies for weed control as a function of crop type, rotation schedule, timing of planting, and the quantity/type of herbicide use, given stochastic herbicide performance. In cases where the cost of yield loss outweighs the economic benefits of reduced pesticide use, taxes could be introduced to encourage farmers to reduce their pollution while still remaining financially viable. Willett and Willett (2008) use LP to formulate the problem of determining a tax rate that minimizes farmer opportunity cost while satisfying public health constraints. They first use stochastic distributed parameter simulation models to assess environmental

pesticide contamination for different scenarios, and then use these results to calculate the risk to public health. The health risk parameter then becomes an input to the LP, which can be solved for different safety levels.

2.1.4 Water conservation

When regional sources of water for irrigation are commonly owned, the problem of equitable distribution among regional farmers arises, as well as the need to use the water at a rate that is no greater than the rate of replenishment of the source. This problem has been modeled as a single-objective optimization problem, with the objective of maximizing farmers' profits, and constraints that limit environmental damage. For example, Schoups et al. (2006) model a farming region to determine the crop mix and the appropriate balance between groundwater and surface water use that maximize regional profit in the face of drought conditions. This single objective is constrained to prevent irrigation rates from causing salinization or becoming greater than recharge rates. The water conservation problem has also been formulated as a multi-objective model that seeks to optimize the tradeoff between farmers' short-term goals (maximizing profits/minimizing costs) and the long-term sustainability of an irrigation source (Gupta et al. 2000, Latinopoulos 2009, Xevi and Khan 2005). Xevi and Khan (2005) model water as the flow among a network of nodes that connect supply nodes to irrigation or urban areas (demand nodes) and then use goal programming to find the optimal crop mix. Raju and Kumar (2005) and Gupta et al. (2000) use multi-objective fuzzy linear programming to account for imprecision in individual farmer goals and utility functions.

Sustainable water use is a dynamic problem, with cumulative effects of short-term consumption decisions impacting long-term sustainability. As such, some water conservation models include an element of time. Cai et al. (2002) achieve this by iteratively solving an LP

to optimize short-term "yearly" water usage. Each iteration is then governed by an "interyear" program that constrains the LP's long-term environmental impact. This "interyear" program is solved using a genetic algorithm. Varela-Ortega et al. (1998) and Ward and Pulido-Velazquez (2008) use dynamic programming to allow the passage of time to be included in their models of the effects of water pricing policies on agricultural water usage and farmer income. Poussin et al. (2010) develop a spatially-explicit computer simulation as a modeling environment to determine the effects of water pricing policies over time.

Barreteau and Bousquet (2000) develop an MAS to study the impact of collective farming community rules on the sustainability of an irrigation system, creating different farmer categories based on cultivation objectives and giving farmer agents from each category different rules and capabilities for making strategic decisions on water usage. Becu et al. (2003) focus their MAS on studying the sustainability impact of different water management schemes on farming systems in which negotiations occur within pairs of upstream and downstream managers of a shared water resource. They create their own biophysical simulator to model the effect of water cycling through the soil and atmosphere and the resulting impact on crop yield and use a simple LP to model crop choice where farmers maximize profits subject to cash, labor, and water availability. Le Bars et al. (2005) model farmer agents that share a water resource for crop irrigation. The farmers take turns requesting shares of water from a single regional water manager, who responds to each request with a proposed share. Each farmer will accept or reject the proposal, based on his current negotiation strategy, which evolves over time as the farmer gains new information. This negotiation cycle continues until all farmers are satisfied. An interesting component of these negotiations is the farmer types: some farmers are "selfish" and ask for more water than

they know they actually need, whereas other farmers are "reasonable" and ask for only what they need.

Some of these models include an element of social sustainability. Several models seek to maximize on-farm employment as well as farmer income (Gupta et al. 2000, Latinopoulos 2009, Raju and Kumar 2005). Other models include nutritional security as an objective, or water for human consumption as a constraint (Cai et al. 2002, Gupta et al. 2000, Ward and Pulido-Velazquez 2008). Models that include social sustainability have been applied to both industrialized and developing regions.

2.1.5 Crop planning

Increased agro-biodiversity, which is diversity of crop types within a food production system, can improve environmental sustainability through increased soil health, reduced soil erosion, and reduced need for synthetic pesticides. It can be achieved through intercropping, which is a technique in which different crops are grown together simultaneously, and/or through crop rotation over different growing seasons.

Optimizing crop rotation schedules for sustainable long-term yields is a well-studied problem, with applications in industrialized and developing regions. Many different optimization techniques have been applied to the problem of maximizing farmer revenue, subject to crop rotation constraints that are based on environmental sustainability considerations. Some modeling techniques that have been used to optimize crop rotation schedules include LPs (dos Santos et al. 2010, El-Nazer and McCarl 1986, Haneveld and Stegeman 2005), evolutionary algorithms (deVoil et al. 2006, Pavon et al. 2009, network optimization (Detlefsen and Jensen 2007), and stochastic modeling (Castellazzi et al. 2008). In addition to these traditional sustainability measures, Belcher et al. (2004) consider carbon

dioxide emissions in their computer simulation model when assessing the sustainability of a cropping system. While similar to other crop rotation models, the model developed by Amede et al. (2004) has a social sustainability focus, in addition to environmental constraints. The objective in their model is to determine cropping strategies that optimize human nutrition, rather than farmer revenues. Optimal schedules are then analyzed to determine their effects on soil erosion. In some cases, a food crop is interspersed with a non-food crop (intercropped), such as a cover crop or a perennial, which can reduce soil erosion, hold soil moisture, act as a windbreak, and provide other benefits to the food crop. Cellette et al. (2010) seek to determine an optimal intercropping strategy so that the benefits of the non-food crop outweigh the cost of maintaining it (e.g.,,, through extra irrigation). Sometimes, the non-food crop can provide additional benefits to the farmer, as in the case of agroforestry. With agroforestry, trees are planted among the food crops, and when the trees mature, they can be used for lumber or fuel, as modeled by Babu et al. (1995). In other cases, multiple food crops with different nutritional requirements and different susceptibilities to pests/disease can be intercropped together. Baumann et al. (2002) model this technique with the objective of suppressing weeds.

2.1.6 Energy use

Sustainable energy use in food production is an issue in both industrialized and developing regions. Developing regions often have limited access to sufficient energy inputs to produce enough food for the community. The LP model presented in Raja et al. (1997) indicates that energy use optimization through proper land allocation can result in higher incomes for farmers, as well as provide sufficient food for the community, without importing food or relying on external energy sources. Jana and Chattophadyay (2005) develop a multi-objective

fuzzy LP to optimize energy use, food production and farmer revenues, focusing on appropriate crop choice and planting times to reduce energy expenditures on irrigation. Both of these models only consider energy use associated with on-farm activities (e.g.,, irrigation, fertilizer application, plowing, transport) and do not include the energy required to produce inputs, such as chemical fertilizer.

By contrast, industrialized regions currently rely on cheap and abundant fossil fuels to supply most of their energy; however, this is not sustainable in the long term, and new energy sources need to be developed to meet the challenges of diminishing access to fossil fuels. One technique that could potentially meet this requirement is the production of biofuel crops (biomass). However, to be a viable solution, biomass production should not compete with food crop production, the net energy yields of growing biomass should be positive, and the system must be cost-effective. Callesen et al. (2010) develop an LP to model such a system under these constraints, as well as other environmental constraints (landscape preservation, minimal nitrate leaching, carbon sequestration in forests). They conclude that for their case study in Denmark, domestic biomass production cannot support domestic energy usage, even if extensive land-use changes are made and petroleum prices increase substantially.

2.1.7 Ecosystem biodiversity

When natural habitats are converted to agricultural systems, the indigenous wildlife often cannot survive the alteration or destruction of their habitat, resulting in migration or local extinction (Tilman et al. 2001). Such a reduction in ecosystem biodiversity is detrimental to food production systems; these species are often instrumental in pollinating crops and controlling pests. However, it is possible for agricultural production and native species to coexist if sufficient land is left unaltered, and this can be mutually beneficial (Quinn 2010).

To ensure economic and environmental sustainability, it is important to effectively allocate land to natural habitat and crop production. Holzkamper and Seppelt (2007) simultaneously optimize profits and ecological value (habitat suitability and biodiversity) on a land-use map. Polhill et al. (2013) develop an MAS to study the impacts of different government incentive schemes on farmers' land management decisions and the resulting species richness outcome in the region. The authors compare the effectiveness of an activity-based incentive scheme (in which farmers are rewarded for the amount of land made available for wildlife habitat) with an outcome-based scheme (in which farmers are rewarded for successfully increasing/maintaining species richness on their land). These incentives influence the farmers' satisficing algorithm and resulting land-use decisions. Experimental results indicate a nonlinear relationship between the incentive reward amount and biodiversity outcomes, which suggests that to be effective, incentive schemes must be tailored to their intended targets.

2.1.8 Multiple environmental elements

Several models address multiple areas of environmental sustainability with equal emphasis. Some of these models are intended to optimize operational decisions and practices, such as land use (Bouman et al. 1999, Roetter et al. 2005), on-farm best management practices (Annetts and Audsley 2002, Foltz et al. 1995, Forster et al. 2000, Srivastava et al. 2002) and food supply chain design (Quadra et al. 2009), to maximize farmer income while minimizing environmental impact or meeting environmental constraints. Other models test the impact of different environmental policies on economic, environmental and social sustainability. Onal et al. (1998) present an LP model that estimates the economic impact on farmers of regulations that limit soil erosion and pesticide runoff. Zander and Kachele (1999), Lopez-

Baldovin et al. (2006) and Manos et al. (2009) take this approach a step further, developing LP and weighted goal programming models to assess farmers' behavioral responses to policy (e.g.,, water tariffs) and the economic, environmental and/or social sustainability implications. Still other models estimate the impact of economic and trade policy changes on sustainability. Saysel et al. (2002) model a proposed large-scale regional development project using their computer simulation (GAPSIM). They show that change in regional economic strategy, such as increasing irrigation and changing production from subsistence to export crops, have significant implications for environmental and social sustainability. Van Ittersum et al. (2008) use their SEAMLESS modeling framework to estimate the impact of large-scale economic policy changes (such as trade liberalization) on global food production systems (including changes in the quantities and types of crops produced, and the resulting nitrate leaching and soil quality measurements).

2.1.9 Summary

Individual farm-level decision-making directly impacts large-scale FSC outcomes and long-term sustainability, which are critical to human and environmental health. Because of the importance of these outcomes, many mathematical models have been developed to explore the impacts of farm management decisions on the FSC. These models typically study the relationship between farm inputs (e.g., crop selection, fertilizers, pesticides, water) and outputs (e.g., food yields, profits, pollutants), with an aim to inform policy and/or guide farmer decision-making. Many optimization models have been developed for this purpose. However, very few of these models are able to capture stochastic or dynamic elements of FSCs, and most of these models only analyze a single stage of the FSC – food production.

They are incapable of modeling the sociological processes that influence decision-making by individual FSC actors (Higgins et al. 2010).

More recently, some MASs of farm management decisions have also been developed, which possess some of the desired capabilities that optimization models lack. The main limitation of the existing multi-agent work in the food supply domain is that it is generally applied only to the food-producing agents (usually farmers), excluding other FSC stages, such as processing and distribution. Additionally, the existing work does not explicitly consider the impacts of FSC structure on economic, environmental and social sustainability. Although MAS allows autonomous, heterogeneous and interactive farmer representation, few of the multi-agent food systems simulations available in the literature make full use of these features. In particular, the farmer agents of many multi-agent models make rational decisions using some type of optimization procedure assuming complete information.

While on-farm management decisions, which are captured by the optimization models and MASs in the existing literature, are indeed critical to FSC sustainability outcomes, the interactions among FSC members and different FSC stages, which define the structure of the FSC, are critical to capture. There is currently no existing literature that describes a modeling methodology to capture and study these aspects of the FSC with respect to long-term sustainability. However, for the case of general supply chains, the literature suggests a methodology: the application of a complex adaptive systems framework using MAS.

2.2 Modeling the FSC as a complex adaptive system using MAS

A complex adaptive system (CAS) is a system of interconnected autonomous entities that make choices to survive and, as a collective, evolves and self-organizes over time (Pathak et al. 2007). A CAS is characterized by complex behaviors that arise as the result of nonlinear

spatio-temporal interactions among a large number of components, in which highly-structured collective behavior emerges over time from the interaction of these components without any centralized control (Surana et al. 2005). A CAS changes inputs to outputs in a nonlinear way because its components interact with one another via a web of feedback loops (Anderson 1999). In such nonlinear systems, slight changes to just a few parameters and/or individual entities can drastically change the behavior of the overall system, which can be very different from the sum of the parts (Anderson 1999). CAS frameworks have been applied to the study of biological and social systems, and more recently to supply chains in the manufacturing and service sectors.

The seminal article by Choi et al. (2001) frames a supply network as a CAS and provides a detailed mapping of each property of a CAS to a supply network. For example, one characteristic of a CAS is self-organization through simultaneous and parallel actions of multiple agents. This property is shared with a supply network, which emerges with no one firm deliberately organizing and controlling it (Choi et al. 2001). Moyaux et al. (2006a) identify that supply chains are composed of heterogeneous, autonomous organizations gathered in large dynamic coalitions, wherein each organization pursues individual goals while satisfying local and global constraints, which is also true of CAS. These constituent organizations exhibit adaptivity and exist in a complex environment with a large number of relationships and interactions, as with a CAS (Pathak et al. 2007). A supply chain is a complex and dynamic network of interrelationships among firms that are constantly in flux, exhibiting unpredictable nonlinear system behaviors (North and Macal 2007, p. 63), which emerge from local decisions that are typically based on imperfect local knowledge (Moyaux et al. 2006a, Swaminathan et al. 1998). A well-known example of such unpredictable supply

chain behaviors is the "bull whip" effect, an emergent phenomenon that results from imperfect local knowledge informing the interactions among supply chain members (Surana et al. 2005).

When a supply chain is framed as a CAS, a key challenge in its design and management is determining what individual agent strategies lead to desired collective behavior; as such, discrete-event simulation (rather than analytical techniques) has been the primary tool for supply chain analysis (Surana et al. 2005, Pathak et al. 2007). However, MAS is designed to address many of the drawbacks of discrete-event simulation, such as its inability to capture changes in system structure over time (North and Macal 2007, p. 75). MAS provides a means of capturing complex cause and effect, nonlinearity, ambiguity, and dynamism (Pathak et al. 2007), all of which are inherent in supply chain behaviors. Because supply chain management is fundamentally concerned with coherence among multiple decision makers, an MAS framework based on explicit communication among agent members is an effective method of analysis (Swaminathan et al. 1998). In an MAS of a supply chain, agents are decision-making members that interact with other supply chain agents (e.g., receiving shipments/orders) and then make decisions (e.g., deciding how much to order/ship) based on their decision rules and information from their environment (North and Macal, pp. 88-89).

To capture the dynamic, stochastic, and multi-faceted elements of a FSC, recent research suggests that FSCs be modeled as complex adaptive systems (Meter 2006, Higgins et al. 2010). The FSC, with its network of interconnected and autonomous actors (e.g., farmers, processors, retailers), is well-suited for analysis as a CAS using MAS. However, there are very few existing MAS models of multi-stage food supply chains in the literature. Deffuant et al. (2002) capture the impact of the diffusion of information among farmers, consumers,

and government agencies on the economic and social benefits of organic farming, which informs farmers' decisions to convert to organic farming practices. In this model, a farmer's social network is determined by geographic proximity, with farmers in the same town communicating more frequently than with distant farmers, and farmers with similar farming systems having greater influence over one another. An interesting feature of this model is the inclusion of uncertainty in whether or not information is modified during the agents' interaction, which captures the difficulty of communicating complex ideas accurately. Archer et al. (2009) develop a discrete-event simulation of a sugar cane supply chain in which the actors are capable of simple decision-making and information-sharing processes.

The paucity of MAS-FSC models in the literature, relative to the vast number of analytical FSC models, may be a consequence of the difficulties inherent in MAS modeling. The seemingly unbounded capability of modeling details using MAS poses one of the most significant challenges to modelers, who must take care not to overwhelm a model with details and assumptions such that the focus on the original research question is lost or diminished (Johnson 1998). The data requirements for modeling an FSC using MAS are also potentially enormous, and finding sources of high-quality quantitative and qualitative data that fulfill the requirements of the model can be very difficult, particularly at the farming stage. In fact, the substantial data requirements alone may account for the sparseness of MAS-FSC models in the literature (Higgins et al. 2010). To overcome these challenges, the model scope and boundary conditions for an MAS-FSC model must be carefully determined. Two main factors will control the boundary conditions: the nature of the research questions being addressed and the availability of good-quality data. In general, as aspects of a model become increasingly detailed, more data is required, which implicitly

predisposes the model to be region-specific and potentially less generalizable. While many MAS models face some or all these challenges to varying extents, there are challenges that are specific to FSC modeling. A thorough analysis of the literature on food systems and food systems modeling reveals that FSCs consist of a combination of five elements that combine to create significant modeling challenges: 1) the natural environment, 2) planning and decision-making processes, 3) interactions among FSC stages, 4) economic processes, and 5) the political and social environment. These challenges are discussed at length in Krejci and Beamon (2012).

Despite these challenges, a major advantage of using MAS to model FSCs lies in its ability to represent interactions among autonomous agents and the emergent system behavior and structures that result. In particular, MAS has been used to study coordination and cooperation in supply chains, with a focus on the value of and conditions for information-sharing among agents. For example, Strader et al. (1998) develop an MAS to study the impact of different information-sharing strategies on order fulfillment cycle time and inventory cost in a supply chain. Moyaux et al. (2006b) also develop an MAS to study different information-sharing strategies, in which the supply chain agents are complex decision makers that select the strategy that maximizes their utility, where utility is a convex combination of inventory holding costs and backorder costs. Managing coordination is important to all types of supply chains, and the FSC is no exception. In particular, farmer decisions regarding coordination with other FSC members – such as whether to coordinate, with whom, and how – and the resulting impacts on FSC structure are of interest.

2.3 FSC coordination

Although farm-level coordination decisions are motivated by individual farmers' objectives of increased profit and/or decreased risk (Gillespie and Eidman 1998, Key 2005), they can have far-reaching and complex implications for overall FSC structural emergence, which in turn impact the outcomes and long-term sustainability of the FSC. Of particular importance is the effect of farmer coordination decisions on the degree of FSC centralization. Coordinated FSC production and distribution can lead to efficiencies and economies of scale through large-scale production and distribution of food (Godfray et al 2010); however, some argue that FSCs with decentralized and diverse structure are desirable because their lower resource intensity makes them inherently more stable and resilient (Dahlberg 2008). Coordination decisions also affect transportation decisions, which impact resource consumption (e.g., fuel). When farmers coordinate, they can consolidate their output and make more efficient transportation choices. However, large-scale coordination can encourage long-distance distribution of volumes that exceed regional consumption, which increases transport fuel consumption. Finally, these decisions impact social and economic measures amongst the farming community, in the forms of income and autonomy. Coordination can help farming communities build economic strength through scale, but if the implemented coordination mechanism involves significant losses to farmer autonomy, the net effect to the overall system can be negative (Lyson 2007, Kirby et al. 2007). Because the types of coordination mechanisms that farmers choose to implement for individual benefit can have positive or negative impacts on overall FSC outcomes, understanding the factors that influence the choice of coordination mechanism is important.

Two types of coordination can occur among FSC members: 1) vertical coordination, which occurs among different FSC echelons, (e.g., between farmers and distributors) and 2) horizontal coordination, which occurs among members within the same FSC echelon. This research focuses on farm-level horizontal coordination, in which farmers form strategic partnerships with other farmers to pool their resources and their outputs for greater efficiency and scale. Such coordination has become increasingly critical for small- and medium-sized farmers to remain profitable, enabling them to access markets in which customers prefer large and consistent volumes and to reduce costs through resource-sharing, particularly in post-harvest processing and distribution (Kirby et al. 2007). However, in deciding whether to coordinate, farmers must balance the potential benefits of coordination with the costs, which include the time, effort, and expenses involved with managing the coordination, as well as a loss of autonomy. This loss of autonomy is of particular importance, because autonomy is one of the most highly-valued aspects of the farming profession (Gasson 1973). In fact, farmers are often willing to sacrifice significant increases in income to maintain their autonomy (Gillespie and Eidman 1998, Key 2005).

Successful farmer coordination, in which all parties benefit from and are satisfied with the arrangement, depends on the selection and implementation of an appropriate FSC coordination mechanism. According to Xu and Beamon (2006), this depends on the coordinating farmers' operating environment, which is characterized by:

- Market factors, such as customer requirements, transport costs, and infrastructure
- The interdependence among the farmers, which can be characterized by the farmers' value of autonomy, their relative sizes, and their financial situations

- Environmental uncertainty, introduced through such factors as demand, prices, and weather
- Information technology in place/available, such as inventory management software to enable knowledge-sharing

The attributes of an appropriate coordination mechanism should match the characteristics of this operating environment. Per Xu and Beamon (2006), relevant coordination mechanism attributes include:

- The resource-sharing structure – possible values can range from no resource sharing among farmers, to operational-level information sharing, to a strategic alliance among coordinated farmers
- The decision style – possible values can range from centralized, in which one member has control and makes decisions for the coordinated group, to decentralized, in which each member makes decisions autonomously
- The level of control – possible values can range from a situation in which members follow strict rules and monitor each other frequently, to a situation in which there is very little monitoring
- Risk/reward sharing – possible values can range from a situation in which the risk-benefit ratio is fair, to a situation in which the risk-benefit ratio is unfair, with one member taking on less risk/responsibility but receives more benefits

For successful coordination, farmers should select a coordination mechanism implementation method that best matches the desired coordination mechanism attributes. Depending on the operating environment and mechanism attributes, examples of appropriate implementation methods include:

- An informal coordination arrangement in which neighboring farmers share equipment and consolidate their products for efficient transport to market, with each farmer making autonomous decisions (including crop selection) and sharing revenues and costs fairly
- A formal coordination structure in which one farmer (the "grower-shipper") acts as a centralized consolidation, processing, and shipping point, creating contracts with supplier farmers to provide a designated crop type that is monitored by the grower-shipper for minimum quality/quantity standards, at a price that unfairly benefits the grower-shipper
- A cooperative coordination structure in which farmers coordinate to produce a variety of products to meet their customers' demands with profits shared fairly and equal votes among members

In all of these examples of farmer coordination mechanism implementation methods, being a part of the coordinated group provides benefits to its members, through shared and efficient use of resources, volume consolidation for better prices, and improved access to markets. However, in each of these examples, the coordinated farmers must pay some type of coordination management cost and lose some degree of autonomy as a result of coordination. Therefore, the decision to coordinate depends on how much a farmer's autonomy is worth to him, how much he stands to gain as a result of the coordination, and how much autonomy he will lose through the coordination, given the characteristics of the coordination partner(s) and the nature of the coordination mechanism.

In this research, an innovative new agent-based methodology is used to study a specific farmer coordination mechanism, the degree to which it is implemented (given different operating environment characteristics), and the FSC structures and sustainability outcomes that result.

Chapter 3 : Model Description

3.1 Model overview

To address the research questions posed in Chapter 1, an agent-based model of a theoretical FSC was developed using NetLogo v. 5.0.2. A list of parameters and variables that are used to describe the model in this chapter can be found in Appendix A.

3.1.1 Model environment

The model environment consists of four distinct geographic regions. Each of these regions is populated with agents that represent participants at different echelons of the FSC. Each geographic region is characterized by its own demand and yield distributions, which allows for regional variability (e.g., some crops might be better suited to certain regional attributes, such as climate or soil type, resulting in different expected yields). Additionally, each region experiences its own weather each season, which partly determines the yield outcomes in that region.

3.1.2 Model entities

The model is composed of three primary agent types, each representing a different FSC echelon: farmers, distributors, and customers. These agents autonomously pursue their own individual objectives and interact with one another to produce, distribute, and purchase different types and classes of crops. Each agent has a designated geographic location in the model (denoted by unique combinations of x- and y-coordinates) and is assigned to one of the four regions. The distances among agents within the same region are relatively small compared with the distances between agents in different regions.

3.1.2.1 Crops

Crops are not agents – they are simple entities that are demanded, produced, and traded by agents. Crops have the following attributes: type, class, unit wholesale price parameters, production and harvest cost, and production change cost. Crops of different types are assumed to be distinct and non-substitutable with regard to customers' demand. Each crop type is further classified as being one of four different crop classes. Two factors determine a crop's class: 1) the production methods used to grow the crop (i.e., organic/conventional) and 2) the distance the crop travels from its source to the point of consumption (i.e., regionally-sourced/distant). Crop class partly determines a crop's value to a customer; for example, customers often value organic crops over conventional crops (and are willing to pay more for them) because of the perceived benefits associated with organic production (e.g increased food safety and nutrition). Table 3.1 shows the characteristics of the different crop classes in the model.

Each crop type/class has its own set of unit wholesale price parameters, which are fixed throughout a simulation replication. At each time-step (where each time-step represents one growing season), a crop type/class unit wholesale price is randomly determined using these parameters. Each crop type/class is also assigned a production cost and a harvest cost, which are measured in dollars per acre, and each pair of different crop types/classes is assigned a production change cost, which is the cost that a farmer must pay to change from one crop/class to another. This cost represents the amount that a farmer would pay to purchase new equipment, acquire new production knowledge, and obtain certification (in the case of organic production).

All crop types/classes are measured in terms of "crop units". The unit cost per unit distance of transporting any of the crop types/classes is assumed to be the same. It is assumed that all crop types are perishable and cannot be stored in inventory from one time-step (i.e., growing season) to the next – any crops left unsold at the end of a time-step are assumed to have no value.

Crop Class #	Crop Class Name	Production Method	Source-Demand Proximity
0	organic+regional	organic	regional
1	organic	organic	distant
2	regional	conventional	regional
3	conventional	conventional	distant

Table 3.1. Characteristics of different crop classes.

3.1.2.2 Farmer agents

Farmers are the only agents that are capable of producing crops. Primary farmer activities include crop type/class selection, production, and sale to distributors. In addition to his region and geographic location, each farmer is assigned a farm "size" in acres (s_f) . A farmer's farm size is constant throughout a model run (i.e., farmers cannot buy or sell land). It is assumed that a farmer will always plant crops on all of the land he owns (i.e., he will not allow any land to lie fallow). In a given season, each farmer is limited to producing a single crop type/class on his land, although a farmer may change crop types/classes from one season to the next, if he is able to afford the associated production change cost.

To engage in crop production and sale, a farmer must have sufficient cash to pay for production, harvest, and transportation costs. It is assumed that farmers do not have access to credit. Therefore, if a farmer does not have sufficient cash to produce, his state changes to "out of business", and he is removed from the model for the duration of the model replication. Although farmers must leave the system if they are no longer financially viable, no new

farmers can join the system during a replication. Farmers accrue or deplete their cash as a result of their seasonal profit, which is the difference between crop sale revenues and costs.

Farmers are motivated to make a profit by their utility function. Farmers each have a convex and increasing utility function, with values for each farmer $f(U_f)$ ranging from 0 to 1 (unitless), which maps their seasonal profit values to utility values. The farmer's only objective is to select, grow, and sell crops to make as large a profit as possible each season, thereby achieving the largest possible personal utility. Farmers are assigned a utility threshold value (unitless) that designates the utility value below which the farmer is "dissatisfied". Farmer dissatisfaction may trigger a change in behavior, such as a decision to switch to a different crop type or class, and/or a decision to join or leave a coordinated farmer group.

It is assumed that farmers are predisposed to work independently. To capture farmers' predisposition to work independently, farmers are assigned an autonomy premium, the value of which determines the amount of extra profit a farmer would need to acquire as a member of a coordinated group to achieve an equivalent utility as an independent producer. For example, if an independent farmer with an autonomy premium of 1 achieved a utility value of 0.80 as a result of acquiring $30,000 in profit last year, as a member of a coordinated group, that farmer would require $30,000 + ($30,000 * 1) = $60,000 dollars in profit in a given season to achieve a utility value of 0.80. Because it is assumed that farmers are predisposed to work independently, a farmer's autonomy premium is always non-negative.

Coordinated farmers each have a "differential" value, designating the percentage over/under their fair share of group yields that they have negotiated as a condition of their joining the coordinated group. Coordinated farmers also have a "current group" attribute,

which is the set of farmers with whom the farmer is currently coordinated. At any point during the simulation, a farmer is either "independent" or "coordinated", meaning that he is either working by himself or part of a coordinated farmer group.

3.1.2.3 Farmer collective agents

The collective sets of farmer agents that comprise coordinated farmer groups are represented by agents that have their own attributes and states but are relatively simple entities, compared with their individual farmer members. These collectives do not have utility functions or objectives that are separate from the individual farmer members'. That is, a collective would not decide, at the expense of individual members, to perform an action to benefit the group as a whole. For example, a group's crop selection decision is based on the votes of the individual members, who are only considering their own individual objectives. Even if the crop selected by the majority of the group would cause some members financial hardship and convince them to leave the group (thereby hurting the group as a whole by reducing its size and influence), the collective does not consider this cost in its decision-making.

3.1.2.4 Distributor agents

A single distributor agent is assigned to each of the four geographical regions. The distributor agent acts as an intermediary between farmers and customers and as an inventory consolidation point. Its primary activities are negotiating crop prices with farmers, purchasing crops from farmers, and selling these crops to customers. A distributor may purchase crops from farmers in any of the four regions; however, it is only allowed to sell to customers that are located in its own region. Unlike farmer agents, distributors do not have utility functions. Instead, they have rule-based motivations to maximize their profits. A distributor's objective is to fill its demand in as few transactions as possible, while paying the

lowest price possible. Each distributor competes with the other distributors for farmers' business and will adapt its procurement strategy as necessary over time in response to successful/unsuccessful bids and system supply-demand ratios.

3.1.2.5 Customer agents

Customer agents in each region represent demand for crops that comes from institutional customers (e.g., schools, grocery stores, restaurants), with each customer representing a certain percentage of their region's demand for each crop type. Each customer belongs to one of two possible preference classes (i.e., Class 0 and Class 1), which determines his preference for certain crop attributes and the rules he uses to substitute when the preferred crop class is not available. The preferences and substitution rules are given in Table 3.2.

Customers are completely described by three attributes: their region, their demand, and their preference class. They are designed to represent individual demand that their respective regional distributors attempt to fill. They do not interact with other agents.

Customer Preference Class	Most Preferred Crop Class	Substitute	Substitution Rule
0	conventional	organic+regional	Will pay conventional price
		organic	Will pay conventional price
		regional	Will pay conventional price
1	organic+regional	organic	If no organic+regional available; will pay organic price
		regional	If no organic available; will pay regional price
		conventional	If no regional available; will pay conventional price

Table 3.2. Characteristics of different customer preference classes.

3.1.3 Process overview

Figure 3.1 provides an overview of all of the processes that occur in the model during a single time-step. Each time-step represents a single growing season, in which farmers produce crops and sell them to distributors, evaluate their utility, make decisions about joining and leaving coordinated farmer production groups, and select crops for next season's production.

3.2 Model details

The following section describes each submodel in detail, including initialization, crop production, crop sale, farmer evaluation, farmer coordination, and crop selection processes. These descriptions include detailed explanations of agent decision-making processes, interactions, and adaptations, as well as details of model parameters and variable updating calculations.

3.2.1 Initialization

At the beginning of each model replication, the agents are created, are assigned to one of the four regions, and are given geographic locations. The values of other agent attributes and system state variables are initialized, and parameter values are read in from input files. Farmers always begin a new replication working independently (i.e., not as part of a coordinated group). They are randomly assigned crop types/classes and are each given a certain amount of startup cash (a model parameter).

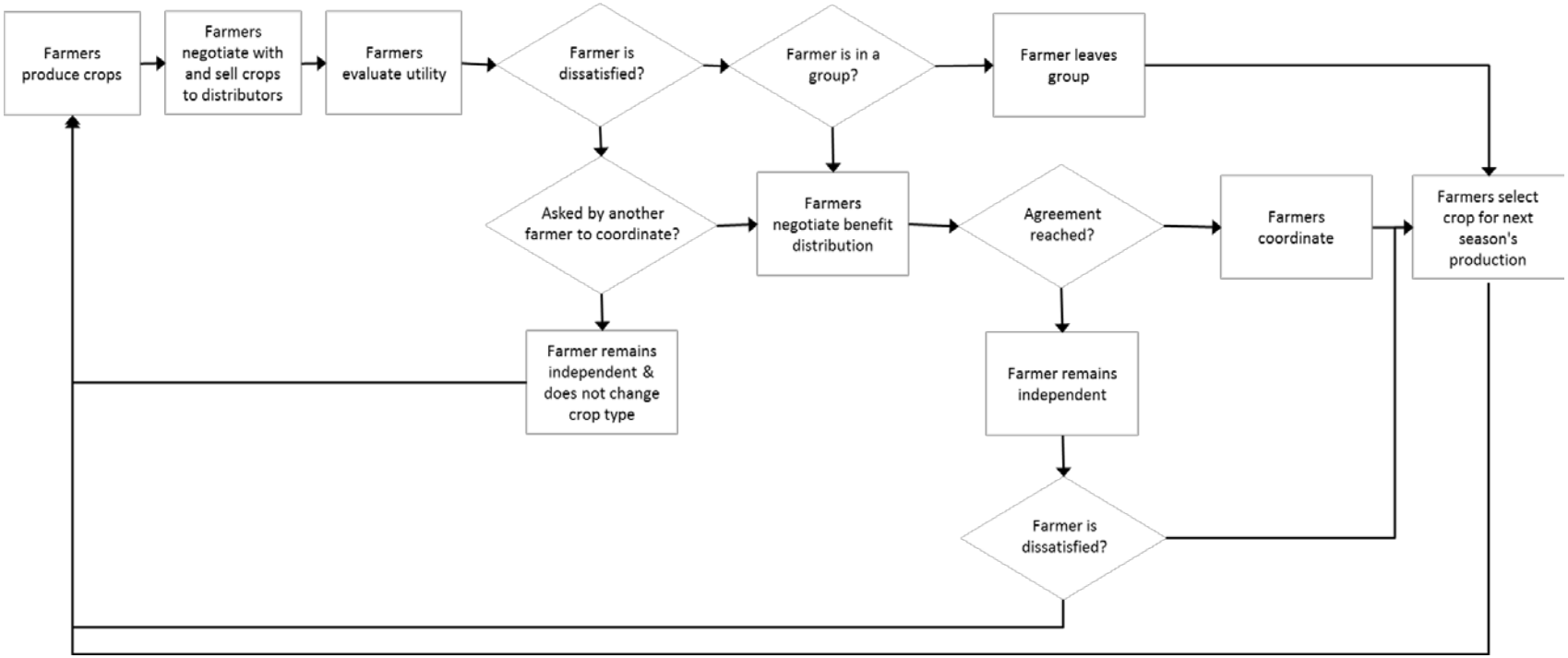


Figure 3.1. Model overview.

3.2.2 Crop production

At the start of each time-step, all farmers produce the crop type/class that they were assigned in the previous time-step. In the crop production submodel (Figure 3.2), farmers are randomly scheduled to produce and harvest their chosen crop. The farmers begin by "planting" their crops, which results in a reduction of their cash by the associated production cost per acre, as well as an incremental decrease in each farmer's crop inertia premium value (σ_c). The inertia premium is set to 1 in the first year of production, and each consecutive year that the farmer produces that same crop thereafter, it is decremented by 0.1 (to a minimum value of 0.1). At this point, a weather factor is determined for each region (μ_r). Each farmer's base yield outcome per acre ($y_{cf(base)}$) is then drawn from a triangular distribution (chosen for its relatively small variance and the ability to restrict variates to non-negative values), using the yield parameters associated with the farmer's chosen crop/class and region. This outcome is then multiplied by the farmer's farm size in acres (s_f) for the total farm yield, which is then multiplied by the regional weather factor (μ_r) to calculate the farmer's actual yield (y_{cf}) for the current time-step:

$$y_{cf} = y_{cf(base)} \times s_f \times \mu_r$$

Each farmer's cash is then reduced by the cost of harvesting his yield.

After harvest, the farmers update their inventory values (η) to reflect their current yields. If a farmer is working independently, he will simply update his own current inventory value. Farmers that are members of coordinated farmer groups consolidate their inventory and update their group inventory value. It is assumed that the group members transport their yields to the group leader's location, which results in a local transport cost for all non-leader farmers. Finally, the profit share value (π_j) for each group member j is calculated, based on

ratio of the inventory that he contributed to the total group inventory, plus his current differential value τ, which is the farmer's group profit premium. A farmer that is not part of a coordinated group has a τ value of zero. When a farmer considers joining a coordination partner/group, his decision to join the group is determined by the value of τ, which is the outcome of negotiations between the farmer and the coordination group. The process of calculating τ for each grouped farmer is described in detail in Section 3.2.5.

$$\pi_j = \frac{\eta_j}{\sum_j \eta_j} + \tau$$

3.2.3 Crop sale

Once the farmers have harvested their crops and transferred them to inventory, the next step is to try to sell the crops to the regional distributors (see Figure 3.3). After regional demands are created (i.e., they are drawn from a triangular distribution, given parameters for each crop type/class and region), crop sales then proceed, one crop at a time. Each farmer/group that has the current crop available in inventory (a "seller") is then assigned a probability of being the next producer to go to market. A seller's probability of being selected is proportional to the seller's relative crop volume, because larger farmers are assumed to have more market clout. However, the actual selection to go to market is stochastic, which reflects the randomness of the timing of market readiness – regardless of volume, the timing of crops' ripeness and harvesting is somewhat outside a farmer's control (e.g., due to weather, local soil conditions, or availability of harvesting labor). In general, it is more desirable to go to market as early as possible, because unfilled demand is greater earlier in the selling period. Therefore, greater volume is a market advantage, and large farmers and farmer groups benefit from this.

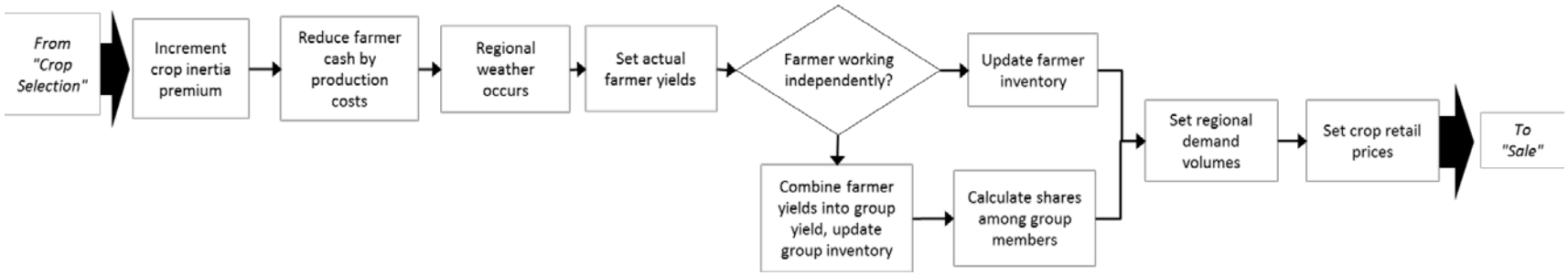


Figure 3.2. Crop production process.

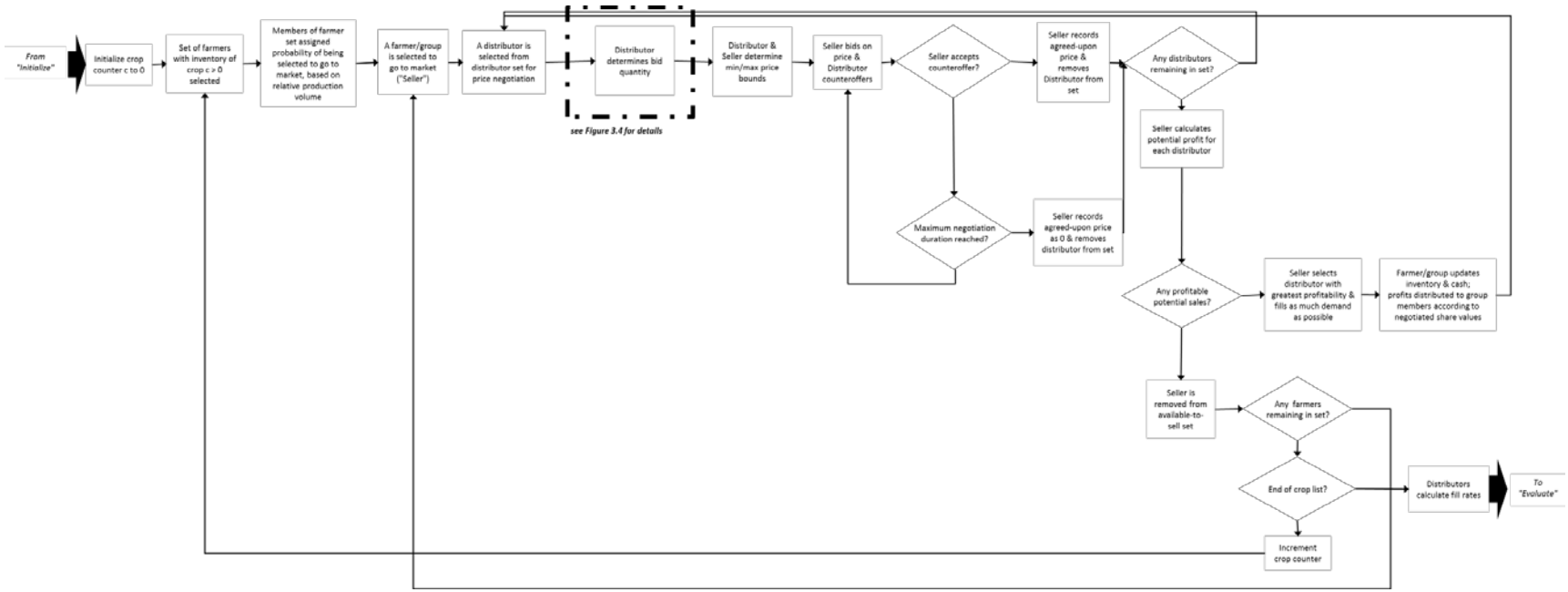


Figure 3.3. Crop sale process.

After being assigned a market selection probability, each seller is randomly selected, one at a time, to market its inventory to the distributors. The current seller must decide which of the distributors is the best (i.e., most profitable) customer, and it will sell as much of its inventory as possible to that distributor. It is assumed that the farmer is selling to the distributor on the "spot market" rather than through contract. Therefore, to make this decision, the seller first needs to negotiate a unit price and a sales volume with each distributor, which tells the seller how much revenue each distributor will provide. The seller then subtracts the respective transport cost from each distributor's revenue value to determine the profit that would be earned from selling to that distributor. The seller then simply selects the distributor that provides the greatest profit and sells it the agreed-upon volume at the negotiated unit price. If the seller has inventory remaining after this sale, it will reevaluate the remaining unselected distributors as before, and will repeat the negotiation and sale process until either it runs out of inventory or there is no remaining distributor demand for the seller's crop at a price that the seller and distributor will accept.

Before the negotiation process can occur, the distributor must decide how much volume it wants to purchase from the seller, and it also requires the distributor and seller to determine their lower and upper bounds on unit price. These agent decision-making processes are described in the next two sections.

3.2.3.1 Distributor bid quantity strategy

A distributor agent's purpose is to act as a consolidation point and an intermediary between farmers and customers by purchasing crops from farmers from any region and selling them to customers in its own region. It is assumed that all of the distributors know their customers' demand and crop preferences exactly each season. However, the distributors do not have

much information about the available supply, which reflects real-life FSC conditions in which distributors have not developed contracts with specific suppliers (Tavella and Hjortso 2012). It is assumed that the distributors know the overall global supply-demand ratio for each crop type each season, as well as the supply-demand ratios for conventional and organic crops by type. This limited information presents a challenge to the distributors as they develop inventory replenishment strategies, particularly in determining the volume to order from each seller that arrives at market. It is assumed that none of the distributors knows how many opportunities there will be to purchase a given crop type/class in a given season. That is, as each seller markets its yield, the distributors do not know how many future producers will follow, nor do they know what crop classes or quantities will be offered by subsequent producers. All they know is that with each successive producer, the probability of there being more producers/supply in the future diminishes.

If a seller arrives on the market and is offering a crop type/class for which a distributor has unfilled most-preferred demand, the distributor's bid quantity decision is simple – it wants to order as much of this crop type/class as it has unfilled demand. However, the bid quantity decision becomes more difficult when the seller is offering a crop class for which a distributor has less-preferred demand. This can occur in two ways: 1) when the distributor's customer would be willing to pay more for a higher crop class than the one offered (e.g., when a conventionally-produced crop is offered but the distributor's customer most prefers organic), or alternatively 2) when the distributor's customer is unwilling to pay the offered crop class's actual market value (e.g., when an organically-produced crop is offered but the distributor's customer is only willing to pay the conventional market price). In the first case, it is assumed that the distributor can upward substitute a lower-class product to the customer,

but that it will incur opportunity cost for doing so. In reality, this substitution could also cost the distributor customer goodwill (because the customer did not get its most-preferred crop class) or prevent the sale entirely (because some customers that prefer organic may not be willing to substitute with conventional food). In the second case, it is assumed that the distributor can downward substitute a higher-class product to the customer, but only at the price the customer is willing to pay. The distributor would incur an actual cost for making this type of substitution, but in reality might also gain customer goodwill for providing a higher-class crop at the lower-class price.

In terms of fill rate alone, it is better for the distributor to fill a customer's demand with a less-preferred crop class than to leave the demand unfilled. However, if the distributor were to only focus on fill rate and ignore its customers' preferences for certain crop attributes, the distributor would potentially incur opportunity costs and lost revenue as a result of substitutions. Additionally, to keep transactions to a minimum, a distributor will attempt to purchase crops in large quantities. However, large purchases can inhibit distributor flexibility in filling demand for particular crop classes accurately, thereby increasing opportunity costs and lost revenue. Finally, each distributor wants to place as competitive a bid as possible with each seller, and larger bids are generally more desirable to the seller. With all of these factors in mind, a distributor must do its best to balance current and expected future opportunity costs and lost revenue with each transaction.

Given that the distributors do not have any information about supply, other than the global supply-demand ratio for each crop, their inventory replenishment strategy is necessarily simple. Figure 3.4 provides an overview of this process. In determining its bid quantity, each distributor first assesses the general class of the crop being offered:

conventional or organic. If the crop is conventional, then the distributor determines how much unfilled most-preferred demand it currently has for the conventional class of the crop; otherwise, it will check its unfilled most-preferred demand for the organic crop. This unfilled demand is the distributors "ideal demand". Next, the distributor compares its actual current inventory of this crop (disregarding crop class) with its current fill-rate goal. The distributor's fill-rate goal is dynamic and increases by a constant amount Δ with every seller that appears on the market. For example, if Δ is set to 0.05, then after the first seller, each distributor hopes to have at least 5% of its demand in stock. After the second producer offering, the goal is to have at least 10% of demand in stock, and so on. This procedure allows the distributor to be more selective about what it purchases when it has plenty of inventory, but forces it to purchase any class available when it does not have much inventory (i.e., it is more desperate). The value of Δ depends on the global supply-demand ratio for the offered crop – the Δ value is smaller if there is more supply than demand, because the distributor is less concerned about filling demand.

If the distributor's inventory of the offered crop meets or exceeds its current fill-rate goal, the distributor will only place a bid if it has unfilled ideal demand for the offered crop, and in this case it will seek to purchase as much of this offering as there is demand for it. Otherwise, it will not bid (i.e., it will set its bid quantity to zero) – it will not purchase any crops of classes that would require downward or upward substitution in filling demand. However, if the distributor is not meeting its current fill-rate goal, it will attempt to fill the gap between actual and goal fill rate with any crop class (i.e., substitutions are allowed). If the distributor has unfilled ideal demand for the offered crop, it will fill as much of this demand as possible (even if this amount exceeds the actual fill-rate-goal difference).

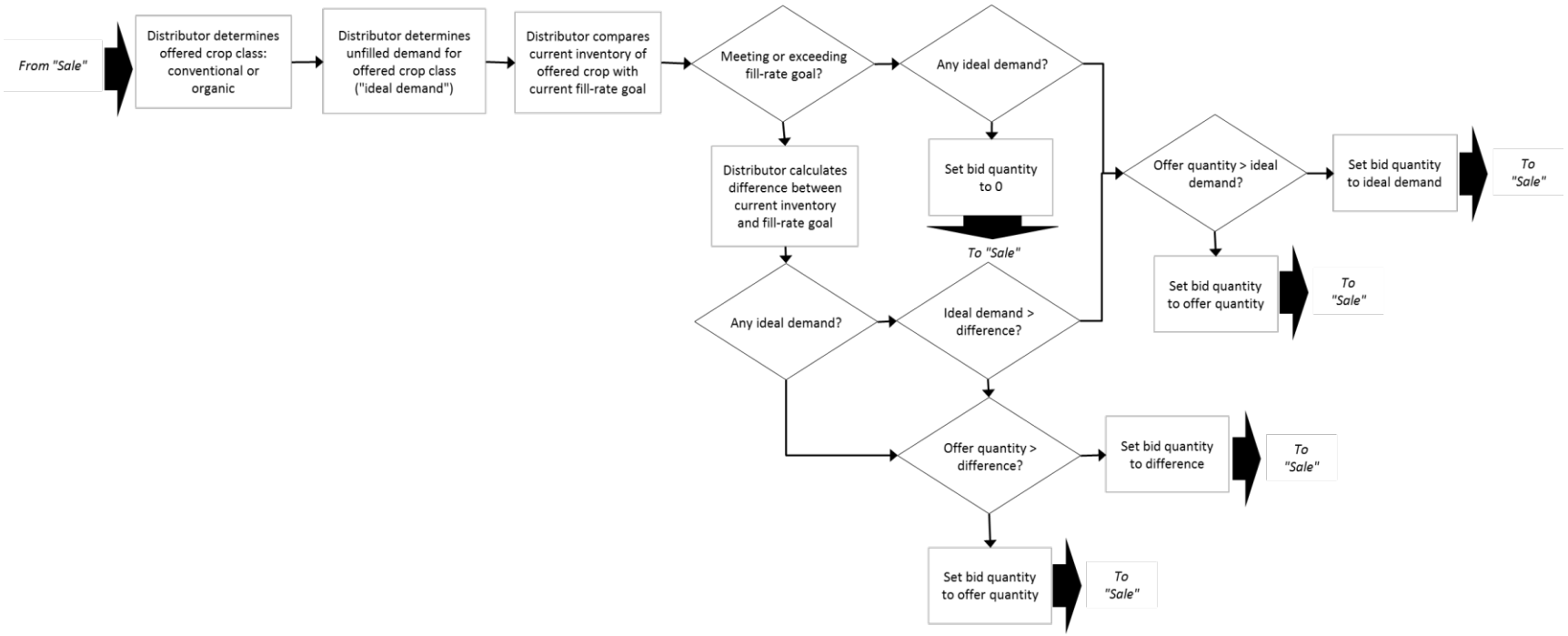


Figure 3.4. Distributor bid quantity determination process.

Otherwise, the distributor will set its bid quantity to the fill-rate-goal difference – it is assumed that the distributor would prefer to fill its demand imperfectly, rather than risking a stock-out. Note that it is assumed that a distributor will never purchase more than its total demand for the offered crop in an effort to more accurately fill demand.

3.2.3.2 Negotiation

If the distributor's bid quantity is greater than zero, the distributor and seller proceed to the next step in the crop sale process: negotiating a unit price. The farmer-distributor negotiation process is based on the assumption of a stable "retail price". The retail price is the price at which the distributor's customer (the retailer) will sell a unit of crop to the end consumer. This price is assumed to be relatively stable, given that retailers want to provide consistent prices to the consumer (Dimitri et al. 2003). The wholesale unit price (u_c) is the unit price the retailer will pay the distributor for crop type/class c. Because the price negotiations and transactions between the distributor and retailer are not explicitly modeled here, and because it is assumed that the retail price is stable, u_c is assumed to be a percentage of the retail price and will therefore also be stable. In keeping with this assumption, each season u_c is drawn from a triangular distribution with a low variance to reflect retail/wholesale price stability while accounting for some small random fluctuations that can occur from season to season, based on retailers' pricing strategies and consumers' preferences. This wholesale unit price (u_c) is used as a basis for calculating upper bounds on z_{cfrv}, which is the unit price that seller f and distributor r agree on for volume v_{cfr} units of crop c (where v_{cfr} is the distributor's bid quantity) after a process of negotiation.

The seller's initial lower bound (z_{clf}) on z_{cfrv} is the unit cost of producing, harvesting, and transporting crop c to distributor r, plus a markup based on the seller's minimum allowable

gross margin ($g_{f(min)}$). The calculation of z_{clf} is based on the equation for calculating gross margin:

$$gross\ margin = \frac{revenue - cost\ of\ goods\ sold}{revenue}$$

The unit transport cost is calculated by first calculating the total cost of transporting v_{cfr} units of crop c from seller f to distributor r:

$$t_{vfr} = \left(\omega \times v_{cfr}\right)^{\varphi} \times {\lambda_{fr}}^{\theta}$$

where ω and φ are volume-cost parameters, λ_{fr} is the distance from seller f to distributor r, and θ is a distance-cost parameter (adapted from Jansson 2006, pp. 74-77). The total transport cost is then divided by v_{cfr} to yield the unit transport cost. The unit cost of producing and harvesting is calculated by dividing the sum of the total seller production cost (p_{cf}) and harvest cost (h_{cf}) for crop c by the seller's total yield of crop c (y_{cf}). The equation for gross margin can then be rearranged to solve for z_{clf}, which is the revenue per unit required to earn the desired gross margin ($g_{f(min)}$), given the unit costs of production, harvest, and transport:

$$z_{clf} = \frac{\left(\frac{p_{cf} + h_{cs}}{y_{cf}} + \frac{t_{vfr}}{v_{cfr}}\right)}{\left(1 - g_{f(min)}\right)}$$

The initial upper price bound for seller f (z_{cuf}) on z_{cfrv} is the current market wholesale unit price (u_c), which is assumed to be known by both the seller and the distributor, and is the same for all distributors in the system.

$$z_{cuf} = u_c$$

The distributor's lower bound on z_{cfrv} is equal to the seller's costs before markup. It is assumed that the distributor knows this value and assumes that the seller would not sell below it.

$$z_{clr} = \left(\frac{p_{cf} + h_{cs}}{y_{cf}} + \frac{t_{vfr}}{v_{cfr}}\right)$$

The distributor's upper bound (z_{cur}) is dynamic throughout the selling subroutine. It is initialized as follows. First, the maximum value of z_{cur} is calculated. This value ($z_{cur(max)}$) depends on the overall system supply-demand ratio for crop *c*. If the system supply of crop *c* is greater than or equal to system demand ($S_c \geq D_c$), the distributors need not worry about being competitive and simply set their maximum upper bound at the start of the selling season to a predetermined minimum value ($z_{cur(min)}$, where $z_{cur(min)} > z_{clr}$), which is a fraction of the wholesale unit price (u_c). However, if the system supply is less than system demand ($S_c < D_c$), then distributors must account for with larger upper bounds to remain competitive. In this case, $z_{cur(max)}$ is a linear function of the supply-demand ratio, with a maximum value of u_c when the supply-demand ratio equals zero, and a minimum value of $z_{cur(min)}$ when the supply-demand ratio equals 1.

$$z_{cur(max)} = \begin{cases} \left(z_{cur(min)} - u_c\right) \times \dfrac{S_c}{D_c} + u_c, & \dfrac{S_c}{D_c} < 1 \\ z_{cur(min)}, & \dfrac{S_c}{D_c} \geq 1 \end{cases}$$

The distributor's upper bound (z_{cur}) is a percentage of $z_{cur(max)}$, and this percentage depends on the seller's volume (v_{cfr}). Specifically, z_{cur} increases as the percentage of the distributor's overall demand for crop *c* that can be filled by the seller $\left(\frac{v_{cfr}}{D_{cr}}\right)$ increases, reflecting distributors' preference for large volumes. The rate at which z_{cur} increases with volume depends on q_r, which represents the strength of the distributor's preference for large volumes. When q_r is large, the relationship between volume and price is strong (i.e.,, the unit price that the distributor is willing to pay becomes directly proportional to the volume as $q_r \rightarrow 1$). It is

assumed that z_{cur} is an exponential function of $\frac{v_{cfr}}{D_{cr}}$, with a lower bound of zero (when $v_{cfr} = 0$) and an upper bound of $z_{cur(max)}$ (when $\frac{v_{cfr}}{D_{cr}} = 1$). If z_{cur} is less than the distributor's lower bound (z_{clr}), then z_{cur} is set to z_{clr}.

$$z_{cur} = \max\left(z_{clr}, \left(\frac{1 - e^{-\frac{\frac{v_{cfr}}{D_{cr}}}{q_r}}}{1 - e^{-\frac{1}{q_r}}}\right) \times z_{cur(\max)}\right)$$

This upper bound z_{cur} is the maximum value that the distributor is willing to pay for a unit of crop *c*, and this value becomes a basis for the distributor-seller negotiation process.

The negotiation process initializes with seller *f* offering z_{cuf} (so $x_{f(0)} = z_{cuf} = u_c$), and distributor *r* counteroffering z_{clr} to the seller. The iterative negotiation process then begins with the seller response of bidding a unit price that is the midpoint between his previous bid, $x_{f(b-1)}$, and the maximum of z_{clf} and $x_{r(b-1)}$; that is,

$$x_{f(b)} = \frac{x_{f(b-1)} - \max(z_{clf}, x_{r(b-1)})}{2} + \max(z_{clf}, x_{r(b-1)})$$

Distributor *r* counteroffers with a unit price that is the midpoint between its own previous bid, $x_{r(b-1)}$, and the minimum of z_{cur} and $x_{f(b)}$; that is,

$$x_{r(b)} = \frac{\min(z_{cur}, x_{f(b)}) - x_{r(b-1)}}{2} + \min(z_{cur}, x_{f(b)})$$

The absolute value of the difference between the seller's offer and the distributor's counteroffer is calculated and compared with the constant δ; if the difference is greater than δ, the bid counter *b* is incremented by 1. If *b* does not exceed *B* (where *B* is the maximum allowable value of *b* before negotiations terminate unsuccessfully) , then bid values are updated and another iteration of the negotiation proceeds, but if *b* exceeds *B*, then the negotiation terminates without price agreement being reached, and z_{cfrv} is set to zero.

However, if the difference between the seller's and distributor's offers does not exceed δ, the seller accepts distributor *r*'s most recent counteroffer and the negotiation terminates, with the agreed-upon price z_{cfrv} set to $x_{r(b)}$. Regardless of the outcome, once the negotiation terminates, seller *f* moves on to the next distributor (setting *r* to *r* + 1). The values v_{cfr} and t_{vfr} are recalculated for distributor (*r* + 1), and negotiations for $z_{cf(r+1)v}$ begin, using the same negotiation process previously described.

Once seller *f* has negotiated prices with all the distributors in the distributor set, he will calculate the net return (revenue minus transport cost) from selling to each distributor:

$$m_{cfvr} = \left(z_{cfrv} \times v_{cfr}\right) - t_{vfr}$$

The seller selects the distributor with the largest return (distributor r_f^*) and sells v_{cfr} units of crop *c* to that distributor:

$$r_f^* = \{r | m_{cfvr} = \max\{m_{cfvr}\} \forall r\}$$

If the seller has enough inventory remaining to fulfill any other distributor's demand for crop *c*, the entire negotiation process starts again. This cycle continues until it is no longer worthwhile for the seller to make a transaction with any distributor (i.e., $m_{cfvr} \leq 0 \; \forall \; r$) .

After each seller has completed negotiations with the entire distributor set and selected a distributor to which to sell, each distributor will adjust $z_{cur(max)}$ depending upon whether he won or lost the sale, in order to stay competitive. If distributor *r* won the current sale *k*, it will reduce its current maximum upper bound for the next round of negotiations. The amount by which it reduces this value depends on the supply-demand ratio – if demand is greater than supply, it will reduce it by a small amount; if supply is greater than demand, it will feel confident enough to reduce it by a larger amount. Regardless, it will never reduce it below $z_{cur(min)}$.

$$z_{cur(max)_{k+1}} = z_{cur(max)_k} - \Delta$$

On the other hand, if distributor *r* lost the current sale *k*, it will increase its current maximum upper bound for the next round of negotiations, in hopes of attracting the next sale with a better offer. It is assumed that the losing distributors do not know how much the winning sale price is, so they must blindly adjust their own price. The amount by which a distributor increases this value depends on the supply-demand ratio – if supply is greater than demand, it will increase it by a small amount; if demand is greater than supply, it will increase it by a larger amount. Regardless, it will never increase it above u_c.

$$z_{cur(max)_{k+1}} = z_{cur(max)_k} + \Delta$$

3.2.4 Farmer evaluation

After all crop sales are finalized, all farmer group profits have been determined, and profits have been allocated to group members, each individual farmer agent next evaluates his resulting financial position and utility (see Figure 3.5). The outcome of this evaluation will direct the farmer's decisions regarding coordination and crop selection. Farmers run this submodel in random order – it is assumed that the farmer decisions are made concurrently, such that the order of submodel scheduling does not matter. First, the farmer determines whether he has enough cash to continue his farming operation – it is assumed that farmers do not have access to credit. Using expected costs, the farmer estimates the cost of producing and selling his current crop next season. For the farmer to stay in business, it is assumed that he must have enough cash to produce, harvest, and transport the expected yield from his entire acreage (i.e., it is assumed that he must plant crops on all of his land). If he does not have enough cash, he is removed from the model for the rest of the replication. His land also effectively disappears from the model – it is not reallocated to other farmers. In reality,

failed farmers' land is sometimes purchased by other farmers, while in other cases (as in this model) the land is purchased by developers and is no longer farmed.

If farmer *f* has enough cash to remain in business, his next step is to calculate the value of his current utility (U_f), which will guide his strategic decision-making regarding future crop selection and coordination. A farmer's utility is based on his current profit value (γ_f^*), which depends on the farmer's group status. If the farmer is working individually, γ_f^* is simply the amount of profit (γ_f) that he received after selling his crops. However, if he is a member of a group, the value of his profit will be reduced by his autonomy premium (α):

$$\gamma_f^* = \frac{\gamma_f}{(1+\alpha)}$$

The utility function form is assumed to be the same for all farmers in the system. It is an exponential utility function that is scaled such that U_f ranges from zero to one and increases monotonically over profit values γ_f^* (Garvey 2008, pp. 71-74):

$$U_f = \frac{1 - e^{\frac{-(\gamma_f^* - \gamma_{f(min)})}{\rho_f}}}{1 - e^{\frac{-(\gamma_{f(max)} - \gamma_{f(min)})}{\rho_f}}}$$

where $\gamma_{f(min)}$ and $\gamma_{f(max)}$ are the minimum and maximum profit parameter values, respectively, for farmer *f*, and ρ_f is the "risk tolerance" of farmer *f*. The value of ρ_f governs the shape of the utility function, where utility decreases with increasing values of ρ_f for a given profit value. Effectively, a farmer with an autonomy premium greater than zero will experience less utility from a given profit value when he is a group member than he would if he were working independently. The farmer's utility value is then appended to his utility history list (i.e., his "memory"). Each season, this utility memory is accessed to determine the farmer's current level of satisfaction.

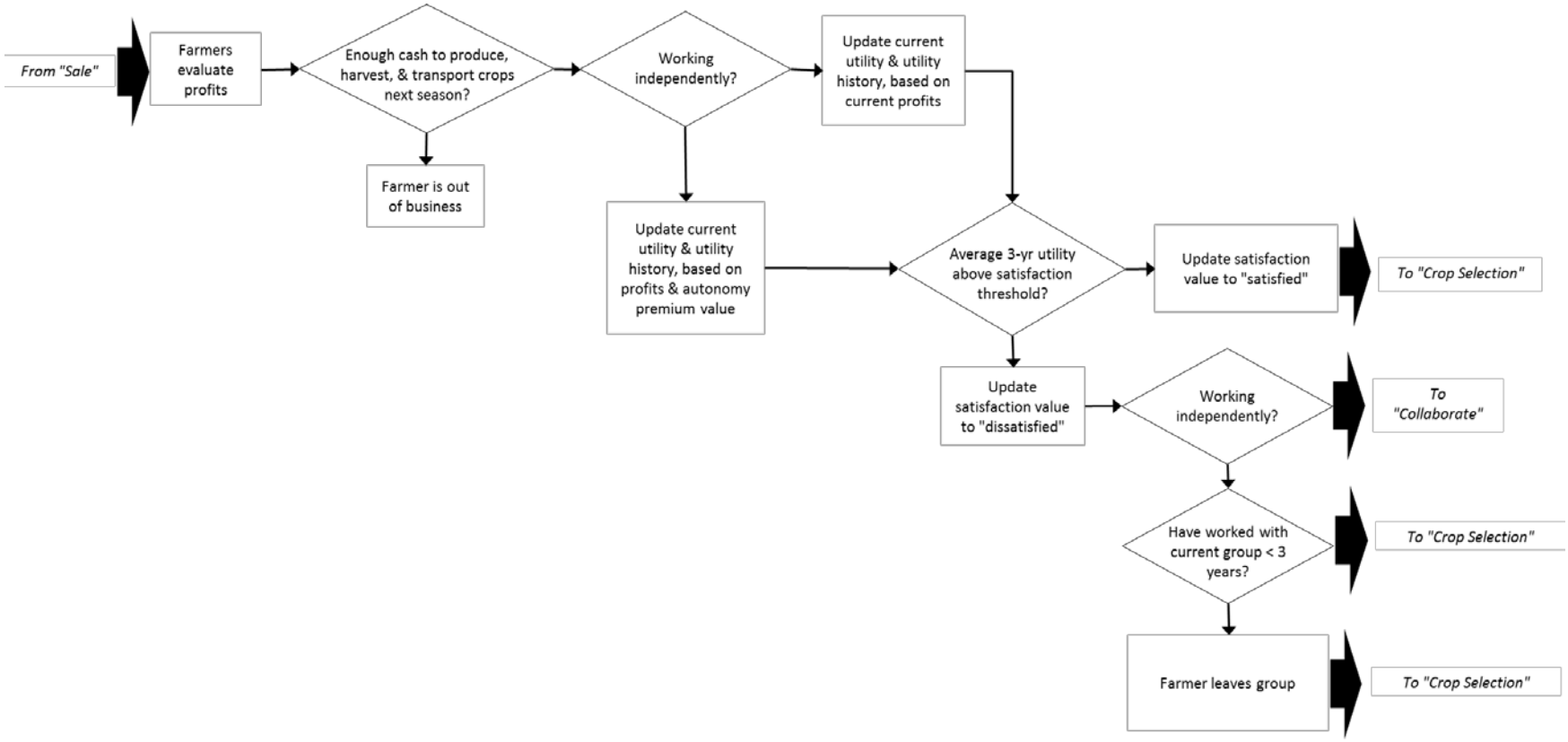


Figure 3.5. Farmer evaluation process.

If the farmer is working independently, at this point he has completed the evaluation process and will proceed on to the farmer coordination submodel. However, if the farmer is a member of a coordinated farmer group, he will continue the evaluation process by reconsidering the value of his group membership. First, the farmer compares his current tenure in the group with the required contract length (which is three seasons). If the farmer has not been a member for at least three seasons, he has not fulfilled his contract obligation and must stay with the group. However, if the farmer has fulfilled the contract obligation, he is free to leave the group if he is dissatisfied. To assess his satisfaction with the group, the farmer accesses his utility history over the period of time in which he has been a group member. He then calculates his weighted average utility over the most recent past three seasons of working in the group, with the more recent seasons weighted more heavily. If his weighted utility falls below his utility threshold, the farmer's state updates to "dissatisfied", and he will leave the group; otherwise, he will remain with the group. Farmers' decisions to leave their group are not conditional on other farmers' decisions – it is assumed that decisions to leave are made concurrently and without sharing information. Therefore, even if a farmer decides to stay with his current group, it is possible that the other group members will decide to leave, and the group will reduce or dissolve.

3.2.5 Farmer coordination

After each farmer has evaluated his current finances and utility, if he is still in business, he will begin the farmer coordination process (see Figure 3.6). The purpose of this process is for the farmer to assess the benefits and costs of farm-level horizontal coordination, in which farmers form strategic partnerships with other farmers to pool their resources and their outputs for greater efficiency and scale. Because the objective of each farmer agent is to

acquire as much annual profit as possible, and farmers prefer to work independently, it follows that for farmers to decide to coordinate with one another, there must be an incentive for doing so that has the potential to increase a farmer's annual profit. As a representation of the size and volume advantages that exist in real life (i.e.,, higher sales volumes typically result in better prices and better access to markets), a volume-based pricing function is used to determine the median price per unit that a farmer will be paid for selling a certain volume. This pricing function is known to all farmers. This relationship between median unit price and volume gives farmers an incentive to coordinate with other farmers – coordination groups consolidate their crops before selling, giving them a volume and price advantage over independent farmers. It is assumed that a farmer can only be a member of one coordination group at a time, contributing his entire yield to that group, and that the group only produces one crop type at a time.

Figure 3.6 describes the farmer coordination process, which is run by farmers in random order. The process begins with each farmer agent assessing his group status (i.e.,, independent or a coordination group member) and his utility. If the farmer is currently a group member, he is not allowed to actively seek coordination, so he exits the coordination process. If the farmer is currently independent but has just left a coordinated group and has not worked independently for at least one season in the interim, he is not allowed to actively seek coordination – it is assumed that after leaving a group, the farmer is not immediately ready to join a new group. However, if the farmer is currently working independently and has been independent for at least one season, the next step is to assess his utility. If he is "dissatisfied" on average (i.e., his average utility is below his threshold value), he begins to seek out other farmers for coordination.

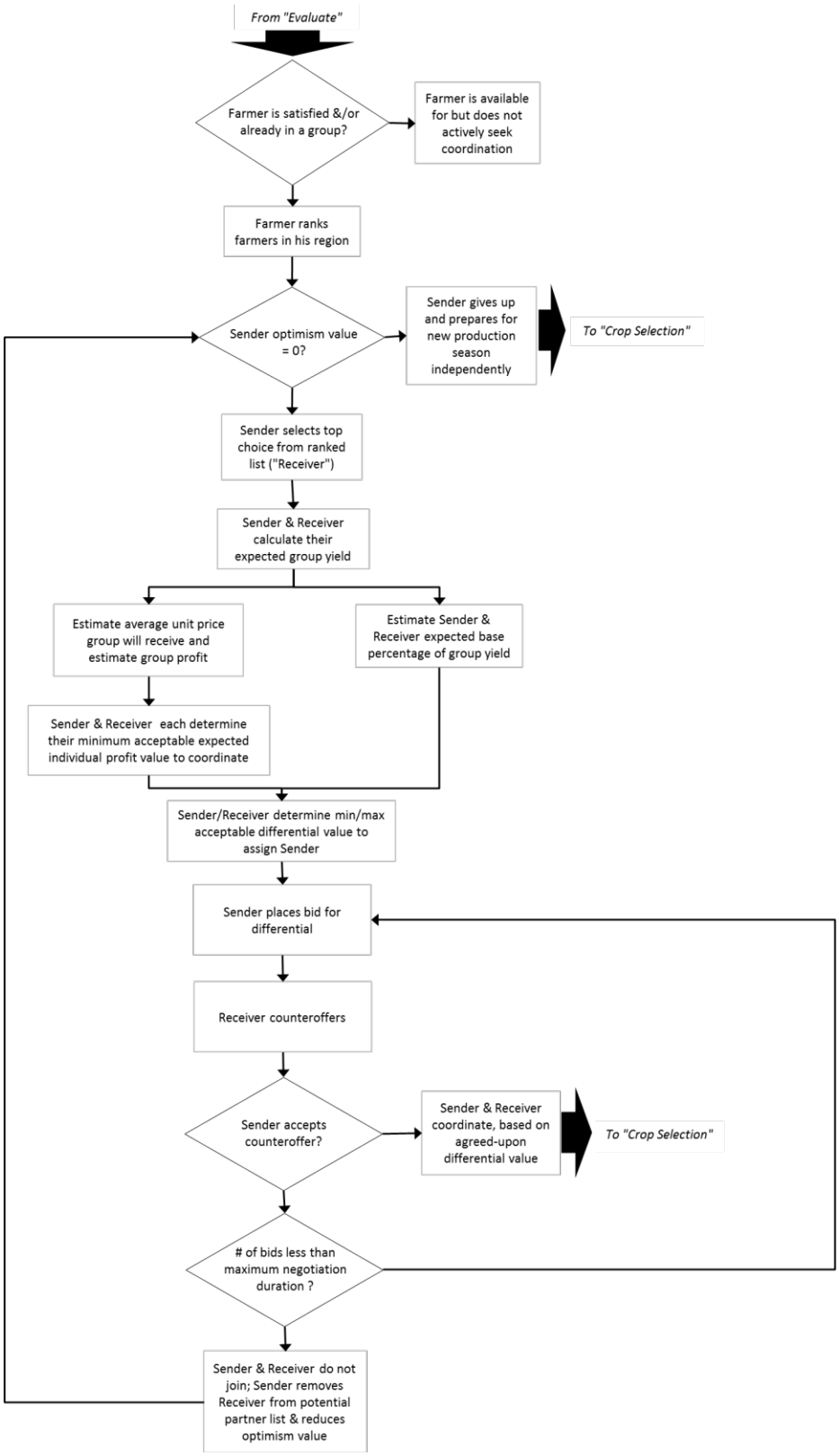


Figure 3.6. Farmer collaboration process.

The farmer begins by ranking other farmers in his region by increasing distance and decreasing profitability, where the distance is weighted more heavily than profitability. This choice mirrors real-life farmers' preferences to work with others that they know and that are located in their own community (Gillespie and Eidman 1998). The seeking farmer (the "Sender") selects the most highly-ranked farmer (the "Receiver"), where the Receiver can be an independent farmer or a member of a coordinated group, but cannot have been rejected by the Sender in any previous searches in the current season. Next, the Sender and Receiver calculate their expected combined yield, a value that is assumed to be known to both Sender and Receiver, which is then applied to the pricing function to determine the expected group profit.

Using these values, as well as their own current profits (γ_f) and autonomy premia (α), the farmers will each calculate a minimum acceptable expected individual profit (β_f) that would convince him to coordinate:

$$\beta_f = \gamma_f + (\gamma_f * \alpha)$$

That is, the expected coordinated profit (γ_{group}) must be at least as large as each farmer's current profit plus an added premium that accounts for his loss of autonomy. If the Receiver is currently a member of a coordinated group, it is assumed that the group has no autonomy premium and is guaranteed to benefit from gaining the Sender as a new member. For the Sender and Receiver, if their expected share of the expected group profit does not exceed their minimum expected profit, the only way that they will consider coordinating is to negotiate a profit premium that will give them an extra share of the group profits. This extra share is τ, the "differential":

$$\tau = \frac{\beta}{\gamma_{group}} - \frac{y_{sender}}{y_{group}}$$

where y_{sender} and y_{group} are the expected Sender and group yields, respectively. A non-zero differential indicates unfair sharing of profits; τ will be positive if the farmer's current profit was larger than expected, negative if the current profit was less than expected, and zero if the current profit equals the expected profit. This suggests that if a farmer is doing poorly, he will be willing to give up some of his fair share just to enable him to join the group. The concept of using a differential as a basis for negotiation is based on Reynolds (1997) and Staatz (1986), which describe the possibility for farmer groups to entice new members with differential premia if it is worthwhile for the group to give up some of their fair share of profits to gain the benefit of the new member's volume.

At this point, the Sender and Receiver begin negotiating the value of the differential that the Sender will be assigned upon coordination. The Sender begins the negotiation process by bidding the maximum differential that he can reasonably expect, which is the value of the Receiver's expected share of profits. The Receiver counteroffers by bidding the minimum differential that he would be willing to give up to the Sender. If the Sender rejects the Receiver's counteroffer, he will respond with a bid that is the midpoint between 1) his most recent bid and 2) either the Receiver's most recent bid or the Sender's minimum value, whichever is larger. The Receiver will respond in kind, and this process will continue until either 1) the difference between the Sender's and Receiver's bids is less than a predetermined amount, in which case they reach agreement, or 2) a predetermined maximum duration of bidding has been reached, in which case the Sender and Receiver are unable to agree on an acceptable differential. If the negotiation is successful, this indicates that the Sender and Receiver believe that coordinating at the agreed-upon differential value is expected to benefit them, and the Sender joins the Receiver in a coordination group. In this case, the Sender has

a three-year "contract" with the Receiver – if the Sender is dissatisfied on average during this three-year period, he can choose to leave the group and begin producing independently again.

If the negotiation is unsuccessful, the Sender's optimism level is reduced. The Sender then selects the next best choice from his ranked list and begins the search process again, continuing iteratively until he successfully coordinates with another farmer or his optimism level equals zero, whereupon he gives up and decides to work independently next season.

3.2.6 Crop selection

The final process that occurs at the end of each time-step is farmer crop selection (see Figure 3.7). The Crop Selection submodel is run by farmer agents in random order (since scheduling does not matter for the outcomes of the submodel) for the selection of the crop type and class for next season's production plan. In this process, each farmer estimates the value of each crop/type class, using a limited knowledge base. Unlike most crop selection models in the literature, in which farmers use optimization to make their decision, this submodel presumes bounded farmer information and computational capacity. It is assumed that the farmer knows the overall system supply-demand ratio for each crop type, as well as expected values for prices, yields, and costs, and he uses this knowledge to make his crop value estimates and finally his crop selection decision.

The first step in the process is determining a farmer's current weighted average utility and comparing this value with the farmer's utility threshold. The weighted average utility value is calculated in a similar way as in the Farmer Evaluation submodel, over the course of the farmer's current experience with this crop type and class. If the farmer's weighted average utility exceeds the threshold, then he does not change his current crop type/class. If his utility falls below the threshold, the farmer will proceed with the crop selection process.

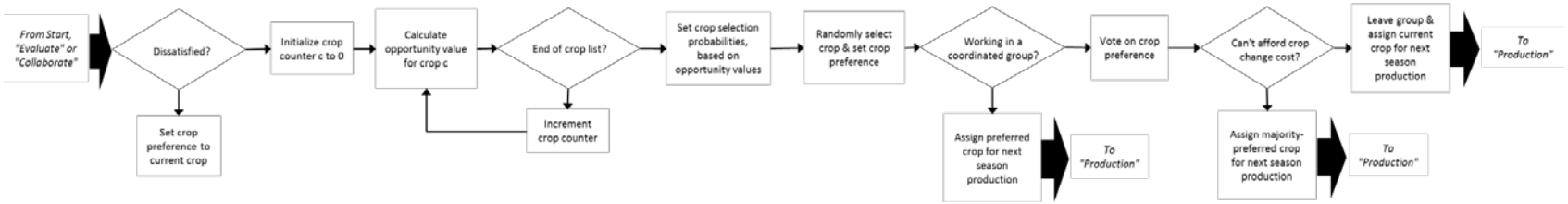


Figure 3.7. Crop selection process.

The next step in the process is the calculation of crop opportunity values (O_c). Each farmer assigns an opportunity value to each crop type/class to help him decide which crop type/class to produce next season. The opportunity value is based on 1) the estimated annual profit for the coming year from growing crop *c*, given that the farmer/group sells his entire expected yield and 2) the estimated market opportunity value for crop c for the coming year. Note that the opportunity value for a given crop is set to zero if the farmer cannot afford to switch to that crop.

A farmer's estimated group profit is the estimated group yield ($y_{c(group)}$) times the expected unit wholesale price for crop *c* (u_c), minus the expected long-haul transport cost to the distributors, which is the average cost (t_{yrf}) of transporting crops from the farmer's group leader to a distributor.

$$\gamma_{c(group)} = y_{c(group)} u_c - \left(\frac{1}{4} \sum_{r=0}^{3} t_{yrf} \right)$$

The expected farmer individual costs are their production costs (p_c), harvest costs (h_c) , the cost of local transport of the farmer's crops to the group leader's farm (l_j), and the cost of changing from the current crop *a* to crop *c* (Q_{ac}), annualized over three years. The farmer's estimated individual profit from crop *c* (γ_{cf}) can then be determined by multiplying the farmer's estimated group profit ($\gamma_{c(group)}$) by the farmer's profit share (π_j) and subtracting the farmer's expected individual costs, and then multiplying this value by the farmer's crop inertia premium (σ_{cf}).

$$\gamma_{cf} = \left(\left(y_{c(group)} u_c - \left(\frac{1}{4} \sum_{r=0}^{3} t_{yrf} \right) \right) \times \pi_j - \left(p_c + h_c + l_j + \frac{Q_{ac}}{3} \right) \right) \times \sigma_{cf}$$

If the crop under consideration (crop c) is the same as the farmer's current crop, then $\sigma_{cf} = 1$; that is, the inertia premium has no effect on crop c's estimated profit value. If crop c is different from the farmer's current crop, the value of the inertia premium depends on the number of consecutive years that the farmer has produced his current crop. The inertia premium is set to 1 in the first year of production, and each consecutive year that the farmer produces that crop thereafter, it is decremented by 0.1 (to a minimum value of 0.1). Therefore, the inertia premium devalues the estimated profit of crops other than the current crop.

The opportunity value for crop c (o_c) is calculated as a percentage of the farmer's estimated profit from crop c (γ_{cf}). The value of the percentage depends on the current system-wide supply-demand ratio for crop c, such that the opportunity value and the supply-demand ratio are inversely proportional.

$$o_c = \left(1 - \frac{S_c}{D_c}\right) \times \gamma_{cf}$$

The overall opportunity value for a given crop c (O_c) depends on the farmer's estimated annual profit value from crop c (γ_{cf}) and the estimated market opportunity value for crop c (o_c). The profit and opportunity factors are weighted (by w_γ and w_o, respectively, where $w_\gamma + w_o = 1$) to represent the relative value that the farmer places on market potential in assigning an overall opportunity value to crop c.

$$O_c = w_\gamma \gamma_{cf} + w_o o_c$$

The farmer calculates the overall opportunity value for all crop types and organic/conventional classes and eliminates any options that have negative opportunity values. The process of making his final selection involves randomness; that is, the farmer does not simply select the crop type/class with the highest opportunity value, but rather is

more likely to select crop types/classes with higher opportunity values, where the probability of selecting crop *c* is proportional to the value of O_c relative to other crops.

The final step in the crop selection process is crop assignment. If the farmer is not working as part of a coordinated farmer group, at this point he simply assigns himself his most preferred crop for production next season. However, if he is a member of a group, the farmers in his group will determine crop assignment collectively through a vote. Each individual farmer will cast his vote, which is weighted by the farmer's differential value. The crop type/class with the greatest number of votes is then assigned to each member of the group. However, if the assigned crop requires a farmer to switch crop type/class and he does not have enough cash to pay for the crop change cost plus next season's production costs, that farmer will exit the group and will assign himself his current crop type/class for next season's production.

Chapter 4 : Experimentation and Results

4.1 Description of experiments

Using the model described in Chapter 3, experiments were performed with an aim to gain a greater understanding of an FSC using MAS and address the research questions posed in Chapter 1. The following section describes the experimental input parameter values, fixed input parameter values, and output metrics that were used in these experiments.

4.1.1 Experimental input parameters

The following six input parameters were selected to be varied experimentally:

- **Autonomy premium (*ap*)**: the autonomy premium for all farmers in the experiment, regardless of size. Experimental values of *ap* were [0, 0.5, 1, 2, 5, 10, 20]. Farmers with an autonomy premium value of zero do not place any value on their autonomy, while farmers with an autonomy premium value of 20 place an extremely high value on their autonomy.
- **Median regional yield (*y*)**: This factor describes the variability of median crop yields (crop units per acre) among the four different regions. When the median regional yield factor is set to "balanced", the median yield for each crop type is the same for all regions. When it is set to "variable", each region has a crop "specialty" – the median yield for that crop is higher in that region than it is in the other regions. Table 4.1 shows the values of the median regional yield per acre for each crop type, region, and level of *y*.

Crop Type	Median Regional Yield - Balanced				Median Regional Yield - Variable			
	R0	R1	R2	R3	R0	R1	R2	R3
0	325	325	325	325	400	300	300	300
1	325	325	325	325	300	400	300	300
2	325	325	325	325	300	300	400	300
3	325	325	325	325	300	300	300	400

Table 4.1. Median regional yield values (crop units per acre) for each crop type and region under "balanced" and "variable" factor levels.

- **Weather pattern (*w*):** This factor describes the variability of the weather conditions, which affect farmers' yields. When the weather pattern is set to "constant", the weather factor in all regions (π_r) is set to 1, which means that the weather has no effect on crop yields. When the weather pattern is set to "variable", in each time-step, the weather factor for each region is drawn from a triangular distribution with a minimum value of 0.10, a median value of 0.80, and a maximum value of 1.
- **Distributor initial upper bound price factor (*ub*)**: This factor describes the percent of the unit wholesale cost (u_c) that defines the upper bound price that all four distributors will use for price negotiations with farmers. Experimental values of *ub* were [0.1, 0.5, 0.9]. When ub is set to 0.1, the distributor's upper bound is only 10% of the crop's wholesale price – thus the farmers are only offered a very low price. In contrast, when ub is set to 0.9, farmers will be offered a much higher price.
- **Distributor pricing coefficient (*q*)**: This factor is the coefficient on all four distributors' pricing function. The effect of this coefficient is to relate volume to unit price. Figure 4.1 shows the shapes of the distributor pricing functions at each experimental value of *q*. As Figure 4.1 shows, for small values of *q* (0.05), a seller that is offering a small volume (relative to the distributor's demand) can get a large percentage of the wholesale price

(u_c). However, when q is large (0.70), a seller with a low volume will only receive a very small percentage of the wholesale price.

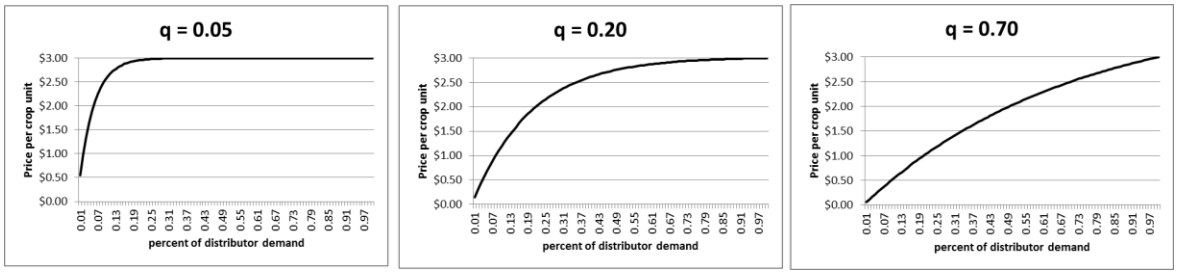


Figure 4.1. Distributor price functions for different experimental values of q.

- **Transportation cost factor (*tc*)**: This factor is a distance-cost parameter. As *tc* increases, the rate of transport cost per unit distance increases, and therefore total transportation cost increases. Figure 4.2 shows an example of the transport cost function from 100 to 5000 distance units with a transport quantity of 5000 crop units. As with empirically-observed freight curves, the transport cost function is non-linear (with freight rates tapering off with increased transport distance) to account for the varying freight rate structures of different carrier sizes, where there are diseconomies of size for loading/unloading but economies of size for transport (Jansson 2006, pp. 74-76).

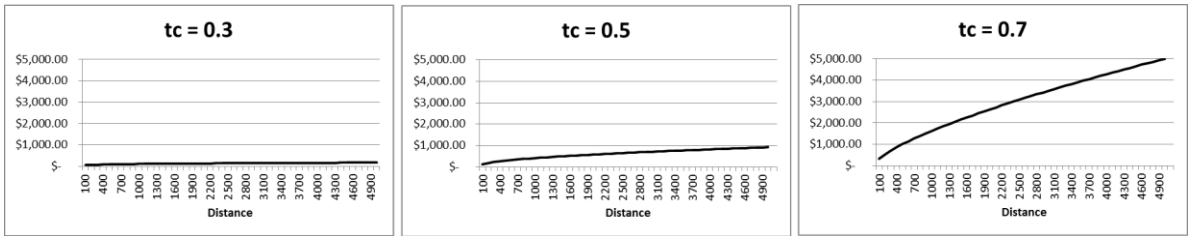


Figure 4.2. Total cost to transport 5000 units for different experimental values of *tc*.

Table 4.2 provides a summary of the factors that were experimentally varied, the symbol used for each factor, the total number of levels, and the values of the factors at each level. All possible combinations of experimental values were used (i.e., a full factorial experimental design), for a total of 756 experiments.

Factor	Description	# of Levels	Experimental Values
ap	farmer autonomy premium	7	0, 0.5, 1, 2, 5, 10, 20
y	median regional yield	2	balanced, variable
w	weather pattern	2	constant, variable
ub	distributor initial upper bound price factor	3	0.1, 0.5, 0.9
q	distributor pricing function coefficient	3	0.05, 0.20, 0.70
tc	transportation cost factor	3	0.3, 0.5, 0.7

Table 4.2. List of experimental factors and values.

4.1.2 Fixed input parameters

Table 4.3 provides a list of fixed (constant) parameter values and their settings for all experiments. Table 4.4 shows Q_{ac} the cost of changing from one crop/class to another.

Input Parameters	Description	Experimental Value
n	number of crops	4
r	number of regions	4
I	number of farmers/region at start of each replication	50
i_{small}	number of "small" farmers per region (25 acres)	30
i_{medium}	number "medium" farmers per region (50 acres)	15
i_{large}	number "large" farmers per region (100 acres)	5
u_c	median unit wholesale price for all crops	$3.00
D_{cr}	median demand for crop c in region r in each time-step	150,000
$g_{f(min)}$	minimum allowable gross margin for seller f	20%
ω	volume-cost multiplier	1
φ	volume-cost exponent	0.3
B	maximum allowable number of negotiations	10
δ	maximum bid difference	0.01
w_y	weight of profit value	0.5
w_o	weight of crop opportunity value	0.5

Table 4.3. List of fixed experimental parameters and associated settings.

From/To	0C	0O	1C	1O	2C	2O	3C	3O
0C	$0	$4000	$10000	$4000	$10000	$4000	$10000	$4000
0O	$4000	$0	$4000	$4000	$4000	$4000	$4000	$4000
1C	$4000	$10000	$0	$10000	$4000	$10000	$4000	$10000
1O	$4000	$4000	$4000	$0	$4000	$4000	$4000	$4000
2C	$4000	$10000	$4000	$10000	$0	$10000	$4000	$10000
2O	$4000	$4000	$4000	$4000	$4000	$0	$4000	$4000
3C	$4000	$10000	$4000	$10000	$4000	$10000	$0	$10000
3O	$4000	$4000	$4000	$4000	$4000	$4000	$4000	$0

Table 4.4. Cost of changing from one crop type/class to another. Numbers represent the crop type, and letters (C/O) represent crop class (conventional/organic).

4.1.3 Output metrics

By varying the experimental input parameters discussed in Section 4.1.1, the model can be used to gain a greater understanding of how these parameters affect FSC sustainability (i.e., environmental, social, and economic sustainability) and structure over time. To measure the impacts of experimentally changing input parameter levels on FSC sustainability and structure, the following nine system output metrics were selected to be studied:

- **System fill rate (*fr*)**: This output metric is a weighted average fill rate over all four distributors in each time-step. This metric captures not only quantity filled but also accuracy – for crop type but disregarding crop class. First, the overall system fill rate for each crop *c* (fr_c) is calculated as the sum of the inventory of crop *c* for all distributors *r* at the end of the time-step (η_{cr}), divided by the overall system demand for crop *c* (D_c):

$$\boldsymbol{fr_c = \frac{\sum_r \eta_{cr}}{D_c}}$$

  The system fill rate for each crop *c* is then used to determine an overall system fill rate (*fr*). The sum of the system fill rate for each crop *c*, multiplied by the system demand for

crop c (D_c, which acts as a weight on the value of each fr_c) is divided by the total system demand for all crops:

$$\boldsymbol{fr} = \frac{\sum_{\boldsymbol{c}}(\boldsymbol{D_c} \times \boldsymbol{fr_c})}{\sum_{\boldsymbol{c}} \boldsymbol{D_c}}$$

The minimum value of the system fill rate is zero, and the maximum value is one. When the system fill rate equals one, this means that the demand for all crop types in all regions has been filled. The system fill rate is an important measure of overall FSC sustainability, describing not only how much volume the system is capable of producing (i.e., its capacity), but also how well the variety of crops produced matches the variety of demand. The variety component is important for consumer satisfaction and nutrition.

- **System supply-demand ratio (*sd*):** This output metric is the sum of the overall system supply of crop c (S_c) divided by the overall system demand for crop c (D_c), over all crop types:

$$\boldsymbol{sd} = \sum_{\boldsymbol{c}} \frac{\boldsymbol{S_c}}{\boldsymbol{D_c}}$$

The supply-demand ratio provides different information about system capacity than the weighted fill rate – whereas the fill rate metric captures how well the system matches the variety of demand, the supply-demand ratio strictly captures volume. As with the fill rate, the minimum value of the supply-demand ratio is 0, but the supply-demand ratio has no maximum bound (i.e., it can be greater than one). It is possible for the fill rate to fall below one while the supply-demand ratio is greater than one. For example, if all the farmers in the system decide to plant crop type 0, there will be an enormous supply of crop type 0 and the supply-demand ratio will likely be large. However, because there is no variety, the fill rate will be low.

- **Number farmers in system (*cf*):** This output metric is the overall number of farmer agents in the system in each time-step. At the start of each replication, there are *I* farmers in the system. Over the course of the replication, farmers may go out of business, causing the number of farmers in the system to be reduced. Thus the number of farmers in the system captures an important aspect of economic and social FSC sustainability (i.e., farmer employment), and, because the farms of out-of-business farmers disappear from the system (rather than being absorbed by other farmers), the number of farmers is also likely to have implications for fill rate (i.e., with fewer farmers, less food is produced).
- **Long-haul distance traveled (*lh*):** This output metric is the overall sum of all farmer-to-distributor transport distances traveled in each time-step. Because the energy for transportation is typically supplied from fossil fuels (which are non-renewable and produce toxic outputs when consumed), transport distance is an important environmental sustainability metric.
- **Farmer local distance traveled (*local*):** This metric is the overall sum of all local farmer transport distances traveled (from each grouped farmer to his group leader for crop consolidation) in the each time-step. As with the long-haul transport, the local transport distance impacts environmental sustainability.
- **Percent grouped farmers (*pg*):** This metric is the percentage of all farmers in the system that are members of a coordinated farmer group (i.e., a farmer collective with at least two members) in each time-step. The percentage of grouped farmers provides information about the extent to which the farmers are coordinating.
- **Number of farmer groups (*cg*):** This metric is the overall number of coordinated farmer groups (i.e., farmer collectives with at least two members) in the system in each time-step.

The total number of farmer groups provides information about the extent of farmer coordination, as well as information about size of the groups that are formed (e.g., if the percentage of grouped farmers is high and the number of farmer groups is low, it can be inferred that the farmer groups are large).

- **90th percentile group size (*p*):** This metric captures the size (i.e., number of members) of the farmer group at the 90th percentile in each time-step. This value provides some indication of the distribution of farmer group sizes. Along with the percentage of grouped farmers and the number of farmer groups, this metric provides information about the overall structure of the FSC in a given time-step.
- **Number of farmer transitions (*transitions*):** This metric is a sum of the number of farmers who join a coordinated farmer group plus the number of farmers who leave a group in a time-step, given that he was in the group for at least the duration of his contract length (i.e., he did not leave immediately after joining due to an inability to afford a crop change cost). Unlike all other output metrics, which capture the final values in the 500th time step, the number of transitions is an average value over all 500 time-steps in a replication. It provides a measure of system volatility.

Table 4.5 provides a summary of the output metrics captured.

Output Metric	Description
fr	system fill rate
sd	system supply-demand ratio
cf	number of farmers in system
lh	total system long-haul distance traveled
local	total system local distance traveled
pg	percent grouped farmers
cg	total number of farmer groups
p	90th percentile farmer group size
transitions	number of farmer group transitions

Table 4.5. List of experimental output metrics captured.

4.2 Results

The results of the experiments described in the previous section are presented in this section. Each combination of experimental input parameter values was run for ten replications with 500 time-steps each. Ten replications were deemed sufficient because variability between replications was observed to be low for all experiments. A value of 500 was chosen for the replication length to allow sufficient time for the system to reach a steady state. Each reported output metric value is an average value over the ten replications. Two different types of results are presented here: 1) final output values at the end of the 500th replication, which are provided for all combinations of experimental input parameter values, and 2) output values captured in each time step over the entire 500-step replication, which are provided for five selected sets of experimental parameter values (scenarios P1-P5; see Table 4.6 for a summary). These parameter sets were selected because they tended to have disparate impacts on farmer behaviors, providing a greater understanding of system behavior over time under different conditions.

The final output values for each experiment were analyzed graphically and using ANOVA. For each ANOVA test, plots of the residuals were created to test for normality. These plots can be found in Appendix B. Nearly all of the residual plots show strong adherence to normality, and none of the plots is severely non-normal. Therefore, conditions for performing ANOVA are assumed to be adequate. Interaction plots for all pairwise-combinations of input parameters were also created (see Appendix C), and no significant statistical interactions were found. Appendix D provides 95% confidence intervals on the means of each output (response) variable for each level of each input factor.

Input Parameter	P1	P2	P3	P4	P5
ap	0, 2, or 20	0, 2, or 20	0, 2, or 20	0, 2, or 20	0, 2, or 20
y	balanced	balanced	balanced	balanced	balanced
w	constant	constant	constant	constant	constant
ub	0.5	0.1	0.9	0.5	0.1
q	0.05	0.05	0.7	0.7	0.7
tc	0.3	0.3	0.7	0.7	0.7

Table 4.6. Experimental parameter values for data captured over time in each time step.

4.2.1 System fill rate and supply-demand ratio

The system fill rate output metric provides a means of understanding how well the farmers in the system are matching and filling demand for each crop type. The fill rate can be compared to the supply-demand ratio to gain an understanding of the system's capacity and accuracy.

4.2.1.1 System fill rate and supply-demand ratio: final values

Overall system fill rate and supply-demand ratio values for each experiment were captured at the end of the 500th time step and were averaged over 10 replications. Figures 4.3 and 4.4 show the main effects of each of the six input parameters on the system fill-rate and supply-demand ratio, respectively. Although the exact values differ, the fill rate and the supply-demand ratio behave almost identically for all experimental values. Constant weather results in a much better fill rate than variable weather, which is an unsurprising result, given that the farmers' yields are higher for constant weather. Overall, increasing values of *q* and *tc* result in significantly lower fill-rate values, while increasing *ub* leads to significantly better fill rates. These results are also somewhat intuitive, because cost increases (which occur when *tc* increases) and price decreases (which occur when *q* increases) cause farmers hardship (and potentially put them out of business), while increased prices (which occur when *ub* increases) improve farmers' financial stability. The main effects of *ap* and *y* are less intuitive. In general, a variable median regional yield (wherein each region can produce one of the four

crops with higher median yields than the other crops) results in a slightly better fill rate than a balanced median regional yield. This result is may indicate that the system is more efficient when regions can specialize. An autonomy premium value of zero yields the highest fill rate; however, autonomy premium values in general do not have much impact on the fill rate.

Tables 4.7 and 4.8 show the results of ANOVA for fill-rate and supply-demand ratio, respectively. These values support the findings from the main effects plots. Although all factors are significant (p-values = 0) and the model fits the data well (R^2 = 85%), it is clear that the weather pattern has the greatest impact on fill rate (F = 17739), while *ub, q*, and *tc* have some effect, *y* has a slight effect, and *ap* has almost no impact.

Tables 4.9a and 4.9b show that there are significant differences (at a 95% confidence level) in mean values of system fill rate for balanced and variable median regional yield factors. These confidence intervals also indicate that fill rate and the supply-demand ratio means are different. Figure 4.5 shows the mean fill rate and supply-demand ratio values with respect to autonomy premium values and median regional yield values. Supply-demand ratio values are significantly larger than the fill rate values when median regional yield values are variable and autonomy premia are low. This suggests that when large groups form (because of the low autonomy premium values) and regions are specialized in the production of one crop type, the system tends to produce more of that crop type than is demanded.

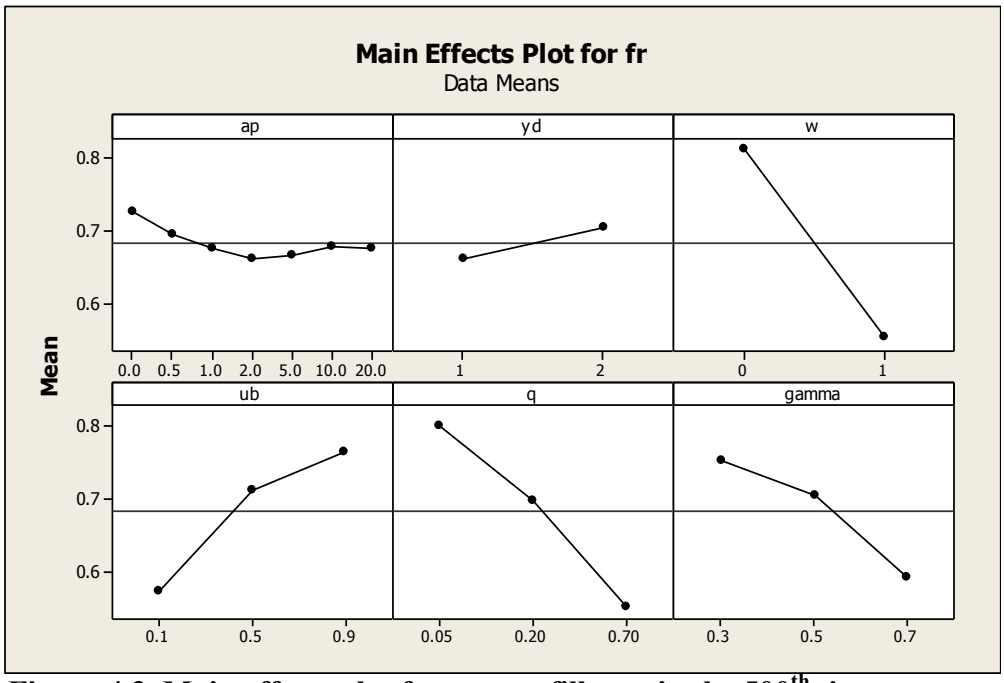


Figure 4.3. Main effects plot for system fill rate in the 500th time-step.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	3.105	0.517	72.720	0.000			
y	1	3.548	3.548	498.830	0.000			
w	1	126.162	126.162	17738.590	0.000			
ub	2	49.511	24.755	3480.660	0.000			
q	2	79.583	39.792	5594.780	0.000			
t	2	34.347	17.173	2414.620	0.000			
Error	7545	53.662	0.007					
Total	7559	349.918				0.084	84.66%	84.64%

Table 4.7. ANOVA output for system fill rate in the 500th time-step.

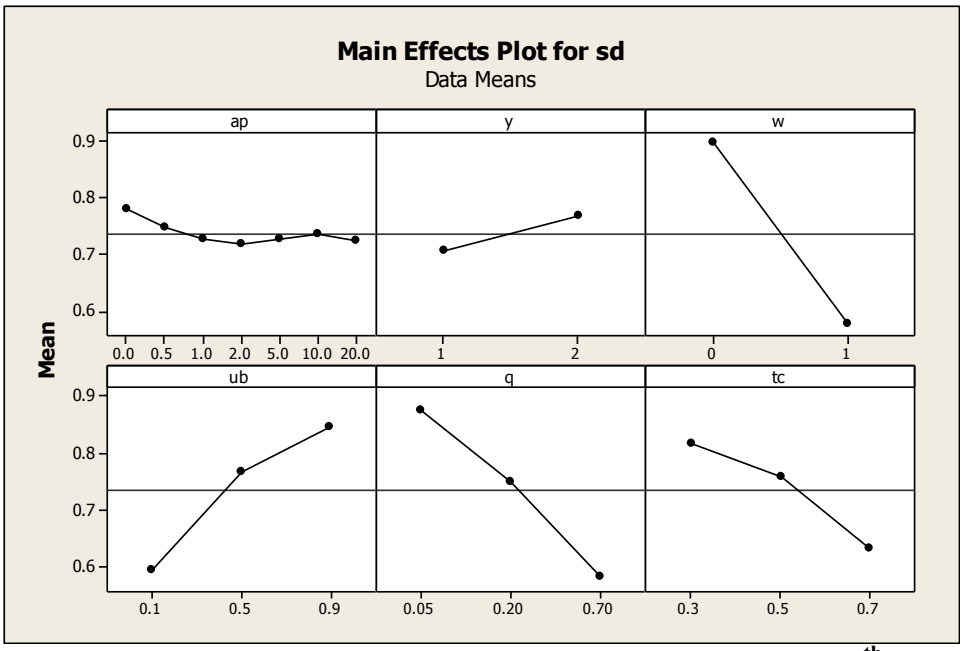


Figure 4.4. Main effects plot for overall supply-demand ratio in the 500th time-step.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	2.709	0.451	50.57	0.000			
y	1	7.231	7.231	810.03	0.000			
w	1	192.835	192.835	21600.67	0.000			
ub	2	82.883	41.442	4642.13	0.000			
q	2	109.743	54.871	6146.49	0.000			
t	2	44.116	22.058	2470.88	0.000			
Error	7545	67.356	0.009					
Total	7559	506.873				0.09448	86.7%	86.69%

Table 4.8. ANOVA output for overall supply-demand ratio in the 500th time-step.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
1	3780	0.6614	0.2125	(----*---)
2	3780	0.7047	0.2157	(----*---)
				0.660 0.675 0.690 0.705

a.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
1	3780	0.7053	0.2426	(---*---)
2	3780	0.7671	0.2708	(----*---)
				0.700 0.720 0.740 0.760

b.

Table 4.9. 95% confidence intervals on a) system fill rate and b) supply-demand ratio in the 500th time-step for balanced (level 1) and variable (level 2) median regional yield.

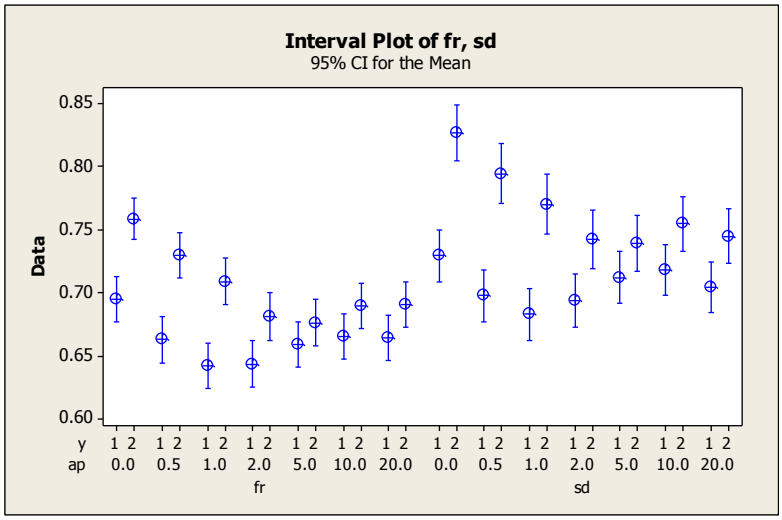


Figure 4.5. Interval plot for fill rate and supply-demand ratios versus autonomy premium and regional yield factor in the 500th time-step.

4.2.1.2 System fill rate: values over time

In addition to the final values presented in the previous section, the system fill rate values were also captured for each time-step over the 500-step replications for experiments P1-P5 (see Table 4.6 for experimental details). The fill-rate value in each time step is an average over 10 replications. Figure 4.6 (a-c) shows plots of the fill rate for each of these five scenarios for autonomy premium values of 0, 2, and 20. The plots for *ap* values of 2 and 20 (Fig. 6b and 6c) are very similar for all scenarios, with the fill rate for experiments P1 and P2 remaining steady throughout the replications, and the fill rate for experiments P3-P5 gradually decreasing to steady states at approximately time-step 300. However, when *ap* is set to zero (Fig. 6a), the fill rate drops much more quickly and achieves a steady state by the 50^{th} time step. As with the analysis on final values in the previous section, differences in autonomy premium values do not appear to have much impact on fill rate for any of the experimental scenarios (P1-P5).

4.2.2 Number of farmers in system

The total number of farmers in the system is a measure of how well the farmers can survive financially over time. When a farmer no longer has enough money to produce crops, he is "out of business" and is removed from the system for the remainder of the replication. There are 200 farmers in the system at the start of each replication. In terms of social sustainability, the greater the number of farmers that remain in the system over time, the more sustainable the system is. The number of farmers in the system at the end of the 500^{th} time-step was captured for all combinations of experimental input parameters, and the number of farmers in each time step was captured for selected experimental scenarios (P1-P5; see Table 4.6 for details).

4.2.2.1 Number of farmers in system: final values

The number of farmers in the system after 500 time-steps (of the 200 original farmers) was captured for all experimental scenarios. The main effects plot showing the main effects of each input parameter's values on the number of farmers is shown in Figure 4.7. As with the system fill rate, the number of farmers in the system in the 500th time-step is strongly affected by the values of *q, tc*, and *ub*, with fewer farmers for higher values of *q* and *tc* (because increased costs make it harder for farmers to survive) and more farmers for increases in *ub* (because higher prices lead to increased farmer incomes and help them survive). Again, the autonomy premium value does not seem to affect outcomes much, although an *ap* of zero leads to improved farmer survival. However, the number of farmers is only slightly affected by the weather pattern and the median regional yield factor. The lack of a strong relationship with weather may indicate that although inclement weather may reduce farmer yields in some time-steps (impacting the fill rate), the farmers have enough "good" seasons to be able to stay afloat financially. One possible explanation for this outcome is the choice of parameters for the regional weather factor distribution – it is possible that the weather is simply not severe often enough to reduce the number of farmers significantly. Another explanation is the relationship between supply and demand on crop prices. When weather reduces the farmers' yields and demand is greater than supply, the distributors will pay the farmers more, which may compensate for the farmers' yield losses.

Table 4.10 provides the results of ANOVA for all six input parameters and the resulting number of farmers in the system in the 500th time step. All parameters have significant effects (p-values = 0), but as was observed in Figure 4.7, the distributor volume-price function coefficient (*q*) and the upper bound price factor (*ub*) are by far the most significant

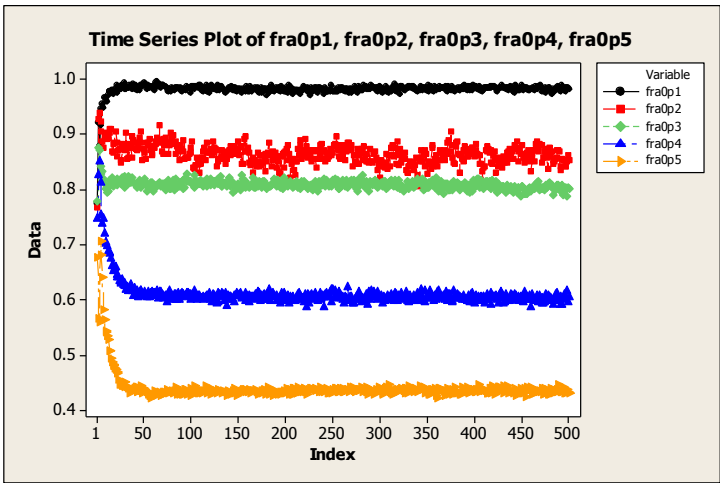
factors (F = 18,234 and 10,818, respectively), while the transport cost factor (*tc*) is somewhat significant, and *ap, y*, and *w* having less impact. Therefore, it seems that the prices that farmers receive have the greatest impact on their ability to survive financially.

Figure 4.8 is a scatterplot of the relationship between the number of farmers in the system and fill rate. Interestingly, fill rate does not increase linearly with the number of farmers.

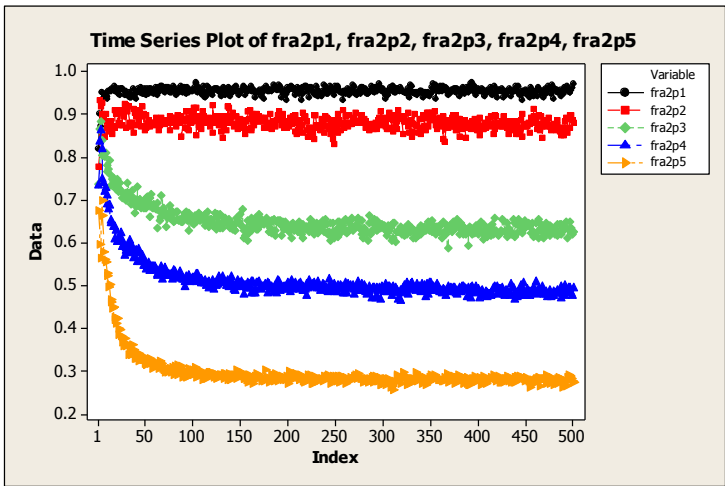
4.2.2.2 Number of farmers in system: values over time

In addition to the final values presented in the previous section, the system fill rate values were also captured for each time-step over the 500-step replications for experiments P1-P5 (see Table 4.6 for experimental details). The fill-rate value in each time step is an average over 10 replications. Figures 4.9a-c show the plots of these values over time. As with fill rate over time, the plots for autonomy premium values of 2 and 20 (Fig. b and c) look similar. They show a gradual decrease in the number of farmers for scenarios P2-P5, reaching what appears to be a steady state at approximately 450 time-steps. In contrast, the plot for an autonomy premium value of zero (Fig. 4.9a) shows a sharp decrease in the number of farmers for scenarios P3-P5, reaching a steady state in 50 time-steps.

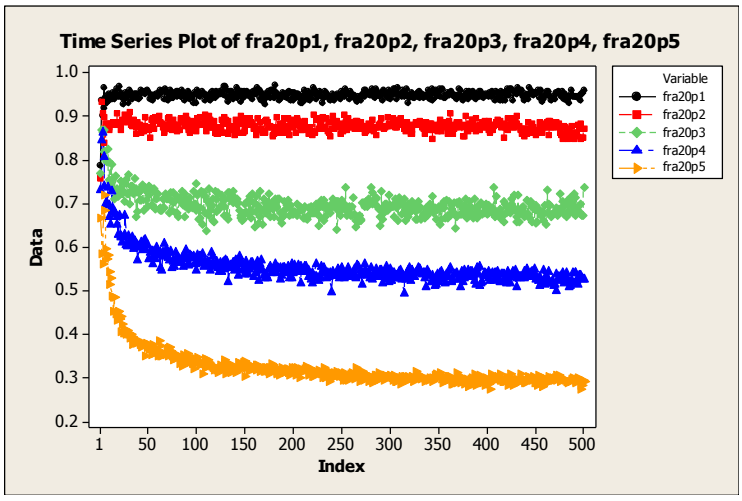
In general, the rate of decrease in the number of farmers over time for each scenario is very similar to the rate of decrease in fill rate over time (see Figures 4.6a-c) for scenarios 1 and 3-5. In scenario P2, however, the fill rate tends to remain steady over the entire replication for all three *ap* values, while the number of farmers decreases. The upper bound price factor in scenario P2 is low (*ub* = 0.1), which causes hardship for the farmers and tends to reduce their numbers, but the values of *q* and *tc* are also low, which benefits farmers. This behavior may be related to the non-linear shape of the scatterplot in Figure 4.8, where the rate of increase in fill rate decreases with an increasing number of farmers.



a.



b.



c.

Figure 4.6. System fill rate values in each time-step for experiments P1-P5. Autonomy premium values are a) 0, b) 2, and c) 20.

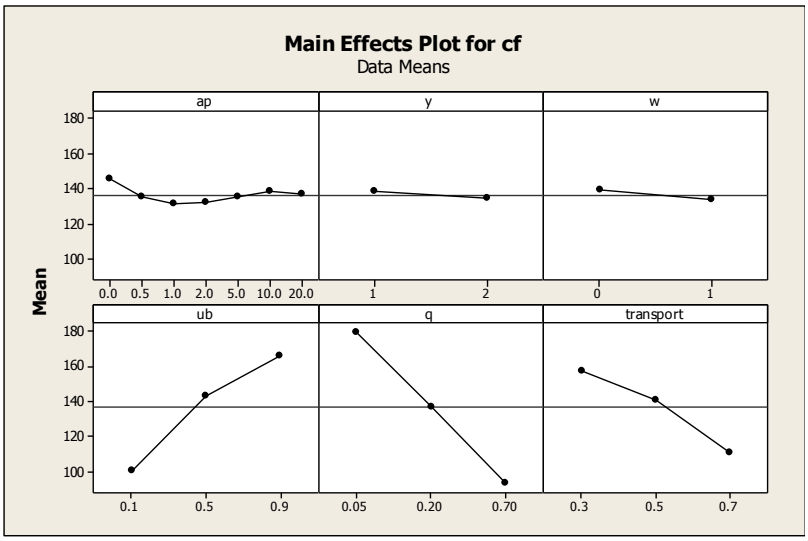


Figure 4.7. Main effects plot for number of farmers in system in the 500th time-step.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	139506	23251	90.82	0.000			
y	1	22634	22634	88.41	0.000			
w	1	48534	48534	189.58	0.000			
ub	2	5538628	2769314	10817.5	0.000			
q	2	9335979	4667989	18234.11	0.000			
t	2	2856377	1428189	5578.79	0.000			
Error	7545	1931543	256					
Total	7559	19873201				16.00	90.3%	90.26%

Table 4.10. ANOVA output for number of farmers in system in the 500th time-step.

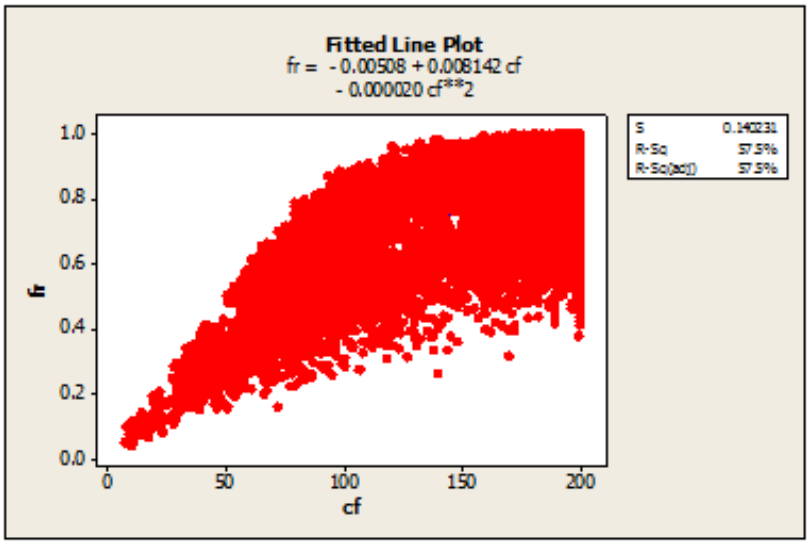


Figure 4.8. Scatterplot of system fill rate versus the number of farmers in the system in the 500th time-step. Best fitted line is a quadratic function.

4.2.3 Transport

The total long-haul (farmer-to-distributor) and local (farmer-to-farmer) transport distances traveled are metrics that reflect the amount of energy consumed in transporting food from farmers to distributors. While total distance traveled (i.e., "food miles") is important, it is also important to differentiate between long-haul and local transport. First, long-haul transport is typically more energy-efficient than local transport, and there is significant infrastructure (in the U.S.) to enable long-haul transport (T. Rusk, personal communication, September 20, 2012). Also, the amount of local transport required in a given system partly quantifies the extra burden for farmers who decide to coordinate with other farmers – while long-haul transport is typically carried out by shipping companies, the local farmer-to-farmer transport often requires that each participating farmer have/borrow a truck, and there must be local storage space and/or refrigerated facilities for consolidation (T. Rusk, personal communication, September 20, 2012). Therefore, local transport is not only an environmental sustainability metric; it is also a proxy for coordination costs to farmers.

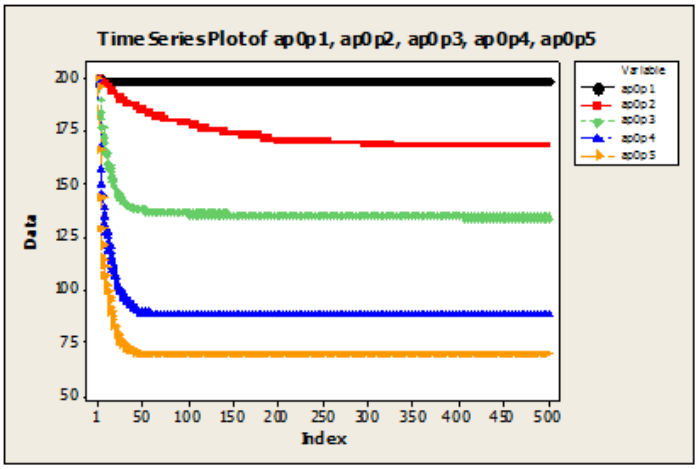
4.2.3.1 Transport: final values

System-wide totals for long-haul and local transport distances traveled in the 500th time-step were captured and averaged over 10 replications. Figures 4.10 and 4.11 show the main effects of each of the six experimental input parameters on total long-haul and local transport distance, respectively. Autonomy premium values have opposite effects on long-haul and local transport distances – the total long-haul distance traveled increases, and the local distance decreases, with increasing *ap* values. This result is intuitive – the extent of farmer coordination is expected to decrease with increasing *ap* values. This result should reduce the number of farmer groups that form and therefore reduce the need for local group

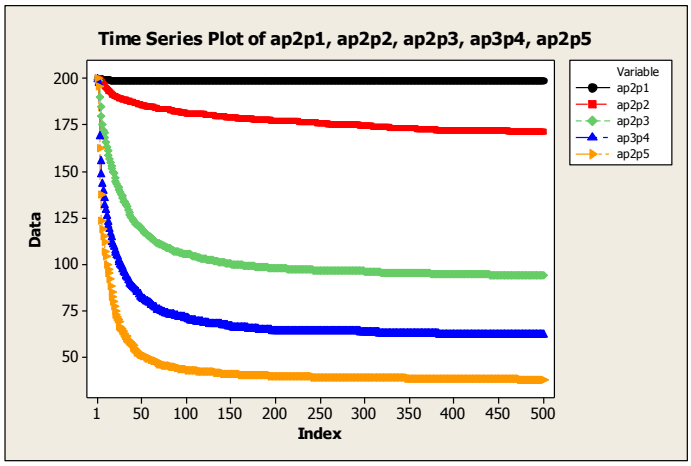
consolidation transport. Long-haul transport distance would be expected to increase for the same reason – with fewer farmer groups, less consolidation among farmers occurs and more long-haul trips are required.

Significant overall reductions in long-haul transport distances are observed for increasing *q* and *tc* values (with little effect on local transport values), while median regional yield and weather have very little impact. This is a similar result as was seen with the number of farmers in the system (see Figure 4.7), and suggests that total transport distance is strongly related to the total number of farmers in the system. The upper bound price factor has different effects on long-haul (non-linear) and local (significant linear increase with increasing *ub* factor) distances traveled.

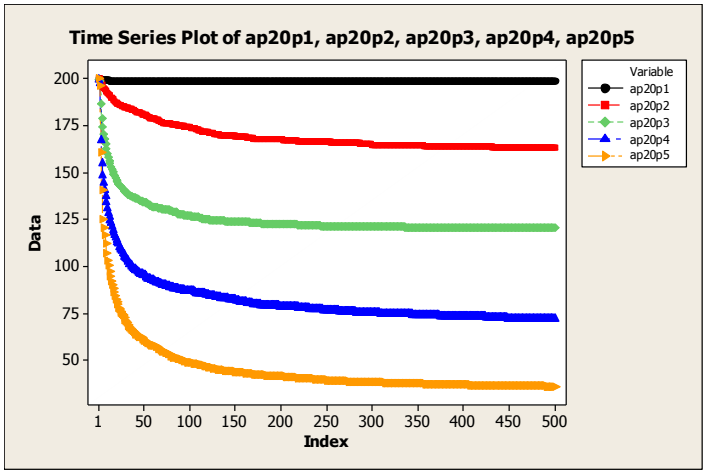
The ANOVA output for long-haul and local transport (Tables 4.11 and 4.12, respectively) further clarify the effects observed in Figures 4.10 and 4.11. The most significant factor in total long-haul distance traveled is transport cost (F = 5404). This result makes intuitive sense – when transport costs are high, farmers would be expected to choose to sell to their own regional distributor rather than distant distributors. The distributor pricing coefficient (*q*) is also a major factor in long-haul transport distance – likely because large values of q result in fewer farmers, which results in less transport overall. The weather pattern and autonomy premium value are also somewhat significant, with a decrease in distanced traveled when weather is variable. In contrast, ANOVA for local transport distance shows that the autonomy premium and upper bound price factor are most significant, followed by the weather pattern. This result suggests that these factors have some influence in the way that farmers form coordinated groups, which affects the amount of local transport that occurs.



a.



b.



c.

Figure 4.9. Number of farmers in system in each time-step. Autonomy premium values are a) 0, b) 2, and c) 20.

Tables 4.13-4.16 show significant differences between mean total long-haul and local transport distances for different weather variability and different levels of the upper bound price factor. Figure 4.12 shows the relationship between total long-haul (Fig. 4.12a) and local (Fig. 4.12b) transport distance traveled and weather patterns, for each experimental autonomy premium value. For long-haul transport, differences caused by the weather factor are only significant for larger autonomy premium values ($ap \geq 2$), and for these values, variable weather causes a significant decrease in long-haul distance traveled. For local transport, significant decreases in distance traveled only occur for lower autonomy premium values ($ap < 2$). Figure 4.13 shows a similar pattern for the relationship between long-haul (Fig. 4.13a) and local (Fig. 4.13b) transport distance and the upper bound price factor. For long-haul transport, the effect of *ub* is significant for higher *ap* values, and for local transport, the effect is only significant at lower *ap* values.

4.2.3.2 Transport: values over time

Figures 4.14 a-c show the total system long-haul distances traveled in each time-step for experiment scenarios P1-P5 (see Table 4.6 for details), where each plotted value is the average for that time-step over 10 replications. Figures 4.14b and c, which show the results when the autonomy premium is 2 and 20, respectively, appear very similar. For scenarios P1 and P2, the distance values immediately achieve steady-state values, with P2 being more variable from one time-step to the next. Scenarios P3-P5 also achieve steady-state values, but do so more gradually (at approximately 50 time-steps). Figure 4.14a shows the results when the autonomy premium is zero. The system behavior is similar to that of the other *ap* values for scenarios P3-P5. However, scenarios P1 and P2 achieve a steady state more gradually (at 100 and 300 time-steps, respectively). Since the plots in Figure 4.9 do not show

a large decrease in the number of farmers in the system over time for scenarios P1 and P2, it can be inferred that the decrease in long-haul transport distance seen in scenarios P1 and P2 in Figure 4.14a is a result of farmer coordination group formation.

Figure 4.15a, which shows the results of local transport distance when the autonomy premium is zero, supports this conclusion regarding scenario P1. This plot shows that local transport distance increases dramatically between the first and 50th time-steps, and then achieves a steady-state value in the 200th time-step. Because local transport only occurs among coordinated farmer groups, this indicates that significant farmer coordination is occurring for scenario P1. The local transport distance values for scenarios P2-P5 also achieve steady-state values in the 50th time-step. Interestingly, scenario P3 exhibits significantly greater steady-state local transport distance than scenarios P2, P4, and P5. Figures 4.15b and c show the results of total local transport distance when the autonomy premium is 2 and 20, respectively. The overall local transport distance in each time-step is much lower, compared with the results in Figure 4.15a, and they show a steady decrease in values over time, whereas the values increase to a steady state when the autonomy premium is zero. This makes intuitive sense – a low autonomy premium would be expected to increase the number of farmer groups in the system, which would increase the amount of total farmer-to-farmer transport.

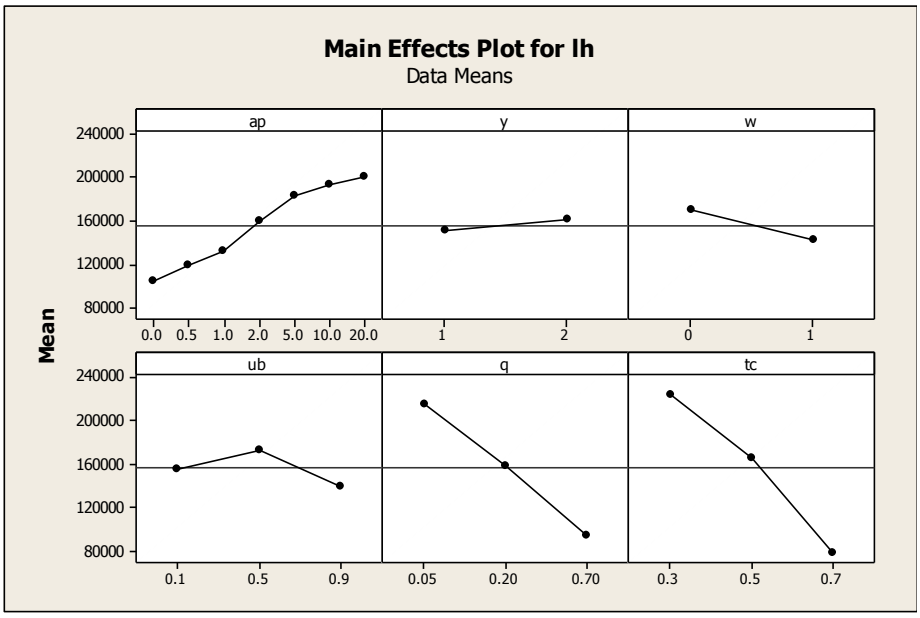


Figure 4.10. Main effects plot for system-wide long-haul distance traveled in the 500th time-step.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	9.316E+12	1.55E+12	616.79	0.000			
y	1	1.688E+11	1.68E+11	67.05	0.000			
w	1	1.362E+12	1.36E+12	543.47	0.000			
ub	2	1.381E+12	6.90E+11	274.31	0.000			
q	2	1.86E+13	9.3E+12	3694.21	0.000			
t	2	2.721E+13	1.36E+13	5404.49	0.000			
Error	7545	1.899E+13	2.51E+09					
Total	7559	7.704E+13				50174	75.3%	75.3%

Table 4.11. ANOVA output for system-wide total long-haul distance traveled in the 500th time-step.

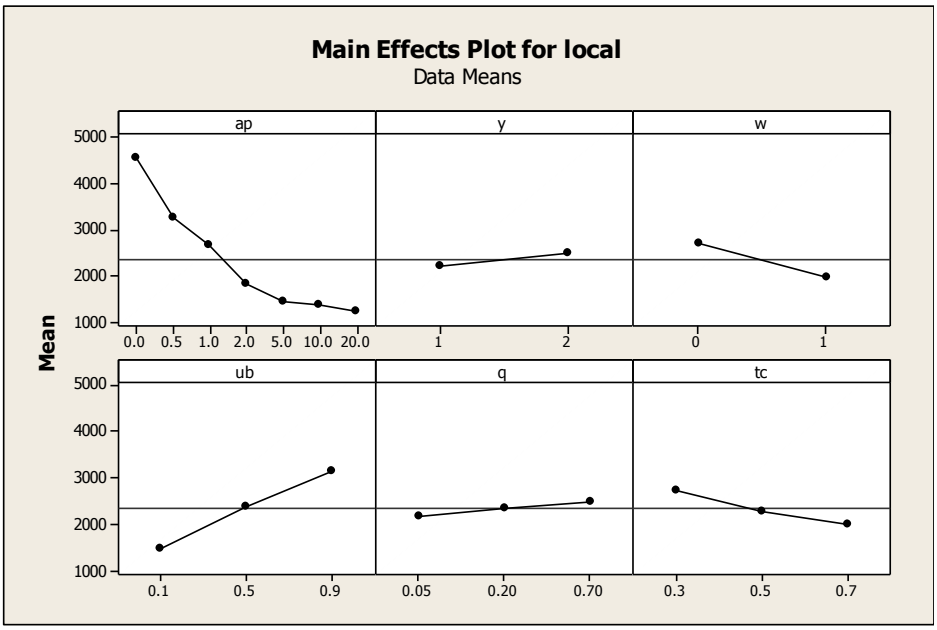


Figure 4.11. Main effects plot for total system-wide local distance traveled in the 500th time-step.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	9750505378	1.625E+09	886.85	0.000			
y	1	152144520	152144520	83.03	0.000			
w	1	1043021207	1.043E+09	569.2	0.000			
ub	2	3615905290	1.808E+09	986.64	0.000			
q	2	131358320	65679160	35.84	0.000			
t	2	702214330	351107165	191.61	0.000			
Error	7545	1.3826E+10	1832431					
Total	7559	2.9221E+10				1353.7	52.7%	52.6%

Table 4.12. ANOVA output for total system-wide local distance traveled in the 500th time-step.

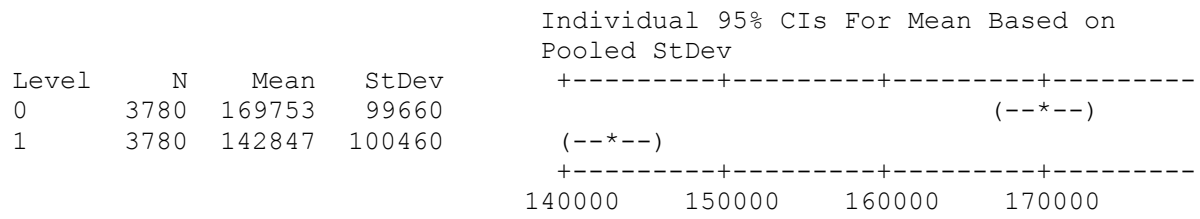


Table 4.13. 95% confidence intervals on the total long-haul distance traveled over 500 time-steps for constant (level 0) and variable (level 1) weather patterns.

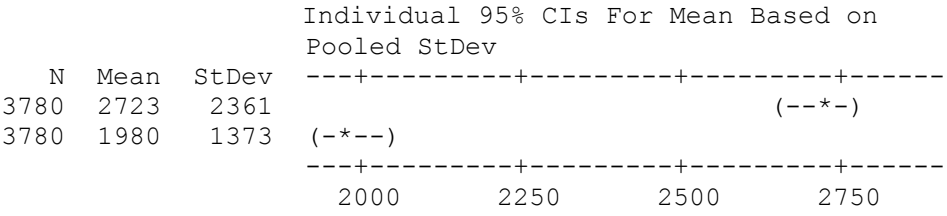


Table 4.14. 95% confidence intervals on the total local distance traveled over 500 time-steps for constant (level 0) and variable (level 1) weather patterns.

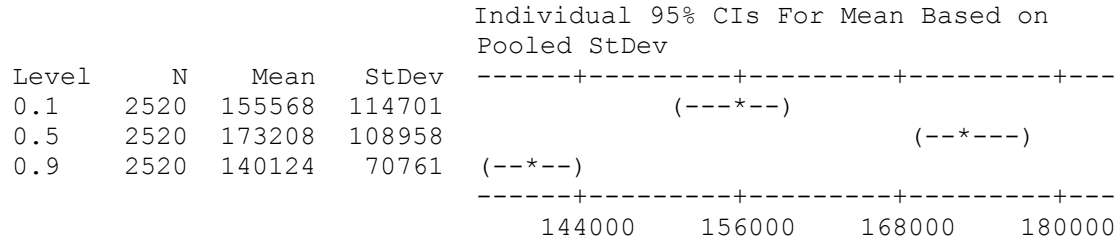


Table 4.15. 95% confidence intervals on total long-haul distance traveled in the 500th time-step for different levels of upper bound price factor.

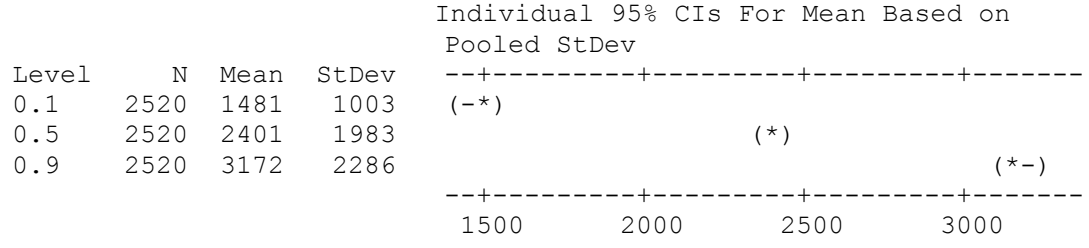
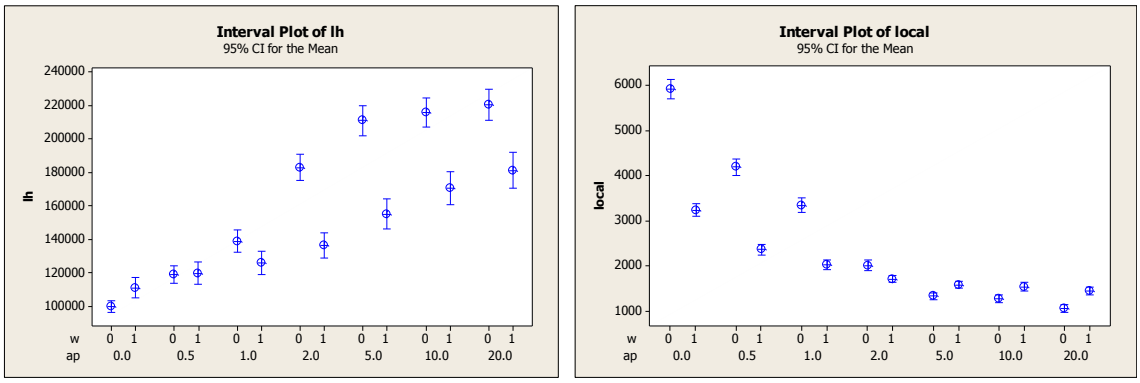
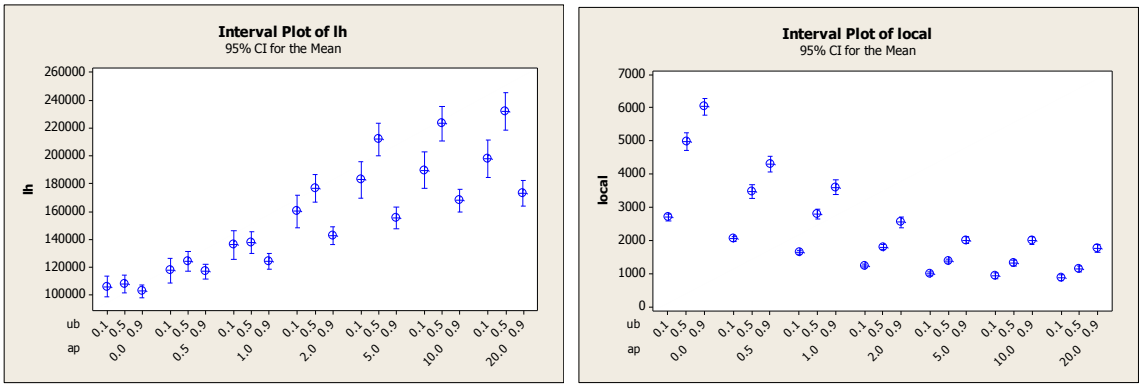


Table 4.16. 95% confidence intervals on total local distance traveled in the 500th time-step for different levels of upper bound price factor.



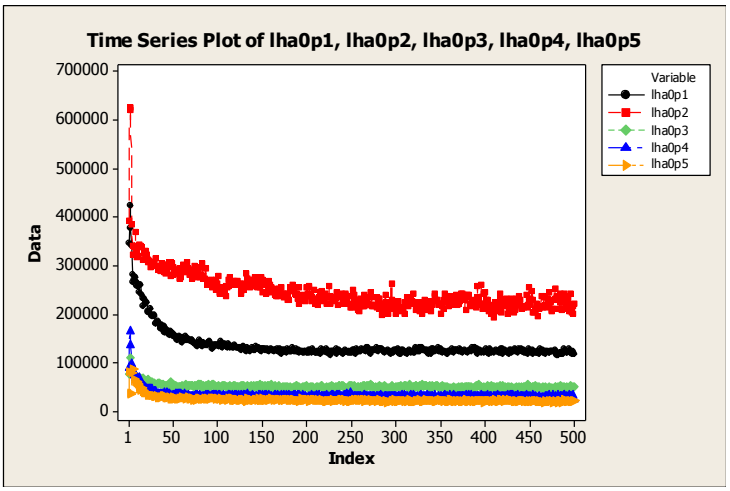
a. **b.**

Figure 4.12. Interval plots for a) long-haul and b) local transport versus autonomy premium and weather pattern.

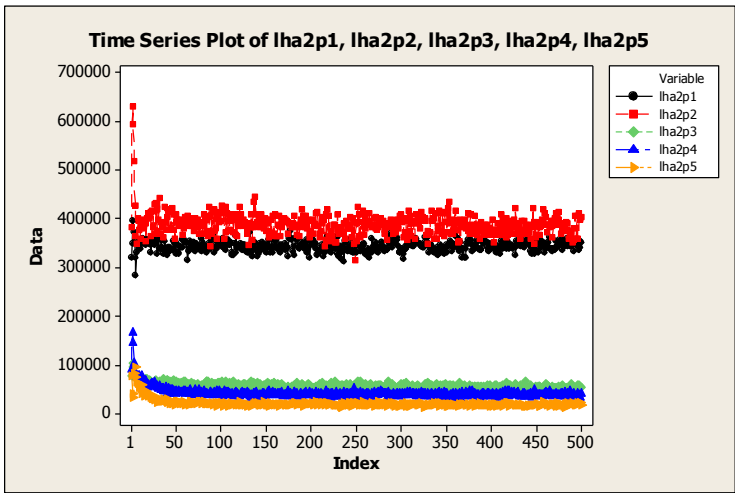


a. **b.**

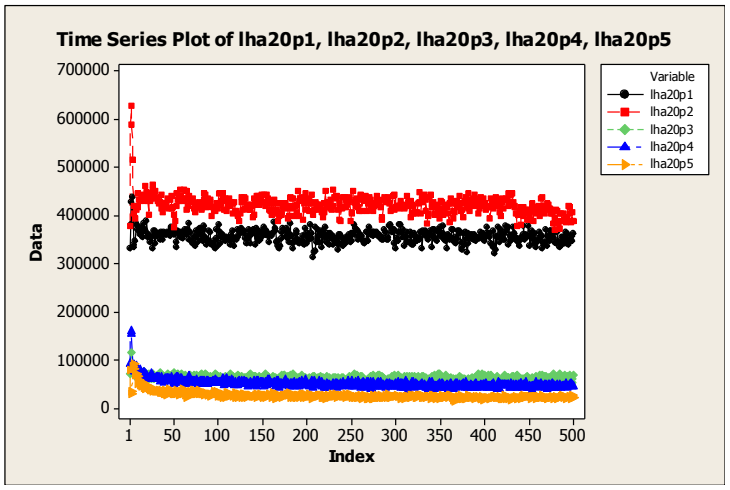
Figure 4.13. Interval plots for a) long-haul and b) local transport versus autonomy premium and upper price bound factor.



a.

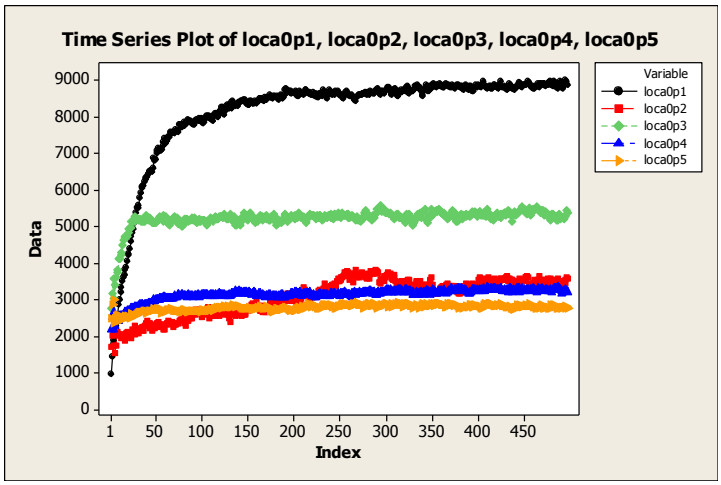


b.

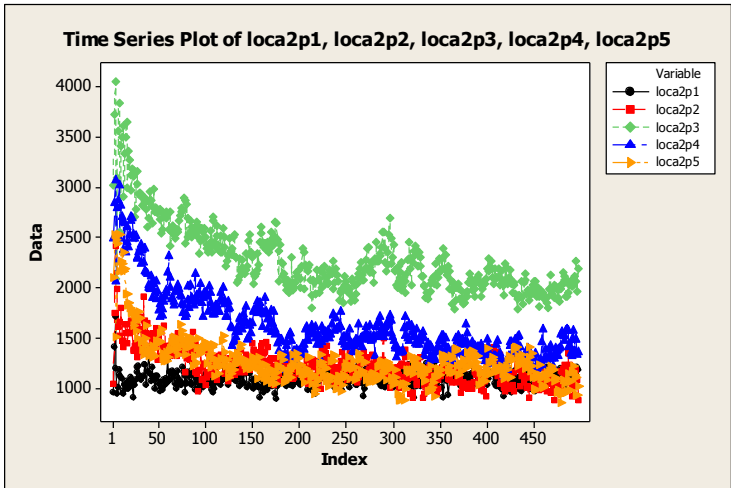


c.

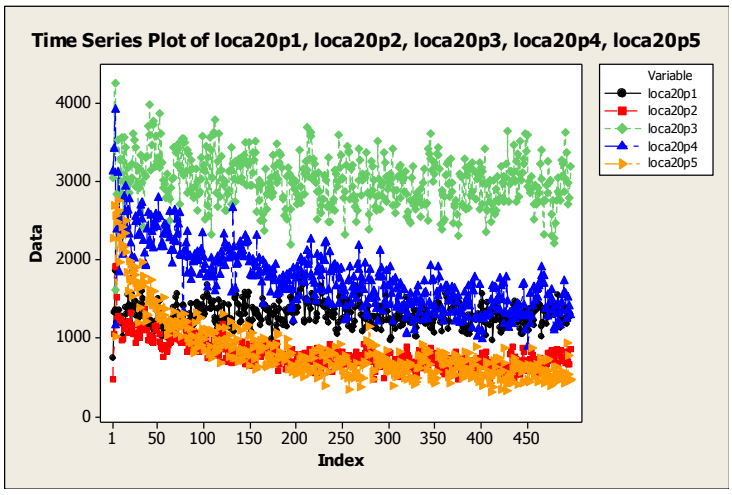
Figure 4.14. Total system-wide long-haul transport distance in each time-step, for ap = a) 0, b) 2, and c) 20.



a.



b.



c.

Figure 4.15. Total system-wide local transport distance in each time-step, for ap = a) 0, b) 2, and c) 20.

4.2.4 Farmer coordination groups

The previous sections discussed the impact of experimentally varying the values of the six input parameters on output metrics that capture aspects of sustainability in the FSC: the overall system fill rate, the number of financially viable farmers in the system, and the total amount of transport distance traveled to move food through the system from producers to their customers. This section describes the impact of these experiments on FSC structure, in terms of the number and size of farmer coordination groups that form: the percentage of grouped farmers, the number of coordinated farmer groups in the system, the group size distribution, and the average number of farmer transitions into and out of farmer groups. In Chapters 1 and 2, it is hypothesized that the FSC structure will impact its overall sustainability. The output presented in this section aims to test this hypothesis.

4.2.4.1 Farmer coordination groups: final values

Values for the percentage of grouped farmers, the number of farmer groups, and the group size 90th percentile values were captured at the end of the 500th time-step, where each experimental output value is an average over 10 replications. The number of farmer group transitions is captured as an average value over the 500 time-steps, and this average is then averaged over 10 replications.

The main effects plot and ANOVA results for the percentage of grouped farmers (shown in Figure 4.16 and Table 4.17, respectively) clearly show that farmer autonomy premium has the greatest impact (F = 5327). The percentage of farmers in coordinated groups decreases linearly with increased autonomy premium. The distributor volume-price function coefficient (q) also has an effect, with the percentage of farmers in groups increasing with increasing values of q. Large values of q appear to act as an incentive for farmers to

coordinate, in an effort to capture higher prices from distributors through increased volume. Table 4.18 emphasizes this relationship.

The main effects plot and ANOVA results for the number of coordinated farmer groups in the system in the 500th replication (shown in Figure 4.17 and Table 4.19, respectively) indicate that the distributor volume-price function coefficient (q) has the greatest impact on the number of groups (F = 2157), with fewer groups existing for larger values of q. Because the percentage of farmers in groups increased with q (as Table 4.18 shows), it can be inferred that increases in the value of q cause fewer, but larger, groups to form. The weather pattern also has an effect, with more groups forming for variable weather than for constant weather. It can be seen in Figure 4.17 and Table 4.19 that the overall percentage of grouped farmers is only very slightly affected by the weather pattern; therefore, it seems that increased weather variability may encourage more, but smaller, groups to form than when the weather is constant. Finally, as with the percentage of grouped farmers, the autonomy premium affects the number of groups, which generally decrease with increasing autonomy premium values. However, the R^2 value for the ANOVA output is not high (57%), indicating that much of the grouping behavior is not explained by the experimental factors.

To further investigate the effects of weather and q values on the number of farmer groups in the system, confidence intervals and interval plots for mean values of number of groups were created (Table 4.20, Table 4.21, and Figure 4.18). Table 4.20 shows a significant difference (at a 95% confidence level) between the mean number of groups for constant (mean = 16.22 groups) and variable (mean = 24.58 groups) weather. Figure 4.18a shows that the effect of weather patterns on the number of groups is extremely pronounced for low autonomy premium values, but the effect decreases with increasing ap values. When

weather is constant, the largest number of groups form when *ap* = 2; when weather is variable, autonomy premium values of 0 and 1 yield the largest number of groups. Table 4.21 shows a significant difference (at a 95% confidence level) between the mean number of groups for each level of *q*, with 29.29, 20.66, and 11.24 groups in the system for *q* values of 0.05, 0.2, and 0.7, respectively. Figure 4.18b shows that when the autonomy premium values are small, increases in *q* cause significant reductions in the number of groups, but when ap = 10 or 20, *q* does not have much effect.

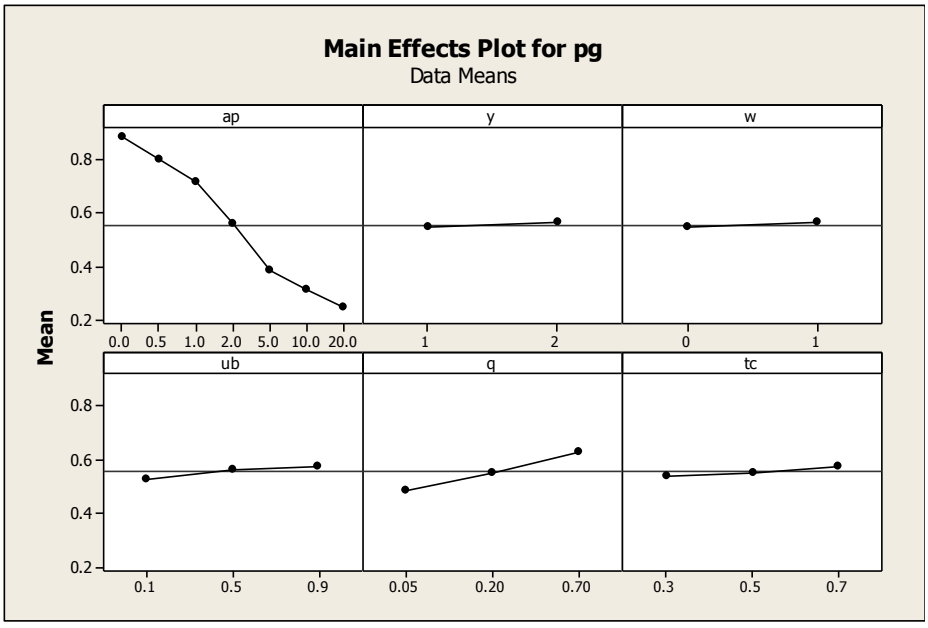


Figure 4.16. Main effects plot for percent of grouped farmers.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	402.016	67.003	5326.94	0.000			
y	1	0.802	0.802	63.8	0.000			
w	1	0.455	0.455	36.15	0.000			
ub	2	3.482	1.741	138.41	0.000			
q	2	26.674	13.337	1060.32	0.000			
t	2	1.83	0.915	72.75	0.000			
Error	7545	94.902	0.013					
Total	7559	530.16				0.112152	82.10%	82.07%

Table 4.17. ANOVA output for percent of grouped farmers.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0.05	2520	0.4853	0.2520	(-*-)
0.20	2520	0.5503	0.2648	(-*-)
0.70	2520	0.6306	0.2574	(-*-)

0.500 0.550 0.600 0.650

Table 4.18. 95% confidence intervals on the percentage of grouped farmers in the 500th time-step for different levels of distributor volume-price coefficient (*q*).

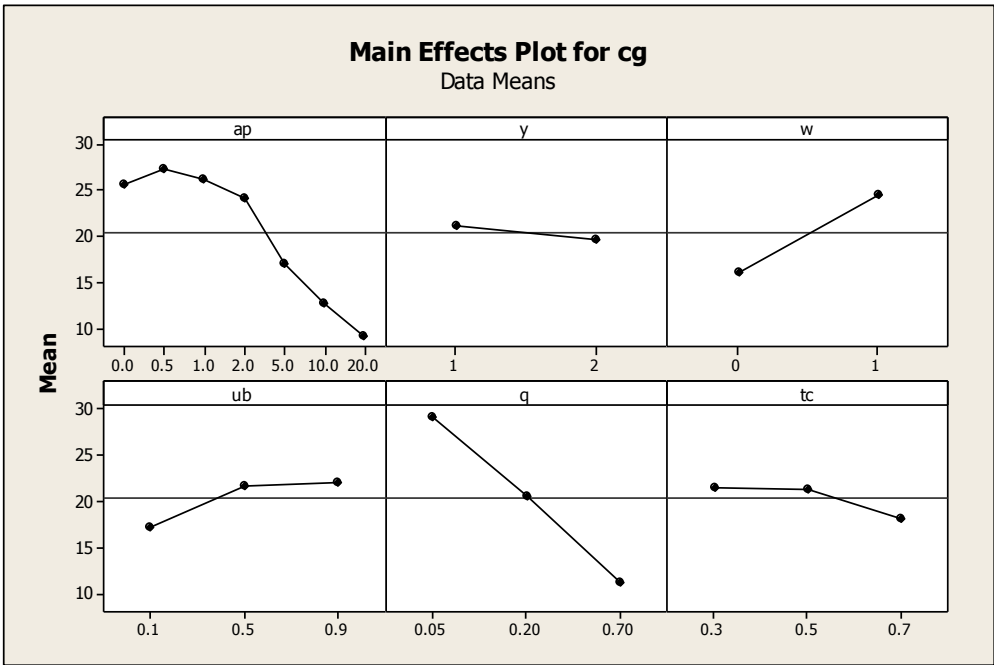


Figure 4.17. Main effects plot for the number of farmer groups.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	342992	57165	600.33	0.000			
y	1	4457	4457	46.81	0.000			
w	1	132093	132093	1387.2	0.000			
ub	2	37351	18676	196.13	0.000			
q	2	410879	205439	2157.46	0.000			
t	2	19257	9628	101.11	0.000			
Error	7545	718457	95					
Total	7559	1665486				9.75822	56.86%	56.78%

Table 4.19. ANOVA output for the number of farmer groups.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0	3780	16.22	9.56	(-*-)
1	3780	24.58	17.73	(-*-)

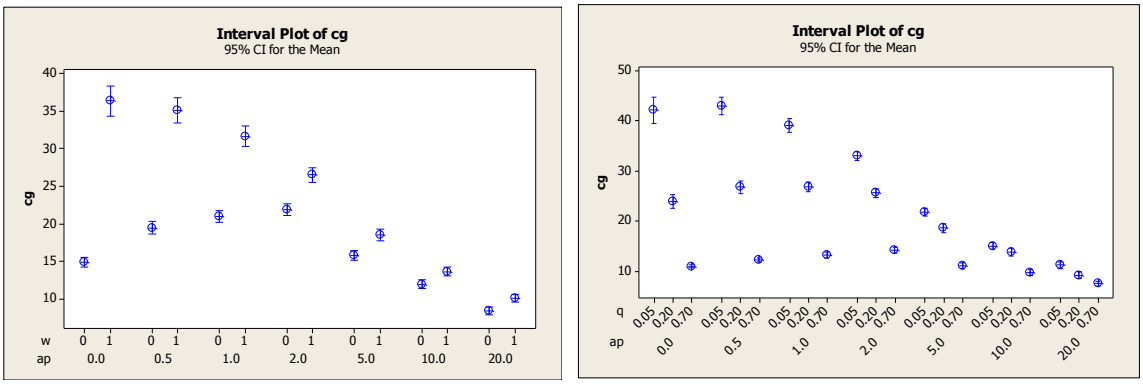
17.5 20.0 22.5 25.0

Table 4.20. 95% confidence intervals on the mean number of groups in the system in the 500th time-step for constant (level 0) and variable (level 1) weather patterns.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0.05	2520	29.29	18.24	(*)
0.20	2520	20.66	11.63	(*)
0.70	2520	11.24	5.50	(*)

15.0 20.0 25.0 30.0

Table 4.21. 95% confidence intervals on the mean number of groups in the system in the 500th time-step for different values of distributor volume-price coefficient (*q*).



a. **b.**

Figure 4.18. Interval plots of the number of coordinated farmer groups for each experimental autonomy premium value and a) weather pattern and b) distributor volume-price coefficient.

To gain a better understanding of the impact of the six experimental input parameter values on the farmer group size, the group size at the 90th percentile in the 500th time-step for each experiment was also captured (*p*). Having this information and information about the number of groups in the system provides information about the distribution of group sizes in the system. For example, if *p* is large and the number of groups in the system is small, this indicates that that there is significant consolidation in a few large groups. The main effects plot in Figure 4.19 and the ANOVA output in Table 4.22 show that the weather pattern has by far the greatest impact on *p* (F = 1059), with variable weather leading to a significant reduction in the size of groups at the 90th percentile. Given that variable weather tends to increase the number of groups in the system and has no effect on the percentage of grouped farmers, this outcome suggests that the effects of variable weather discourage large groups from forming and instead encourage many small groups to form. However, the R^2 value for the ANOVA output is low (45%), which indicates that the resulting values of *p* are not necessarily well-explained by the experimental factors. Table 4.23 shows a significant difference in mean values (at a 95% confidence level) of *p* for constant (mean = 8.80 members) and variable (mean = 5.69 members) weather. Figure 4.20a shows that the strength of the effect of weather on the 90th percentile group size increases with decreasing autonomy premium. Table 4.24 shows a significant difference in mean values (at a 95% confidence level) of *p* for different levels of upper bound price factor: 5.23, 7.37, and 9.15 members at *ub* levels of 0.1, 0.5, and 0.9, respectively. Figure 4.19, Table 4.24, and Figure 4.20b show that the upper bound price factor also has a strong effect on the value of *p*; when *ub* is set to its lowest value (0.1), *p* is significantly lower, indicating that when prices are low, farmers tend to be less inclined to form large groups. This outcome seems somewhat

counterintuitive; however, it is likely that it is partly a consequence of the severe reduction in the number of farmers in the system that occurs when *ub* is very low. Also, when *ub* is very low, it seems that the volume-price advantage of working in large groups may not be sufficient to keep farmers satisfied and convince them to remain in groups – that is, economies of scale cannot compensate for severely low upper bound prices.

The average total number of farmer transitions into and out of coordinated groups was also captured as a measure of the system's volatility. The main effects plot in Figure 4.21 and the ANOVA output in Table 4.25 indicate that the experimental factors with the largest impact on the number of transitions are the weather pattern (F = 1297) and the distributor volume-price coefficient *q* (F = 1133). Overall, variable weather significantly increased the number of transitions, compared with constant weather. The number of transitions tended to decrease with increasing values of *q* and decrease with increasing values of the upper bound price factor. This result suggests that farmer coordination behavior tends to be more volatile when prices are strong. Tables 4.26, 4.27, and 4.28 show significant differences (at a 95% confidence level) in the mean number of group transitions for different levels in weather (33.4 transitions for constant, 44.5 transitions for variable), upper bound price factor (31.9, 40.0, and 45.0 transitions for *ub* levels of 0.1, 0.5, and 0.9, respectively), and distributor volume-price coefficient (46.5, 41.4, and 29.0 transitions for *q* levels of 0.05, 0.2, and 0.7, respectively). Figures 4.22a and c indicate that the weather pattern and the value of *q* have a significant impact on the average number of group transitions per time-step when the autonomy premium levels are low ($ap \leq 2$). Figure 4.22b indicates that the impact of the upper bound price factor is only significant when autonomy premium levels are greater than 0.5.

The main effects plot for the mean number of transitions for each autonomy premium level yielded an unexpected result: the number of transitions increases from *ap* = 0 to *ap* = 2, peaks at *ap* = 2, and then decreases for larger autonomy premium values. Although these behaviors are interesting, the R^2 value for the ANOVA output is not high (52%), again suggesting that the experimental factors do not completely explain the transition behavior of the farmers.

Figure 4.23 is a scatterplot that shows the relationship between the number of transitions and the total number of farmer groups. There is a significant relationship between the two (p-value = 0); however, it is not clear whether an increased average number of transitions leads to more farmer groups, or if more transitions occur when there are more (and smaller) groups in the system. It seems more likely that the latter is the case – smaller groups provide less volume-price benefit than large groups, which would discourage "loyalty" in farmers and encourage them to leave groups more frequently.

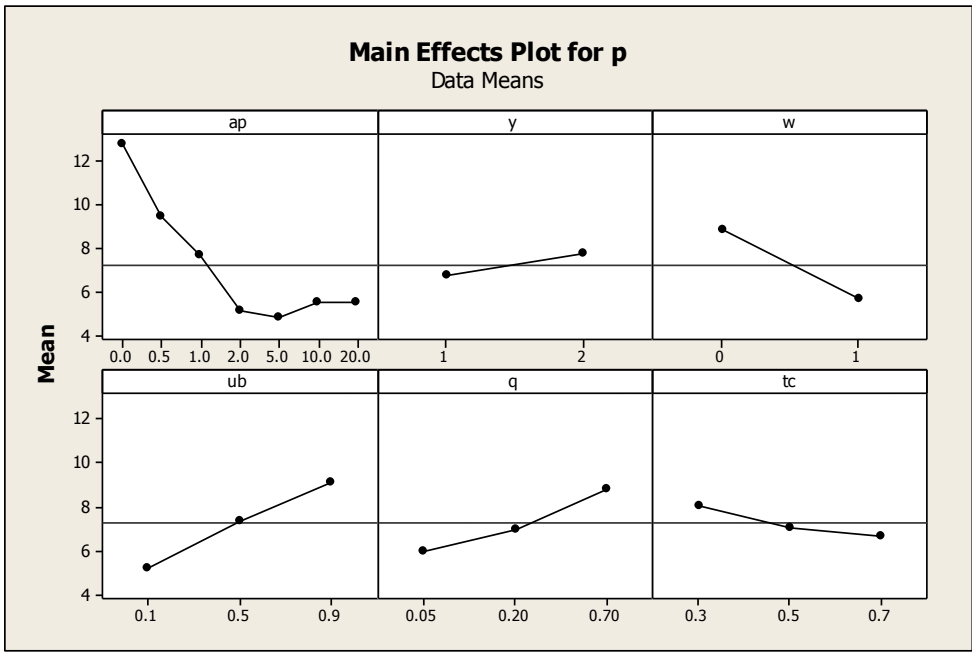


Figure 4.19. Main effects plot for 90th percentile group sizes.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	55471.2	9245.2	535.19	0.000			
y	1	1846.8	1846.8	106.91	0.000			
w	1	18301.1	18301.1	1059.43	0.000			
ub	2	19368.3	9684.2	560.6	0.000			
q	2	10422.5	5211.2	301.67	0.000			
t	2	2567.1	1283.6	74.3	0.000			
Error	7545	130336	17.3					
Total	7559	238312.9				4.16	45.3%	45.2%

Table 4.22. ANOVA output for 90th percentile group sizes.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0	3780	8.803	6.288	(-*-)
1	3780	5.691	4.322	(-*-)

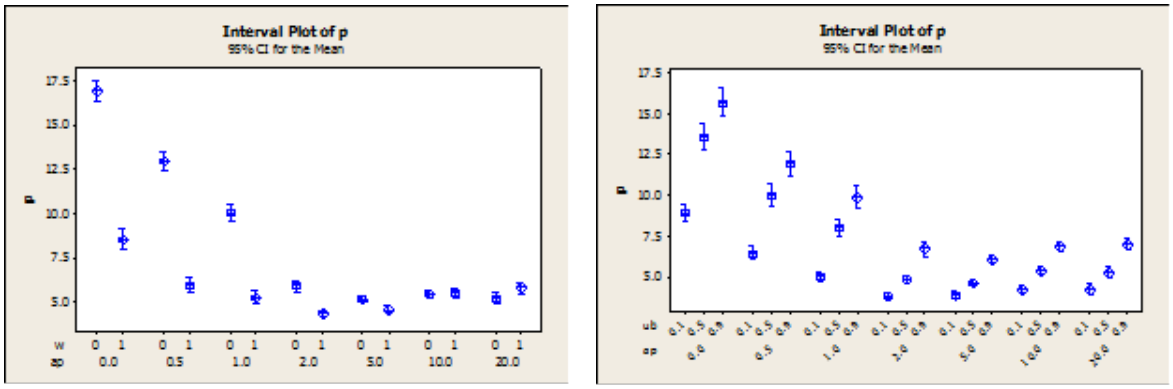
6.0 7.0 8.0 9.0

Table 4.23. 95% confidence intervals on the mean 90th percentile group size in the 500th time-step for constant (level 0) and variable (level 1) weather patterns.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0.1	2520	5.230	3.630	(-*)
0.5	2520	7.366	5.721	(*-)
0.9	2520	9.145	6.404	(-*-)

6.0 7.2 8.4 9.6

Table 4.24. 95% confidence intervals on the mean 90th percentile group size in the 500th time-step for different levels of upper bound price factor.



a. **b.**

Figure 4.20. Interval plots for the 90th percentile group sizes for each experimental autonomy premium value versus a) weather patterns and b) upper bound price factors.

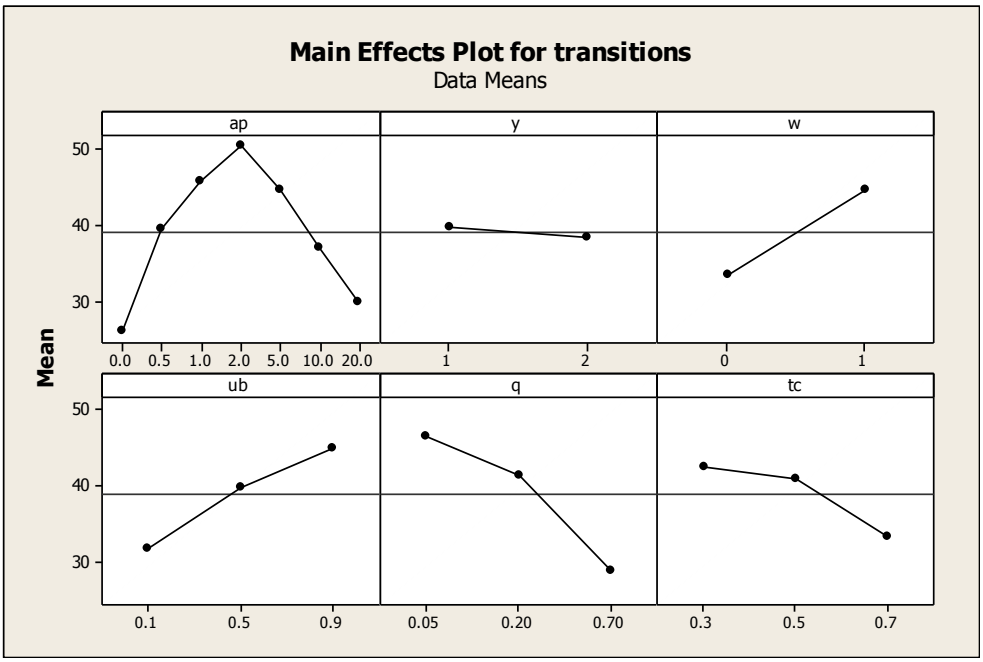


Figure 4.21. Main effects plot for the average number of farmer group transitions per time-step.

Source	DF	SS	MS	F	P	S	R-Sq	R-Sq(adj)
ap	6	493270	82212	454.04	0.000			
y	1	2961	2961	16.35	0.000			
w	1	234862	234862	1297.1	0.000			
ub	2	222034	111017	613.13	0.000			
q	2	410237	205118	1132.83	0.000			
t	2	121765	60882	336.24	0.000			
Error	7545	1366154	181					
Total	7559	2851282				13.456	52.1%	52.00%

Table 4.25. ANOVA output for number of group transitions per time-step, averaged over 500 time-steps.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0	3780	33.37	17.19	(*-)
1	3780	44.51	19.92	(-*-)
				35.0 38.5 42.0 45.5

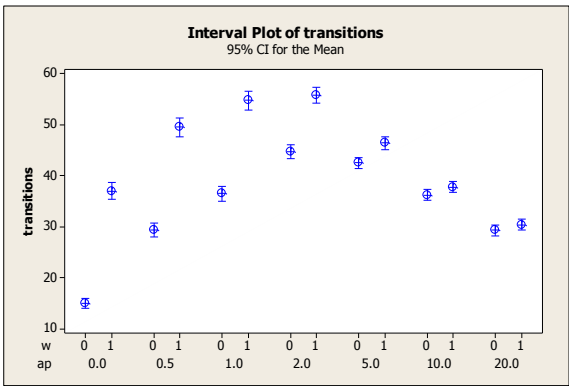
Table 4.26. 95% confidence intervals on the mean number of group transitions over 500 time-steps for constant (level 0) and variable (level 1) weather patterns.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0.1	2520	31.89	18.48	(-*-)
0.5	2520	39.87	19.64	(-*)
0.9	2520	45.07	17.79	(-*)
				32.0 36.0 40.0 44.0

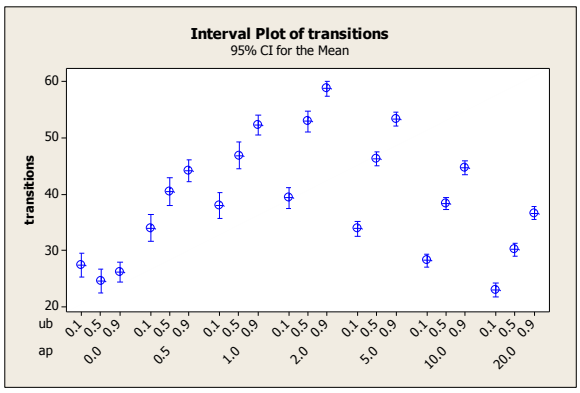
Table 4.27. 95% confidence intervals on the mean number of group transitions in the 500th time-step for different levels of upper bound price factor.

Level	N	Mean	StDev	Individual 95% CIs For Mean Based on Pooled StDev
0.05	2520	46.49	18.37	(*)
0.20	2520	41.39	18.42	(-*)
0.70	2520	28.95	17.10	(-*)
				30.0 35.0 40.0 45.0

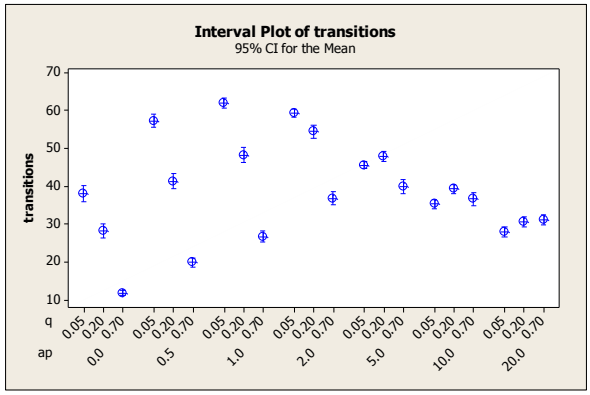
Table 4.28. 95% confidence intervals on the mean number of group transitions in the 500th time-step for different levels of distributor volume-price coefficient (*q*).



a.



b.



c.

Figure 4.22. Interval plots of the average number of transitions in the 500th time-step for each experimental value of autonomy premium and a) weather pattern factor, b) upper bound price factor level and c) distributor volume-price function coefficient.

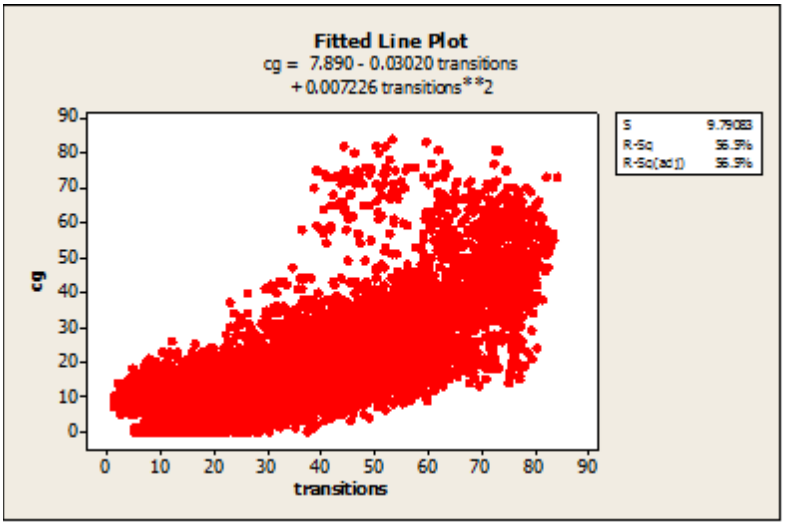


Figure 4.23. Scatterplot of the number of farmer groups versus the average number of group transitions per time-step.

4.2.4.2 Farmer coordination groups: values over time

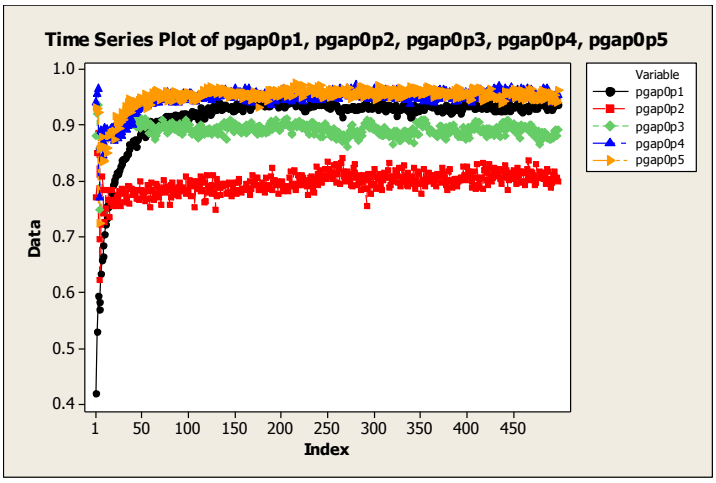
Figure 4.24 shows the values of the percentage of grouped farmers at the end of each time-step for five experimental scenarios (P1-P5, see Table 4.6 for details on these scenarios) for three different levels of autonomy premium value, where each value shown is the mean over 10 replications. Figure 4.24a, (*ap* = 0) shows a rapid increase in the percentage of grouped farmers, which reaches steady-state values for all five scenarios in or before the 50th time-step. The values for all scenarios are quite large (≥ 90%) at steady state, with the exception of the P2 scenario, which falls just below 80%. Figure 4.23b (*ap* = 2) shows more gradual change over time, with a decrease in the percentage of grouped farmer to a steady-state value by the 250th time-step. An exception is the scenario P1, in which farmers are most likely to remain satisfied – the values for this scenario immediately drop to approximately 30% and remain steady for 500 time-steps. Figure 4.24c (*ap* = 20) shows a variety of behaviors, but in general, the percentage of grouped farmers decreases to a steady state value over time. In some scenarios this happens rapidly (i.e., P1-P3) but in others is more gradual and is more variable throughout the replication (i.e., P4 and P5).

Figure 4.25 shows the values of the total number of farmer groups at the end of each time-step for the same five experimental scenarios. Regardless of autonomy premium value, the number of groups in the system decreased over time and achieved what appear to be a steady state values. In Figure 4.25a (*ap* = 0), scenarios P1 and P2 show the number of groups very gradually decreasing over 300 time-steps to a steady state value. In contrast, the other scenarios reach a steady state more rapidly (within 50 time-steps). In Figure 4.25b (*ap* = 2), scenario P1 reaches a steady state (although with somewhat large variability between time-steps) almost immediately. The number of groups in scenario P2 decreases gradually

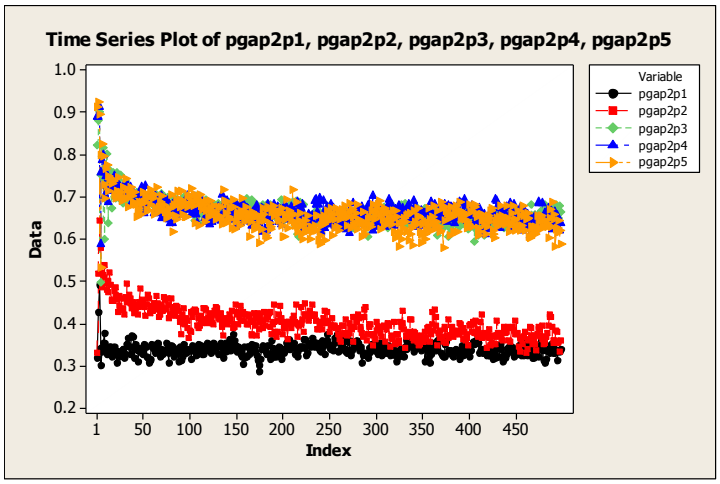
(over 300 time-steps) and eventually matches scenario P1 at just under 30 groups. Scenarios P3-P5 show very behavior that is very similar to their behavior in Figure 4.25a (when *ap* = 0), although the time to reach a steady state is longer (at approximately 150 time-steps). Figure 4.25c (*ap* = 20) shows similar behavior in the number of groups over time for all five scenarios.

Figure 4.26 shows the values of the 90th percentile group size at the end of each time-step for each experimental scenario. In Figure 4.26a (*ap* = 0), Scenario P2 shows a gradual increase in 90th percentile group size for the first 300 time-steps, then a decrease over the next 100 time-steps, and finally a slight increase. In contrast, the values for the other scenarios appear to increase steadily and then achieve what appear to be steady states, with very large groups forming in Scenario P1. Figure 4.26b (*ap* = 2) shows the 90th percentile group size gradually falling (although it is not certain that a steady state is achieved) for scenarios P3-P5, and remaining steadily at low values (3 to 5 members/group) for scenarios P1 and P2. Figure 4.26c (*ap* = 20) show high variability between time-steps, with no obvious patterns or steady states for any of the scenarios.

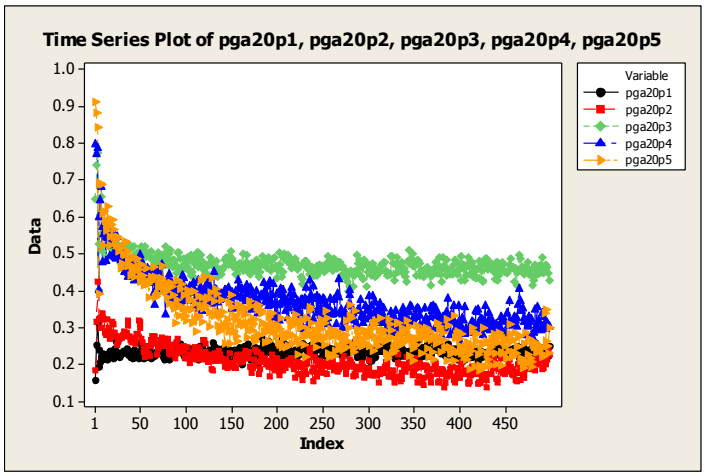
Figure 4.27 shows the number of transitions into and out of farmer groups in each time-step for each experimental scenario. For all three autonomy premium values (*ap* = 0, 2, and 20; Figures 4.27a, b, and c, respectively), the number of transitions decreases to a steady state value relatively rapidly – in 50 time-steps for *ap* = 0 and within 100 time-steps for *ap* = 2 and 20. The only exception is scenario P2 when *ap* = 0. In this case, the number of transitions gradually decreases to a steady-state value (approximately 50 per time-step) in 300 time-steps.



a.

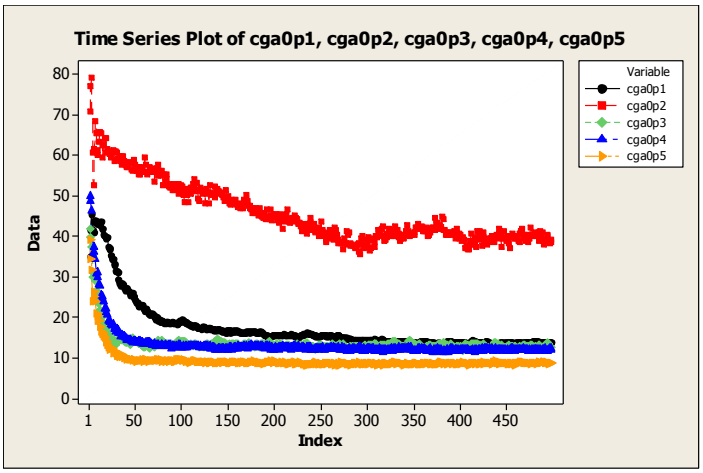


b.

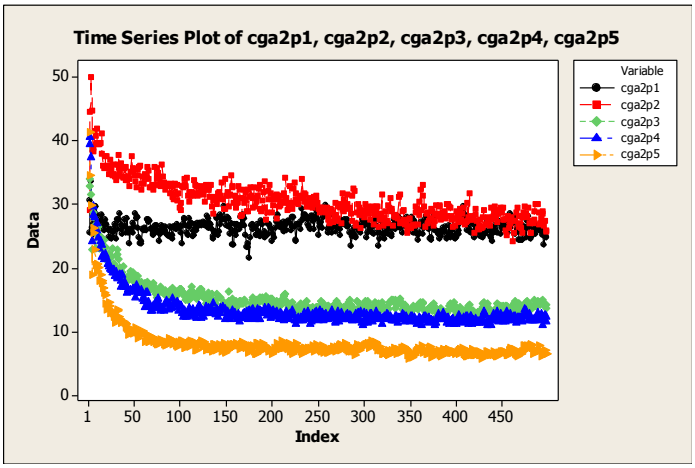


c.

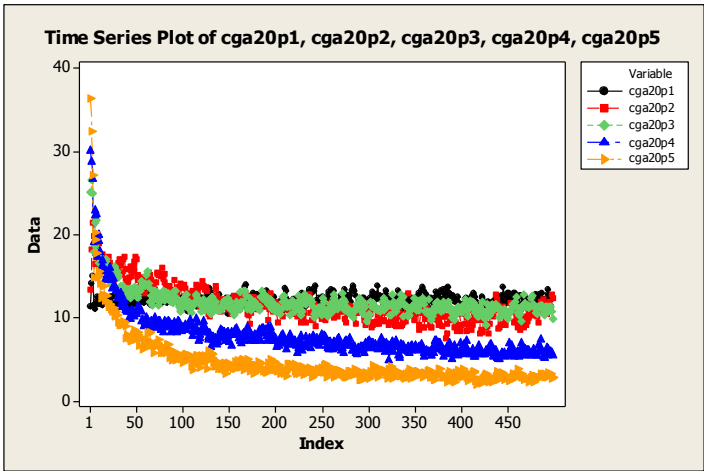
Figure 4.24. Percentage of farmers in groups in each time-step, for a) ap = 0, b) ap = 2, and c) ap = 20.



a.

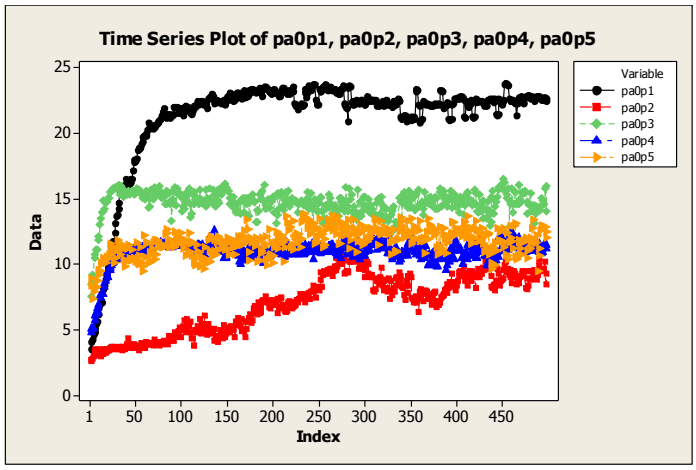


b.

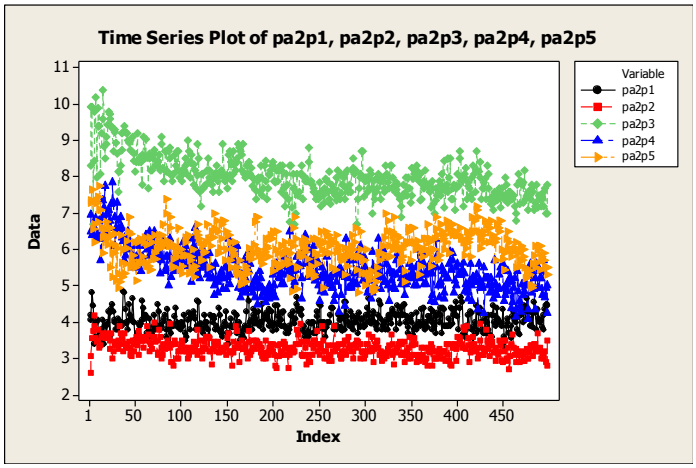


c.

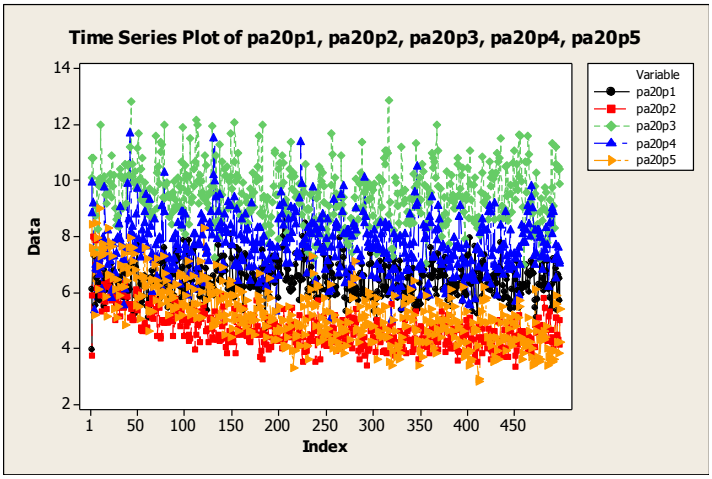
Figure 4.25. Total number of farmer groups in each time-step, for a) ap = 0, b) ap = 2, and c) ap = 20.



a.

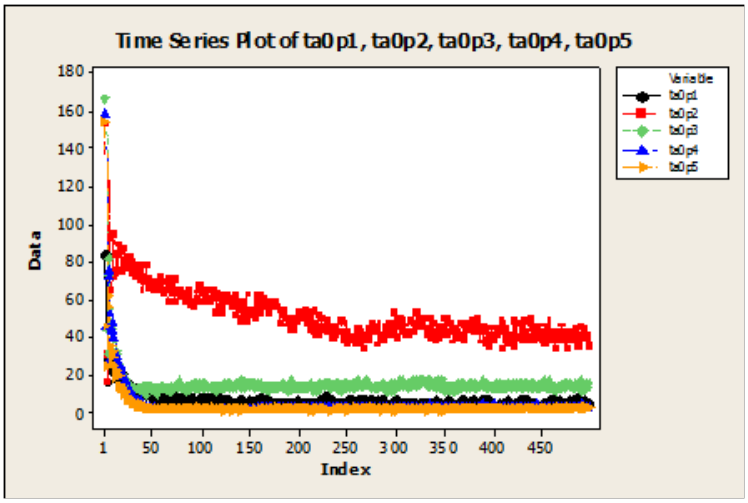


b.

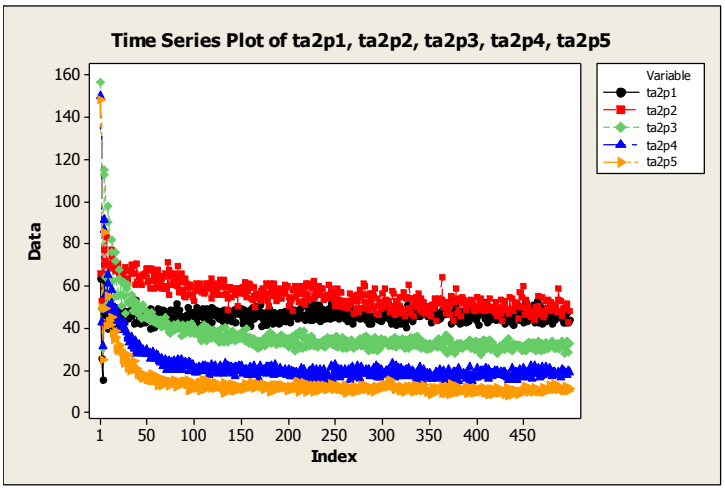


c.

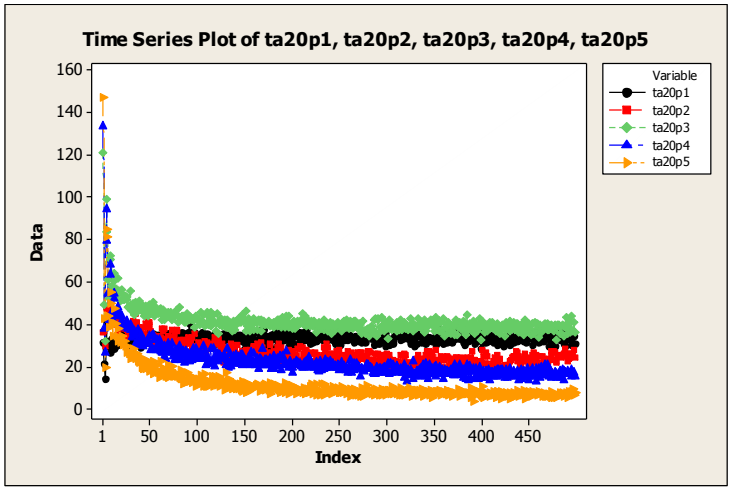
Figure 4.26. Total number of farmer groups in each time-step, for a) ap = 0, b) ap = 2, and c) ap = 20.



a.



b.



c.

Figure 4.27. Total number of farmer group transitions in each time-step, for a) ap = 0, b) ap = 2, and c) ap = 20.

4.2.5 Relationships between coordination metrics and other output metrics

Figures 4.28 and 4.29 are matrices of scatterplots that show the relationship between the FSC sustainability output metrics (fill rate, supply-demand ratio, number of farmers in the system, and transport distances) and farmer coordination metrics (percentage of grouped farmers, the number of farmer groups in the system, the 90th percentile group size, and the average number of group transitions) in the 500th time-step. Other than a strong positive linear relationship between the total local transport distance traveled and 90th percentile group size, there are no clear relationships between farmer coordination behavior and the selected FSC sustainability metrics.

4.2.6 Summary of results and discussion

As shown in the interaction plots in Appendix C, there was very little statistical interaction among input factors. Therefore, it is appropriate to summarize the experimental results for each output variable in terms of its overall response to changes in input factor levels. Table 4.29 shows a summary of the overall effects on output variables for increasing input factor levels. The actual 95% confidence intervals on the mean output variable values for each factor and level are provided in Appendix D.

	fr	sd	cf	lh	local	pg	cg	p	transitions
ap	↔	↔	↔	↑	↓	↓	↓	↓	↑↓
y	↑	↑	↓	↑	↑	↑	↓	↑	↓
w	↓	↓	↓	↓	↓	↑	↑	↓	↑
ub	↑	↑	↑	↑↓	↑	↑	↑	↑	↑
q	↓	↓	↓	↓	↑	↑	↓	↑	↓
tc	↓	↓	↓	↓	↓	↑	↓	↓	↓

Table 4.29. Overall effects on mean values of output variables for increasing levels of input factors (confidence level = 95%). ↑ = increase, ↓ = decrease, ↑↓ = variable effect, ↔ no significant effect.

4.2.6.1 Experimental results: FSC coordination and structural metrics

The impacts of input parameters on farmer coordination behavior were at times unexpected. These results are therefore interesting in their own right in terms of the emergent coordination behavior among agents. The results of the experiments focused on four key output metrics related to FSC coordination and structure:

- **Percent grouped farmers**
- **Number of farmer groups in the system**
- **90th percentile group size**
- **Number of farmer group transitions**

One interesting result is that the average number of farmer group transitions per time-step does not follow a clear pattern with respect to autonomy premium values – the average number of transitions peaks at an autonomy premium value of 2. This behavior suggests that this autonomy premium value may be a tipping point for farmer coordination volatility. It seems that at lower autonomy premium values (ap = 0, 0.5, 1), farmers tend to join groups and remain in those groups for longer periods of time, and for higher autonomy premium values (ap = 5, 10, 20), farmers tend to remain ungrouped, but farmers with ap = 2 tend to be frequently dissatisfied, whether they are in a group or not, and therefore change their state often.

Another interesting result is that the average number of transitions per time-step increases with increasing upper bound price factor and also increases with decreasing distributor volume-price coefficient value, which suggests that farmer coordination behavior is more volatile when prices (and therefore revenues) are highest. This result is surprising, because farmers are more satisfied when their profits are large and are therefore expected to make fewer transitions. For the upper bound price factor, this effect is only significant for moderate and high autonomy premium values ($ap \geq 1$), and for the volume-price factor, this

effect is only significant for low and moderate autonomy premium values ($ap \leq 5$). This outcome appears to be partly a result of there being more farmers in the system at the end of a replication when pricing conditions are favorable to farmers (i.e., there is more opportunity for transitions when there are more farmers), but this does not explain the differences across different autonomy premium values.

The farmer coordination behavior and resulting FSC structure changed significantly in response to changes in weather variability – although the overall percentage of grouped farmers was not affected by the weather factor, the weather was a highly-significant factor in determining the total number of farmer groups in the system, and it was by far the most significant factor in determining the 90th percentile group size. Variable weather conditions resulted in a system structure that was characterized by relatively many small farmer coordination groups, with a mean value of 24.58 groups, and a 90th percentile size of 5.69 members on average, over all experiments in the 500th time-step. In contrast, constant weather resulted in a mean value of 16.22 groups, and a 90th percentile size of 8.80 members on average, over all experiments in the 500th time-step. Variable weather also resulted in significantly more group transitions per time-step on average than constant weather. Therefore, it seems that the difference in the characteristics of system structures under constant and variable weather conditions is a result of frequent farmer transitions into and out of groups, which prevents large groups from forming. It appears that often the benefits of joining a coordinated farmer group were outweighed by the negative impacts of the weather.

Similarly, reducing the distributor volume-price coefficient (q) resulted in a significant increase in the number of farmer groups and a decrease in group size. When q is 0.05, the mean number of groups in the system in the 500th time step is 29.3, with a mean 90th

percentile size of 6.0 members; when q is 0.7, the mean number of groups in the system is 11.2, with a mean 90th percentile size of 8.8 members. This result is not entirely surprising – for smaller farmers to survive when q is large would require that they form groups that are sufficiently large enough to ensure adequate prices from the distributors.

4.2.6.2 Experimental results: FSC sustainability metrics

To gain an understanding of the impacts of system input parameter levels and resulting FSC structures on long-term FSC environmental, social, and economic sustainability, the results of the experiments focused on the following four key output metrics:

- **System fill rate**: a measure of social sustainability, capturing the ability of the FSC to provide adequate nutrition (in terms of volume and variety) to consumers
- **Number of farmers in the system**: a measure of economic and social sustainability, which captures the ability of farmers' operations to survive and indicates employment levels
- **Total long-haul transport distance:** a measure of environmental sustainability, capturing "food miles" and the amount of energy (i.e., fossil fuels) the system uses at a given capacity level
- **Total local transport distance**: another measure of environmental sustainability, and also a proxy for overall coordination costs in the system.

An analysis of the results indicates that the factor with largest impact on system fill rate (other than the weather variability, which is an obvious effect) is the distributor volume-price coefficient (q), although the upper price bound factor (ub) also has a large impact. These factors are also the most important factors in determining the number of farmers in the system in the 500th time step. This seems to suggest that the total number of farmers in the system is the most important factor affecting the system fill rate, although the relationship between number of farmers and fill rate is not linear – the rate of increase in fill rate decreases with an increasing number of farmers. This result suggests that distributors' focus on having a small number of large suppliers is the factor that is most detrimental to FSC

sustainability. Small-sized farmers are simply unable to survive when margins are low and distributors pay more to achieve economies of scale.

Even when farmers join coordinated groups to achieve large-scale volumes, they still frequently fail when q is large. This may be a result of small farmers grouping with large farmers out of desperation but not reaping enough benefits from the coordination to survive. Although the small farmers gain from the economies of scale and market power of large farmers, the large farmers can take advantage of the power imbalance in the relationship and can take more than their fair share of the profits. In this case, when the group has a "bad" season (e.g., the market was already saturated with the crop type that the group chose to produce in that season, leading to low profits), a large farmer can survive a short-term downturn, whereas a small farmer cannot. The experiments described in Chapter 4 did not specifically study the impacts of the characteristics (e.g., size) of the constituent members of coordinated farmer groups on overall farmer success, group stability, nor system fill rate, and this is an interesting area for further study.

Although the transport cost factor did not significantly affect farmer coordination behavior (i.e., increasing transport costs did not cause farmers to coordinate more), it did have an impact on the total system transport distance traveled. At first glance it seems that farmers chose to sell within their own region, rather than to distant distributors, more frequently when transport costs were high. However, high transport costs also significantly reduced the number of farmers in the system, and analysis of total distance traveled per farmer in the system suggests that increasing transport costs reduces the number of farmers in the system, which necessarily reduces the total amount of distance traveled by all farmers.

Perhaps the most surprising result of these experiments is the conclusion that the FSC sustainability metrics in this system are not affected by farmer coordination behavior. It seems that the number and size of farmer groups have very little impact on fill rate, farmer survival, or transport distances. Some experiments resulted in systems with few groups at all, while others resulted in systems with many small groups, while still others developed a few large groups. Regardless of this variety of system structures, none seemed to be more or less beneficial to the sustainability metrics than another.

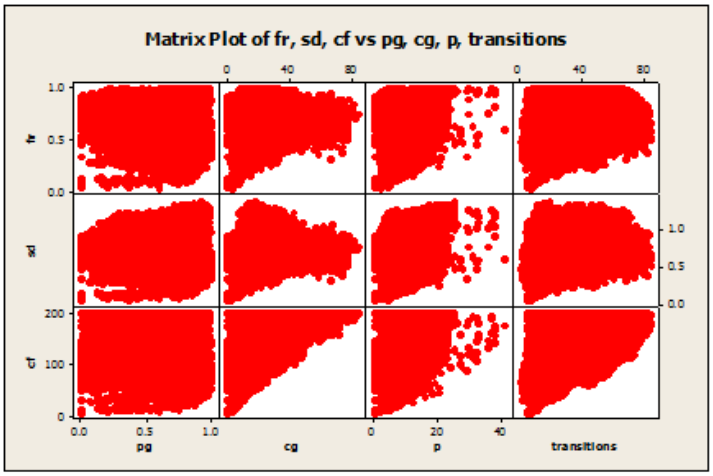


Figure 4.28. Scatterplots of final values (after 500 time-steps) for system fill rate, supply-demand ratio, and number of farmers versus percent grouped farmers, number of groups, 90th percentile group size, and average number of transitions.

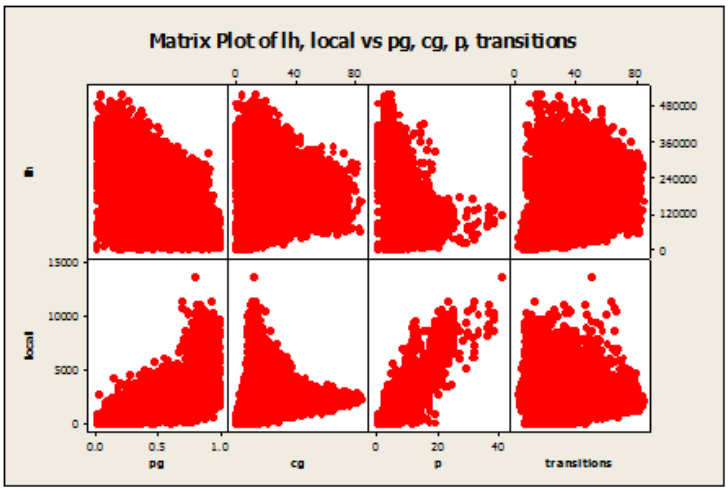


Figure 4.29. Scatterplots of final values (after 500 time-steps) for long-haul and local transport distances versus percent grouped farmers, number of farmer groups, 90th percentile group size, and average number of group transitions.

Chapter 5 : Conclusion and Future Work

5.1 Conclusion

Food supply chain (FSC) outcomes and long-term sustainability are critical to human and environmental health. While the modern industrial FSC is capable of producing enormous quantities of food and distributing it globally, it also faces serious challenges with long-term environmental, social, and economic sustainability. Individual FSC member decisions regarding production practices (i.e., farm management decisions) are critical to FSC sustainability outcomes, and these individual-level decisions have been the focus for research on FSC sustainability improvements. However, it is believed that overall FSC structural characteristics also have important implications for long-term system sustainability. In particular, the complexity of the modern industrial FSC has been significantly reduced as a result of consolidation and centralization. This change in structure has led to increases in efficiency due to economies of scale, but it is also thought to have been detrimental to FSC sustainability and resilience. Existing models of FSC sustainability have not investigated this issue, partly because the most commonly-used modeling methods (i.e., optimization and discrete-event simulation) are not capable of capturing the nonlinear and adaptive behaviors of the FSC that lead to emergent structures. This research proposes an agent-based modeling methodology to study FSC structural emergence and long-term sustainability.

5.1.1 Research questions

This research has developed an agent-based methodology that can be used to investigate the impacts of individual-level behaviors and external variability on overall FSC sustainability and FSC structural emergence. The effects of these resulting emergent FSC structures on system sustainability can then also be determined. The development of this agent-based

modeling methodology included the development of a multi-agent simulation model of an FSC, and subsequent experimentation with this model has addressed and provided insight into answers to the following research questions:

RQ0: What factors (controls/incentives) lead to the emergence of a FSC that exhibits sustainable resource use and sufficient outputs in the long term?

The results of the experiments in this research indicate that producing sufficient outputs depends on having sufficient producers in the system. Therefore, for sustainability, the FSC must support the economic survival of enough farmers to produce sufficient quantities and varieties of food to fulfill consumer demand. The factors that had the most influence on farmer survival were 1) the distributor volume-price coefficient and 2) the upper bound on the unit price that distributors were willing to pay farmers. When distributors placed a high value on large volumes, small farmers were often unable to succeed, unless they were able to form a farmer group that became large enough to produce a significant enough volume to earn an adequate price from the distributors. Also, unsurprisingly, fewer farmers can survive when distributors are offering lower prices. A reduction in the number of farmers in the system corresponded to a reduction in system fill rate. Therefore, although low prices for farmers may result in lower food prices for consumers in the short term, this benefit could be outweighed in the long term if the low prices prevent the survival of a sufficient number of farmers to provide the quantity and variety of food that consumers need to thrive.

Resource use was captured in terms of total system transport distance, which is a sustainability metric that is commonly referred to as “food miles”. Because the source of energy required for food transport in modern industrial FSCs is typically fossil fuels (which are non-renewable and produce greenhouse gases when burned), reducing total system

transport distance should improve the environmental sustainability of the system. The results of the experiments suggest that total long-haul transport distance (from farmers to distributors) decreases when more and larger farmer coordination groups form, but that the total local transport distance (among the farmers in coordinated groups) increases. When there are more and larger farmer groups, the total transport distance decreases, but because local transport is often much less efficient than long-haul transport, the reduction in long-haul distance that results from farmer coordination could be somewhat outweighed by the impacts of increased inefficient local transport.

RQ1: How do variable actor characteristics and external forces influence the emergence of an FSC's structure over time?

In the model, external forces that act on the FSC are represented by the weather pattern factor. In the experiments described in this research, this factor had two levels: constant and variable. The farmer coordination behavior and resulting FSC structure changed significantly in response to changes in weather variability – variable weather conditions resulted in a system structure that was characterized by many small farmer coordination groups, while constant weather resulted in the formation of fewer, larger groups.

Although most of the characteristics of the farmer and distributor agents do not vary throughout the course of an experiment, different levels of the farmer autonomy premium factor captured the impact of varying an important FSC actor characteristic. The results of these experiments show that low autonomy premium values tend to result in increased farmer coordination, with a high percentage of farmers forming a small number of large groups that remain relatively stable over time. In contrast, high autonomy premium values tend to result

in less farmer coordination and greater group volatility, with a lower percentage of farmers forming a large number of small groups.

RQ2: What do the intermediate/transitional stages of FSC structural emergence look like, in terms of FSC metrics, the rate of change, and the potential for a steady-state structure?

Observations of sustainability metrics and coordination structural metrics over time (i.e., in each time-step) were captured for five selected experimental scenarios at three different levels of autonomy premia. For most of these experiments, the values of the output metrics appeared to converge to steady-state values over the course of 500 time-steps. In many cases, this convergence was relatively rapid (< 50 time-steps) and the observed values typically showed low variability about a steady-state value after convergence. However, larger autonomy premium values tended to lead to increased volatility of farmer coordination groups when the experimental scenario factor levels were favorable to the farmer (i.e., when the prices were high and the distributors' volume-price coefficient was low). Under these conditions, the number of groups and size of groups did not appear to converge.

In general, for a low autonomy premium value, a relatively small number of large farmer coordination groups tended to form in a short amount of time and remain stable in the long run. For a moderate autonomy premium value, the sizes of groups tended to be smaller, and in the experiments in which pricing parameters favored farmers, there tended to be a larger number of these smaller groups. For a high autonomy premium value, farmers tended to form few highly unstable groups, and group sizes were generally small but changed frequently (jumping from medium-sized to small) from one time-step to the next, particularly when pricing conditions were unfavorable. For moderate and high autonomy premium values, there were significantly more group transitions when prices were high, while

experimentation at low autonomy premium values did not show this behavior. However, when the autonomy premium value was low to moderate, the number of group transitions was significantly higher when the distributors' volume-price coefficient was low, whereas this impact was not observed for moderate or high autonomy premium values.

RQ3: What is the impact of initial, transitional and emergent FSC structure on long-term sustainable resource use and outputs?

The results of these experiments indicate that the FSC structures that emerged, when measured in terms of percentage of grouped farmers, the total number of farmer groups, and the 90th percentile group size at the end of each time-step, had very little observable impact on system fill rate or the number of farmers in the system. When the number and/or size of coordinated farmer groups was very large, the long-haul transport distances decreased, but this was accompanied by an increase in total local transport distance, which often relies on less-efficient modes of transport than long-haul trips. Based on these results alone, it is unclear whether increased farmer coordination results in an overall decrease in energy consumption and greenhouse gas outputs.

5.1.2 Contribution

The main contribution of this research is the development of an agent-based methodology that can be used to gain an increased understanding of the impacts of micro-level individual attributes, behaviors, decisions, interactions, and adaptations on structural development of FSCs over time, and the implications of these developments for long-term sustainability. Previous research on modeling methodologies for FSCs and sustainability has focused primarily on the development of static and deterministic models of single-echelon (e.g., farm) operations to study the relationships between farm inputs and outputs, with an aim to guide

farmer decision-making. This new agent-based methodology, which uses a multi-agent simulation model to perform experimentation, allows an investigation of the impacts of interactions among multiple FSC echelons on the resulting FSC structural development over time and system sustainability outcomes.

5.2 Future work

Many new research questions about FSC structural emergence and sustainability have arisen based on the results of the experiments presented in this research. Such questions include:

- How does farm size distribution impact sustainability and structural outcomes?
- What is the relationship between FSC structure and farmer adoption of sustainable production processes (e.g., organic, local)?
- What are the impacts of increasing customer agency and allowing coordination to occur among farmers and customers?
- How does information sharing among FSC actors influence individual and overall system outcomes?
- How do vertical coordination and contracting affect system outcomes?
- What other factors (e.g., relationships, community and social values) influence coordination decisions among FSC actors?

Additional research and model developments and enhancements will be necessary to address these questions. Future research will involve 1) applying new metrics and input parameters to the model in its current form, allowing additional experimentation to address inconclusive outcomes, and 2) further developing the model to incorporate new agent and system capabilities that will help to increase the realism of the model and allow for the investigation of FSC aspects that were not addressed in here.

5.2.1 Additional experiments with current model

The results of this research have suggested new avenues of experimentation and analysis using the model in its current state. One area of interest is the impact of farmer size on system sustainability metrics and farmer coordination behavior. For the experiments described here, a certain distribution of farmer sizes (in acres) was used: (20) 100-acre farmers, (40) 50-acre farmers, and (120) 25-acre farmers. Further experimentation would allow investigation into the effects of different distributions of farmer size on structural and sustainability outcomes. Another important area of study is the impact of imbalance of farmer size and power in groups and how this affects smaller farmers' coordination behaviors and survival. Also, relating farmers' autonomy premia values to their size, and making these values heterogeneous throughout the system, is another area for experimentation with the current model.

Improved understanding of the impact of long-haul versus local transport on environmental sustainability is also worth exploring in greater depth. Given assumptions about the relative energy consumption and pollutant generation of different modes of transport, it is possible that there are optimal points of balance at which a reduction in long-haul distance achieved through coordination is worth the increase in local distance traveled.

Additional experimentation with the production of organic crops is also of interest. Farmer agents' decisions to produce organic rather than conventional crops would have a significant impact on the environmental sustainability outcomes of the system. Experimentation with different classes of customer demand, as well as costs, prices, and yields of organic production, could lead to an increased understanding of the impact of organics on system structure and sustainability.

5.2.2 Model enhancements

To address other new research questions, the current model can be extended and enhanced to capture additional agent and system attributes and behaviors.

5.2.2.1 Agent decision-making

A very interesting area for further exploration using this agent-based methodology is the impact of the availability and quality (e.g., accuracy, truthfulness) of information that guides agent decisions. For example, the farmers in the current model make decisions about which crop to produce based on very limited knowledge of the global supply-demand ratio for each crop type. In reality, although farmers do not have complete or perfect information, they typically have more information about markets than this. Whether this additional information is actually helpful to the farmers, and what the implications of additional information are for system structure and sustainability, is a topic for future research using this agent-based methodology. Farmer coordination decisions and distributor purchasing decisions can also be enhanced to account for the availability of additional information.

5.2.2.2 Agent interactions

In the current model, there are two types of agent interactions: coordination between farmers in the same region, and the crop price negotiation and sale that occurs between farmers and distributors. One area for future research is further development of these interactions. In the current model, farmers record their profits in each time-step in their "memory", and this informs their future decisions regarding crop selection and whether to seek/leave a coordination group. In real FSCs, these types of decisions depend not only on the agent's own past experience, but also on information gathered from external sources. For example, a farmer's neighbor can give him advice on which farmers in their region are the most

reliable/advantageous for coordination, or whether coordination is valuable at all, based on his past experience or information he received from others.

In the current model, the algorithm for the negotiations that occur among coordinating farmers and farmers and distributors does not allow for complex agent strategies. To increase the realism of the model, the negotiations between agents could be based on a more complex algorithm or heuristic. For example, under certain conditions, farmers might determine that it is worthwhile to negotiate under the assumption of fair sharing of profits among the group.

Another area for future research is the impact of adding new types of interactions. In the experiments described in this research, customer agents do not negotiate with distributors or provide them with any feedback on their performance (e.g., how well they meet the customer's demand in each time-step). Giving customer agents this ability will greatly enhance the range of research questions the model can address.

5.2.2.3 Agent adaptation

An area with significant potential for future model development is agent adaptation. There are many possibilities for increased adaptability in all FSC agent types. One example is a "learning" process by which agents remember the quality of past interactions other agents, thereby becoming more likely in the future to engage with agents with whom they had positive experiences. Another example is an adaptation mechanism by which distributor agents can dynamically adjust their volume-price coefficient, depending on their fill rate. Still another example is adaptive farmer utility functions, which could allow for neighbors' comparative financial success to impact a farmer's utility for a given amount of profit.

5.2.2.4 System enhancements

In the current model, crops are assumed to be highly perishable and cannot be stored from one growing season to the next. This restriction can be removed and distributors/farmers/new agents can process and/or store crops in inventory. It is also assumed that one crop type cannot substitute for another for customer demand fulfillment, which is not typically true in reality, and rules for substitutions can be implemented.

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Appendix A: List of Parameters and Variables

Parameters

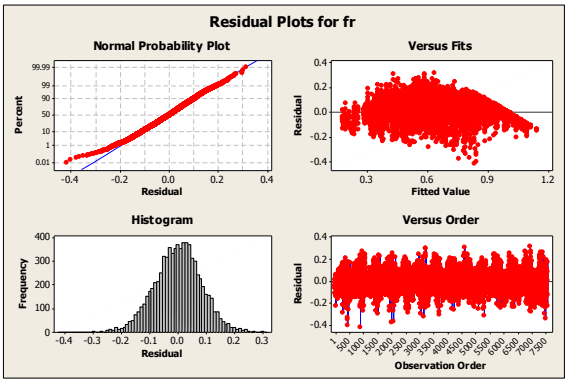
n = number of crop types in system
a = farmer's current crop, $a \in \{0, \dots, n\}$
c = current crop under consideration, $c \in \{0, \dots, n\}$
u_c = expected unit wholesale price for crop c ($/crop unit)
r = region/distributor, $r \in \{0, \dots, R\}$
i = number of farmers per region
f = farmer/farmer group (the seller), $f \in \{0, \dots, i\}$
s_f = farm size of farmer f (acres)
$g_{f(min)}$ = minimum allowable gross margin for seller *f*
t_{vfr} = cost of transporting v units of crop *c* from the seller *f* to distributor *r* ($)
ω = a volume-cost parameter used to calculate transport costs
φ = a volume-cost parameter used to calculate transport costs
λ_{fr} = distance from seller *f* to distributor *r* (distance units)
θ = a distance-cost parameter used to calculate transport costs
q_r = coefficient on distributor r's pricing function
b = current number of negotiation iterations between the distributor and seller
B = maximum allowable value for b before negotiations terminate unsuccessfully
δ = maximum difference between farmer's bid and distributor's counteroffer to reach agreement ($/crop unit)
α = farmer autonomy premium
Q_{ac} = cost of changing from crop a to crop c ($)
w_γ = weight of profit value in determining O_c
w_o = weight of opportunity value in determining O_c

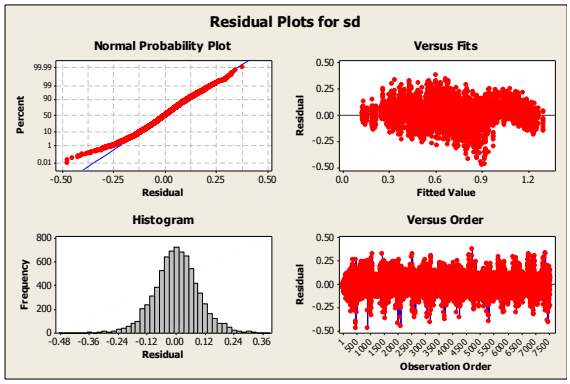
Variables

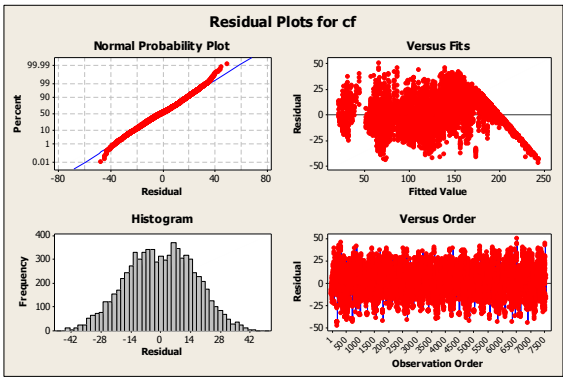
η_j = current inventory of farmer group member *j* (crop units)
η_r = current inventory of distributor *r* (crop units)
l_j = local transport cost from group member j to group leader ($)
π_j = profit share of farmer group member *j*
τ_j = differential value of farmer group member *j*
z_{cfrv} = agreed-upon unit price distributor *r* pays seller *f* for volume *v* units of crop *c* ($/crop unit)
v_{cfr} = the maximum volume of crop *c* that the seller *f* can sell to distributor *r*
z_{clf} = seller's lower bound for crop *c* unit price ($/ crop unit)
z_{cuf} = seller's upper bound for crop *c* unit price ($/crop unit)
p_{cf} = total production cost of crop *c* for seller *f* in a given season ($)
h_{cf} = total harvest cost of crop *c* for seller *f* in a given season ($)
y_{cf} = seller's actual total yield for crop *c* in a given season (crop units)
D_c = overall system demand for crop c (crop units)
S_c = overall system supply of crop c (crop units)
z_{clr} = distributor r's lower bound for crop c unit price ($/crop unit)

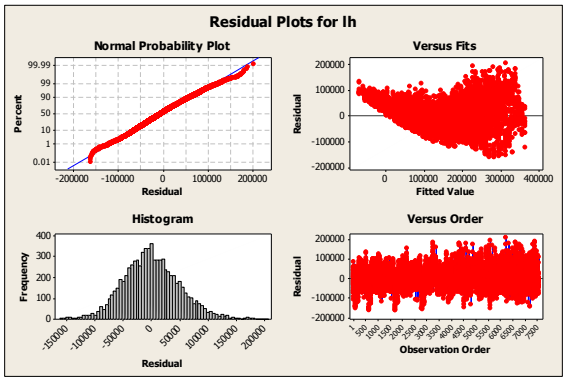
$z_{cur(max)}$ = distributor r's current maximum upper bound for crop c unit price ($/crop unit)
$z_{cur(min)}$ = distributor r's minimum upper bound for crop c unit price – a constant ($/crop unit)
z_{cur} = distributor r's actual upper bound for crop c unit price ($/crop unit)
$x_{f(b)}$ = current seller bid at bid b ($/crop unit)
$x_{f(b-1)}$ = previous seller bid at bid (b – 1) ($/crop unit)
$x_{r(b)}$ = current distributor r bid ($/crop unit)
$x_{r(b-1)}$ = previous distributor r bid at bid (b-1) ($/crop unit)
D_{cr} = distributor r's overall demand for crop c this season (crop units)
m_{cfvr} = net return to seller f from selling v units of crop c to distributor r ($)
k = current count of negotiations that have occurred this season
r_f^* = distributor providing with winning bid to seller *f*, $r_f^* \in \{0,1,2,3\}$
γ_f^* = current profit value of farmer f ($)
γ_f = current actual profit of farmer f ($)
U_f = current utility value of farmer f
$\gamma_{i(min)}$ = minimum profit parameter value for farmer f ($)
$\gamma_{i(max)}$ = maximum profit parameter vale for farmer f ($)
ρ_f = risk tolerance for farmer f
β_f = minimum acceptable expected individual profit value of farmer f to convince him to coordinate ($)
$y_{c(sender)}$ = expected Sender yield for crop c (crop units)
$y_{c(group)}$ = expected group yield for crop c (crop units)
σ_{cf} = crop inertia premium for farmer f
O_c = overall opportunity value for crop c
γ_{cf} = estimated profit value for farmer f from producing crop c ($)
$\gamma_{c(group)}$ = estimated group profit value from producing crop c ($)
o_c = estimated market opportunity value for crop c ($)
μ_r = current weather factor for region r
$y_{cf(base)}$ = base yield of crop c for farmer f (crop units per acre)

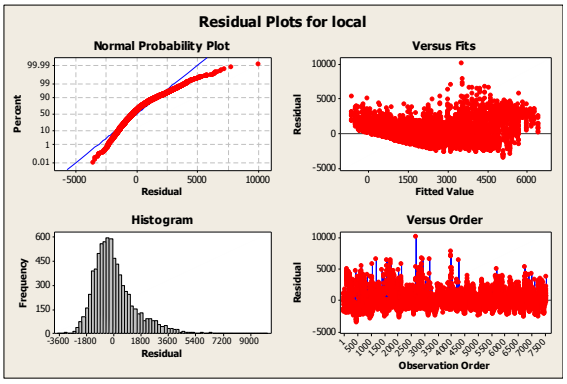
Appendix B: Residual Plots for Output Variables

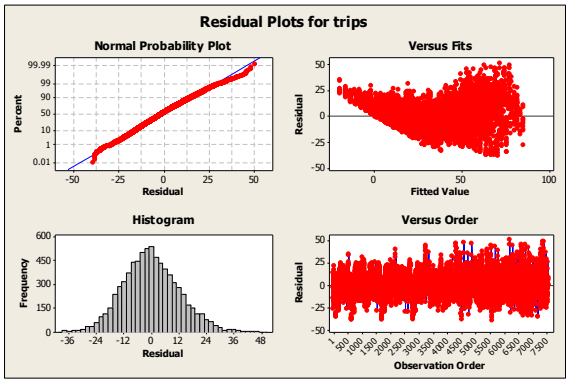


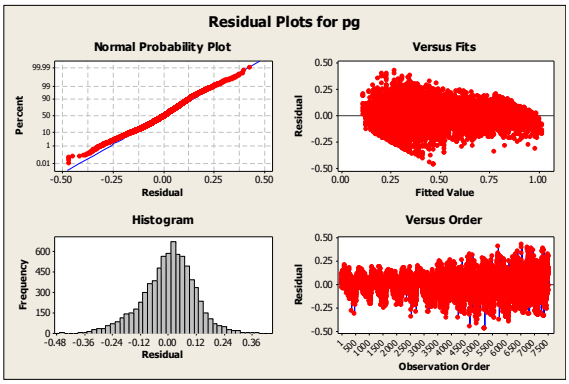


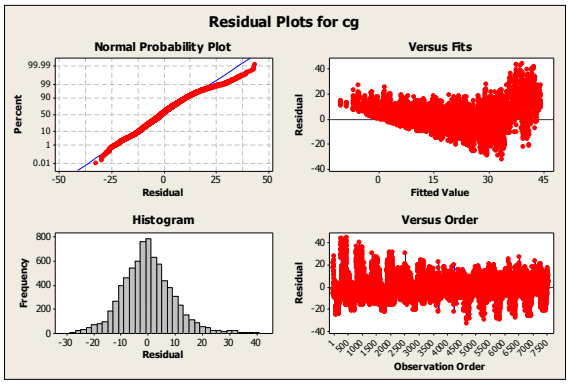


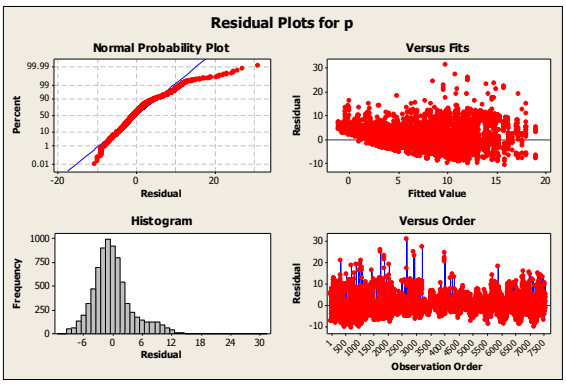


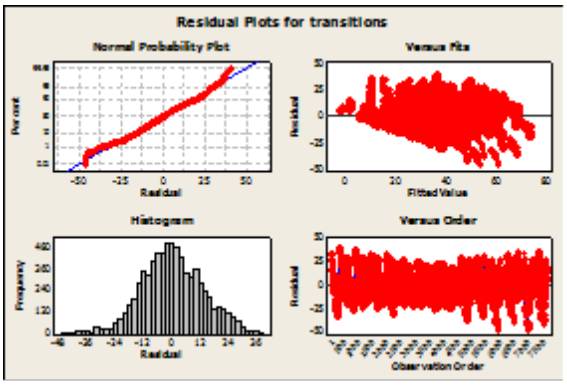




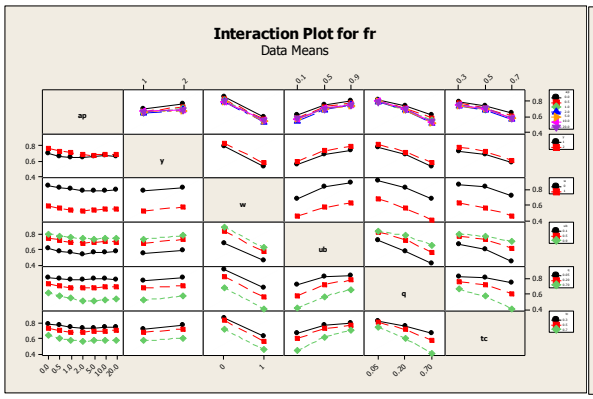


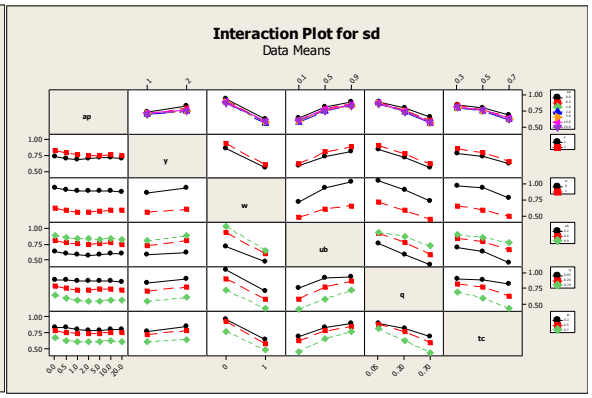


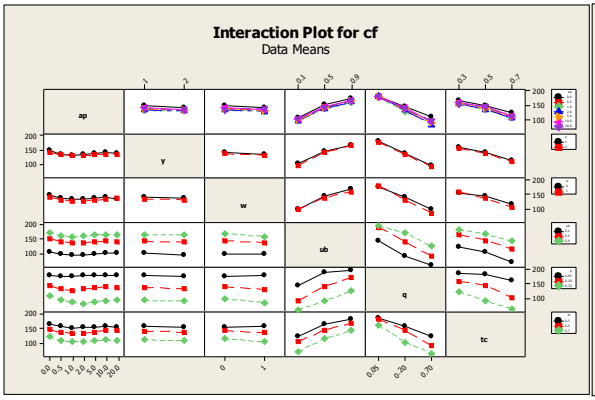

Residual Plots for p
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

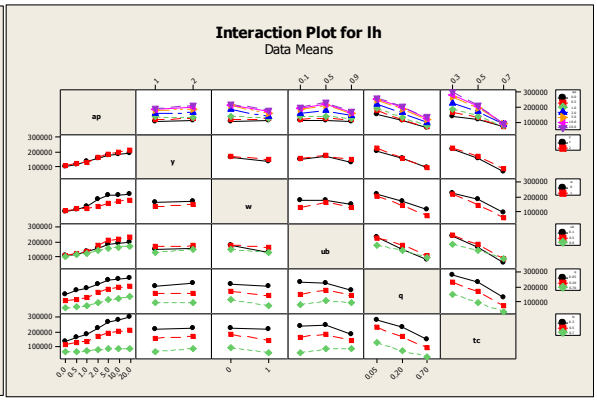

Residual Plots for transitions
Normal Probability Plot
Percent
Residual
Versus Fits
Residual
Fitted Value
Histogram
Frequency
Residual
Versus Order
Residual
Observation Order

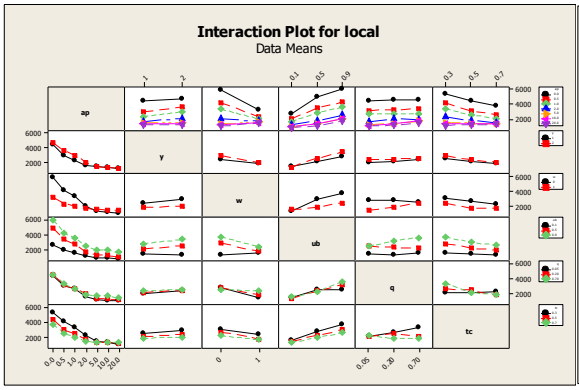
Appendix C: Interaction Plots for Output Variables

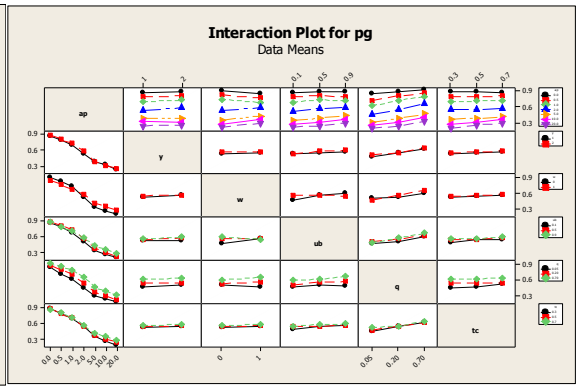


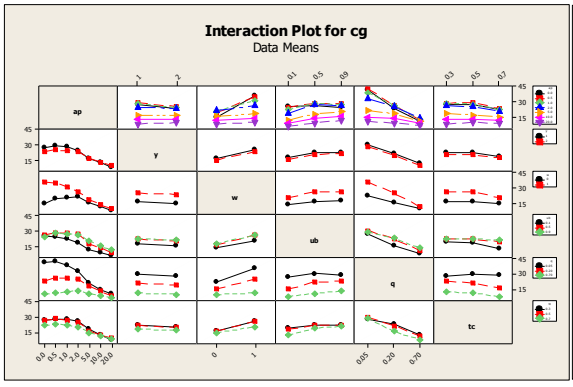


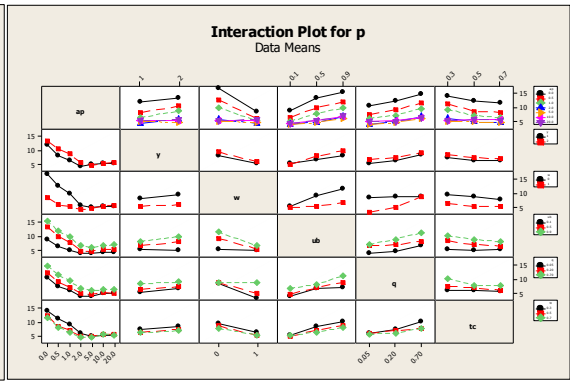












Appendix D: Confidence Intervals on Mean Output Variable Values

One-way ANOVA: fr versus ap

```
Source    DF        SS      MS      F      P
ap         6    3.1046  0.5174  11.27  0.000
Error   7553  346.8131  0.0459
Total   7559  349.9178

S = 0.2143   R-Sq = 0.89%   R-Sq(adj) = 0.81%


                              Individual 95% CIs For Mean Based on Pooled StDev
Level     N    Mean   StDev    +---------+---------+---------+---------
 0.0   1080  0.7265  0.2058                          (-----*----)
 0.5   1080  0.6961  0.2163                (----*-----)
 1.0   1080  0.6752  0.2183          (----*----)
 2.0   1080  0.6622  0.2227     (----*----)
 5.0   1080  0.6673  0.2145       (----*----)
10.0   1080  0.6772  0.2106           (----*----)
20.0   1080  0.6770  0.2112           (----*----)
                                +---------+---------+---------+---------
                              0.650     0.675     0.700     0.725
Pooled StDev = 0.2143
```

One-way ANOVA: fr versus y

```
Source    DF        SS      MS      F      P
y          1    3.5478  3.5478  77.42  0.000
Error   7558  346.3700  0.0458
Total   7559  349.9178

S = 0.2141   R-Sq = 1.01%   R-Sq(adj) = 1.00%


                              Individual 95% CIs For Mean Based on
                              Pooled StDev
Level     N    Mean   StDev  ----+---------+---------+---------+-----
1      3780  0.6614  0.2125  (----*---)
2      3780  0.7047  0.2157                              (----*---)
                              ----+---------+---------+---------+-----
                                0.660     0.675     0.690     0.705
Pooled StDev = 0.2141
```

One-way ANOVA: fr versus w

```
Source    DF        SS        MS        F      P
w          1  126.1619  126.1619  4261.48  0.000
Error   7558  223.7559    0.0296
Total   7559  349.9178

S = 0.1721   R-Sq = 36.05%   R-Sq(adj) = 36.05%


                              Individual 95% CIs For Mean Based on
                              Pooled StDev
Level     N    Mean   StDev  --+---------+---------+---------+-------
0      3780  0.8123  0.1649                                      (*)
1      3780  0.5539  0.1789  (*)
                              --+---------+---------+---------+-------
                              0.560     0.630     0.700     0.770
Pooled StDev = 0.1721
```

One-way ANOVA: fr versus ub

```
Source    DF        SS       MS       F      P
ub         2   49.5109  24.7555  622.75  0.000
Error   7557  300.4069   0.0398
Total   7559  349.9178

S = 0.1994   R-Sq = 14.15%   R-Sq(adj) = 14.13%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  ------+---------+---------+---------+---
0.1    2520  0.5726  0.2088  (*-)
0.5    2520  0.7124  0.2044                (-*)
0.9    2520  0.7642  0.1840                          (*-)
                            ------+---------+---------+---------+---
                                0.600     0.660     0.720     0.780

Pooled StDev = 0.1994
```

One-way ANOVA: fr versus q

```
Source    DF        SS       MS        F      P
q          2   79.5834  39.7917  1112.35  0.000
Error   7557  270.3344   0.0358
Total   7559  349.9178

S = 0.1891   R-Sq = 22.74%   R-Sq(adj) = 22.72%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  --+---------+---------+---------+-------
0.05   2520  0.8005  0.1548                                    (*)
0.20   2520  0.6982  0.1897                       (*)
0.70   2520  0.5505  0.2176  (*)
                            --+---------+---------+---------+-------
                            0.560     0.630     0.700     0.770

Pooled StDev = 0.1891
```

One-way ANOVA: fr versus tc

```
Source    DF        SS       MS       F      P
tc         2   34.3470  17.1735  411.26  0.000
Error   7557  315.5708   0.0418
Total   7559  349.9178

S = 0.2043   R-Sq = 9.82%   R-Sq(adj) = 9.79%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  ---+---------+---------+---------+------
0.3    2520  0.7524  0.1724                                  (*-)
0.5    2520  0.7051  0.2014                        (-*-)
0.7    2520  0.5917  0.2344  (*-)
                            ---+---------+---------+---------+------
                             0.600     0.650     0.700     0.750

Pooled StDev = 0.2043
```

One-way ANOVA: sd versus ap

```
Source    DF        SS      MS     F      P
ap         6    2.7086  0.4514  6.76  0.000
Error   7553  504.1644  0.0668
Total   7559  506.8730

S = 0.2584   R-Sq = 0.53%   R-Sq(adj) = 0.46%


                            Individual 95% CIs For Mean Based on Pooled StDev
Level     N    Mean   StDev  ---------+---------+---------+---------+
 0.0   1080  0.7777  0.2575                          (-----*-----)
 0.5   1080  0.7458  0.2663             (-----*-----)
 1.0   1080  0.7262  0.2660    (-----*------)
 2.0   1080  0.7178  0.2658  (-----*-----)
 5.0   1080  0.7255  0.2556    (-----*-----)
10.0   1080  0.7362  0.2499        (-----*------)
20.0   1080  0.7242  0.2466    (-----*-----)
                            ---------+---------+---------+---------+
                                   0.725     0.750     0.775     0.800

Pooled StDev = 0.2584
```

One-way ANOVA: sd versus y

```
Source    DF        SS      MS       F      P
y          1    7.2314  7.2314  109.39  0.000
Error   7558  499.6416  0.0661
Total   7559  506.8730

S = 0.2571   R-Sq = 1.43%   R-Sq(adj) = 1.41%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev   -+---------+---------+---------+--------
1      3780  0.7053  0.2426   (---*---)
2      3780  0.7671  0.2708                                (----*---)
                             -+---------+---------+---------+--------
                            0.700     0.720     0.740     0.760

Pooled StDev = 0.2571
```

One-way ANOVA: sd versus w

```
Source    DF        SS        MS        F      P
w          1  192.8348  192.8348  4640.98  0.000
Error   7558  314.0382    0.0416
Total   7559  506.8730

S = 0.2038   R-Sq = 38.04%   R-Sq(adj) = 38.04%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  ---+---------+---------+---------+------
0      3780  0.8959  0.2185                                  (*
1      3780  0.5765  0.1881  (*
                            ---+---------+---------+---------+------
                             0.60      0.70      0.80      0.90

Pooled StDev = 0.2038
```

One-way ANOVA: sd versus ub

```
Source    DF        SS       MS       F      P
ub         2   82.8830  41.4415  738.63  0.000
Error   7557  423.9899   0.0561
Total   7559  506.8730

S = 0.2369   R-Sq = 16.35%   R-Sq(adj) = 16.33%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  ------+---------+---------+---------+---
0.1    2520  0.5951  0.2211  (*)
0.5    2520  0.7679  0.2503                          (-*)
0.9    2520  0.8457  0.2383                                    (-*)
                            ------+---------+---------+---------+---
                                0.630     0.700     0.770     0.840
Pooled StDev = 0.2369
```

One-way ANOVA: sd versus q

```
Source    DF        SS       MS        F      P
q          2  109.7427  54.8713  1044.15  0.000
Error   7557  397.1303   0.0526
Total   7559  506.8730

S = 0.2292   R-Sq = 21.65%   R-Sq(adj) = 21.63%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  --------+---------+---------+---------+-
0.05   2520  0.8764  0.2168                                      (-*)
0.20   2520  0.7500  0.2361                        (*)
0.70   2520  0.5822  0.2344  (*)
                            --------+---------+---------+---------+-
                                  0.640     0.720     0.800     0.880
Pooled StDev = 0.2292
```

One-way ANOVA: sd versus tc

```
Source    DF        SS       MS       F      P
tc         2   44.1164  22.0582  360.22  0.000
Error   7557  462.7566   0.0612
Total   7559  506.8730

S = 0.2475   R-Sq = 8.70%   R-Sq(adj) = 8.68%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  ------+---------+---------+---------+---
0.3    2520  0.8157  0.2264                                (-*-)
0.5    2520  0.7598  0.2497                        (-*)
0.7    2520  0.6331  0.2647  (-*)
                            ------+---------+---------+---------+---
                                0.660     0.720     0.780     0.840

Pooled StDev = 0.2475
```

One-way ANOVA: cf versus ap

```
Source    DF        SS     MS     F      P
ap         6    139506  23251  8.90  0.000
Error   7553  19733695   2613
Total   7559  19873201

S = 51.11   R-Sq = 0.70%   R-Sq(adj) = 0.62%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean  StDev  ------+---------+---------+---------+---
 0.0   1080  145.43  45.86                          (----*----)
 0.5   1080  135.42  49.90         (----*----)
 1.0   1080  131.46  51.95  (----*----)
 2.0   1080  132.19  54.01   (----*----)
 5.0   1080  135.58  53.44         (----*----)
10.0   1080  138.29  51.80             (----*-----)
20.0   1080  136.92  50.41           (----*----)
                           ------+---------+---------+---------+---
                             132.0     138.0     144.0     150.0

Pooled StDev = 51.11
```

One-way ANOVA: cf versus y

```
Source    DF        SS     MS     F      P
y          1     22634  22634  8.62  0.003
Error   7558  19850567   2626
Total   7559  19873201

S = 51.25   R-Sq = 0.11%   R-Sq(adj) = 0.10%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean  StDev  ----+---------+---------+---------+-----
1      3780  138.20  51.29                   (-------*-------)
2      3780  134.74  51.21  (-------*-------)
                           ----+---------+---------+---------+-----
                           134.0     136.0     138.0     140.0

Pooled StDev = 51.25
```

One-way ANOVA: cf versus w

```
Source    DF        SS     MS      F      P
w          1     48534  48534  18.50  0.000
Error   7558  19824668   2623
Total   7559  19873201

S = 51.22   R-Sq = 0.24%   R-Sq(adj) = 0.23%


                           Individual 95% CIs For Mean Based on Pooled StDev
Level     N    Mean  StDev     -+---------+---------+---------+--------
0      3780  139.00  47.92                          (------*------)
1      3780  133.94  54.31     (------*-----)
                           -+---------+---------+---------+--------
                           132.5     135.0     137.5     140.0

Pooled StDev = 51.22
```

One-way ANOVA: cf versus ub

```
Source    DF        SS       MS        F      P
ub         2   5538628  2769314  1459.95  0.000
Error   7557  14334573     1897
Total   7559  19873201

S = 43.55   R-Sq = 27.87%   R-Sq(adj) = 27.85%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean  StDev   -+---------+---------+---------+--------
0.1    2520  100.57  43.44   (*)
0.5    2520  142.92  48.56                        *)
0.9    2520  165.92  38.02                                   (*)
                            -+---------+---------+---------+--------
                           100       120       140       160

Pooled StDev = 43.55
```

One-way ANOVA: cf versus q

```
Source    DF        SS       MS        F      P
q          2   9335979  4667989  3347.75  0.000
Error   7557  10537223     1394
Total   7559  19873201

S = 37.34   R-Sq = 46.98%   R-Sq(adj) = 46.96%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean  StDev  ---+---------+---------+---------+------
0.05   2520  179.38  28.19                                    (*
0.20   2520  136.72  42.59                  (*
0.70   2520   93.31  39.68  *)
                           ---+---------+---------+---------+------
                            100       125       150       175

Pooled StDev = 37.34
```

One-way ANOVA: cf versus tc

```
Source    DF        SS       MS       F      P
tc         2   2856377  1428189  634.24  0.000
Error   7557  17016824     2252
Total   7559  19873201

S = 47.45   R-Sq = 14.37%   R-Sq(adj) = 14.35%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean  StDev  -------+---------+---------+---------+--
0.3    2520  157.73  39.75                                 (*)
0.5    2520  140.93  48.56                       (*)
0.7    2520  110.75  53.08  (*)
                           -------+---------+---------+---------+--
                                120       135       150       165

Pooled StDev = 47.45
```

One-way ANOVA: lh versus ap

```
Source    DF           SS           MS       F      P
ap         6  9.31647E+12  1.55275E+12  173.17  0.000
Error   7553  6.77234E+13   8966422653
Total   7559  7.70399E+13

S = 94691   R-Sq = 12.09%   R-Sq(adj) = 12.02%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  -------+---------+---------+---------+--
 0.0   1080  105429   60159  (-*-)
 0.5   1080  119304   71556       (-*-)
 1.0   1080  132367   79211           (-*-)
 2.0   1080  159567   93533                   (-*-)
 5.0   1080  183127  109863                           (-*-)
10.0   1080  193363  112688                               (*-)
20.0   1080  200943  119308                                 (-*-)
                           -------+---------+---------+---------+--
                             120000    150000    180000    210000

Pooled StDev = 94691
```

One-way ANOVA: lh versus y

```
Source    DF           SS           MS      F      P
y          1  1.68801E+11  1.68801E+11  16.60  0.000
Error   7558  7.68711E+13  10170820311
Total   7559  7.70399E+13

S = 100850   R-Sq = 0.22%   R-Sq(adj) = 0.21%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  ---------+---------+---------+---------+
1      3780  151575  100419  (-------*-------)
2      3780  161025  101280                          (-------*-------)
                           ---------+---------+---------+---------+
                               152000    156000    160000    164000

Pooled StDev = 100850
```

One-way ANOVA: lh versus w

```
Source    DF           SS           MS       F      P
w          1  1.36817E+12  1.36817E+12  136.65  0.000
Error   7558  7.56717E+13  10012131469
Total   7559  7.70399E+13

S = 100061   R-Sq = 1.78%   R-Sq(adj) = 1.76%


                           Individual 95% CIs For Mean Based on Pooled StDev
Level     N    Mean   StDev       +---------+---------+---------+---------
0      3780  169753   99660                                  (--*--)
1      3780  142847  100460       (--*--)
                                  +---------+---------+---------+---------
                           140000    150000    160000    170000

Pooled StDev = 100061
```

One-way ANOVA: lh versus ub

```
Source    DF           SS           MS      F      P
ub         2  1.38112E+12  6.90561E+11  68.98  0.000
Error   7557  7.56587E+13  10011742569
Total   7559  7.70399E+13

S = 100059   R-Sq = 1.79%   R-Sq(adj) = 1.77%


                            Individual 95% CIs For Mean Based on
                            Pooled StDev
Level     N    Mean   StDev  ------+---------+---------+---------+---
0.1    2520  155568  114701              (---*--)
0.5    2520  173208  108958                          (--*---)
0.9    2520  140124   70761  (--*--)
                            ------+---------+---------+---------+---
                             144000    156000    168000    180000

Pooled StDev = 100059
```

One-way ANOVA: lh versus q

```
Source    DF           SS           MS        F      P
q          2  1.86000E+13  9.30000E+12  1202.61  0.000
Error   7557  5.84399E+13   7733209031
Total   7559  7.70399E+13

S = 87939   R-Sq = 24.14%   R-Sq(adj) = 24.12%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean  StDev   ----+---------+---------+---------+-----
0.05   2520  216123  99156                                      (*)
0.20   2520  158112  91470                    (*)
0.70   2520   94665  70716   (*)
                            ----+---------+---------+---------+-----
                           105000    140000    175000    210000

Pooled StDev = 87939
```

One-way ANOVA: lh versus tc

```
Source    DF           SS           MS        F      P
tc         2  2.72111E+13  1.36055E+13  2063.41  0.000
Error   7557  4.98288E+13   6593722718
Total   7559  7.70399E+13

S = 81202   R-Sq = 35.32%   R-Sq(adj) = 35.30%


                           Individual 95% CIs For Mean Based on Pooled StDev
Level     N    Mean  StDev     -+---------+---------+---------+--------
0.3    2520  224387  99880                                        (*)
0.5    2520  166098  84388                           (*
0.7    2520   78414  51805     (*
                               -+---------+---------+---------+--------
                           80000    120000    160000    200000

Pooled StDev = 81202
```

One-way ANOVA: local versus ap

```
Source    DF           SS          MS       F      P
ap         6   9750505378  1625084230  630.41  0.000
Error   7553  19470334723     2577828
Total   7559  29220840100

S = 1606   R-Sq = 33.37%   R-Sq(adj) = 33.32%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level     N  Mean  StDev  --------+---------+---------+---------+-
 0.0   1080  4566   2562                                    (*)
 0.5   1080  3268   2011                           (*)
 1.0   1080  2674   1740                     (*)
 2.0   1080  1854   1219           (*
 5.0   1080  1449    862     *)
10.0   1080  1400   1032    (*)
20.0   1080  1249   1055  *)
                         --------+---------+---------+---------+-
                              2000      3000      4000      5000

Pooled StDev = 1606
```

One-way ANOVA: local versus y

```
Source    DF           SS          MS      F      P
y          1    152144520   152144520  39.56  0.000
Error   7558  29068695580     3846083
Total   7559  29220840100

S = 1961   R-Sq = 0.52%   R-Sq(adj) = 0.51%


                         Individual 95% CIs For Mean Based on Pooled StDev
Level     N  Mean  StDev    -+---------+---------+---------+--------
1      3780  2210   1799    (----*----)
2      3780  2493   2111                          (----*----)
                           -+---------+---------+---------+--------
                         2160      2280      2400      2520

Pooled StDev = 1961
```

One-way ANOVA: local versus w

```
Source    DF           SS          MS       F      P
w          1   1043021207  1043021207  279.76  0.000
Error   7558  28177818893     3728211
Total   7559  29220840100

S = 1931   R-Sq = 3.57%   R-Sq(adj) = 3.56%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level     N  Mean  StDev  ---+---------+---------+---------+------
0      3780  2723   2361                               (--*-)
1      3780  1980   1373  (-*--)
                         ---+---------+---------+---------+------
                         2000      2250      2500      2750

Pooled StDev = 1931
```

One-way ANOVA: local versus ub

```
Source    DF           SS          MS       F      P
ub         2   3615905290  1807952645  533.60  0.000
Error   7557  25604934810     3388241
Total   7559  29220840100

S = 1841   R-Sq = 12.37%   R-Sq(adj) = 12.35%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level     N  Mean  StDev  --+---------+---------+---------+-------
0.1    2520  1481   1003   (-*)
0.5    2520  2401   1983                (*)
0.9    2520  3172   2286                             (*-)
                          --+---------+---------+---------+-------
                         1500      2000      2500      3000

Pooled StDev = 1841
```

One-way ANOVA: local versus q

```
Source    DF           SS        MS      F      P
q          2    131358320  65679160  17.06  0.000
Error   7557  29089481780   3849343
Total   7559  29220840100

S = 1962   R-Sq = 0.45%   R-Sq(adj) = 0.42%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level     N  Mean  StDev  ----+---------+---------+---------+-----
0.05   2520  2190   2000  (-----*------)
0.20   2520  2352   1982            (-----*-----)
0.70   2520  2513   1903                        (-----*------)
                         ----+---------+---------+---------+-----
                          2160      2280      2400      2520

Pooled StDev = 1962
```

One-way ANOVA: local versus tc

```
Source    DF           SS         MS      F      P
tc         2    702214330  351107165  93.04  0.000
Error   7557  28518625770    3773803
Total   7559  29220840100

S = 1943   R-Sq = 2.40%   R-Sq(adj) = 2.38%


                         Individual 95% CIs For Mean Based on
                         Pooled StDev
Level     N  Mean  StDev  ---+---------+---------+---------+------
0.3    2520  2749   2362                            (--*--)
0.5    2520  2296   1872             (--*--)
0.7    2520  2009   1495  (--*--)
                         ---+---------+---------+---------+------
                         2000      2250      2500      2750

Pooled StDev = 1943
```

One-way ANOVA: pg versus ap

```
Source    DF        SS       MS        F      P
ap         6  402.0158  67.0026  3949.23  0.000
Error   7553  128.1443   0.0170
Total   7559  530.1602

S = 0.1303   R-Sq = 75.83%   R-Sq(adj) = 75.81%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  --------+---------+---------+---------+-
 0.0   1080  0.8820  0.0656                                      *
 0.5   1080  0.7959  0.0878                                  (*
 1.0   1080  0.7109  0.1133                              (*
 2.0   1080  0.5557  0.1403                        (*
 5.0   1080  0.3834  0.1487                  *)
10.0   1080  0.3133  0.1574              (*
20.0   1080  0.2465  0.1653          *)
                           --------+---------+---------+---------+-
                                 0.40      0.60      0.80      1.00
Pooled StDev = 0.1303
```

One-way ANOVA: pg versus y

```
Source    DF        SS      MS      F      P
y          1    0.8024  0.8024  11.46  0.001
Error   7558  529.3578  0.0700
Total   7559  530.1602

S = 0.2646   R-Sq = 0.15%   R-Sq(adj) = 0.14%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  ---+---------+---------+---------+------
1      3780  0.5451  0.2610  (-------*--------)
2      3780  0.5657  0.2682                    (--------*-------)
                           ---+---------+---------+---------+------
                            0.540     0.550     0.560     0.570
Pooled StDev = 0.2646
```

One-way ANOVA: pg versus w

```
Source    DF        SS      MS     F      P
w          1    0.4547  0.4547  6.49  0.011
Error   7558  529.7054  0.0701
Total   7559  530.1602

S = 0.2647   R-Sq = 0.09%   R-Sq(adj) = 0.07%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev   -+---------+---------+---------+--------
0      3780  0.5476  0.2877   (--------*-------)
1      3780  0.5632  0.2395                   (-------*--------)
                            -+---------+---------+---------+--------
                           0.540     0.550     0.560     0.570

Pooled StDev = 0.2647
```

One-way ANOVA: pg versus ub

```
Source    DF        SS      MS      F      P
ub         2    3.4819  1.7409  24.98  0.000
Error   7557  526.6783  0.0697
Total   7559  530.1602

S = 0.2640   R-Sq = 0.66%   R-Sq(adj) = 0.63%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  --+---------+---------+---------+-------
0.1    2520  0.5264  0.2831  (----*----)
0.5    2520  0.5623  0.2674                    (----*----)
0.9    2520  0.5776  0.2397                              (----*----)
                           --+---------+---------+---------+-------
                           0.520     0.540     0.560     0.580

Pooled StDev = 0.2640
```

One-way ANOVA: pg versus q

```
Source    DF        SS       MS       F      P
q          2   26.6735  13.3368  200.18  0.000
Error   7557  503.4867   0.0666
Total   7559  530.1602

S = 0.2581   R-Sq = 5.03%   R-Sq(adj) = 5.01%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  -----+---------+---------+---------+----
0.05   2520  0.4853  0.2520  (-*-)
0.20   2520  0.5503  0.2648              (-*-)
0.70   2520  0.6306  0.2574                                (-*-)
                           -----+---------+---------+---------+----
                              0.500     0.550     0.600     0.650

Pooled StDev = 0.2581
```

One-way ANOVA: pg versus tc

```
Source    DF        SS      MS      F      P
tc         2    1.8302  0.9151  13.09  0.000
Error   7557  528.3300  0.0699
Total   7559  530.1602

S = 0.2644   R-Sq = 0.35%   R-Sq(adj) = 0.32%


                           Individual 95% CIs For Mean Based on
                           Pooled StDev
Level     N    Mean   StDev  --------+---------+---------+---------+-
0.3    2520  0.5380  0.2846  (------*------)
0.5    2520  0.5525  0.2611           (------*------)
0.7    2520  0.5757  0.2461                      (------*------)
                           --------+---------+---------+---------+-
                                 0.540     0.555     0.570     0.585

Pooled StDev = 0.2644
```

One-way ANOVA: cg versus ap

```
Source    DF       SS     MS       F      P
ap         6   342992  57165  326.48  0.000
Error   7553  1322494    175
Total   7559  1665486

S = 13.23   R-Sq = 20.59%   R-Sq(adj) = 20.53%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ---+---------+---------+---------+------
 0.0   1080  25.67  20.83                                    (*-)
 0.5   1080  27.30  17.48                                       (-*)
 1.0   1080  26.34  14.33                                     (-*)
 2.0   1080  24.25  10.97                                  (*-)
 5.0   1080  17.15   8.49                        (*-)
10.0   1080  12.80   7.08               (-*)
20.0   1080   9.27   6.18  (-*)
                          ---+---------+---------+---------+------
                          10.0      15.0      20.0      25.0
```

One-way ANOVA: cg versus y

```
Source    DF       SS    MS      F      P
y          1     4457  4457  20.28  0.000
Error   7558  1661029   220
Total   7559  1665486

S = 14.82   R-Sq = 0.27%   R-Sq(adj) = 0.25%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ------+---------+---------+---------+---
1      3780  21.17  15.32                          (-----*------)
2      3780  19.63  14.31  (-----*------)
                          ------+---------+---------+---------+---
                             19.60     20.30     21.00     21.70

Pooled StDev = 14.82
```

One-way ANOVA: cg versus w

```
Source    DF       SS      MS       F      P
w          1   132093  132093  651.08  0.000
Error   7558  1533393     203
Total   7559  1665486

S = 14.24   R-Sq = 7.93%   R-Sq(adj) = 7.92%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  -------+---------+---------+---------+--
0      3780  16.22   9.56  (-*-)
1      3780  24.58  17.73                                    (-*-)
                          -------+---------+---------+---------+--
                              17.5      20.0      22.5      25.0

Pooled StDev = 14.24
```

One-way ANOVA: cg versus ub

```
Source    DF       SS     MS      F      P
ub         2    37351  18676  86.68  0.000
Error   7557  1628135    215
Total   7559  1665486

S = 14.68   R-Sq = 2.24%   R-Sq(adj) = 2.22%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ------+---------+---------+---------+---
0.1    2520  17.27  13.93  (---*---)
0.5    2520  21.71  15.76                          (---*--)
0.9    2520  22.22  14.27                             (---*--)
                          ------+---------+---------+---------+---
                             17.6      19.2      20.8      22.4

Pooled StDev = 14.68
```

One-way ANOVA: cg versus q

```
Source    DF       SS      MS        F      P
q          2   410879  205439  1237.44  0.000
Error   7557  1254607     166
Total   7559  1665486

S = 12.88   R-Sq = 24.67%   R-Sq(adj) = 24.65%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ---------+---------+---------+---------+
0.05   2520  29.29  18.24                                       (*)
0.20   2520  20.66  11.63                   (*)
0.70   2520  11.24   5.50  (*)
                          ---------+---------+---------+---------+
                                15.0      20.0      25.0      30.0

Pooled StDev = 12.88
```

One-way ANOVA: cg versus tc

```
Source    DF       SS    MS      F      P
tc         2    19257  9628  44.20  0.000
Error   7557  1646230   218
Total   7559  1665486

S = 14.76   R-Sq = 1.16%   R-Sq(adj) = 1.13%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ----+---------+---------+---------+-----
0.3    2520  21.63  15.29                               (----*----)
0.5    2520  21.42  15.09                              (----*---)
0.7    2520  18.14  13.85  (----*----)
                          ----+---------+---------+---------+-----
                           18.0      19.2      20.4      21.6

Pooled StDev = 14.76
```

One-way ANOVA: p versus ap

```
Source    DF        SS      MS       F      P
ap         6   55471.2  9245.2  381.91  0.000
Error   7553  182841.8    24.2
Total   7559  238312.9

S = 4.920   R-Sq = 23.28%   R-Sq(adj) = 23.22%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N    Mean  StDev  --+---------+---------+---------+-------
 0.0   1080  12.714  7.844                                    (*)
 0.5   1080   9.444  6.614                          (*)
 1.0   1080   7.631  5.389               (-*)
 2.0   1080   5.109  3.151    (*-)
 5.0   1080   4.845  2.216   (*-)
10.0   1080   5.489  2.800      (*)
20.0   1080   5.496  3.530      (*)
                          --+---------+---------+---------+-------
                          5.0       7.5      10.0      12.5

Pooled StDev = 4.920
```

One-way ANOVA: p versus y

```
Source    DF        SS      MS      F      P
y          1    1846.8  1846.8  59.03  0.000
Error   7558  236466.2    31.3
Total   7559  238312.9

S = 5.593   R-Sq = 0.77%   R-Sq(adj) = 0.76%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  --+---------+---------+---------+-------
1      3780  6.753  5.049  (----*----)
2      3780  7.741  6.090                              (----*----)
                          --+---------+---------+---------+-------
                          6.65      7.00      7.35      7.70
Pooled StDev = 5.593
```

One-way ANOVA: p versus w

```
Source    DF        SS       MS       F      P
w          1   18301.1  18301.1  628.69  0.000
Error   7558  220011.8     29.1
Total   7559  238312.9

S = 5.395   R-Sq = 7.68%   R-Sq(adj) = 7.67%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  -----+---------+---------+---------+----
0      3780  8.803  6.288                                  (-*-)
1      3780  5.691  4.322  (-*-)
                          -----+---------+---------+---------+----
                             6.0       7.0       8.0       9.0

Pooled StDev = 5.395
```

One-way ANOVA: p versus ub

```
Source    DF        SS      MS       F      P
ub         2   19368.3  9684.2  334.25  0.000
Error   7557  218944.6    29.0
Total   7559  238312.9

S = 5.383   R-Sq = 8.13%   R-Sq(adj) = 8.10%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  --------+---------+---------+---------+-
0.1    2520  5.230  3.630  (-*)
0.5    2520  7.366  5.721                (*-)
0.9    2520  9.145  6.404                          (-*-)
                          --------+---------+---------+---------+-
                                6.0       7.2       8.4       9.6

Pooled StDev = 5.38
```

One-way ANOVA: p versus q

```
Source    DF        SS      MS       F      P
q          2   10422.5  5211.2  172.81  0.000
Error   7557  227890.4    30.2
Total   7559  238312.9

S = 5.491   R-Sq = 4.37%   R-Sq(adj) = 4.35%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  --+---------+---------+---------+-------
0.05   2520  5.978  5.614  (-*-)
0.20   2520  6.954  5.459          (--*-)
0.70   2520  8.809  5.399                          (-*-)
                          --+---------+---------+---------+-------
                          6.0       7.0       8.0       9.0

Pooled StDev = 5.491
```

One-way ANOVA: p versus tc

```
Source    DF        SS      MS      F      P
tc         2    2567.1  1283.6  41.15  0.000
Error   7557  235745.8    31.2
Total   7559  238312.9

S = 5.585   R-Sq = 1.08%   R-Sq(adj) = 1.05%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev   -+---------+---------+---------+--------
0.3    2520  8.042  6.665                          (----*---)
0.5    2520  7.039  5.318         (----*---)
0.7    2520  6.661  4.570   (---*----)
                           -+---------+---------+---------+--------
                          6.50      7.00      7.50      8.00

Pooled StDev = 5.585
```

One-way ANOVA: transitions versus ap

```
Source    DF       SS     MS       F      P
ap         6   493270  82212  263.33  0.000
Error   7553  2358012    312
Total   7559  2851282

S = 17.67   R-Sq = 17.30%   R-Sq(adj) = 17.23%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ----+---------+---------+---------+-----
 0.0   1080  25.97  19.40  (*-)
 0.5   1080  39.45  21.99                    (*-)
 1.0   1080  45.63  21.42                              (*-)
 2.0   1080  50.22  18.28                                    (-*)
 5.0   1080  44.43  14.21                           (*-)
10.0   1080  37.02  13.05               (-*)
20.0   1080  29.86  12.66      (-*)
                          ----+---------+---------+---------+-----
                           28.0      35.0      42.0      49.0

Pooled StDev = 17.67
```

One-way ANOVA: transitions versus y

```
Source    DF       SS    MS     F      P
y          1     2961  2961  7.86  0.005
Error   7558  2848321   377
Total   7559  2851282

S = 19.41   R-Sq = 0.10%   R-Sq(adj) = 0.09%


                          Individual 95% CIs For Mean Based on Pooled StDev
Level     N   Mean  StDev    -+---------+---------+---------+--------
1      3780  39.57  19.45                      (--------*--------)
2      3780  38.31  19.38    (-------*--------)
                            -+---------+---------+---------+--------
                          37.80     38.50     39.20     39.90

Pooled StDev = 19.41
```

One-way ANOVA: transitions versus w

```
Source    DF       SS      MS       F      P
w          1   234862  234862  678.44  0.000
Error   7558  2616420     346
Total   7559  2851282

S = 18.61   R-Sq = 8.24%   R-Sq(adj) = 8.22%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ------+---------+---------+---------+---
0      3780  33.37  17.19  (*-)
1      3780  44.51  19.92                                (-*-)
                          ------+---------+---------+---------+---
                             35.0      38.5      42.0      45.5

Pooled StDev = 18.61
```

One-way ANOVA: transitions versus ub

```
Source    DF       SS      MS       F      P
ub         2   222034  111017  319.09  0.000
Error   7557  2629248     348
Total   7559  2851282

S = 18.65   R-Sq = 7.79%   R-Sq(adj) = 7.76%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev   --+---------+---------+---------+-------
0.1    2520  31.89  18.48   (-*-)
0.5    2520  39.87  19.64                (-*)
0.9    2520  45.07  17.79                          (-*)
                           --+---------+---------+---------+-------
                          32.0      36.0      40.0      44.0

Pooled StDev = 18.65
```

One-way ANOVA: transitions versus q

```
Source    DF       SS      MS       F      P
q          2   410237  205118  635.01  0.000
Error   7557  2441046     323
Total   7559  2851282

S = 17.97   R-Sq = 14.39%   R-Sq(adj) = 14.37%


                          Individual 95% CIs For Mean Based on
                          Pooled StDev
Level     N   Mean  StDev  ----+---------+---------+---------+-----
0.05   2520  46.49  18.37                                    (*)
0.20   2520  41.39  18.42                        (-*)
0.70   2520  28.95  17.10  (-*)
                          ----+---------+---------+---------+-----
                           30.0      35.0      40.0      45.0

Pooled StDev = 17.97
```

One-way ANOVA: transitions versus tc

```
Source    DF       SS     MS       F      P
tc         2   121765  60882  168.56  0.000
Error   7557  2729517    361
Total   7559  2851282

S = 19.01   R-Sq = 4.27%   R-Sq(adj) = 4.25%


                          Individual 95% CIs For Mean Based on Pooled StDev
Level     N   Mean  StDev    -+---------+---------+---------+--------
0.3    2520  42.49  19.68                                  (--*-)
0.5    2520  41.00  18.53                             (--*-)
0.7    2520  33.33  18.79    (-*--)
                            -+---------+---------+---------+--------
                          33.0      36.0      39.0      42.0

Pooled StDev = 19.01
```

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EDUCATION

University of Washington, Seattle, WA
Ph.D., Industrial and Systems Engineering — December 2013
Dissertation: "Complex Adaptive Food Supply Systems"
Advisor: Dr. Benita M. Beamon

Purdue University, West Lafayette, IN
M.S., Industrial Engineering — December 2004
Thesis: "The Effects of Initial Microstructure on the Properties of Machined Steel Chips and Their Use in Powder Metallurgy Applications"

Bradley University, Peoria, IL
B.S., Industrial Engineering (summa cum laude) — December 2001

REFEREED PUBLICATIONS

Krejci, Caroline C. and Benita M. Beamon (2013), "Modeling Food Supply Chain Sustainability Using Multi-Agent Simulation," *The International Journal of Social Sustainability in Economic, Social and Cultural Context*, Vol. 8, No. 3, pp. 143-157.

Krejci, Caroline C. and Benita M. Beamon (2010), "Environmentally-Conscious Supply Chain Design in Support of Food Security," *Operations and Supply Chain Management: An International Journal*, Vol. 3, No. 1, pp. 14-29.

Balcik, Burcu, Benita M. Beamon, **Caroline C. Krejci**, Kyle M. Muramatsu, and Magaly Ramirez (2010), "Coordination in Humanitarian Relief Chains: Practices, Challenges, and Opportunities," *International Journal of Production Economics*, Vol. 126, No. 1, pp. 22-34.

REFEREED PROCEEDINGS

Krejci, Caroline C. and Benita M. Beamon (2013), "Modeling the Impacts of Farmer Coordination on Food Supply Chain Structure," presented at the 2013 CSSSA Annual Conference, Santa Fe, New Mexico, USA.

Krejci, Caroline C. and Benita M. Beamon (2012), "Modeling Food Supply Chains Using Multi-Agent Simulation," presented at the 2012 Winter Simulation Conference, Berlin, Germany.

Krejci, Caroline C. and Benita M. Beamon (2010), "Disaster Resilience and Environmentally-Sustainable Food Supply Chains," presented at the 2010 Conference of the Production and Operations Management Society, Vancouver, Canada.

RESEARCH EXPERIENCE

University of Washington, Seattle, WA September 2008-June 2010
Research Assistant – Department of Industrial & Systems Engineering
Research areas: supply chain coordination for humanitarian relief, simulation modeling of food supply chains.

Purdue University, West Lafayette, IN August 2002-July 2004
Research Assistant – Center for Materials Processing & Tribology
Research area: compaction of nano-crystalline steel powders sourced from machined chips.

TEACHING EXPERIENCE

University of Washington March 2011-March 2012
Instructor – Department of Industrial & Systems Engineering

- Simulation (IND E 424) – 1 quarter, 40 undergraduate/graduate students (Winter 2012)
- Probability & Statistics for Engineers (IND E 315) – 2 quarters, 40 & 150 undergraduate students (Summer & Fall 2011)
- Multi-Agent Simulation (IND E 498) – 1 quarter, 15 undergraduate/graduate students (Spring 2011)
    - New course design and development – 1 quarter, supported by UW Huckabay Teaching Fellowship (Fall 2010)

University of Washington January 2009-December 2012
Teaching Assistant – Department of Industrial & Systems Engineering

- Probability & Statistics for Engineers (IND E 315) – 3 quarters, 150/40/150 undergraduate students (Spring, Summer, Fall 2012)
- Simulation (IND E 424) – 1 quarter, 20 undergraduate/graduate students (Winter 2011)
- Design of Experiments (IND E 316) – 1 quarter, 40 undergraduate students (Winter 2009)

INDUSTRIAL EXPERIENCE

VillageReach, Seattle, WA Dec.-March 2009 & June-Sep. 2010
Supply Chain Analyst

- Designed supply chain analysis tool for Mozambican vaccine distribution program – enabled field data collection, data analysis, and cost comparisons.

Lutron Electronics Co., Inc., Coopersburg, PA June 2005-May 2008
Operations Engineer

- Project manager: designed raw material supply chain for new Mexican assembly plant.
- Operations team leader for Ivalo Lighting (Lutron subsidiary): led manufacturability design initiatives, implemented inventory tracking and kanban systems, developed production standards, trained employees.
- Developed capacity planning tool for manufacturing plants (worldwide implementation), developed automated scheduling tool for power panel production, implemented job scheduling process improvements for Integrated Systems Division.

United Parcel Service, Indianapolis, IN August 2004-May 2005
Industrial Engineering Management Trainee

- Analyzed and redesigned driver delivery and pickup routes to improve operational efficiency.
- Helped implement and support new electronic package handling and sorting system.
- Developed forecasts for seasonal labor requirements.

The Boeing Company, St. Louis, MO May 2001-July 2001
Intern – Estimating

- Analyzed project-specific technical, cost, and scheduling data for Military Aerospace Support and prepared cost estimates.

Bradley University, Peoria, IL May 1999-August 1999
Student Consultant – Industrial Assessment Center

- Researched client manufacturing processes, developed productivity assessments, and provided recommendations for operational efficiency improvements.

Caterpillar, Inc., Peoria, IL May 1998-August 1998
Student Consultant

- Designed layout improvement alternatives for Advanced Materials Technology Division office and laboratory workflows.

HONORS & AWARDS

UW Industrial & Systems Engineering Outstanding Graduate Student Award, 2012
UW SWE Outstanding Female Industrial & Systems Engineering Graduate Student, 2012
UW College of Engineering Student Innovator Teaching Award, 2011
UW Industrial & Systems Engineering Outstanding Graduate Student Award, 2011
UW Huckabay Teaching Fellowship, 2010
UW Industrial & Systems Engineering Outstanding Teaching Assistant Award, 2009

SERVICE & LEADERSHIP

UW Alpha Pi Mu President, 2009-2011
UW IIE Graduate Student Representative, 2008-2010

COMPUTER PROFICIENCIES

Engineering software: Arena, NetLogo, AutoMod, ProModel, Minitab
Programming languages: FORTRAN, Visual Basic, Java
Material requirements planning (MRP): JD Edwards World & Interactive Query
Information processing: Microsoft Word, Excel, PowerPoint, Access, Visio