ANALYTIC AND AGENT-BASED APPROACHES:

MITIGATING GRAIN HANDLING RISKS

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ABSTRACT

Agriculture is undergoing extreme change. The introduction of new generation agricultural products has generated an increased need for efficient and accurate product segregation across a number of Canadian agricultural sectors. In particular, monitoring, controlling and preventing commingling of various wheat grades is critical to continued agri-food safety and quality assurance in the Canadian grain handling system.

The Canadian grain handling industry is a vast regional supply chain with many participants. Grading of grain for blending had historically been accomplished by the method of Kernel Visual Distinguishability (KVD). KVD allowed a trained grain grader to distinguish the class of a registered variety of wheat solely by visual inspection. While KVD enabled rapid, dependable, and low-cost segregation of wheat into functionally different classes or quality types, it also put constraints on the development of novel traits in wheat.

To facilitate the introduction of new classes of wheat to enable additional export sales in new markets, the federal government announced that KVD was to be eliminated from all primary classes of wheat as of August 1, 2008. As an alternative, the Canadian Grain Commission has implemented a system called Variety Eligibility Declaration (VED) to replace KVD. As a system based on self-declaration, the VED system may create moral hazard for misrepresentation. This system is problematic in that incentives exist for farmers to misrepresent their grain. Similarly, primary elevators have an incentive to commingle wheat classes in a profitable manner. Clearly, the VED system will only work as desired for the grain industry when supported by a credible monitoring system. That is, to ensure the security of the wheat supply chain, sampling and testing at some specific critical points along the supply chain is needed.

While the current technology allows the identification of visually indistinguishable grain varieties with enough precision for most modern segregation requirements, this technology is relatively slow and expensive. With the potential costs of monitoring VED through the current wheat supply chain, there is a fundamental tradeoff confronting grain handlers, and effective handling strategies will be needed to maintain historical wheat uniformity and consistency while keeping monitoring costs down. There are important operational issues to efficiently testing

grain within the supply chain, including the choice of the optimal location to test and how intensively to test. The testing protocols for grain deliveries as well as maintaining effective responsiveness to information feedback among farmers will certainly become a strategic emphasis for wheat handlers in the future.

In light of this, my research attempts to identify the risks, incentives and costs associated with a functional declaration system. This research tests a series of incentives designed to generate truthful behavior within the new policy environment. In this manner, I examine potential and easy to implement testing strategies designed to maintain integrity and efficiency in this agricultural supply chain.

This study is developed in the first instance by using an analytic model to explore the economic incentives for motivating farmer's risk control efforts and handlers' optimal handling strategies with respect to testing cost, penalty level, contamination risks and risk control efforts. We solve for optimal behavior in the supply chain assuming cost minimization among the participants, under several simplifying assumptions. In reality, the Canadian grain supply chain is composed of heterogeneous, boundedly rational and dynamically interacting individuals, and none of these characteristics fit the standard optimization framework used to solve these problems. Given this complex agent behavior, the grain supply chain is characterized by a set of non-linear relationships between individual participants, coupled with out of equilibrium dynamics, meaning that analytic solutions will not always identify or validate the set of optimized strategies that would evolve in the real world. To account for this inherent complexity, I develop an agent-based (farmers and elevators) model to simulate behaviour in a more realistic but virtual grain supply chain.

After characterizing the basic analytics of the problem, the grain supply chain participants are represented as autonomous economic agents with a certain level of programmed behavioral heterogeneity. The agents interact via a set of heuristics governing their actions and decisions. The operation of a major portion of the Canadian grain handling system is simulated in this manner, moving from the individual farm up through to the country elevator level. My simulation results suggest testing strategies to alleviate misrepresentation (moral hazard) in this

supply chain are more efficient for society when they are flexible and can be easily adjusted to react to situational change within the supply chain.

While the idea of using software agents for modeling and understanding the dynamics of the supply chain under consideration is somewhat novel, I consider this exercise a first step to a broader modeling representation of modern agricultural supply chains. The agent-based simulation methodology developed in my dissertation can be extended to other economic systems or chains in order to examine risk management and control costs. These include food safety and quality assurance network systems as well as natural-resource management systems.

Furthermore, to my knowledge there are no existing studies that develop and compare both analytic and agent-based simulation approaches for this type of complex economic situation. In the dissertation, I conduct explicit comparisons between the analytic and agent-based simulation solutions where applicable. While the two approaches generated somewhat different solutions, in many respects they led to similar overall conclusions regarding this particular agricultural policy issue.

ACKNOWLEDGEMENTS

DEDICATION

I dedicate this thesis to my wife – Xiaodong Rachel Nie, and my daughter - Athena Qianya Nie. Thank you for your love and support all the time.

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NOMENCLATURE

ACRONYMS

AAFC	Agriculture and Agri-Food Canada
CGC	Canadian Grain Commission
CIGI	Canadian International Grains Institute
CWB	Canadian Wheat Board
CWRS	Canadian Western Red Spring
KVD	Kernel Visual Distinguishability
VED	Variety Eligibility Declaration

ROMAN SYMBOLS

C_s	Total sampling cost, dollars
C_{sr}	Total sampling and sample retention cost, dollars
c_e	Farmer's risk control effort cost, dollars
c_1	Truck sample test cost at test point 1 (truck testing), dollars/sample
c_2	Primary elevator bin sample test cost at test point 2 (bin testing), dollars/sample
f_1	Penalty for farmer's misrepresented wheat when the misrepresentation is detected at test point 1 (truck testing), dollars/bushel
f_2	Penalty for farmer's misrepresented wheat when the misrepresentation is detected through tracing triggered by detected contamination at test point 2 (bin testing), dollars/bushel
f_3	Penalty for farmer's misrepresented wheat when the misrepresentation is detected through tracing trigger by detected contamination at test point 3 (railcar testing), dollars/bushel
f_{p2}	Primary elevator's profit loss for contaminated wheat detected at test point 2 (bin testing), dollars/bushel

f_{p3}	Primary elevator's profit loss for misrepresented wheat detected at test point 3 (railcar testing) (profit loss due to wheat quality loss plus penalty imposed by the terminal elevator), dollars/bushel
k	Farmer's risk control technology index
m	Contamination multiplier, which expressed by the number of deliveries contaminated in a bin by a misrepresented delivery unloaded in the same bin
mq	Volume of wheat in a contaminated bin, bushels
N	Total delivery years
n	Total number of farmers
q	Volume of wheat for a delivery from a farmer, bushels

GREEK SYMBOLS

α	Misrepresentation rate of the farmer, $0 \le \alpha \le 1$
$(1-\alpha)$	Probability of consistent declaration
$\alpha\beta$	Probability that a farmer's misrepresented delivery is detected. Detected delivery will be priced at discount and pay penalty for the misrepresented volume
$\alpha(1-\beta)$	Probability that a farmer's misrepresented delivery is not detected
β	Truck test rate at test point 1, $0 \le \beta \le 1$
β_b	Bin test rate at test point 2, $0 \le \beta_b \le 1$
β_t	Railcar test rate at test point 3, $0 \le \beta_t \le 1$
$n\beta_t$	The probability that a misrepresented railcar is detected, where $n\beta_t \le 1$. n is a multiplier which is not less than 1[1].

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[1] Assumed that there are a bins and each bin can load b railcars. If h railcars are randomly tested at the terminal elevator, a contaminated bin will be identified with a probability $(1-\dfrac{C_{(a-1)b}^{h}}{C_{ab}^{h}})$. Then the probability multiplier $n = (1-\dfrac{C_{(a-1)b}^{h}}{C_{ab}^{h}})(\dfrac{ab}{h})$. Please refer to Appendix C for more information.

SUPERSCRIPTS

T	Time, year
J	Cost objective function

SUBSCRIPTS

b	Primary elevator bin
e	Farmer's effort
f	Farmer
g	Delivery sequence in a year
i, j	Index number
p	Primary elevator
s	Sampling
sr	Sampling and sample retention
t	Terminal elevator

CHAPTER 1

INTRODUCTION

1.1 Background

For many years, Canada has enjoyed a superior reputation with customers for supplying wheat that consistently and uniformly meets the agreed sale specification. Canada earned this reputation by enforcing a reliable quality assurance system that involves all supply chain participants, beginning with plant breeders, and involving producers, grain handlers, marketers and end-users. A key strength of this system is the ability to segregate grain according to class, type and grade, thus enabling end-users to purchase shipments of grain with predictable processing qualities.

There are a number of economic and agronomic regulations in the Canadian wheat industry to regulate the behavior of all participants in this quality focused export industry. These regulations have been working effectively, contributing much to the quality reputation and competitiveness of Canadian wheat. A key component of the Canadian quality system for wheat and other grains was the use of Kernel Visual Distinguishability (KVD) for segregation (Oleson, 2005).

KVD was a visual system that identified classes of wheat within the production and grain handling systems. It allowed a grain grader to distinguish the class of a registered variety solely by visual inspection, which was very important because different classes of wheat perform very differently when processed. KVD was unique to Canada and had been successfully used for many years as an effective tool to keep wheat classes separate. KVD had worked well because Canada had maintained a strict variety registration system that required all licensed varieties conform to the prescribed visually distinctive kernel features for each class.

Before a variety could be registered for production in Canada, it had to undergo careful scrutiny for end use quality, agronomic performance and disease resistance, and be proven equal or better

than all those criteria for the reference variety for its class. It also had to demonstrate that the variety conformed with the visual distinguishability requirements used to segregate wheat of different classes. As a result, each of the eight major classes of wheat had been assigned a combination of seed-coat color and physical kernel configuration that is visually distinguishable from other classes and the varieties within each class were visually similar. This specified that a variety of wheat with the kernel features of one of the wheat classes would have certain quality characteristics. Under this condition, when a farmer delivered wheat to the primary elevator, for example, elevator agents could segregate the wheat into the appropriate class and grade according to visual appearance. So KVD enabled rapid, dependable, and low-cost segregation of wheat into different classes or quality types in the handling system and thus had been essential to maintain uniformity of quality within shipments and consistency of quality from shipment to shipment (CGC, 2005).

Despite its advantages, there was a significant cost associated with KVD. In the KVD system, if a new variety with superior characteristics did not meet the KVD's appearance standard, it could not be registered, grown or sold by farmers. Breeders had to incorporate KVD characteristics in their variety selection process. As such KVD was a significant constraint for wheat breeders developing wheat varieties that impedes progress in variety development and slowed the rate of productivity growth for the wheat sector. Given this, there had been pressure to abandon the KVD system due to the proliferation of wheat classes in western Canada. KVD was also under some pressure due to the demand for special quality types for niche markets.

Over the past few years, there had been intensive discussions about moving away from KVD as a variety identification and grading system and developing alternatives to KVD. In response to this impediment to innovation, the Canadian Grain Commission (CGC) directed an effort towards eliminating the wheat quality control system dependency on KVD (CGC, 2007). Meanwhile, others suggested that KVD should not be phased out before ensuring the maintenance of the consistency and uniformity of Canadian wheat (Burden et al., 2003). These individuals also warned that any relaxation of KVD registration requirements should be done gradually, giving some time for the grain handling system to prepare for alternatives.

In spite of warnings about changing the current grading system away from KVD, on February 11, 2008, the federal government announced that the KVD requirement for variety registration would be eliminated from all eight classes of wheat as of August 1, 2008. In the meantime, the CGC proposed a more flexible wheat segregation system called Variety Eligibility Declaration (VED) that would replace the existing KVD regulation. In a VED system, the farmer would declare which varieties they are delivering into the handling and transportation system. This would remove the requirement that each variety be visually distinguishable from varieties in other wheat classes. Ultimately, the costs associated with the VED system are not well understood and could be significant due to the current absence of technology necessary to prevent mix-ups or commingling of grain classes in the bulk handling and transportation system. Some industry participants still doubt whether VED could be made to work effectively, while the CGC insists that the cost of doing nothing would be greater than the cost of proceeding with VED. The CGC also claims that as the only alternative available at present, the VED is the best choice for maintaining varietal segregation in a non-visual quality control system (Paul, 2006).

1.2 Problem Statement

In the past under KVD, elevator managers and terminal operators could be reasonably confident that they could accurately identify the class of wheat delivered to their facility merely by looking at samples from the truck or rail car because the visual appearance of the kernel was indicative. There are a number of uncertainties to consider as KVD is replaced by the VED system. The fundamental problem with the VED grading system is that there is an incentive for the farmer to potentially misrepresent the product (Furtan et al., 2003). Similarly, primary elevators also have an incentive to commingle different wheat classes for financial gain. After removing the variety registration requirement for KVD, new varieties could be introduced without requiring that they be visually distinguishable from other classes of wheat, and could generate class misrepresentation when there is a financial gain from doing so. Simply put, under VED, a wheat variety with low quality can be more easily misrepresented as a wheat variety with high quality since they are no longer required to be visually distinguishable from each other. In addition, non-registered varieties, often from the United States, also present a serious problem for the Canadian

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sector (CGC, 2003). A farmer could attempt to declare a non-registered variety as an existing eligible one since varieties can no longer be definitively identified. This issue could become even more important in the presence of non-registered genetically modified (GM) varieties. And lessons from the Canadian flax industry are critical to note here. In 2009, the contamination of Canadian flax exports to the European market with a GM flax was confirmed. This contamination greatly harmed the reputation of Canadian flax production in the world market (CBAN, 2012).

While technologies currently exist to identify visually indistinguishable wheat varieties, this technology requires a laboratory setting, are relatively slow to perform, and are very costly compared to the KVD system (CGC, 2006). This means in the current supply chain, a testing intensity needed to guarantee varietal accuracy will involve high costs (Langen, 2011). Although considerable effort is still being made to develop affordable, reliable and rapid variety identification (VID) technology that can be used outside of a laboratory setting, it is not available as of this writing, and will not likely be available for some years to come.

Before such technologies are developed, there are clearly risks under VED that could jeopardize Western Canada's traditional competitive advantage in wheat markets. Under VED, there will likely be a significant increase in handling costs, for example, forcing separate binning of deliveries until variety and quality can be identified several hours or days later. Generally, the existence of visually indistinguishable varieties has the potential to seriously compromise the Canadian quality assurance system if varieties are misrepresented anywhere within the grain handling system. Undetected varietal misrepresentations would effectively result in contamination of one type of wheat with another and could lead to significant financial losses for grain handling companies and marketers or even damage the overall reputation and competitiveness of Canadian wheat in the world market. Facing these challenges, the goal of this thesis is to identify those effective wheat handling strategies applicable to the grain handling supply chain that will best help maintain varietal consistency in the post-KVD era.

1.3 Study Motivation

The adoption of VED will bridge a gap between now and the time when inexpensive and rapid varietal testing is available. Under VED, Canada's traditional objective of maintaining wheat competitiveness, enhancement of marketability and assurance of wheat quality will not change. To meet this objective, it is assumed that the Canadian federal government maintains the responsibility to deliver excellence and innovation in grain quality and quantity assurance, research, and producer protection.

As described, a VED system is currently in use in various parts of the world, for example by the wheat industry in Australia as well as the soybean industry in eastern Canada. From an economic and contractual perspective, it is clear that self-declaration product quality systems like VED work best when backed up with credible monitoring and enforcement. But in fact they also require the presence of deterrents to misrepresentation of the product. Another strong element contributing to the success of this kind of system is the potential deterrent in order to reduce the potential to damage buyer/seller relationships. Given the inherent complexities of these challenges, there are strong incentives for researchers to work out effective novel handling policies under VED, creating a favourable environment to facilitate the implementation of VED in the grain handling supply chain.

This study will examine strategies to mitigate handling risks and reduce corresponding costs, integrating key factors such as on-farm risk, misrepresentation, sampling, testing, handling, transportation, and penalties across the complete grain supply chain from producers to terminal elevators, instead of simply focusing on a particular segment of the supply chain as has been done in related prior work. With the support of simulation models and methods that can capture the complexities inherent in this problem, this thesis also seeks to understand the interactions and dynamics of the supply chain under VED so as to quantify the risks and costs under foreseeable handling scenarios. This framework will make a unique contribution to the existing literature.

1.4 Objectives

The objective of this dissertation is to identify a set of varietal testing strategies that will maintain the integrity of the wheat supply chain under VED while keeping handling costs relatively low. In addition, the costs and risks to supply chain participants will be quantified. Since the goal of modern logistics is "to get the right goods or services to the right place, at the right time, and in the desired condition, while making the greatest contribution to the firm" (Ballou, 1999), this research will also help to identify the structure of future grain logistics under VED.

To meet these objectives, static microeconomic theory as well as dynamic economic simulation will be applied to explore both the analytic and simulated effects of possible wheat handling strategies on the misrepresentation behavior of producers, staying mindful of the interaction between producers behavior on wheat handling testing strategies. To start, a basic principal agent model is developed of the economic incentives inherent in the VED system so as to identify handling strategies that will optimize contamination risks and costs. This static analytic framework is then extended in a dynamic sense through agent-based simulation of the problem, where this latter methodology allows for the incorporation of individual heterogeneity, interaction, adaptation and feedback in the system. Given the inherent complexities of the problem, the goal of the latter analysis is to identify handling and management strategies that help to minimize system handling costs, as well as to assess the distribution of risks and costs among system participants under these handling or management strategies.

1.5 Thesis Structure

There are six chapters in this thesis. Chapter 1 serves as an introduction to the policy issue that motivates this research. In Chapter 2, the Canadian wheat quality assurance system is described in detail. The structure of KVD and VED will be explained as well as the opportunities and challenges that arise in a post-KVD environment. In Chapter 3, both farmer (agent) and elevator (principal) objective functions within a supply chain are defined and solved in order to identify optimal risk mitigation strategies. Given the nature of the situation, potential moral hazard

behavior among the participants is explored. Chapter 4 motivates and explains the development of an agent-based dynamic simulation model of the grain handling supply chain under VED. The simulation model will help identify superior testing strategies in this complex grain handling environment and also facilitate the quantification of the costs and risks of VED for supply chain participants. Chapter 5 extends the simulation analysis to examine various policy scenarios of interest. Comparisons between different handling strategies are performed to determine a set of good strategies for handlers under foreseeable situations. Furthermore, a comparison between the analytic solutions and the simulated model solutions is described in this chapter. Finally, Chapter 6 offers some conclusions and highlights areas for further research.

CHAPTER 2

THE CANADIAN WHEAT INDUSTRY

2.1 Introduction

In the Canadian grain handling system, KVD had been a highly effective method for ensuring consistency and uniformity[2] of wheat delivered to customers. KVD was a visual wheat classification system that identified different types of wheat within the production and grain handling systems. It had worked so well because it enabled rapid, dependable, and low-cost segregation of wheat into different functional classes within the handling system since the visual appearance of wheat is indicative of intrinsic and processing quality. Despite these advantages, the KVD method also had some weaknesses (CGC, 2005),

1. It placed constraints on wheat breeders' ability to quickly improve agronomic characteristics of wheat, such as yield, disease resistance, or maturity rate.

2. KVD also constrained the development of wheat varieties with improved quality characteristics for traditional end-uses, or different quality characteristics for new and diverse end-uses, including non-milling wheat for feed or fuel use.

The CGC had recognized the limitations of KVD as a segregation tool and had directed a significant and sustained effort towards eliminating the grain quality control system's dependency on it. On February 11, 2008, the federal government announced that KVD would be eliminated from all eight classes of wheat as of August 1, 2008 and a new system called VED was introduced. Therefore since 2008, farmers must sign a declaration (or affidavit) when they

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[2] A customer purchases a certain class and grade of wheat in October and again in May. If there is little variation in the appearance and quality of those shipments over time it is said to be consistent. It is said to be uniform if there is little difference in these factors throughout the whole shipment (i.e. from hold to hold in the ship) (Oleson, 2003).

deliver grain attesting to the eligibility of the variety they are delivering. The declaration is required by each company and delivery point that they deliver to.

Undoubtedly, movement away from KVD as a segregation tool is fundamentally altering the Canadian grain system and has had a significant impact on the Canadian wheat industry. Such a change affects relevant participants including seed breeders, grain producers, grain handlers and marketers, and therefore requires their support and cooperation to preserve Canada's reputation as a producer of quality wheat. To fully understand the impact of the removal of KVD on the functions and costs of the grain handling system and understand the future of Western Canadian wheat quality assurance, it is necessary to know the historical Canadian wheat handling and quality control system, as well as the character and functionality of KVD and VED and issues related to them.

2.2 Canadian Wheat Handling and Quality Control System

2.2.1 Canadian Wheat Handling System

Canada's prairie wheat industry has grown significantly since it began in 1878. Today, moving Canada's prairie wheat production from farms to world markets is done within a supply chain of enormous magnitude. CIGI (1993) described the wheat flow in the wheat handling system as follows: farmers produce wheat and store it on their farms; to move their wheat production, producers must load and haul farm truckloads of wheat to primary elevators; after that, wheat must be loaded on railcars from primary elevators and shipped to domestic consumers or hauled a long distance to export terminal elevators; finally, ships must be scheduled into Canada's ports to be loaded with wheat from the terminal elevators for the world market.

The primary elevator accumulates small lots of grain (sorted by class and grade) from individual farmers until there is enough to fill railcars. Current primary elevators are most often located beside rail tracks. Each elevator possesses a specially designed structure capable of receiving, storing and shipping grain in bulk lots. Terminal elevators, like primary elevators, historically followed railway construction to provide facilities to unload railcars, store, process and load the grain into ships. Several large export terminals are located on the West Coast of Canada

(Vancouver and Prince Rupert), while other terminals are located at Thunder Bay on Lake Superior and Churchill on Hudson Bay. There are also transfer elevators along the St. Lawrence Seaway where grain is off loaded and then transferred to ocean vessels. In addition, there are a growing number of inland terminals which also ship grain to the export terminals. Virtually all of the wheat moving from the primary elevator or inland terminal to ocean or Great Lakes terminals is transported by rail. Typically, each train carries only one class of wheat. Railcars move into the export terminal. They are unloaded, the wheat is placed in bins, cleaned and then loaded onto vessels. The wheat is normally kept separate by the class and grade. Shipments of wheat designated for the United States may be by either ship or train (grain designated for the United States may also originate from an inland terminal) (CP, 2013).
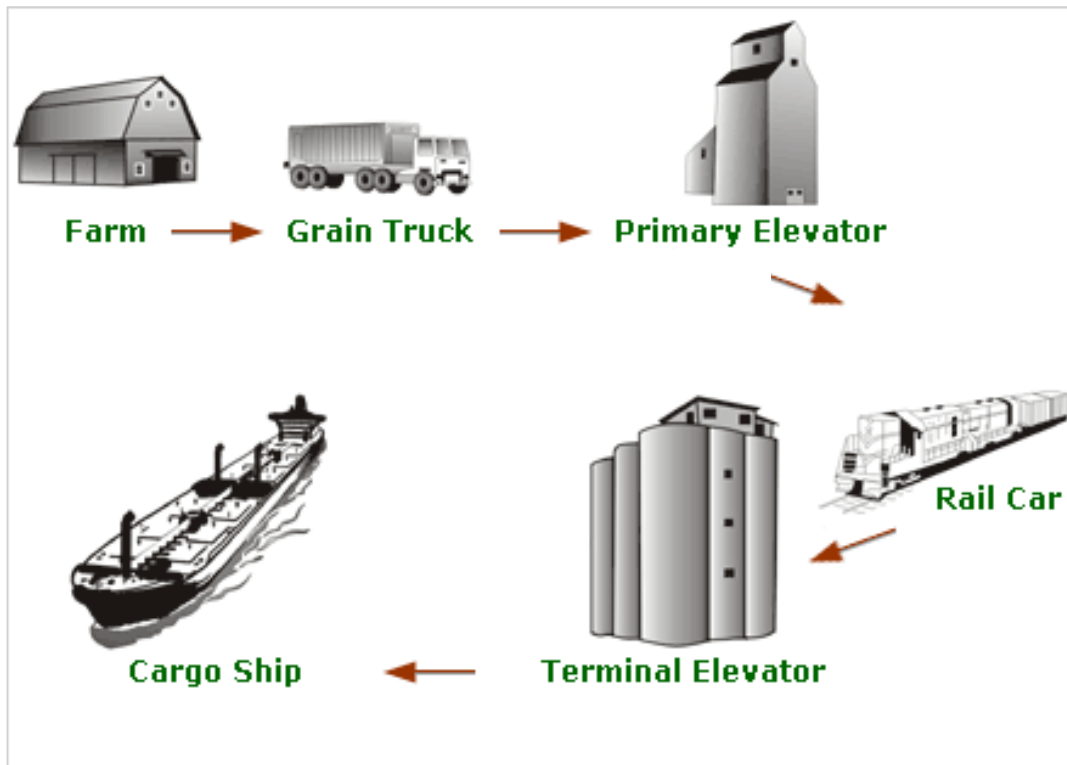
Figure 2.1 Wheat Flow in Wheat Handling System (CGC, 2003, Page 8)

2.2.2 Canadian Wheat Quality Control System

Canada has an enviable reputation for supplying wheat that uniformly and consistently meets agreed sales specifications. Such an achievement can be ascribed to Canada's wheat quality

control system. Quality control refers to the preservation of the normal natural quality of grain from the time it is received at a primary elevator to the time it leaves terminal elevators for export or for delivery to the domestic market (CIGI, 1993). Canada's grain quality control system is designed to consistently provide domestic and export customers with the quality of grain they require, year after year. A key strength of this system is the ability to segregate and handle grain according to quality, from producer delivery to the point of export, thus enabling end-users to purchase shipments with predictable processing qualities.

Quality control of Canadian grain falls largely under the jurisdiction of the CGC. The CGC is responsible for establishing and maintaining standards of quality for Canadian grain and regulating grain handling in Canada to ensure a dependable commodity for domestic and export markets. The commission's quality control system involves every phase of the grain industry from development of new varieties to delivery of grain to consumers. Wheat quality control in Western Canada has evolved over the last decades and is now made up of four key elements: varietal development and registration, grading system, uniformity, and cleanliness and safety. (CWB, 2008). A detailed description is offered here for the first element, which provides the cornerstone for KVD implementation.

The CGC (2003, 2005) offerS a detailed description on the requirements for grain variety development and registration in the KVD era. New varieties were registered only after careful evaluations for their end-use quality performance, agronomic performance and disease resistance characteristics were performed. Samples of new varieties developed by plant breeders were submitted to the Commission's Inspection Division for a report on kernel characteristics. Varieties of significantly different quality must be visually distinguishable from each other by kennel characteristics. Samples were also examined for grading patterns determined on the basis of uniformity of kernel type. Each new wheat variety registered would need to fall into one of eight specified Western Canada wheat classes[3] and be visually distinguishable from all other classes of wheat. Varieties of inferior quality that were not easily distinguishable from varieties

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[3] The eight Western Canadian wheat classes (for 2008) were: Canada Western Red Spring (CWRS), Canada Western Amber Durum (CWAD), Canada Western Extra Strong (CWES), Canada Prairie Spring Red (CPSR), Canada Prairie Spring White (CPSW), Canada Western Soft White Spring (CWSWS), and Canada Western Hard White Spring (CWHWS). As of 2011, the ninth Western Canadian wheat class is introduced: Canada Western General Purpose (CWGP). CGC (2012) states that varieties in CWGP are not required to meet KVD registration requirement and may be undistinguished from varieties within other classes of wheat.

of higher quality might be excluded from registration to prevent them from reducing the overall quality of Canadian grain. As a result, wheat kernels in each class possessed a distinctive and unique look, as well as overall color and configuration, while varieties registered in a class would exhibit very similar end-use performance. The CGC referred to these visual characteristics as kernel visual distinguishability, or KVD, and this particular grading system was unique to Canada. KVD had been a vital aspect of western Canada's unique quality control system after it was established and provided substantial benefits by facilitating exports of high quality wheat for customers over decades (Dexter et al., 2006).

2.3 KVD

In the KVD era, because of the KVD constraint on wheat registration, each of the Western Canadian wheat classes had been assigned a combination of seed-coat color and physical kernel configuration that were different and distinctive from each other. KVD made producers determine visually that any wheat seed they purchased was the class they intended to grow. The visual differences had to be significant enough to also permit elevator operators to readily distinguish one type of wheat from another as it moved from farms to primary elevators and terminals, permitting delivered wheat to be put in the appropriate segregated bin, ready for shipment in different railcars. Grain inspectors could check that shipments of one class of wheat were not contaminated by another and confirm that railcars and shiploads of wheat meet buyer's requirements.

A variety of wheat with the kernel shape of one of the wheat classes had certain quality traits and processing characteristics. The relationship between kernel feature and quality had been bred to be quite direct. Due to KVD, elevator managers and terminal operators in the grain handling system could be reasonably confident that they knew the class of wheat delivered to their facility merely by looking at truck or railcar samples. On export, the Canadian Grain Commission could also certify wheat shipments based on the visual grading of wheat shipments. In this manner, declaration of the delivery's varietal composition by the farmer (or primary elevator manager, in the case of deliveries to terminals) was generally unnecessary.

This situation changed when KVD was removed as a registration requirement for all Western Canadian wheat classes. Although varieties put forward for registration have to meet all other registration requirements for quality, disease resistance and agronomics, they can be alike in appearance with wheat in another wheat class. In a declaration system, if one of these varieties is misrepresented or inadvertently mixed with other varieties during handling, wheat handlers would be unable to detect a problem without testing a sample. If undetected, Canada's established reputation for guaranteed high quality wheat could be threatened by an increased likelihood of mix-ups between wheat classes.

Ultimately, the goal of the CGC is to develop a quality control system that removes the agronomic constraints of KVD without losing its benefits. If the existence of visually indistinguishable wheat classes brings problems to the Canadian wheat quality control system, any future VED system should be validated so as to best maintain the historical consistency and uniformity of Western Canadian wheat (CGC, 2005).

2.4 VED and Related Issues

2.4.1 VED

As an alternative to KVD, VED was enacted by the CGC as the policy for segregating and moving grain through the handling system. Under VED, every time wheat changes hands there is a legal declaration made comprised of a variety eligible for a specific class. Documentation and sample retention would also make it possible to trace grain in a cargo right back to elevators and farmers who made deliveries, allowing monitoring and enforcing accountability, thereby theoretically assuring the quality of wheat shipments.

 The CGC (2010) lists the following policy changes in this regard, implemented after August 1, 2008

- VED, a varietal declaration system as part of a quality management system for Western Canadian wheat, was introduced.

- When a farm delivers wheat, the farmer has to sign a declaration form (refer to Appendix A for more information about the form). By signing the form, the farmer attests that the wheat being delivered is eligible for a specific class of Western Canada wheat.

- As of August 1, 2011, a ninth wheat class was created to meet the needs of the feed and industrial sectors – Canada General Purpose– with disease resistance and agronomic criteria, but with no quality requirements.

After removing the variety registration requirement for KVD, a new class of wheat (CWGP) was introduced without requiring that varieties in this class be visually distinguishable from other existing classes of wheat (CGC, 2012). In fact, a tenth wheat class has also been introduced - Canada Western Experimental, but there are no eligible varieties for CWE as of this writing. Under the VED system, incoming varieties in this class are not required to meet the KVD registration requirement either. In fact, varieties in new classes of wheat or new varieties in existing classes are likely to be similar in physical appearance to other already existing wheat varieties, but could differ significantly in quality. The potential increase in visually indistinguishable varieties may threaten the safety of the Canadian wheat quality assurance system. If introduced into the grain supply chain, varieties that are not visually distinguishable from registered varieties may cause problems with the quality assurance system because they do not perform the same as registered varieties.

2.4.2 Challenge of Visually Indistinguishable Varieties under VED

By way of example, the newly introduced varieties in the ninth class are not necessarily visually distinguishable from each other or the existing eight classes of wheat (CGC, 2012). Because visual requirements are relaxed to facilitate variety development, more varieties may be introduced and some of them may be visually indistinguishable from other varieties that belong to different wheat classes in the future. Due to the time lag between variety registration and adoption, it is anticipated that in the short run these varieties will not create an immediate KVD conflict with the main varieties of Western Canada wheat, for example CWRS, since look-alike varieties have not yet entered the system in large volumes. In the long run, the conflict may be unavoidable if newly registered visually indistinguishable varieties grow. Together with the visually indistinguishable non-registered varieties, they will increase the likelihood of mix-ups

between wheat classes and thus challenge the function of the wheat quality control system in western Canada.

The visually indistinguishable non-registered varieties have been a problem to wheat handling even under KVD. In 2002, a grain company reportedly lost several hundred thousand dollars when a train shipment of milling wheat was downgraded to feed because it contained excessive levels of non-registered US wheat varieties. KVD as a visual identification method could not solve the visually indistinguishable non-registered variety problem (CGC, 2009). The CGC (2005) states that it hopes such a problem can be solved by VED.

If producers or handlers know precisely the varieties of wheat they grow or handle and honestly make declarations on their deliveries, there will be no misrepresentation problem. Otherwise, these future varieties will have potential to compromise the Canadian quality assurance system if they are misrepresented anywhere within the grain handling system without detection. Such mistakes can result in commingling and could lead to significant financial losses for grain handling companies and marketers. Such losses will ultimately be shared by all the supply chain participants and that outcome does not meet the CGC's objectives under VED.

2.4.3 VED Objectives

The CGC's stated objectives for a VED system are as follows (CGC, 2003):

1. To protect and broaden Canadian producers' access to grain markets by strengthening the grain quality assurance system;

2. To provide producers with a broader range of choices in what they grow and sell;

3. To provide end-users more choices in what they buy, while continuing to meet their need for consistent, uniform quality.

In the KVD era, elevator handlers could identify particular classes of wheat delivered by the farmer solely on a visual basis. The switch from KVD means that along the supply chain, wheat has to be identified and segregated on some basis other than visual appearance. It is much more critical that grain handlers are made familiar with formal documentation and operational

procedures for handling grain. In short, due to the potential problems with VED, there could be considerably more management effort required to operate with the same level of certainty that KVD provided.

2.4.4 Problems with VED

Participant cooperation and support is a prerequisite for success in any quality control system. Their attitudes and efforts determine the functional performance of the system. If participants each individually are made to take responsibility for their actions, misrepresentation problems should rarely occur. But under VED, it is expected that there will be an increase in the likelihood of supply chain participants' misrepresentation behavior. In this regard, Furtan et al. (2003) defined two types of participants operating under VED. The first is one who misrepresents the wheat variety in order to gain a better price. The second is one who instead does not use due care and diligence in producing, handling, and transporting wheat, with the unintended consequence that wrong varieties end up in a particular wheat class. Because each party's action is unobservable to a second party, it would necessarily be difficult to identify whether an individual made mistakes intentionally or not under VED.

On one hand, the problem with the VED system is that there is a built in incentive for the farmer, as well as the primary or terminal operator, to potentially misrepresent the product. For example, suppose that a non-CWRS variety, visually indistinguishable from a CWRS variety, is represented as a CWRS variety. Because CWRS receives a greater price than most other wheat classes, a farmer who misrepresents the variety of wheat delivered could potentially make a financial gain. Similarly, grain handlers have an incentive to commingle wheat classes and make a financial gain. But the consequence of a commingling of wheat classes is that it could result in the downgrade of a bin or a vessel of grain upon export.

On the other hand, the existence of visually indistinguishable varieties could also make farmers confused about the wheat classes or varieties they actually grow. Then these varieties could be easily misrepresented when farmers deliver them to the elevator. At the elevator stage, visually indistinguishable varieties cannot be readily sorted from each other. If these are misrepresented without detection, such varieties can then enter the elevator and result in increased costs at some

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point in the handling chain. In addition, it is likely that visually indistinguishable varieties increase the probability of operation errors during wheat handling and transportation.

In spite of these issues, existing grain declaration systems seem to work well in the grain industry at other locations. These include the Australian wheat industry as well as the soybean industry in eastern Canada. But the economics of incentives tell us that as described, VED will only be sustainable if supported by a functional monitoring system that includes sampling, testing, and traceability along with serious deterrents in the case of misrepresentation of the variety or class of grain. And to start, due to the existence of visually indistinguishable wheat varieties under VED, non-visual technology for variety identification is needed to support the monitoring system.

2.4.5 Variety Identification Technology

In general, with strict monitoring and testing along with proper deterrents to misrepresentation, variety eligibility declarations can be used to keep grain segregated in a manner consistent with historical Canadian standards. From the latter perspective, the ideal alternative to KVD would be some kind of automated test that could quickly and cheaply identify grain at the elevator when a producer delivered it. In fact, the demand for variety identification testing in Western Canada has increased over the past number of years because customers are seeking grains with more specific quality characteristics and for more diverse end-uses (CGC, 2009). Yet under VED, maintaining such a need becomes more urgent because new visually indistinguishable varieties have been introduced with more new visually indistinguishable varieties potentially introduced in the future. To ensure consistent and uniform quality of wheat shipments, the CGC and grain handlers are becoming increasingly dependent on technological developments to monitor and detect the presence of unwanted visually indistinguishable varieties in shipments of wheat. For this reason, development of rapid variety identification methods to facilitate and monitor purity of variety specific segregation has become a major research direction in Canada (CGC, 2009).

In fact, the CGC has developed several non-visual methods for variety identification. Two protein fingerprinting techniques are used: polyacrylamide gel electrophoresis (PAGE) and high performance liquid chromatography (HPLC) (CGC, 2009). Although very useful for certain purposes, these two techniques cannot distinguish all varieties. To augment its testing

capabilities, the CGC has also developed microsatellite-based DNA fingerprinting (CGC, 2009). These three biochemical methods are used to support the Canadian quality assurance system by monitoring the variety composition of railcars and vessels carrying grain. While these methods are accurate and replicable, they are laboratory based, require skilled technicians and to date, are not widely available. They are also relatively expensive and take time to yield results. The monitoring program based on these methods provides the industry with information to help them better manage the handling system, but intensive monitoring using these systems will compromise any potential benefits of wheat handling. So to improve the efficiency of grain monitoring, the CGC has been putting efforts into developing a rapid and affordable variety identification technology to facilitate and monitor the purity of variety specific segregation (Dexter et al., 2006). While still under development, if this technology proves successful, it would constitute a major step forward for quality assurance under VED.

A reliable VED system would focus on detecting misrepresentation upon entry into the supply chain instead of at export position. Doing so will prevent misrepresented deliveries from entering the supply chain before commercial damages are realized. And even if contamination happens, traceability, otherwise known as a trace-back process, could be enacted to find the source upstream of supply chain by referring to retained samples and testing them. In light of this, it is clear that the utility of a variety identification technology for testing determines the functional performance of VED. A rapid and affordable variety identification technology can greatly improve the efficiency of detecting contamination and tracing it back ("traceability") to determine its sources under a VED system.

2.4.6 Traceability under VED

The VED concept concerns "involved declaration of class eligibility and facilitated traceability in the event of detection of a contamination." (Oleson, 2003). In turn, the International Organization for Standardization (ISO) (1994) defines traceability as the "ability to trace the history, application or location of an entity by means of recorded identifications".

Under the VED system, wheat would no longer be segregated by visual characteristics. Producers or handlers instead must declare the class of their grain upon delivery to the primary elevator or the terminal elevator. As grain moves through the handling system, the CGC (2003)

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proposed that legislation should require that samples be taken and declarations be signed as grain changed hands, thus theoretically making it possible to trace detected misrepresented varieties back to a prior stage in the supply chain and determine the cause or the source of the problem. In this case, those responsible for the misrepresentation could be held accountable for their actions, and could be subject to penalties in the form of fines, suspensions, downgrades or other sanctions. Therefore, traceability is indispensable for the safety of wheat handling under VED given that monitoring and testing are imperfect. It is believed that a well-established traceability mechanism backed up by a penalty system will provide effective incentives to supply chain participants for segregation efforts (Viterra 2007; CWB 2008)

When contamination problems occur in grain handling and damages result, there are economic incentives to identify the contamination source upstream in the supply chain by testing the retained samples because delays in tracking the sources of contamination always increase the cost of rectifying mistakes. In the case of wheat contamination, if the costs of applying traceability are less than the benefits coming from contamination identification through traceability, then traceability will be economically viable. There are three incentives to pursue traceability: first, contamination sources can be identified so that further contamination and damage can be avoided; second, penalties on offenders can partially cover any contamination loss; third, the deterrence effect of traceability motivates participants' liability incentives for delivering eligible wheat products, eventually contributing to the safety of wheat handling (Pouliot et al., 2008).

2.4.7 Consideration for VED Implementation

In terms of the functionality of VED in Canada, first of all, it must be effective in ensuring consistent and uniform quality of wheat shipments. As discussed, KVD had been highly effective in ensuring consistency and uniformity, so that a VED system replacing KVD should not compromise the quality of shipments of Canada's premium wheat classes. In a very competitive world market, the Canadian grain industry cannot afford the cost of a questionable reputation. To meet these objectives, some essential factors determining the functional performance of a VED system must be carefully considered.

First, an effective VED system is required to motivate producers' efforts on risk control via an efficient risk sharing scheme. To what extent producers know the varietal composition of their wheat production and shipment influences the contamination risks and costs along the wheat supply chain in a VED system. Since some varieties are visually indistinguishable, preventing commingling mistakes could be difficult and costly for the typical on-farm practice. But under VED, producers are required to sign legally-binding declarations specifying what class of wheat they are delivering. Under this system, damage liability is shifted to rest almost entirely with producers[4], meaning they will have to spend more to reduce their financial liability. There are resources a producer can put into the risk control to reduce the risk of producing undesired wheat varieties, such as purchasing certified seed from seed breeders or having the saved or common seed tested at a private lab before planting, as well as enhancing documentation for on-farm practice. Even if undesired visually indistinguishable wheat is produced, there is a simple way to avoid misrepresenting it, by having samples variety tested by a laboratory before delivery. The level of efforts a farmer intends to utilize determines the extent of a farmer's confidence in the wheat variety produced.

Second, a sound VED system requires efficient testing strategies. The biggest challenge to grain companies in the future will be the management of visually indistinguishable inventory in the bulk handling system. Under KVD, the handlers relied heavily on visual distinguishability to move product through the system. Removing this functionality means that grain companies will have to invest in alternative means to manage and track inventory movement. Testing wheat at different stages of handling could reduce the chance of commingling mistakes or prevent these mistakes from going further in the supply chain. But currently, due to the high cost of testing, complete testing at each potential testing point is not economical unless the misrepresentation situation is severe. Yet incomplete tests will increase the risk that commingling mistakes go undetected and multiply into significant commercial damages. Efficient test strategies should identify the appropriate balance between the associated costs and benefits. But all else equal,

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[4]The liability is made clear in the wording of the sample declaration (CGC, 2012). It states: "I acknowledge the Producer will be held accountable in accordance with authority granted within the Acts. I further acknowledge and agree that the Canadian Wheat Board may consider the Producer to be in default of his/her delivery contracts and, in addition to any other remedies available to it, it may cancel any contracts of the Producer. In addition, the Grain Handling Company may jointly with the Canadian Wheat Board or severally, claim against the Producer for all claims, damages, losses and costs (including legal fees) that may result."

when the probability of farmer misrepresentation increases the need for testing increases and thus handling costs will also increase.

Third, an effective VED system should be supported by traceability and some kind of penalty mechanism. It has been suggested that a declaration should be signed at each transfer point in the handling system. Complete documentation of where wheat came from and where it went in the supply chain should be required each time grain is moved. Ideally, representative samples should be taken from each delivery at each transfer point in the supply chain and be retained for an appropriate period for trace-back purposes. While testing can occur at specific critical points to detect misrepresented or contaminated wheat varieties, good documentation and sample retention would make it possible to trace shipments back to each elevator and farmer if there are problems. Subsequent testing of retained samples could be used to identify the cause or source of contamination and thereby initiate procedures to remedy the situation. Finally, a set of penalties should be in place that can be applied when a misrepresented or commingled wheat class has been detected, with the penalty enforced in the face of violation. Without financial penalties and enforcement, testing and traceability are ineffective in deterring any individuals inclined to misrepresent or engage in careless grain handling practices.

Furtan et al. (2003) suggested that the goal of such a penalty and enforcement system is to provide a disincentive for participants to misrepresent their wheat as well as provide an incentive for all participants to invest in activities which reduce the probability of misrepresentation occurring. From an economic perspective, in order to achieve deterrence from an individual who may potentially misrepresent their deliveries, the expected value of the penalty cannot be less than that of the expected gain achievable through misrepresentation. Otherwise, individuals may neglect to take the necessary measures to prevent misrepresentation.

Last, a penalty and enforcement system will require considerable efforts to design. The present Grain Act and Regulations do not provide a timely or appropriate penalty system framework for misrepresentation behavior in the grain handling system (CSTA, 2012). To effectively provide incentives for reducing the likelihood of misrepresentation risks, a strong penalty and

enforcement system is needed. Furtan et al. (2003) proposed three options for penalty systems: 1) torts[5], 2) penalties meted out by the courts, and 3) an administrative penalty system[6].

In the first penalty option, industry participants damaged by variety misrepresentation of others would pursue compensation for damage through tort action. The second option includes court imposed fines and imprisonment for offences. The current Canadian Grain Act (2012) provides for maximum fines ranging from nine to eighteen thousand dollars for an individual and thirty to sixty thousand dollars for a corporation, depending on the category of offence and the level of conviction, or to imprisonment for a term not exceeding two years, or both. The third option involves suspensions and financial penalties. Regarding the suspension issue, Furtan et al. (2003) proposed that the CGC could attempt to build up a trust system with farmers. In such a system, 'trust' would substitute for sampling and testing as the CGC become familiar with individual farmers and their behavior. A farmer who generates suspicion will be penalized by more intensive sampling and testing more until such a time as the desired trust level was re-established. In this case, costly testing would be billed to offenders. With respect to the financial penalty option, a regulatory agency such as CGC could be given the authority to levy fines for infractions up to a certain amount. In fact, today if a grain company disagrees with a grain commission ruling, its only option is to fight it in court, an expensive option for both sides (Dawson, 2013). Such a proposed penalty system can avoid costly, complicated, and sometimes lengthy court processes when dealing with offences which may be straightforward and not very contestable (Furtan et al., 2003). The amount of the penalty set for a specific offender should have a positive relationship to the magnitude of varietal contamination losses incurred by the misrepresentation. In addition, it may also be useful to have penalties that are increasingly progressive for repeat offences.

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[5] A tort is a civil law offence which causes another person to suffer loss or harm resulting in legal liability for the person who committed the original offence. The source or cause of legal action is not necessarily a crime since harm may have been due to negligence, but not criminal negligence. The victim is allowed to sue the offender for monetary losses via a lawsuit. In order to win, the case, the plaintiff must show that the action (or lack of action) was the recognizable cause of their harm (Lindon and Butterworths, 2011).

[6] The administrative penalty system is a civil penalty regime that secures compliance with legislation through the application of (monetary) penalties. The legal authority may impose monetary penalties based on the type, frequency, and severity of the infraction. In fact, many penalties are graduated and often take the compliance history of the client into consideration (CBSA, 2012).

Given the importance of maintaining wheat class integrity and to provide effective deterrents for misrepresentation behavior, the Canadian Grain Act or related regulations will need to provide a robust framework for building up a penalty and enforcement system. In addition, the Canadian Grain Commission should be given the authority for applying a system of monetary penalties for misrepresentation in the face of verified violations. Although a penalty and enforcement system is an attempt to guard against certain undesirable outcomes, ideally any system should avoid the tendency to overkill with an excess of rules and procedures in a quest to ensure that those outcomes never occur. There needs to be a balance struck between taking risks and regulatory overload. To deliver favorable benefits to all grain supply participants, the process of forming appropriate regulations should necessarily involve consultations with farmers, grain companies and others in the grain industry (Dawson, 2009).

2.4.8 Costs of VED

The implementation of the VED system in Canada will introduce new risks and potentially significant costs into the grain supply chain, although it will not be an easy task to determine either the costs or the exact risks. Some analysis indicates that while there are tangible gains available in moving away from KVD (Oleson, 2003; Burden et al., 2003), the costs of implementing an efficient VED system are also significant (Furtan et al., 2003). Prior research has made clear that producers and industry stakeholders would have to make considerable changes to their old style of operations to operationalize the VED system. In sum, there are a whole array of new costs associated with wheat handling in the VED system as compared to those associated with the former KVD system (Oleson, 2003). These include:

1. Cost of VED implementation. As discussed, the new system will have many direct and indirect costs including sampling, sample retention, testing, tracing, documentation and an administrative penalty system.

2. Any loss of VED system performance. The existence of non-registered and new registered visually indistinguishable varieties can cause problems for the wheat quality control system and generate costs, e.g. those varieties can increase the probability of misrepresentation and faulty operation which can lead to cross contamination.

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Under VED, coupled with an increase in visually indistinguishable wheat varieties, the probability of misrepresentation of any kind will increase during the handling process. Documentation, sampling and testing should take place at different stages of wheat handling. The logic for this level of diligence is that if a problem can be detected before the wheat is loaded onto a vessel for shipment, then corrective action can be taken. In this way, the high cost of downgrading a train or a vessel full of loaded wheat can be avoided. If there are contamination problems, documentation and sampling at each transfer point would make it possible to detect the point at which unacceptable levels of unwanted varieties entered the system.

By assumption, handlers' testing strategies focus on pursuing their own profit maximization over time. Economic costs in the system may be substantial and should provide incentives for handlers to develop strategies to minimize the losses. Ultimately, the benefits of a VED system must be sufficient to justify its costs.

2.5 Grain Issues Involved in This Study

The objective of this research is to model a set of varietal testing strategies designed to ensure the safety and quality of western Canadian wheat under VED, while keeping handling costs relatively low. However, there are some essential considerations that need to be integrated into the models.

To maintain the integrity of the wheat supply chain, one of the top priorities under a VED system is to prevent visually indistinguishable wheat varieties from contaminating each other. The CGC (2005) argues that the long-term solution to this issue lies in the development of rapid and affordable variety identification technology. However, because rapid variety tests are currently not available, a short to medium-term solution must be increased monitoring for visually indistinguishable varieties, backed-up by some laboratory testing, along with the existence of penalty deterrents for misrepresentation of grain.

Since current testing is slow and expensive, intensive testing in the supply chain is not economical unless the misrepresentation situation is severe. Exactly how to distribute testing in

deliveries and keep it responsive to system and information feedback is an essential issue for future wheat handlers. In light of this, there are important operational issues to consider, including the decision about the optimal location to test, how intensively to test, appropriate penalty levels, feasibility of traceability, and so on.

A significant logistical challenge lies in the issue of accountability. The CGC (2010) identified accountability as being a critical success factor for grain handling. Just as Transportation Canada (2010) noted, a lack of accountability has been a major drawback in operating and regulatory environments. While it is relatively easy to describe a VED system and propose that each participant in the grain handling system will be held accountable for any variety or quality problems, actual implementation of such a system faces great challenges. In this regard, AAFC (1998) proposed that accountability can be achieved through direct contracting with an enforced financial penalty agreed upon by the relative parties in the case of underperformance. The latter policy should motivate supply chain participants to manage risks and accept losses when it occurs.

The mechanism to enforce accountability under VED needs some effort to develop. The CGC (2003) proposed that such a mechanism could be government regulated: the party who is damaged by the misrepresentation of grain would be permitted to sue the party who misrepresented the grain, or the mechanism could be industry self-regulated through litigation or possible arbitration. Any legislation would need to specify penalties for misrepresentation of grain deliveries. From an economic incentive perspective, a penalty system could motivate handler effort on controlling wheat handling risks but a liability system cannot (Gray, 2010). In fact, a penalty system would make handlers share the losses from farmer misrepresentation while a liability system would make such losses unconditionally covered by offenders. Thus, handlers have no economic incentive to prevent farmer's misrepresentation at all in a liability system. Of course, in a penalty system, the penalty cannot be unbounded but would need to be carefully regulated. Note that if handlers feel free to set the penalty imposed on an offender so that the contamination losses from misrepresentation can be covered completely, a penalty system will provide no economic incentives on handlers for risk control, similar to the liability system.

It is expected that more industry level discussion will take place in order to decide upon strategies to handle wheat under VED. When making such decisions, an emphasis should be placed on the potential impact that individual decisions may have on other portions of the wheat quality system and supply chain. Hopefully, in this way, an appropriate balance can be found under VED between maintaining Canada's high reputation for wheat quality and keeping logistical costs down.

The primary economic incentive behind participant behaviors in this supply chain is the pursuit of cost minimization (or profit maximization). Participants' risk management behaviors are influenced by moral hazard because there are costs involved in their segregation efforts, making an individual participant's objective inconsistent with the greater objective of grain quality assurance. In the next chapter, a set of analytic models are developed in order to examine how and to what extent participant behaviors are governed by rules of cost minimization. Analytically, I examine how producers respond to a changeable environment, e.g. testing intensity and penalties for offences, and how elevator operators allocate testing among producers corresponding to commingling risks and potential losses associated with a VED system, i.e. a farmer's misrepresentation probability, as well as a contamination penalty served by the terminal operators. These analyses provide a framework which enables us to develop better methods of providing participants with correct incentives for contributing to the overall security of the wheat handling system.

CHAPTER 3

A WHEAT SUPPLY CHAIN OPERATING UNDER VED:

AN ANALYTICAPPROACH

3.1 Introduction

Pressures for adopting VED come from concerns about potential increases in commingling problems stemming from the introduction of visually indistinguishable wheat varieties. These varieties could be unregistered ones which have already brought problems to wheat handling during the KVD era, or else other varieties that have been introduced or may be introduced in the future. By removing the variety registration requirement for KVD, new classes of wheat with new varieties or new varieties designated as the existing classes of wheat could be introduced to enable additional sales in new markets without requiring that they actually look any different from existing wheat classes. For example, Canadian General Purpose wheat, a newly introduced class after KVD was removed, describes varieties that may not be readily distinguished from other varieties within other classes of wheat. Visual indistinguishability increases the likelihood of (intentional or unintentional) misrepresentation of a variety by farmers or other industry participants. Simply put, a wheat variety of low quality could potentially be misrepresented as a variety with higher quality if they are not somehow readily (visually) distinguishable from each other. Facing this challenge, it has become essential to develop efficient handling strategies for grain safety and quality assurance.

From an economic perspective, the supply chain participants' objective is profit maximization (or cost minimization). Generally, it is assumed that mitigating wheat risks facilitates the reduction of handling costs. But any risk mitigation will only be achieved through additional supply chain participant efforts, which generate costs. Thus there is a fundamental tradeoff between effort and the risks confronting participants. In light of this, there are important operational issues within the grain supply chain, including farmer's choice of risk control efforts, handlers' choices on strategies to mitigate contamination risks, as well as how these choices are

affected by other factors in the decision process. To clarify these issues, I start by focusing on participant cost functions and then solving the respective cost minimization problems.

Under cost minimization, participant decision making behavior in this situation may be affected by moral hazard. Participants' risk control efforts stemming from incentives may lead to deviations from the overall goal of maintaining grain handling system security. One way to maintain handling system security is to create an efficient risk sharing scheme that makes a participant's costs rely on the mitigation effort they choose to undertake. To explore ways of realizing better grain security thorough risk sharing schemes, we need to solve the problem of minimizing the cost functions of various parties in the supply chain.

In this chapter, what I refer to as a most likely wheat handling system under VED will be developed. This permits the development of a set of analytic models based on the objective (cost) functions of the farmer and a primary elevator. All the elements of the targeted system, including costs and risks at each node of the system, are included in these functions. The functions also allow for different combinations of testing points with or without functional mechanisms for traceability. More importantly, the solution of the farmer's objective function indicates how the farmer's risk control effort responds to economic incentives. In turn, the solutions of the primary elevator objective functions will identify the best testing strategies at each test point in the handling system, as well as provide insight on how other factors influence those testing strategies. Since supply chain participants' behavioral decision-making is affected by moral hazard problems which threaten the security of wheat handling, this chapter opens discussion on these problems along with potential ways to eliminate them.

3.2 The Objective Functions of Farmers and Primary Elevators

This study only focuses on the wheat export market of Canadian Western Red Spring wheat (CWRS). It is assumed that each farmer is endowed with an amount of land, labor and capital which yield a certain production capacity to produce wheat (CWRS, No.1). In turn, farmers are responsible for offering documentation and signing product variety declaration when delivering

their products to elevator. So it is a farmer's responsibility to ensure the class of the information provided on a signed declaration when delivering the products to the primary elevator is correct.

With the use of visually indistinguishable varieties in a VED system, farmers could inadvertently or intentionally misrepresent the varieties on delivery. If not detected, misrepresented wheat will enter the supply chain and contaminate other eligible wheat. In the same way, the primary elevator handlers would also misrepresent delivery if contaminated wheat gets delivered to the terminal elevator. To avoid economic losses, the primary elevator handlers plan to conduct tests at various stages in the supply chain to determine if wheat declared as eligible contains any undesirable varieties. It is also assumed that contaminated wheat exceeding the tolerance standard will be diverted to other wheat flows, e.g. feed, at the stage where it is found to be undesirable in the supply chain. If possible, a traceability mechanism will be enacted to track contamination sources upstream in the chain. This will be done by testing retained samples, and detected offenders will be penalized.

3.2.1 Farmer and Handler Misrepresentation Behaviors

In this analysis, when a non-CWRS delivery is declared as eligible CWRS, misrepresentation occurs. In the case of misrepresentation, it would be difficult to identify whether individuals misrepresent their deliveries intentionally or not. For simplicity, this study excludes intentional misrepresentation from farmers or elevator handlers' declaration behaviors, so that offenders can only unintentionally make the wrong variety declaration. Based on this, the study assumes inherent uncertainty for a farmer to deliver eligible wheat.

The existence of visually indistinguishable varieties other than CWRS could render farmers confused about the varieties they actually grow, and then these varieties could be mistakenly misrepresented at the primary elevator if farmers believe they are CWRS. In addition, it is assumed that each farmer potentially misrepresents the deliveries with certain likelihood and the level of this probability is determined by the amount of risk control effort, plus the level of farmer risk control technology. Formally, a farmer j's misrepresentation rate at year T is defined as a function of the risk control effort and the risk control technology as given below,

$$\alpha_j^T = e^{-\frac{c_{ej}^T}{k_j^T}} \qquad (3\text{-}1)$$

where T=1, 2, 3…N, and j=1~n. Note that a higher value of c indicates a higher level of effort and a lower value of k indicates a higher level of technology.

Risk control effort is effectively a measure of the resources a farmer puts into risk control for avoiding the problem of misrepresentation. This could be in the form of time, labour, capital or facility investment in on-farm practices for preventing commingling. Risk control effort has a negative relationship with the misrepresentation rate - the higher the risk control effort, the more accurately the farmer understands the variety of wheat grown, and the lower the probability that the farmer will misrepresent grain delivery. Risk control technology is a signal of the capacity a farmer has to control the risks of misrepresentation. Such technology might cover a broad range of factors, including the technique of accurately recording on-farm practices, knowledge about distinguishing among wheat varieties produced, collecting other information about risk control, ability to learn from experience, and so on. A farmer's technology level is negatively related with the probability that the farmer misunderstands the wheat variety actually grown.

If a farmer's misrepresented deliveries are not detected and are unloaded in primary elevator bins, wheat in those bins will be contaminated by an undesired wheat variety. Handling errors can also lead to contamination. Handlers will misrepresent their railcar deliveries if contaminated wheat is not detected when those railcars are loaded at the primary elevator.

3.2.2 Wheat Handling System Involved in This Study

When wheat is delivered to the primary elevator, several potential events may occur in sequence. These can include: (1) handlers take representative wheat samples from trucks, (2) samples may or may not be tested, (3) wheat is unloaded from trucks, (4) wheat is stored in large bins in the elevator, (5) bins are sampled, (6) bin samples may be tested before loading, (7) wheat is loaded on railcars for shipment to the terminal elevator, (8) rail cars are sampled, (9) rail cars may be tested after leaving the elevator but before loading at a terminal elevator. Under VED, if bin contamination or railcar contamination is detected, traceability mechanisms are activated to

identify the source of contamination. Note that wheat segregation issues that might arise beyond the terminal elevator are not captured in this study.

Figure 3.1 shows a stylized wheat handling system as assumed in this study. Here, there are three potential test points under the proposed system under VED. These are: (1) a truck test before unloading wheat into primary elevator bins; (2) a primary elevator bin test before loading wheat into railcars; (3) a railcar test before loading wheat into the terminal elevator bins. In addition, there are two points where a traceability mechanism appears to be necessary - (1) contaminations detected at test point 2; (2) contaminations detected at test point 3.
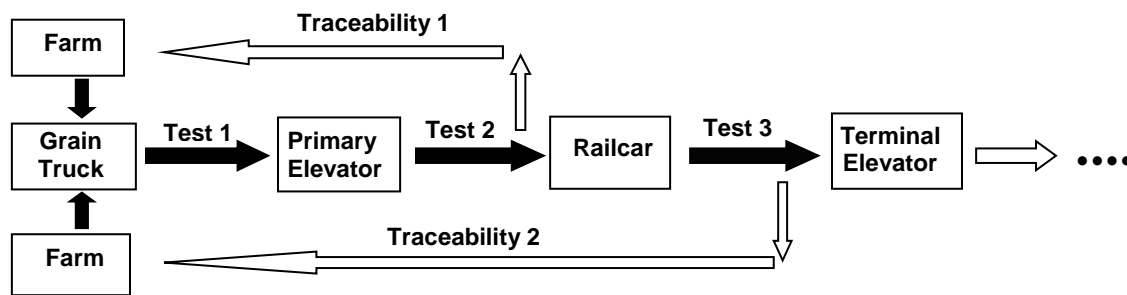
Figure 3.1 Testing and Tracing Points in a Stylized Wheat Handling System

If a misrepresented delivery is detected by the primary elevator, either through direct truck sample testing or contamination tracing, the delivered products will be downgraded, perhaps even to feed grade with a much lower price[7]. A formal penalty will be imposed on the offender if misrepresentation results in contamination losses to handlers. It is assumed that the penalty amount increases with the volume of misrepresented wheat and the contamination loss resulting from misrepresentation.

Critically, due to the high cost of sample testing, there is a tradeoff between test costs and contamination detection. To maximize expected profits, the primary elevator handlers may not test farmer deliveries or elevator bins with a fixed test rate. Ideally, an efficient test strategy should account for sampling and testing costs along with the potential benefits resulting from testing and traceability.

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[7] The tolerance level for other classes or varieties in CWRS for various grades is provided in Appendix H. The price difference by grade for the CWRS, 13.5% protein is provided in Appendix I.

At test point 1, the handlers sample wheat from farmer's deliveries, possibly testing deliveries to evaluate whether the variety and quality of tested wheat is consistent with the declaration. If a farmer inaccurately represents the delivery and it is tested by elevators, the misrepresentation is exposed and the misrepresented wheat will be downgraded. It is possible that primary elevators will impose a penalty on the offender, regardless of whether the misrepresentation of wheat actually resulted in any actual financial damage.

If the misrepresented delivery is not tested, misrepresentation will not be found, and then this misrepresented wheat will be unloaded in the primary bin and blended with other eligible wheat in the bin. This contaminates wheat in the whole bin, potentially lowering the assessed wheat quality of the bin. The primary elevator bin test (at test point 2) occurs at the time when the primary elevator is loading railcars to deliver wheat to the terminal elevator. The primary elevator handlers possibly test bins before loading railcars. If there is any contamination detected, the primary elevator is likely to trace it back to farmers to identify the contamination source through testing the retained samples. If any delivery misrepresentation is detected through sample testing, handlers will impose a penalty on the offender.

In a situation where contaminated bins are not detected and contaminated wheat is loaded in railcars and delivered to the terminal elevator, the primary elevator is misrepresenting some railcar deliveries. If there are misrepresented railcars detected by the terminal elevator's testing for railcars (at test point 3), the primary elevator will suffer price reductions plus any additional fines imposed by the terminal elevators. The primary elevator can either be the final underwriter of the total system loss or instead trace it back to farmers to find the offenders. In the latter case, any offender detected through traceability will be penalized.

In this study, we assume that a penalty system will be applied in the case of traceability. Any retrieved loss from tracing (penalty) will only partly cover the contamination loss. Recall that if all the contamination loss can be covered completely through tracing (for example, in a liability system), the handlers will have no incentive to perform tests on truck deliveries or primary elevator bins for mitigating contamination risks during handling.

3.2.3 Farmer and the Primary Elevator Objective Functions

As mentioned previously, to model farmer and handler incentives to mitigate wheat production and handling risks, the analysis needs to start by constructing the farmer's cost objective function and the primary elevator's cost objective function.

The objective cost functions are based on the following assumptions:

1. A farmer's wheat deliveries are consistent throughout a year, and they are either eligible CWRS or non-CWRS (CWRS is the most common type of wheat grown in Canada and will be used as the base variety here).
2. Test accuracy is 100%[8].
3. There are no contamination sources other than farmer's misrepresentation.
4. There is no intentional misrepresentation. Farmers make declarations based on their honest, sometimes incorrect, perception of the variety being delivered.
5. The waiting time for truck or railcar sample testing does not incur any costs on related parties.
6. For a system with a traceability mechanism, traceability will be enacted when there is any contamination detected at any test point.
7. A penalty system will be applied in the case of an offence and the penalty can be perfectly enforced without costs.
8. When computing costs, the model does not allow for a farmer or a handler's insurance obtained against loss or damage from misrepresentation.

9. Handlers have perfect information about a farmer's behavior pattern.

The analysis of the farmer and the primary elevator's objective functions and optimal solutions will be based on possible operation combinations. There are four cases examined:

Case 1: tests on railcars are included (test point 3).

Case 2: tests on trucks and test on railcars are included (test points 1 and 3).

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[8] A current testing technique called polyacryamide gel electrophoresis (PAGE) can "fingerprint" grain varieties while allowing for a range of accuracy levels up to 98% (CBH, 2012). The test costs vary WITH test accuracies. To improve testing efficiency, A handler may choose tests with different accuracies at different stages of the supply chain. For example, handlers may increase the accuracy (and the cost) of sample testing as getting closer to the end-use customer (Furtan, 2003). Due to the effects of testing accuracy on testing strategies, this assumption needs to be relaxed in future research on this topic.

Case 3: tests on bins and tests on railcars are included (test points 2 and 3).

Case 4: tests on trucks, tests on bins and tests on railcars are included (test points 1, 2 and 3).

In addition, two different situations are considered in each case,

(a) There is no traceability.
(b) There is traceability.

If there is traceability involved, sampling will occur at each test point and representative samples will be retained for tracing. If there is no traceability involved (case (b)), sampling will be only for testing purposes, and no sample is retained for traceability while sample retention costs are saved.

3.2.3.1 Case 1: One Test Point - Test Point 3

We start with the simplest case where only a terminal test is considered. The only test point is located at the terminal elevator where the railcars will be tested before loading wheat into terminal bins. There is no testing through the previous stages of the supply chain.

Objective functions and their solutions for case 1 are developed as follows:

(a) In case 1, even if contamination is detected at the terminal elevator, no traceability is activated. In turn, it is assumed that the farmer's risk control effort is convertible to a monetary equivalent and that effort is a function of farmer's misrepresentation rate. The farmer's objective function becomes[9]:

$$J_1 = c_e q_1 \tag{3-2}$$

That is, a farmer's choice about the level of risk control effort has nothing to do with the primary elevator and the terminal elevator's handling strategies. The farmer is completely isolated from detection risk and thus has no incentive to put any effort on preventing misrepresentation risks. As a result, the wheat handling system would likely be exposed to the highest commingling risks from farmer misrepresentations.

The primary elevator's expected handling cost is:

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[9] Refer to the table of notation for symbol description.

$$J_2 = f_{p3} \sum \alpha_i m_i (n_i \beta_t) q_i \qquad (3\text{-}3)$$

In this case, the primary elevator handlers do not sample and test deliveries of farmers. They save money on sampling, testing and sample retention. Since there is no testing at either test point 1 or test point 2, all farmer misrepresented deliveries will enter the supply chain and contaminate other eligible wheat in the system, and all contaminated wheat will be delivered to the terminal elevator. The primary elevator losses become apparent in the railcars of misrepresented wheat that are detected at the terminal elevator. In this context, there are no control variables for the primary elevator, and the primary elevator has to absorb all the losses resulting from wheat contamination.

(b) Under the condition that a traceability mechanism is available, if there is any detected contamination, the primary elevator will trace back upstream in the supply chain to identify offenders and penalize them. In this case, the farmer's expected cost is,

$$J_1 = f_3 \alpha (n \beta_t) q_1 + c_e q_1 \qquad (3\text{-}4)$$

Minimizing the farmer's objective function, the first order condition with respect to the farmer's misrepresentation probability α is:

$$\frac{\partial J_1}{\partial \alpha} = [f_3 (n \beta_t) - \frac{k}{\alpha}] q_1 = 0 \qquad (3\text{-}5)$$

Then,

$$\alpha = \frac{k}{f_3 (n \beta_t)} \qquad (3\text{-}6)$$

Compared with case (a), the terminal elevator's test rate on railcars and the related penalty will now affect the farmer's risk control effort choice. A farmer's effort choice is determined by f_3, the penalty for an offender detected by tracing railcar contamination, and β_t, the terminal elevator's test rate on railcars. The railcar test rate determines the probability of detecting misrepresented railcars and thus determines the probability of identifying traceability offences.

The primary elevator's objective function is:

$$J_2 = f_{p3} \sum \alpha_i m_i (n_i \beta_t) q_i + c_1 \sum \alpha_i m_i (n_i \beta_t) q_i$$
$$- \sum f_{3i} \alpha_i (n_i \beta_t) q_i + C_{sr1}$$

(3-7)

When compared with the cost function without traceability, this function contains sample retention costs, traceability costs as well as retrieved loss (penalty) from tracing.

Since there is no testing at test point 1, the primary elevator bins will unavoidably be contaminated if there are misrepresented truck deliveries. The absence of testing at point 2 leaves any contaminated wheat undetected until it is moved to the terminal elevator. Contamination losses can be partially covered by penalties collected from offenders through traceability. Traceability can be enacted by detected misrepresented railcars at the terminal elevator. Through referring to related documentation and retention samples, handlers can ultimately target offenders. Obviously, farmer misrepresentation incentives can be reduced if traceability deterrence can be enhanced through either increasing the tracing probability or imposing a higher penalty on offenders.

3.2.3.2 Case 2: Two Test Points - Test Points 1 and 3

In this case, a combination of two test points is considered. These are a test before the primary elevator and a test at the terminal elevator. There is no bin testing in this case.

The objective functions and their solutions for case 2 are as follows:

(a) If there is no traceability associated with the second test, the farmer's cost function is:

$$J_1 = f_1 \alpha \beta q_1 + c_e q_1$$

(3-8)

The first order condition taken with respect to α is:

$$\frac{\partial J_1}{\partial \alpha} = [f_1 \beta - \frac{k}{\alpha}] q_1 = 0$$

(3-9)

Then,

$$\alpha(\beta) = \frac{\kappa}{f_1\beta} \tag{3-10}$$

Equation 3-10 shows that farmer misrepresentation rate has a negative relationship with the primary elevator's test rate and the penalty level for misrepresentation. Using equation 3-10, Figure 3.2 illustrates how α (on the Z-axis), the misrepresentation rate for farmer with risk control effort c, responds to the change in value of the test rate β (X-axis) and the penalty f_1 (Y-axis). Note as well that the value of β is located in the interval (0,1] and the value of f_1 is located in (0,10]. In the situation when $k=0.5$, that resulted in $\alpha \in [0.05,1]$.

In the situation where the test rate β or penalty level f_1 are close to zero, α is then equal to 1 or very close to 1, meaning that the farmer has few or no incentives to prevent misrepresentation. When the elevator operates with a higher test rate or penalty level, farmers would prefer to put in more effort to mitigate contamination risks, thus lowering their misrepresentation probability. From this point of view, a high penalty level combined with a low test rate can have the same effect on lowering farmer misrepresentation rate as a high test rate combined with a low penalty level.
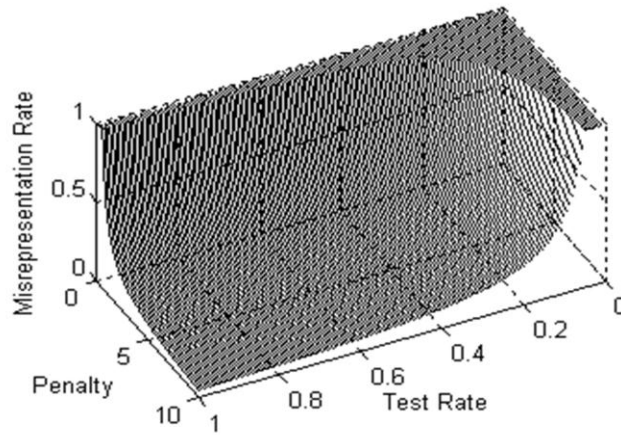

Figure 3.2 Farmer's Misrepresentation Response to Test Rate and Penalty Level

By way of comparison, the primary elevator's cost objective function is:

$$J_2 = c_1 \sum \beta_i q_i + f_{p3} \sum \alpha_i (1-\beta_i) m_i (n_i \beta_t) q_i - \sum f_{1i} \alpha_i \beta_i q_i + C_{s2} \tag{3-11}$$

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With a first order condition with respect to β,

$$\frac{\partial J_2}{\partial \beta_i} = [c_1 + f_{p3}\alpha_i' m_i(n_i\beta_t)]q_1 = 0 \tag{3-12}$$

Under a perfect information assumption (see assumption 9 above), handlers know the farmer's cost function and also know the farmer's response pattern to testing. In this instance,

$$\alpha'(\beta) = -\frac{\kappa}{f_1\beta^2} \tag{3-13}$$

And after appropriate replacement,

$$\beta_i^* = \sqrt{\frac{k(n_i\beta_t)mf_{p3}}{c_1 f_{1i}}} \tag{3-14}$$

When there is no traceability, the primary elevator's test rate is positively related to β_t, the terminal elevator's test rate for railcars, f_{p3}, the penalty level for detected misrepresented railcars, and m, the contamination multiplier. When the values of these three parameters increase, the potential loss from misrepresented trucks also grows. Then the best choice for the primary elevator handlers is to increase the test rate to prevent misrepresented trucks from entering the supply chain. Recall that the test rate is negatively related to c_1, the truck sample test cost, so that a high test cost can weaken handlers' economic incentive to test.

The primary elevator expected handling costs decreases with the level of f_1 if there is misrepresentation. To start, the penalty level is a deterrent to farmer's misrepresentation behavior, and when the penalty level for detected misrepresentation increases, a farmer would prefer to strengthen their effort to avoid possible misrepresentation. A lower misrepresentation rate leads to less intensive testing, saving testing costs (the first item in equation 3-11). Second, a lower misrepresentation rate lowers the primary elevator's probability to misrepresent the delivery at the primary elevator and thus reduces potential misrepresentation loss (the second item in equation 3-11). Third, as mentioned earlier, a farmer always keeps constant the expected misrepresentation losses from truck testing (the third item in equation 3-11). Obviously, the

primary elevator handlers always prefer a higher penalty level for offences. If this penalty is extremely high such that handlers can unconditionally cover their contamination losses, the primary elevator's test rate will approach zero, meaning that handlers will have no incentive to prevent misrepresented wheat from entering the handling system. In light of this set of conclusions, a penalty system should be preferred to a liability system for supporting grain safety and quality assurance in the supply chain.

(b)When traceability is possible, the farmer's cost objective function is:

$$J_1 = f_1\alpha\beta q_1 + f_3\alpha(1-\beta)(n\beta_t)q_1 + c_e q_1 \tag{3-15}$$

And the first order condition with respect to α is:

$$\frac{\partial J_1}{\partial \alpha} = [f_1\beta + f_3(1-\beta)(n\beta_t) - \frac{k}{\alpha}]q_1 = 0 \tag{3-16}$$

Then,

$$\alpha(\beta) = \frac{\kappa}{[f_1 - f_3(n\beta_t)]\beta + f_3(n\beta_t)} \tag{3-17}$$

Specially, if β=1,

$$\alpha(\beta) = \frac{\kappa}{f_1} \tag{3-18}$$

In this situation, we can see that the only factor influencing the farmer's misrepresentation rate is the penalty imposed if detected. If the penalty remains constant, the misrepresentation rate will stay constant.

If $\beta\neq1$, a farmer's misrepresentation rate is negatively related to the primary elevator's test rate and penalty level for farmers. In fact, the differential of misrepresentation rate with respect to test rate is:

$$\alpha'(\beta) = -\frac{\kappa[f_1 - f_3(n\beta_t)]}{\{[f_1 - f_3(n\beta_t)]\beta + f_3(n\beta_t)\}^2} \tag{3-19}$$

Thus the relationship between the farmer misrepresentation rate and the primary elevator test rate is determined by two factors, f_1 and f_3 $(n\beta_t)$. If a farmer misrepresented a delivery and was detected at the truck test before unloading, he or she will suffer a loss f_1. If the farmer's misrepresentation was not detected at the truck test, his or her probability of being detected via tracing from detected railcar contamination is $n\beta_t$ meaning that the expected loss from misrepresentation is f_3 $(n\beta_t)$. A high value of f_1 or a low value of f_3 or β_t can make $f_1 > f_3(n\beta_t)$; conversely, a low value of f_1 or a high value of f_3 or β_t can make $f_1 < f_3$ $(n\beta_t)$. Thus under different conditions, a farmer's best response to the truck testing rate can differ.

The figure 3.3 illustrates the relationship between marginal misrepresentation rate and test rate. For ease of exposition, this particular figure is generated under the condition $k=0.5$, $f_1=4$, $f_3=6$, and $n\beta_t = 0.4$, making $f_1 > f_3(n\beta_t)$ and $n\beta_t = 1$ so that $f_1 < f_3$ $(n\beta_t)$ respectively. If $f_1 > f_3(n\beta_t)$, for example, under the condition that the terminal test rate is very low, the value of $\alpha'(\beta)$ in equation 3-18 will be negative, shown as the red line in figure 3.3. Under this condition, the farmer's misrepresentation rate will fall with the primary elevator's test rate. Thus, when a farmer's penalty of being detected at the truck test point is greater than expected loss of being detected by the tracing, truck testing deterrence is greater than the tracing deterrence. In this case if a farmer can choose, he or she will prefer being detected through tracing to being detected at the truck test. However, if $f_1 < f_3$ $(n\beta_t)$, the conclusions flip in the opposite direction, shown in the blue line in the figure. If both terms are equal in value, the primary elevator's test rate will have no influence on the farmer's misrepresentation rate. In other words, for a farmer who misrepresented their deliveries, if the loss from detection at the truck test is the same as the expected loss resulting from tracing, they will not care whether they are detected at the truck test point or not.
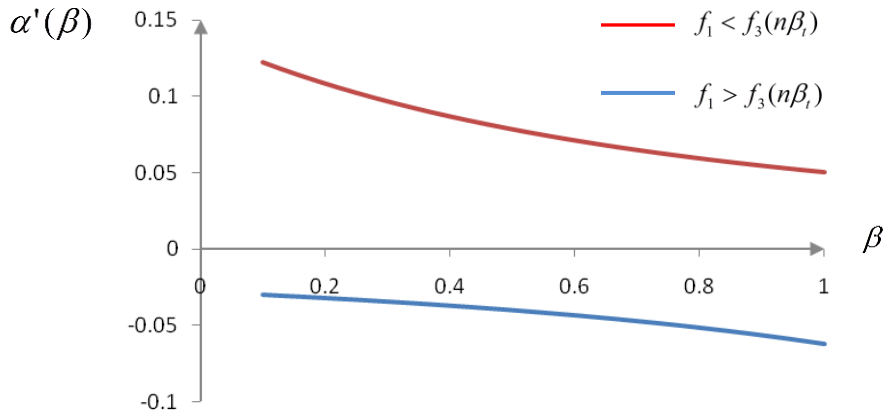
Figure 3.3 Relation between Farmer's Marginal Misrepresentation Rate and Test Rate

To clarify the discussion above, Figure 3.4 shows how the farmer's misrepresentation rate responds to the change in primary elevator test rate and the change in penalty provided by the primary elevator to farmer (equation 3-17). For ease of exposition, Figure 3.4 was created under the conditions that $k=0.5$, $f_3=6$, $n\beta_t=0.4$, $\beta\in(0.04,1)$ and $f_1\in(1.1,10.7)$.
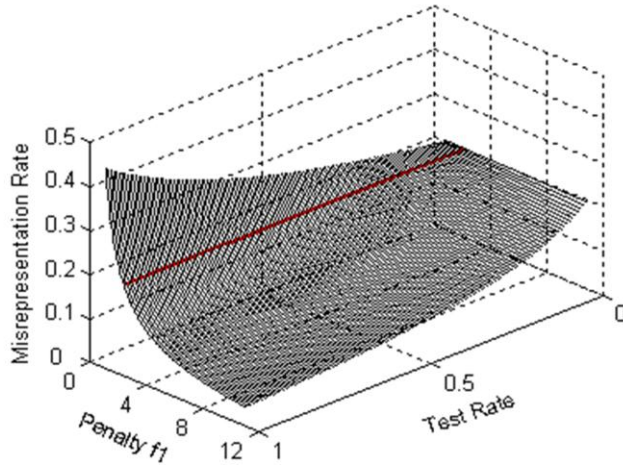

Figure 3.4 Relationship between Farmer's Misrepresentation Rate,
Test Rate and Penalty Level

For example, when the penalty level f_1 equals 2.4 (the red line on figure 3.4), $f_1=f_3(n\beta_t)$, making $\alpha'(\beta)=0$. When the penalty is fixed at 2.4 units, the primary elevator's test rate will have no influence on farmer's risk control effort. That is, under such a condition, a farmer will not care

whether he or she is detected at the truck test or at the tracing activated by detected contamination. When $f_1 > 2.4$, which in turn makes $f_1 > f_3(n\beta_t)$, a farmer's misrepresentation rate will decrease with the test rate; when $f_1 < 2.4$, which makes $f_1 < f_3(n\beta_t)$, a farmer's misrepresentation rate will increase with test rate. Clearly, a high penalty level reduces the farmer's incentives to misrepresent the deliveries. Figure 3.4 also shows that the marginal penalty effect is more significant when the primary elevator's testing level is higher.

When traceability is involved, the primary elevator's cost objective function becomes:

$$J_2 = c_1 \sum \beta_i q_i + f_{p3} \sum \alpha_i (1 - \beta_i) m_i (n_i \beta_t) q_i + c_1 \sum (n_i \beta_t)(1 - \beta_i) \alpha_i m_i q_i$$
$$- \sum f_{1i} \alpha_i \beta_i q_i - \sum f_{3i} \alpha_i (1 - \beta_i)(n_i \beta_t) q_i + C_{sr2}$$
(3-20)

The first order condition with respect to β is:

$$\frac{\partial J_2}{\partial \beta_i} / q_1 = c_1 + f_{p3} \alpha_i' (1 - \beta_i) m_i (n_i \beta_t) - f_{p3} \alpha_i m_i (n_i \beta_t) - c_1 (n_i \beta_t) \alpha_i m_i$$
$$+ c_1 (n_i \beta_t)(1 - \beta_i) \alpha_i' m_i - f_{1i} \alpha_i' \beta_i - f_{1i} \alpha_i - f_{3i} \alpha_i' (1 - \beta_i)(n_i \beta_t) + f_{3i} \alpha_i (n_i \beta_t) = 0$$
(3-21)

Then,

$$\beta_i = 1 - \frac{\alpha_i}{\alpha_i'} + \frac{c_1 - f_{1i} \alpha_i'}{[m f_{p3}(n_i \beta_t) + c_1(n_i \beta_t) m_i + f_{1i} - f_{3i}(n_i \beta_t)] \alpha_i'}$$
(3-22)

And as we can see,

$$\frac{\alpha_i}{\alpha_i'} = 1 - \beta_i - \frac{f_{1i}}{f_{1i} - f_{3i} n \beta_t}$$
(3-23)

So after replacement,

$$\beta_i^* = \frac{\sqrt{\frac{f_{1i} k(n_i \beta_t) m(f_{p3} + c_1)}{c_1}} - f_{3i}(n_i \beta_t)}{f_{1i} - f_{3i}(n_i \beta_t)}$$
(3-24)

Thus the primary elevator's optimal test rate is negatively related to the truck sample test cost c_1, and is positively related with f_{p3}, the penalty imposed on railcars detected by the terminal elevator and m, the contamination multiplier. To illustrate, the relationship between the test rate β and f_1, the penalty imposed on detected trucks at test point 1, or f_3, the penalty on the farmer who misrepresented and was subsequently detected at the second tracing, is shown in Figure 3.5. For ease of exposition, the figure is generated under the conditions that $k=0.5$, $m=6$, $c_1=0.4$, $f_{p3}=5$, $n\beta_t=0.3$, $f_1 \in (3.4, 6.6)$ and $f_3 \in (5.6, 8.2)$. The resulting test rate $\beta \in [0.37, 0.72]$, shows that under above given conditions, the optimized way of testing is to test truck deliveries proportionally, with testing intensity influenced by the levels of the penalties f_1 and f_3.
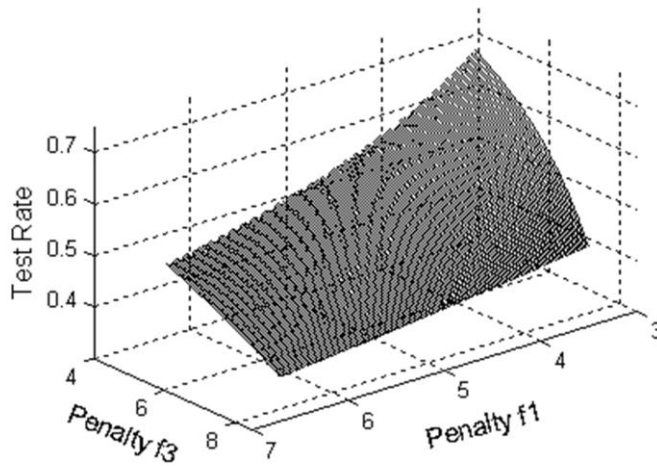

Figure 3.5 Response of Test Rate to Changes in Penalty Levels

The change in f_1, the penalty level for a detected truck, has two effects on β. On one hand, when f_1 increases, β should increase for more penalty collections from farmers. On the other hand, the increase in β allows for the penalty to affect farmer misrepresentation behavior. An increase in f_1 leads to a lower farmer misrepresentation rate, and accordingly, the test rate for the farmer should be reduced. Under the given range for penalties in this case, the latter effect dominates the former, meaning that the primary elevator's test rate decreases with f_1.

In the same way, the change in f_3 also has two effects on the primary elevator's test rate. First, when f_3 increases, the deterrence to the farmer will increase and less testing on truck deliveries will be necessary. Second, the increase in f_3 increases the possible penalty collection from tracing

and so decreases the primary elevator's incentive to test truck deliveries. These two effects work in the same direction, making the primary elevator's test rate decrease with f_3. When f_3 can be set extremely high so that any contamination losses are completely covered by imposed penalties on offenders, handlers again will lose their incentive to test any farmer deliveries. Under this extreme situation, it is clear that quality cannot be assured. From this perspective, an appropriate penalty level for any detected offence is essential to maintain handlers' incentives for contributing to grain handling quality.

3.2.3.3 Case 3: Two Test Points - Test Points 2 and 3

In this case, another combination of two testing points consisting of the primary elevator bin test and a railcar test at the terminal are considered.

Writing out the objective functions and their solutions for case 3:

(a) If there is no traceability, the farmer's objective function becomes:

$$J_1 = c_e q_1 \tag{3-25}$$

which is the same as case 1 (a), meaning that if there is no traceability involved, a farmer will not suffer any loss from the misrepresentation. Intuitively, the farmer will take the lowest risk control effort which can result in a high misrepresentation probability.

The primary elevator's objective function in this case is:

$$J_2 = c_2 \beta_b \sum q_i + f_{p2} \beta_b \sum \alpha_i m_i q_i + f_{p3} \sum \alpha_i m_i (1 - \beta_b)(n_i \beta_t) q_i + C_{s3} \tag{3-26}$$

The first order condition with respect to the elevator bin test rate β_b is:

$$\frac{\partial J_2}{\partial \beta_b} = c_2 \sum q_i + f_{p2} \sum \alpha_i m_i q_i - f_{p3} \sum \alpha_i m_i (n_i \beta_t) q_i \tag{3-27}$$

So if $\frac{\partial J_2}{\partial \beta_b} < 0$, i.e. $(c_2 \sum q_i + f_{p2} \sum \alpha_i m_i q_i) < f_{p3} \sum \alpha_i m_i (n_i \beta_t) q$, $\beta_b^* = 1$. If $\frac{\partial J_2}{\partial \beta_b} > 0$,

i.e. $(c_2 \sum q_i + f_{p2} \sum \alpha_i m_i q_i) > f_{p3} \sum \alpha_i m_i (n_i \beta_t) q_i$, $\beta_b^* = 0$. However, if $\frac{\partial J_2}{\partial \beta_b} = 0$, there is no

difference between taking the bin test and not taking the bin test.

(b) The primary elevator can trace back to find offenders if contamination is detected. The farmer's objective function becomes:

$$J_1 = f_2 \alpha \beta_b q_1 + f_3 \alpha (1 - \beta_b)(n\beta_t)q_1 + c_e q_1 \qquad (3\text{-}28)$$

In order to minimize J_1, the first order condition with respect to α is:

$$\frac{\partial J_1}{\partial \alpha} = [f_2 \beta_b + f_3(1 - \beta_b)(n\beta_t) - \frac{k}{\alpha}]q_1 = 0 \qquad (3\text{-}29)$$

then,

$$\alpha = \frac{\kappa}{f_2 \beta_b + f_3(1 - \beta_b)(n\beta_t)} \qquad (3\text{-}30)$$

meaning that when $\beta_b \neq 1$, the farmer's misrepresentation rate is negatively related to the penalty level and the terminal elevator's test rate on the farmer.

If $\beta_b = 1$,

$$\alpha = \frac{\kappa}{f_2} \qquad (3\text{-}31)$$

When the primary elevator handlers undertake a complete test on bins before loading railcars, all contaminated bins will be found and thus all misrepresented farmers will be detected and traced and there will be no misrepresented railcars at the terminal. In this situation, the terminal elevator's testing on railcars will have no relation to farmer benefits. So farmers will only care about the penalty level for offenders detected through bin contamination tracing. If the penalty stays constant, the farmer's misrepresentation rate will stay constant.

The differential of misrepresentation rate with respect to bin test rate is:

$$\alpha'(\beta_b) = -\frac{\kappa[f_2 - f_3(n\beta_t)]}{[f_2 \beta_b + f_3(1 - \beta_b)(n\beta_t)]^2} \qquad (3\text{-}32)$$

so that the relationship between the farmer's misrepresentation rate and the primary elevator bin's test rate is determined by both the value of f_2, the penalty from misrepresentation detected at tracing resulting from detected contamination at the primary elevator bins, and the value of

$f_3(n\beta_t)$, the farmer's expected loss from misrepresentation detected at tracing resulting from detected railcars at the terminal elevator if misrepresentation went undetected at the bin test.

Figure 3.6 shows the relationship between the marginal misrepresentation rate and primary bin test rate. For ease of exposition, this figure is generated under the conditions $k=0.5$, $f_2=5$ $f_3=6$, and $n\beta_t=0.4$, making $f_2>f_3(n\beta_t)$ and $n\beta_t=1$, making $f_2<f_3(n\beta_t)$ respectively. Note that if $f_2>f_3(n\beta_t)$, the value of $\alpha'(\beta_b)$ in equation 3-30 will be negative. Under this condition, the farmer's misrepresentation rate falls with the primary elevator bin's test rate, shown by the red line in figure 3.6. However, if $f_2<f_3(n\beta_t)$, this will switch as indicated by the blue line in Figure 3.6. If both terms are equal in value, the primary elevator's test rate will have no influence on the farmer's misrepresentation rate. In this latter case, when other variables remain unchanged, the farmer's misrepresentation rate will stay constant even if the bin test rate increases or decreases.
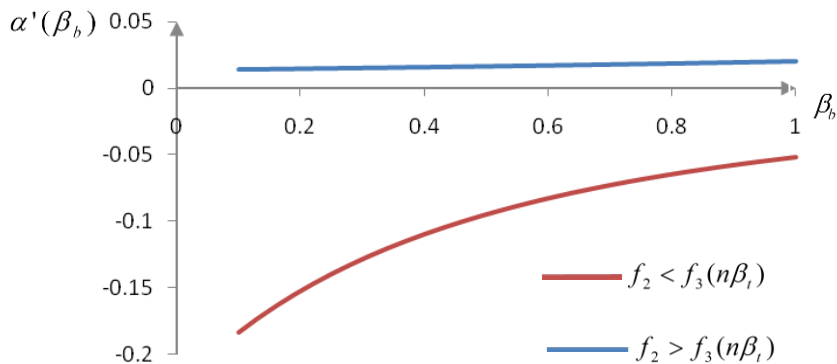
Figure 3.6 Relationship between Farmer's Marginal Misrepresentation Rate and Primary Elevator's Bin Test Rate

Figure 3.7 shows how the farmer's marginal misrepresentation rate corresponds to the change in primary elevator bin test rate and the change in penalty charged by the primary elevator on the farmer when traceability was enacted (equation 3-30). For ease of exposition, Figure 3.7 was created using the conditions $k=0.5$, $f_3=6$, $n\beta_t=0.4$, $\beta_b \in (0.04,1)$ and $f_2 \in (0.1,9.7)$. We can see that when the penalty level f_2 equals 2.4 (the red line on figure 3.7), $f_2=f_3(n\beta_t)$, making $\alpha'(\beta)=0$.
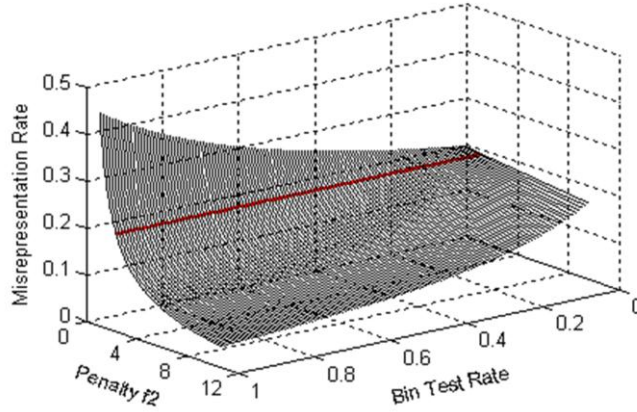
Figure 3.7 Relationship between Farmer's Misrepresentation
Rate, Bin Test Rate and Penalty Level

When the penalty is fixed at 2.4 dollars/bushel, the primary elevator's test rate will have no influence on farmer's risk control effort. Under such a condition, a farmer will not care whether he or she is detected at the truck test or at the tracing activated by the detected contamination. When $f_2 > 2.4$, which in turn makes $f_2 > f_3(n\beta_t)$, the farmer's misrepresentation rate will decrease with the bin test rate; and when $f_2 < 2.4$, which in turn makes $f_2 < f_3(n\beta_t)$, the farmer's misrepresentation rate will increase with the bin test rate.

The primary elevator's objective function in this situation is:

$$
\begin{aligned}
J_2 &= c_2 \beta_b \sum q_i + f_{p2} \beta_b \sum \alpha_i m_i q_i \\
&+ f_{p3} \sum \alpha_i m_i (1 - \beta_b)(n_i \beta_t) q_i + c_1 \beta_b \sum \alpha_i m_i q_i \\
&+ c_1 \sum (n_i \beta_t)(1 - \beta_b) \alpha_i m_i q_i - \sum f_{2i} \alpha_i \beta_b q_i \\
&- \sum f_{3i} \alpha_i (1 - \beta_b)(n_i \beta_t) q_i + C_{sr3}
\end{aligned}
\tag{3-33}
$$

To minimize J_2, we derive the first order condition with respect to β_b:

$$
\begin{aligned}
\frac{\partial J_2}{\partial \beta_b} / q_i &= c_2 + f_{p2}(\alpha_i m_i + \beta_b \alpha_i' m_i) + f_{p3}[\alpha_i' m_i (1 - \beta_b)(n_i \beta_t) \\
&- \alpha_i m_i (n_i \beta_t)] + c_1[(n_i \beta_t)(1 - \beta_b)\alpha_i' m_i - (n_i \beta_t)\alpha_i m_i] \\
&- f_{2i}[\alpha_i' \beta_b + \alpha_i] - f_{3i}[\alpha_i'(1 - \beta_b)(n_i \beta_t) - \alpha_i (n_i \beta_t)] = 0
\end{aligned}
\tag{3-34}
$$

So that,

$$\beta_b = 1 - \frac{\alpha_i}{\alpha_i'} + \frac{c_2 + (m_i f_{p2} - f_{2i})\alpha_i'}{[(n_i b_t)(m_i f_{p3} - f_{3i} + c_1 m_i) - (m_i f_{p2} - f_{2i})]\alpha_i'} \tag{3-35}$$

From the above we see that:

$$\frac{\alpha_i}{\alpha_i'} = 1 - \beta_b - \frac{f_{2i}}{f_{2i} - f_{3i} n \beta_t} \tag{3-36}$$

And after replacement,

$$\beta_b^* = \frac{\sqrt{\dfrac{k f_{2i}(n_i \beta_t)(m f_{p3} - f_{3i} + c_1 m) - k f_{3i}(n_i \beta_t)(m f_{p2} - f_{2i})}{c_2} - f_{3i}(n_i \beta_t)}}{f_{2i} - f_{3i}(n_i \beta_t)} \tag{3-37}$$

Figure 3.8 below shows the change in β corresponding to changes in f_2, the penalty for offenders detected at bin contamination tracing, and f_3, the penalty for offenders detected at the railcar contamination tracing. For ease of exposition, the figure is generated under conditions $k=0.1$, $m=6$, $f_3=5$, $c_1=0.3$, $c_2=0.1$, $n\beta_t = 0.3$, $f_2 \in (4.0, 8.8)$ and $f_3 \in (5.1, 9.9)$. The resulting test rate is $\beta \in (0, 0.47)$.

Under the specified ranges for penalties in this case, the primary elevator's testing incentive increases with f_2 if f_3 is at a high level (accompanied by a low level of test rate in Figure 3.8). If f_3 is at a low level (accompanied by a high level of test rate), the testing incentive increases with f_2 when f_2 is at a low level and then decreases with f_2 when f_2 is high. The reason for this is the same as that for case 2 (b) – the increase in penalty has two effects on testing incentives: while penalty collection generates more incentives to test, the increase in the penalty has a negative impact on the farmer's misrepresentation rate, reducing incentives for testing. If the former effect dominates the latter one, an increase in testing intensity is a better choice for handlers, and vice versa.
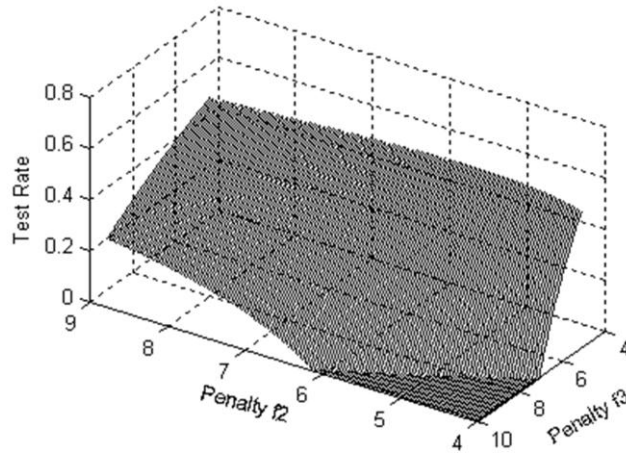
Figure 3.8 Relationship between Test Rate and Traceability Penalty

In this case, the test rate always decreases with the penalty f_3 under the given range of the penalty. Just as Figure 3.8 shows, when this penalty reaches a high enough level so that it can cover the losses resulting from detected railcar contamination, primary elevator handlers will have no incentives to perform any bin testing for the purpose of preventing mix-ups.

3.2.3.4 Case 4: Three Test Points - Test Points 1, 2 and 3

In this case, three test points are considered. These consist of tests before and after the primary elevator, and tests at the terminal.

The objective functions for case 4 are the following:

(a) If there is no traceability at the bin test and terminal test points, the farmer's objective function is the same as that in case 2 (a):

$$J_1 = f_1 \alpha \beta q_1 + c_e q_1 \qquad (3\text{-}38)$$

The first order condition with respect to α is:

$$\frac{\partial J_1}{\partial \alpha} = [f_1 \beta - \frac{k}{\alpha}] q_1 = 0 \qquad (3\text{-}39)$$

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Then,

$$\alpha(\beta) = \frac{\kappa}{f_1 \beta} \tag{3-40}$$

In turn, the primary elevator's objective function is:

$$J_2 = c_1 \sum \beta_i q_i + c_2 \beta_b \sum (1 - \alpha_i \beta_i) q_i + f_{p2} \beta_b \sum (1 - \beta_i) \alpha_i m_i q_i$$
$$+ f_{p3} \sum \alpha_i (1 - \beta_i) m_i (1 - \beta_b)(n_i \beta_t) q_i - \sum f_{1i} \alpha_i \beta_i q_i + C_{s4} \tag{3-41}$$

The first order condition with respect to β is:

$$\frac{\partial J_2}{\partial \beta_i} / q_i = c_1 + f_{p2} \beta_b \alpha_i^{'} m_i + f_{p3} \alpha_i^{'} m_i (1 - \beta_b)(n_i \beta_t) = 0 \tag{3-42}$$

So,

$$\beta_i^* = \sqrt{\frac{k(1 - \beta_b)(n_i b_t) m f_{p3} + \beta_b m f_{p2}}{c_1 f_{1i}}} \tag{3-43}$$

which is same as in case 3 (a), where the β_b equals either 1 or 0. And when $\beta_b = 1$,

$$\beta_i^* = \sqrt{\frac{m f_{p2}}{c_1 f_{1i}}} \tag{3-44}$$

And when $\beta_b = 0$,

$$\beta_i^* = \sqrt{\frac{k(n_i b_t) m f_{p3}}{c_1 f_{1i}}} \tag{3-45}$$

(b) If there is traceability in the system, the farmer's objective function becomes:

$$J_1 = f_1 \alpha \beta q_1 + f_2 \alpha (1 - \beta) \beta_b q_1 + f_3 \alpha (1 - \beta)(1 - \beta_b)(n \beta_t) q_1 + c \, q_1 \tag{3-46}$$

The first order condition with respect to α is:

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$$\frac{\partial J_1}{\partial \alpha} = [f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t) - \frac{k}{\alpha}]q_1 = 0 \qquad (3\text{-}47)$$

So that,

$$\alpha = \frac{\kappa}{f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)} \qquad (3\text{-}48)$$

Clearly, the farmer misrepresentation rate has a negative relationship with the penalty level for offenders and the terminal elevator test rate for railcars. With respect to other variables, this relationship can be shown as follows:

$$\frac{\partial \alpha}{\partial \beta} = -\frac{\kappa[f_1 - f_2\beta_b - f_3(1-\beta_b)(n\beta_t)]}{[f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)]^2} \qquad (3\text{-}49)$$

If the fine associated with detected misrepresentation from the truck test is less than the sum total of the expected loss from the primary elevator bin contamination tracing and the railcar contamination tracing if the misrepresentation was left undetected at the truck test, i.e. $f_1 < f_2\beta_b + f_3(1-\beta_b)(n\beta_t)$, the farmer's misrepresentation rate will grow with the primary elevator's test rate, and vice versa.

The partial derivative of α with respect to β_b is:

$$\frac{\partial \alpha}{\partial \beta_b} = -\frac{\kappa[f_2(1-\beta) - f_3(1-\beta)(n\beta_t)]}{[f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)]^2} \qquad (3\text{-}50)$$

Again, under different situations, the farmer's misrepresentation rate can have varying relationships with the test rate for the primary elevator bin. If the farmer's expected tracing penalty stemming from the bin test is greater than that from the railcar contamination tracing, i.e. $f_2(1-\beta) > f_3(1-\beta)(n\beta_t)$, the farmer's misrepresentation rate will be negatively related to the primary elevator bin's test rate, and vice versa.

The first order condition with respect to c,

$$\frac{\partial J1}{\partial c}/q_1 = \alpha'[f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)] - \frac{k}{\alpha} = 0 \tag{3-51}$$

From $\alpha = e^{-\frac{c_e}{k}}$, it is the case that $c_e = \kappa \ln\frac{1}{\alpha}$. After replacement,

$$c_e^* = \kappa \ln\frac{f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)}{\kappa} \tag{3-52}$$

Thus the farmer's desired risk control efforts now have a positive relationship with the penalty level. A severe penalty level makes farmers exert more effort to keep a lower misrepresentation rate. The effort is also positively related to the terminal elevator's test rate because traceability puts a deterrent on farmers. The relationships between the farmer's efforts, and the truck test rate β or the primary bin test β_b rate are determined by values of the other parameters in this case.

The primary elevator's objective function is (also refer to Appendix B for a detailed description of this function):

$$\begin{aligned}
J_2 &= c_1\sum\beta_i q_i + c_2\beta_b\sum(1-\alpha_i\beta_i)q_i + f_{p2}\beta_b\sum(1-\beta_i)\alpha_i m_i q_i \\
&+ f_{p3}\sum\alpha_i(1-\beta_i)m_i(1-\beta_b)(n_i\beta_t)q_i + c_1\beta_b\sum(1-\beta_i)\alpha_i m_i q_i \\
&+ c_1\sum(n_i\beta_t)(1-\beta_b)(1-\beta_i)\alpha_i m_i q_i - \sum f_{1i}\alpha_i\beta_i q_i - \sum f_{2i}\alpha_i(1-\beta_i)\beta_b q_i \\
&- \sum f_{3i}\alpha_i(1-\beta_i)(1-\beta_b)(n_i\beta_t)q_i + C_{sr4}
\end{aligned} \tag{3-53}$$

Solving for the optimal test rate for farmer i to minimize J_2,

$$\begin{aligned}
\frac{\partial J_2}{\partial \beta_i}/q_i &= c_1 - c_2\beta_b(\alpha_i'\beta_i + \alpha_i) + f_{p2}\beta_b[(1-\beta_i)\alpha_i'm_i - \alpha_i m_i] \\
&+ f_{p3}[\alpha_i'(1-\beta_i)m_i(1-\beta_b)(n_i\beta_t) - \alpha_i m_i(1-\beta_b)(n_i\beta_t)] + c_1\beta_b[(1-\beta_i)\alpha_i'm_i - \alpha_i m_i] \\
&+ c_1[(n_i\beta_t)(1-\beta_b)(1-\beta_i)\alpha_i'm_i - (n_i\beta_t)(1-\beta_b)\alpha_i m_i] - f_{1i}(\alpha_i'\beta_i + \alpha_i) \\
&- f_{2i}[\alpha_i'(1-\beta_i)\beta_b - \alpha_i\beta_b] - f_{3i}[\alpha_i'(1-\beta_i)(1-\beta_b)(n_i\beta_t) - \alpha_i(1-\beta_b)(n_i\beta_t)] = 0
\end{aligned} \tag{3-54}$$

So,

$$\beta_i = 1 - \frac{\alpha_i}{\alpha_i'} + \frac{c_1 - (c_2\beta_b + f_{1i})\alpha_i'}{[(1-\beta_b)(n_ib_t)(mf_{p3} - f_{3i} + c_1m_i) + \beta_b(mf_{p2} - f_{2i} + c_1m_i) + c_2\beta_b + f_{1i}]\alpha_i'} \qquad (3\text{-}55)$$

After replacement,

$$kAB\beta - k[f_1 - \beta(f_3 - f_1) + \beta\beta_b(f_3 - f_2)]A$$
$$+ c_1[f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)]^2 + k(f_{1i} + c_2\beta_b)B = 0 \qquad (3\text{-}56)$$

where

$$A = (1-\beta_b)(n_ib_t)(mf_{p3} - f_{3i} + c_1m_i) + \beta_b(mf_{p2} - f_{2i} + c_1m_i) + c_2\beta_b + f_{1i} \qquad (3\text{-}57)$$

$$B = f_{1i} - f_{2i}\beta_b - f_{3i}(1-\beta_b)(n\beta_t) \qquad (3\text{-}58)$$

To obtain the optimal test rate β, we need to work out the bin test rateβ_b. To start, we find the optimal test rate on primary elevator bins that minimizes J_2:

$$\frac{\partial J_2}{\partial \beta_b} / q_i = c_2(1 - \alpha_i'\beta_i) - c_2\beta_b\alpha_i'\beta_i + f_{p2}[(1-\beta_i)\alpha_im_i + \beta_b(1-\beta_i)\alpha_im_i]$$
$$+ f_{p3}[\alpha_i'(1-\beta_i)m_i(1-\beta_b)(n_i\beta_t) - \alpha_im_i(1-\beta_i)(n_i\beta_t)]$$
$$+ c_1[\beta_b(1-\beta_i)\alpha_im_i + (1-\beta_i)\alpha_im_i]$$
$$+ c_1[(n_i\beta_t)(1-\beta_b)(1-\beta_i)\alpha_im_i - (n_i\beta_t)(1-\beta_i)\alpha_im_i]$$
$$- f_{1i}\alpha_i'\beta_i - f_{2i}[\alpha_i'(1-\beta_i)\beta_b + \alpha_i(1-\beta_i)]$$
$$- f_{3i}[\alpha_i'(1-\beta_i)(1-\beta_b)(n_i\beta_t) - \alpha_i(1-\beta_i)(n_i\beta_t)] = 0 \qquad (3\text{-}59)$$

So that,

$$\beta_b = 1 - \frac{\alpha_i}{\alpha_i'} + \frac{c_2 + [(1-\beta_i)(mf_{p2} - f_{2i} + c_1m_i) - (f_{1i} + c_2)\beta_i]\alpha_i'}{[(1-\beta_i)(n_ib_t)(mf_{p3} - f_{3i} + c_1m_i) - (1-\beta_i)(mf_{p2} - f_{2i} + c_1m_i) + c_2\beta_i]\alpha_i'} \qquad (3\text{-}60)$$

And after replacement,

$$kDE\beta_b = k(E+F)D - c_2c^2 + k[(1-\beta)(mf_{p2} - f_2 + c_1m) - (f_1 + c_2)\beta]E \qquad (3\text{-}61)$$

where

$$D = (1-\beta)(n_i b_t)(mf_{p3} - f_{3i} + c_1 m_i) - (1-\beta)(mf_{p2} - f_{2i} + c_1 m_i) + c_2\beta$$
$$E = f_{2i}(1-\beta) - f_{3i}(1-\beta)(n_i b_t)$$
$$F = f_{1i}\beta + f_{2i}(1-\beta)\beta_b - f_{3i}(1-\beta)(n_i b_t)(1-\beta_b)$$

After replacing β_b in equation 3-56, the optimal solution β^* can be found. Subsequently, by replacing β^* in equation 3-61, the optimal solution for β_b can be obtained. Because the process of deduction is algebraically difficult, the general solutions for the optimal test rate will not be derived here. Instead, using given parameter and variable values, the cost optimization problem can be shown easily. For example, under the conditions that $k=0.1$, $m=6$, $c_1=0.3$, $c_2=0.1$, $n\beta_t=1$, $f_{p2}=4$, $f_{p3}=5$, $f_1=4$, $f_2=10$ and $f_3=12$, the solutions for equations 3-56 and 3-61 are:

$$\beta_i = \begin{bmatrix} 0.9879 - 0.0382i \\ 0.9879 + 0.0382i \\ 0.3749 \\ 2.1109 \end{bmatrix} \qquad \beta_b = \begin{bmatrix} 213.35 + 0.8768i \\ 213.35 - 0.8768i \\ 0.0477 \\ 17.3735 \end{bmatrix}$$

meaning that the optimal solution for the test rate is:

$$\begin{cases} \beta_i^* = 0.3749 \\ \beta_b^* = 0.0477 \end{cases}$$

based on equation 3-48, with a corresponding farmer's misrepresentation rate of $\alpha^* = 0.011$.

Theoretically, each testing scheme developed above would be optimal for primary elevator handlers with respect to a specific combination of test points with or without traceability. And the distribution of costs among participants changes from case to case. However, if there are certain values of interest for variables and parameters, these results can help identify the system cost distribution between farmers and elevators and then determine which test scheme would be preferred by primary elevator handlers for minimizing their handling costs.

3.3 Moral Hazard and Incentives

3.3.1 Introduction

Since a supply chain participant's risk control effort is related to costs, there is a trade-off between supply chain participant costs and risks. In this context, the farmer and handler decision making process is unavoidably affected by moral hazard.

Moral hazard is common in cases of asymmetric information between participants in a transaction. Examples commonly include insurance, labor contracting and the delegation of decision-making responsibility. Generally, moral hazard may occur if a party that is insulated from risk has more information about its actions and intentions than the party paying for the negative consequences of the risk. The party insulated from risk may behave more recklessly than it would behave if it were fully exposed to the risk. Holmstrom (1979) stated that the problem of moral hazard may arise when individuals engage in risk sharing under conditions such that their privately taken actions affect the probability distribution of outcome. Kreps (1990) considered moral hazard in a circumstance where one party to a transaction may undertake certain actions that affect the other party's valuation of the transaction but the second party cannot monitor/enforce perfectly. Foster (1994) further defined moral hazard applied to the labor market in a way that the amount of an input supplied by a worker to a task will depend positively on the extent to which that input is rewarded. When discussing agri-environmental policy modeled as a social welfare maximization problem, Ozanne (2001) recognized the potential trade-off between increased environmental benefit and increased cost of monitoring compliance. He stated that moral hazard arises in a situation where the conservation authority cannot verify perfectly that all farmers participating in a scheme are fully abiding by their contractual obligations, i.e. monitoring is imperfect. This provides farmers with an incentive to renege on their contracts, for if they are successful in avoiding detection by the conservation authority, they can receive the compensation payment without incurring the costs implied by their contractual obligations. In fact, Ozanne's particular topical definition of moral hazard is more suitably applied in this study.

Moral hazard situations are very common in agriculture. Foster (1994) established a method for testing for the existence of moral hazard in a labour market. Their findings offer evidence that

workers supply more effort under a piece-rate payment scheme or in self-cultivation on their own land compared to time-wage employment. Ghatak (2000) provided more evidence from farm-level data showing that both the mean and the variance of output will be greater in farms that are cultivated under fixed rent contracts as opposed to sharecropping contracts. Finally, Alexander (1999) compared producer's efforts on improving tomato quality under different contractual schemes. His evidence shows the pervasiveness of moral hazard: in agriculture, producers put more effort into producing high quality product under a price incentive contract than under a fixed price contract.

A number of authors have explored solutions for specific moral hazard problems. Many of those studies have been concerned with what has become known as the principal-agent problem. Holmstrom (1979) used a model to discuss the role of imperfect information in a principal-agent relationship subject to the moral hazard problem. A necessary and sufficient condition for imperfect information to improve in contracts based on the payoff alone is derived and a characterization of the optimal use of such information is given. By creating additional information systems or by using other available information about the agent's action or the state of nature, contracts can be improved. Hueth (1999) examined the structure of contractual relations between growers and first handlers in fruit and vegetable markets. When there are asymmetry of information problems resulting in moral hazard in the provision of fruit or vegetable quality, a set of incentive instruments, e.g. input control, monitoring, measuring and price risk, could be used to coordinate relations between growers and intermediaries and alleviate the moral hazard problem. The author provides evidence from California about how these instruments are employed.

Taken together, these studies provide insight on how to alleviate the moral hazard problem through risk sharing adjustments. All those studies emphasize as well that proper monitoring is usually an effective method to solve or alleviate moral hazard problems. However, none of the studies referenced established the mathematical relationship between agent input efforts and the strength of contract incentives. In addition, they did not assess the level of moral hazard under specific incentive mechanisms nor offer a clear picture of the trade-off between incentives and moral hazard. So the measures suggested to alleviate moral hazard are often ambiguous instead of explicit and practical.

In this study, the primary elevator's variety test on deliveries provides producers direct incentives to put efforts on controlling misrepresentation risks. The producers' compensation depends on their success at the assigned task: delivering an eligible variety of product. If the primary elevator handlers detect a variety of wheat that is undesirable, they will refuse to pay the contractual price but a discounted price instead and possibly also impose a penalty on offenders for any contamination which results. If handlers do not undertake complete testing on each delivery, it is possible that a misrepresented delivery will not be identified. The producer may take advantage of incomplete testing by reducing their effort at ensuring varietal eligibility. As a result, the primary elevator will commonly share the contamination risks resulting from such reduction of effort, creating moral hazard problems. In the same way, a moral hazard problem can also affect the decision making behavior and effort of primary elevator handlers in a situation where the terminal elevator undertakes incomplete testing on their railcar deliveries.

Of course, the optimal solution identified under moral hazard is not first-best[10]. There are two reasons for this. First, resources need to be spent on monitoring. Second, misrepresentation attributable to lack of effort may lead to contamination and thus economic loss. The first-best solution can only be obtained in a circumstance where moral hazard is absent.

3.3.2 Moral Hazard under Free Testing

To maximize own profit, a farmer in the VED world intends to put less effort than the socially optimal level if there is a non-vanishing probability that the (misrepresented) delivery will not be tested (detected) or that the penalty level is less than the appropriation. In all cases, perfect monitoring and enforcement may be impossible, resulting in an imperfect risk sharing scheme and making the moral hazard issue part of the farmer's decision making behavior.

When misrepresented wheat enters the supply chain, wheat quality loss will result and wheat handling costs will increase. The increased cost will be ultimately shared among the supply chain participants. Under a condition of known misrepresentation, to ensure the safety of the wheat supply chain, elevator handlers must monitor farmer behavior. In this study, monitoring

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[10] When the moral hazard problem is identified with the Principal-Agent model, the first-best situation is defined by the assumption that the principal can observe the Agent's action. In that case he can order the Agent to choose the efficient action, or, equivalently, the Principal can penalize the Agent if he does not choose the efficient action, and then choose the prices and penalties that achieve the optimal risk sharing (Salanie, 1997).

objectives can only be realized through testing. When a farmer's misrepresentation is severe, it appears that more human and facility resources should be put into testing to avoid contamination risks. Undoubtedly, the existence of these moral hazard problems raises costs for wheat handling and potentially compromises the overall efficiency of the wheat quality assurance system.

As discussed, the typical remedy for moral hazard is the introduction of proper incentives. This means structuring a scheme so that the agent who undertakes the actions will, in their own best interest, take actions that the principal would prefer. If incentives can be effectively designed to make the agent with moral hazard bear fully the consequences of the actions, an ideal risk sharing scheme is established and the moral hazard problem can be mitigated.

In the specific case examined in this thesis, the risk sharing relationship between the primary elevator and the farmer differ from well-established situations like those between an insurer and the person being insured, or a manager of a firm and the worker. The farmer's risk control effort and the primary elevator's testing intensity directly influence the distribution of risk between them. They can control their own fates through seeking the optimal level of risk sharing. Although the elevator handler cannot observe the true actions of farmer risk control effort, for example, on-farm practices, they can provide incentives through monitoring the outcome of the farmer's action by testing their product, and there is a probability that moral hazard can be alleviated or eliminated under specific testing schemes with appropriately chosen penalty levels. At one end of the spectrum of possibilities, one (costly) example would be complete testing of farmer deliveries.

If the farmer understands elevator handlers will completely test his or her deliveries and any detected misrepresentation will be penalized, he or she would like to substitute putting appropriate risk control effort for expecting luck. The appropriate level of effort depends on the penalty level set for offenders. Ideally, the penalty should be designed to equal the monetary amount of damage resulting from the misrepresented delivery (Gray, 2010). Such a penalty is required to eliminate moral hazard when the farmer makes the production decisions on risk control effort. Taking the solution from Case (4b) (Section 3.2.3.4) as an example (three test locations with traceability), note that when the primary elevator does not perform complete testing on all farmer's deliveries, there exists a moral hazard problem. Under the (heroic and

premature) assumption that sample testing is free, the optimal choice of the primary elevator is to test each delivery of farmer at the earliest test location, the truck test point. Under these conditions, any and all misrepresentations of farmers will be detected. In this case, the farmer's optimal response is (based on equation 3-39),

$$\alpha = \frac{\kappa}{f_1} \tag{3-62}$$

The magnitude of α is determined by f_1, the penalty for detected misrepresentation at the truck test point. This raises a question: what penalty level can generate incentives for farmers to provide mitigation efforts and eliminate moral hazard problems? From the definition of moral hazard, one can make the following supposition: when the penalty exactly equals the expected damage resulting from farmer misrepresentation, the farmer will put in appropriate effort to remove moral hazard. The logic for this conclusion is that if the penalty from the offender must cover all the damage made by the misrepresentation, all the misrepresentation risks will be taken by the offender. Note also that this penalty should include the cost of sampling and testing. That is, the primary elevator should not bear any consequence from misrepresentation. If the penalty imposed on offender is less than the resulting damage or say the primary elevator shields against some economic loss, the moral hazard problem will arise to affect producer choice decisions regarding effort. As a result, there will be an appropriate level of effort that should be offered by the producer in a situation in which there is no moral hazard involved.

Figure 3.9 shows the privately optimal α in which there possibly is a moral hazard problem, and α^*, resulting from the optimal effort level a farmer takes under the condition that there is no moral hazard. In this case, the lower the test rate, the more the deviation between the privately optimal effort from the one without moral hazard. So when the truck test rate increases, more information concerning a farmer's misrepresentation behavior is perceived and thus moral hazard is reduced. The truck test rate changes the distribution of risk sharing between the farmer and the primary elevator. Under an assumption of free testing, the test rate will necessarily reach 100 percent and all misrepresentations will be exposed to detection and penalty. That is, the detected farmers will assume full consequences and responsibility for their behavior. Under this situation, a well-designed penalty level can provide an incentive for the farmer to eliminate moral hazard when making decisions about choosing the effort level on risk control. The optimal

incentive under complete testing requires an offender penalty consistent with possible misrepresentation damage to the value of the supply chain.
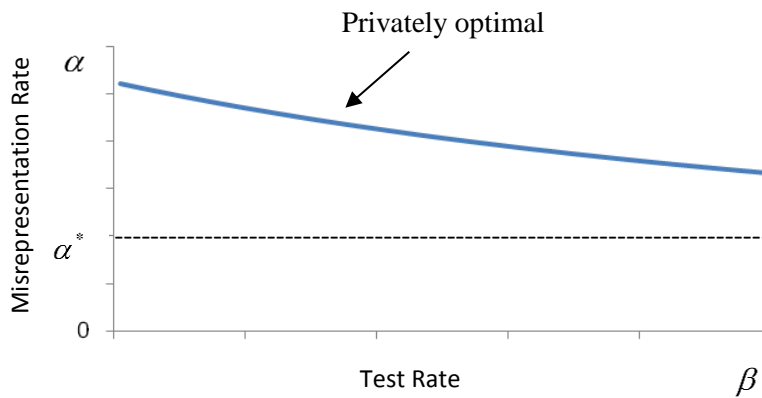
Figure 3.9 Privately Optimal Misrepresentation Rate

Unfortunately under VED, cheap and effective testing technologies are not available. Sample testing is costly and with imperfect precision. Conducting full tests on all farmer deliveries will almost certainly not fulfill the primary elevator's economic objectives. Even if the primary elevator tests each farmer delivery under VED, it still cannot be certain all misrepresentations will be detected due to imperfect test precision. In both situations, it is unavoidable that the primary elevator must bear some risks from farmer misrepresentation. From this point of view, the relationship between the farmer and the primary elevator under VED is characterized by moral hazard. As mentioned above, the optimal solution to incentive compatibility under moral hazard is not first-best in a social welfare sense (Holmstrom, 1977), meaning that the full information and static solutions derived in this chapter all fall under the shadow of moral hazard. So they cannot be called the social optimum but are private optimum.

3.3.3 Moral Hazard under Vertical Integration

As a matter of fact, there will exist moral hazard as soon as the objectives of the parties differ (Salanie, 1997). To pursue the private optimum, parties restrict attention to their own benefit without considering the welfare of the whole economy. There is possibly a significant loss of economic efficiency as a result of self-interested behavior. Sometimes, it is said that the moral hazard problem could be solved by "selling the firm to the agent." Although this case has little

practical interest for this work, from a theoretical respective, this analysis will also explore how some degree of vertical integration within the supply chain could help eliminate moral hazard problems.

The idea that vertical integration can eliminate moral hazard problems is not new. Vetter (2002) used a credence goods case to demonstrate that vertical integration is one efficient way of dealing with the moral hazard problem when monitoring is costly. But the effectiveness of integration to eliminate moral hazard can be reduced by freely available monitoring. Holmstrom (1982) showed how workers' ownership of a firm (with the appropriate sharing rule) fully eliminates moral hazard problems. Baker (2001) noted integration is efficient in some circumstances precisely because integration eliminates moral hazard. These studies showed the efficiency of vertical integration on alleviating or eliminating moral hazard problems.

Consider a case in which homogeneous farmers are the owner of the primary elevator and the terminal elevator. Here the meaning of "homogenous" is not only that the farmers have the same productivity and technology, but also that they own the same share of the company. The farmer, the primary elevator and terminal elevator's economic objectives, originally somewhat separated, are now fully aligned. For simplicity, it is assumed end consumers are perfect monitors about the variety of wheat they purchased, i.e. any misrepresented wheat can be precisely detected by consumers. Reversing the status of those farmers will reverse their pattern of behavior as well. Now the producer responses under two circumstances are discussed: one is that there is no testing at any transfer point, and the other is that tests are taken at each transfer point. In both circumstances, traceability is not needed because it increases the handling cost. In any case, the vertically integrated company should be responsible for any misrepresentation damage. In the former circumstance, the cost function for the integrated company is:

$$J = c\, q_i + f_{p4} \sum \alpha\, m\, q \tag{3-63}$$

The first order condition with respect to α,

$$\alpha = \frac{k}{f_{p4} m} \tag{3-64}$$

The term $f_{p4}m$ just represents the value of penalty or profit loss resulting from detected misrepresentation. If the value of this term equals the damage from misrepresentation, the above equation indicates the optimal response of the farmer. When knowing one has to fully undertake the consequences and responsibilities of one's action, one will choose one's efforts without moral hazard considerations.

In this case, the misrepresented wheat cannot be detected until it moves to the farthest point in the supply chain. The resulting loss will be greater than that if misrepresented wheat can be detected at an earlier point in the supply chain. Compared with the optimal α solved above under a private optimum condition (equation 3-62), this optimal α is smaller, indicating a higher level of optimal efforts without moral hazard.

In the second circumstance, there is testing at each wheat transfer point. Then the associated cost function is:

$$
\begin{aligned}
J &= c\ q_1 + c_1 \sum \beta q\ + c_2 \beta_b \sum (1 - \alpha\ \beta\ )q\ + c_3 \sum \alpha\ (1 - \beta\ )m\ (1 - \beta_b)(n\ \beta_t)q \\
&+ f_{p2}\beta_b \sum (1 - \beta\ )\alpha\ m\ q\ + f_{p3}\sum \alpha\ (1 - \beta\ )m\ (1 - \beta_b)(n\ \beta_t)q \\
&+ f_{p4}\sum \alpha\ (1 - \beta\ )m\ (1 - \beta_b)(1 - n\ \beta_t)q\ + C_{sr}
\end{aligned}
\tag{3-65}
$$

Solving for the first order condition with respect to α,

$$
\alpha = \frac{\kappa}{(f_{p1} + c_1)\beta + (f_{p2} + c_2)\beta_b(1 - \beta)m + (f_{p3} + c_3)(1 - \beta)m(1 - \beta_b)(n\beta_t) + f_{p4}(1 - \beta)m(1 - \beta_b)(1 - n\beta_t)}
$$

$$\tag{3-66}$$

The denominator represents the possible losses if delivered wheat is misrepresented. The terms $(f_{p1}+c_1)$, $(f_{p2}+c_2)$ and $(f_{p3}+c_3)$ represent the exact economic damage if misrepresentation is detected at each test location, respectively. If f_{p4}, the penalty imposed on misrepresentation by consumers, exactly equals the economic loss from consumer rejection of the misrepresented variety, the above equation represents the optimal response of farmers without moral hazard. In this case, the test cost plays an essential role in determining the magnitude of optimal efforts. When test costs are low, the handlers (farmers) will tend to test more and so more potential

misrepresentation losses will be avoided. As a result, the marginal benefit of effort becomes less, lessening the farmer's incentive to increase input efforts.

The optimal test strategy renders the marginal testing cost equal to the marginal testing benefit. When the marginal cost is less than the marginal benefit, an increase in testing intensity will be an efficient way to increase the profit of the company. Doing so also prevents misrepresented wheat from moving further in the supply chain, decreasing contamination risks and reducing related damages to the grain value chain. When misrepresented wheat is present, the company will bear more risks if there is no testing at each wheat transfer point rather than when there are tests at some transfer points. From this point of view, the magnitudes of producer efforts without moral hazard are not identical in different situations. For example, in this vertical integration case, the producer's efforts without moral hazard are greater when there is no interior testing in the integrated company than when there are interior tests.

3.3.4 Moral Hazard under Infinite Penalty

A penalty imposed on offenders plays an essential role on the producer decision about choosing efforts regarding risk control. From the elevator handler's perspective, an infinite penalty is preferred. If the penalty could approach infinity, moral hazard problems will be eliminated even if testing is incomplete. In the free test and vertical integration cases, to eliminate the moral hazard problem, it is emphasized that the penalty needs to be equal to the resulting damage from misrepresentation. If the penalty surpasses the resulting damage, can the moral hazard problem still be eliminated? There is no doubt that the producer will put in greater effort at reducing misrepresentation if the penalty is higher. As a result, there are no moral hazard problems. But there will be over cautiousness problems. Producers will overact to a higher penalty level and maintain higher risk control efforts than optimal. In this case, the marginal benefit of efforts is decreasing with effort levels, so when the effort level is extremely high, the marginal benefit from it approaches zero.

In either case, greater efforts at reducing misrepresentation are always desired by the primary elevator. But from the social welfare provision, such efforts are not necessarily efficient. In a social optimum, the marginal social costs equal to the marginal social benefit. When the marginal cost of effort is less than the marginal benefit of effort, there is no problem as the

primary elevator gives more incentives to producers. If the marginal cost is greater than the marginal benefit, farmer overactions may compromise social efficiency. Although a high penalty can eliminate moral hazard problems inherent in producer decisions on effort, it is not at all assured that a high penalty can increase social efficiency. A large penalty for avoiding a small loss resulting from misrepresentation is not a socially efficient outcome. Such a conclusion is also consistent with that of Mirrlees (1999) in the context of moral hazard in health insurance, who argued that there is no loss of economic efficiency as a result of self-interested unobservable behavior under the condition that individuals take too much care rather than too little.

3.3.5 Moral Hazard in a Handling System With/Without Traceability

A grain handling system with traceability can ensure that offenders are ultimately identified even if their misrepresented deliveries enter the supply chain without detection. Undoubtedly, handlers confront more risks if they operate a handling system without traceability: they must bear all the economic losses if contaminations occur at any stage of the supply chain. When there is no traceability, a farmer enjoys the opportunity of evading responsibility even if he or she misrepresents delivery sometimes. From this point of view, a system without traceability can generate or buttress a farmer's moral hazard problem. Taking case 2 (Section 3.2.3.2) and case 4 (Section 3.2.3.4) as examples, the moral hazard problem becomes more serious in a system without traceability than in a system with traceability when there is no complete testing at test point 1, i.e. the farmer misrepresentation rate in the former system is greater than that in the latter.

Table 3.1 Farmer Misrepresentation Probability in System With or Without Traceability

Case	Without Traceability	With Traceability
Case 2	$\dfrac{\kappa}{f_1\beta}$	$\dfrac{\kappa}{f_1\beta + f_3(1-\beta)(n\beta_t)}$
Case 4	$\dfrac{\kappa}{f_1\beta}$	$\dfrac{\kappa}{f_1\beta + f_2(1-\beta)\beta_b + f_3(1-\beta)(1-\beta_b)(n\beta_t)}$

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3.3.6 Summary

In general, when the farmer chooses the effort on risk (misrepresentation) control, the moral hazard problem will be eliminated when the following three conditions are all satisfied:

1. Testing is free, which means every time wheat changes hands, complete sample testing will be taken.

2. Testing precision is perfect. Once a wheat sample is tested, the variety and purity will be determined with full accuracy.

3. The penalty for misrepresentation is equal to potential damage to the value of supply chain.

When the handling strategies are different, moral hazard problems evaluated by due efforts are different. With respect to the effort without moral hazard under these different situations, the value of α^* possibly differs from each other. Take former case 3 (b) as an example, if the test is free, the primary elevator will test each elevator bin before loading wheat in the railcars. Under such a condition,

$$\alpha^* = \frac{\kappa}{f_2} \tag{3-67}$$

Here f_2 equals to quality loss of wheat in the contaminated bin. The amount of damage depends on the volume of wheat contaminated and the contamination level. Normally, the farther a misrepresented delivery moves in the wheat flow, the greater the contamination damage. If a farmer knows he or she will be traced and detected due to detected bin contamination resulting from the misrepresentation, the effort response will be greater than in the situation where he or she will be surely detected in the truck test (equation 3-62).

Possibly the contamination loss is great enough to make an offender bankrupt if one is required to make a payment equal to the full loss of potential profit. As alluded to earlier, to protect farmers, normally this penalty is set at an upper limit (Canadian Grain Act, 2012). The extra amount over the upper limit of a penalty needs to be shouldered by other parties, e.g. the primary

elevator. However, it is possible that the practical penalty level is less than the resulting damage. If the penalty level is low enough to provide the required deterrence, moral hazard will be still present even if any misrepresentations can be detected accurately. The upper limit of the penalty can be another reason for weakening the incentives for farmers to put in effort, generating a moral hazard problem.

When the primary elevator takes a proportionate test on farmer's deliveries, a higher penalty helps alleviate moral hazard and thus induces the farmer to take efforts approaching the desired optimum. If the penalty is infinite, even if the test rate is low, moral hazard will be eliminated. The upper limit on penalty for offenders narrows the scope for the penalty as a complementary method for the test rate on motivating effort.

Generally, there is a moral hazard problem if the upper limit of a penalty for an offence is less than the possible damage resulting from undetected misrepresentation. Based on a limited penalty assumption, if either of the following two conditions is satisfied, the moral hazard problem relevant to this policy issue will be aggravated:

1. There is no test point at which related samples are fully tested. Such a situation generally exists, under the condition of costly testing, complete testing is almost impossible.

2. The test precision is imperfect. There exists a probability that the farmer misrepresented the delivery and still is tested, but is not detected.

Due to the costs of monitoring behavior, a perfect perception of an agent's behavior is impractical. Casual observation indicates that imperfect information is extensively used in practice to alleviate moral hazard (Holmstrom, 1978). It can also be shown that any information about an agent's action, even imperfect, can be used to improve the welfare of both the principal and the agent (Harris, 1977). Clearly, one cannot expect imperfect monitoring to solve the moral hazard problem. In this case, to pursue the private optimum, the primary elevator probably should test farmer deliveries proportionally (refer to Figure 3.5 and Figure 3.8) instead of testing completely and allow the moral hazard problem to exist to some degree.

Moral hazard problems also exist in handlers' behavior. When the terminal elevator handlers do not completely test railcar deliveries or the penalty for farmer in case of offences is high, the

primary handlers' testing decision will be characterized by moral hazard. In the former situation, incomplete testing will lower the primary elevator handlers' incentive for testing because they do not need to bear all the misrepresentation responsibility (refer to equation 3-14 in case 2(a) and equation 3-44 in case 4(a)). In the latter situation, the handlers have no incentives at all to test at any point because all contamination losses can be covered by penalties from offenders (refer to equations 3-14 and 3-44, Figure 3.5 in case 2(b) and Figure 3.8 in case 3(b)). In this situation, the handlers only need to establish a formal traceability system whereby they can trace the source when there are contaminations detected somewhere within the supply chain. There are measures that will give primary elevator handlers incentives for greater testing. Either an upper limit on the penalty imposed on traced farmers who misrepresent their deliveries or a high penalty on detected misrepresented railcars can each force handlers to share risks from their due efforts and thus mitigate their moral hazard problems.

3.4 Summary

The specification of appropriate handling strategies in the new VED wheat supply chain will be important due to the potentially large consequences on system reliability and parties' profitability associated with any particular choice of handling strategy. Among these strategies include choice of test location, testing intensity and penalty levels for those offenders who are detected and can be traced. The objective of this chapter has been to compute optimal strategies for wheat handlers so as to minimize the costs and risks associated with wheat handling under VED.

In this chapter, using a reasonable set of assumptions, supply chain participants' cost functions were specified through incorporating different testing locations, and with or without a traceability mechanism, in a stylized VED wheat supply chain. The solutions of the set of optimization problems functions provide a guide for analyzing how these related factors affect testing strategies and also for exploring ways under which the moral hazard problem inherently present in the new supply chain can be mitigated or eliminated.

Because testing is costly, taking complete testing on farmer deliveries may not meet the primary elevator's objectives unless the misrepresentation situation is severe. Proportional testing makes the primary elevator suffer some risks from misrepresentation and raises moral hazard problems

in the farmer's choice of effort (misrepresentation) decision. Under the assumption of zero cost testing, the moral hazard problem can be solved. But another way to eliminate the VED moral hazard problem could be the vertical integration of the wheat production supply chain. In both cases, the elimination of moral hazard requires adequate incentives generated through penalties on offenders. Of course, such penalties should be not less than the resulted damage by misrepresentation.

As might be expected, a high penalty is preferred by the elevator handlers because of the strong incentives it gives for motivating effort from farmers. A higher penalty helps alleviate moral hazard problems, but it may bring on an excessive caution problem. These findings suggest that farmers are sensitive to the penalty level that could be imposed in the case of an offence. Any increase in the penalty will squeeze more effort from farmers, but when a penalty level drives up efforts from farmers such that the marginal cost surpasses the marginal benefit of effort, this penalty level will not be socially efficient. But if this misrepresentation penalty is set at a level below the measurable damage resulting from individual misrepresentation, a farmer may suboptimally reduce the effort. This is another way to generate moral hazard problems for farmers in the VED supply chain.

Without question, the farmer is exposed to very different misrepresentation risks under different wheat handling schemes. A system misrepresentation test can generate different distributions depending on where it is conducted and as well, the penalty for identified misrepresentation could be set at levels from finite to infinite. Handling strategy combinations indicate various risks the farmer should take if misrepresenting the delivery and thus provide the farmer different incentives with respect to their efforts to control risks. In fact, the magnitude of farmer's efforts without moral hazard varied according to the test and penalty system applied.

While moral hazard problems add costs to wheat handling, alleviating them by increasing test intensity is also costly. If the expected cost of inducing the farmer to select a high level of effort is too high, the primary elevator will probably refuse to do that, and instead, the primary elevator would tend to try to induce some lower level of effort from the farmer at a lower cost, allowing moral hazard problems to exist in equilibrium. When those moral hazard problems are present, the first-best societal outcome may not be possible to achieve. Instead, the primary elevator's

testing strategies must be designed to achieve the second-best (under moral hazard and hence with a need for costly supervision) such that the system handling costs are minimized.

Although explicitly solvable, the analytic models in this chapter do not provide a very realistic perspective on handling strategies. The testing strategies are developed based on the assumption that the grain handlers know the cost function of farmers and thus know the response of farmers to testing adjustment and make perfect use of information. In reality, grain handlers only have limited information about farmers. Actually, the great challenge confronted by handlers is how to develop an effective testing strategy while depending on limited information from imperfect monitoring of effort. From the elevator's perspective, the issue becomes understanding how to use the imperfect information about farmer's misrepresentation behavior to infer the farmer's actual risk control effort.

The inability to accurately identify the farmer's actual effort level will negatively affect the efficiency of tests distributed among heterogeneous farmers, making handlers necessarily subject to bounded rational behavior. For example, a farmer with high effort may be tested more than another farmer with low effort due to the elevator handlers' incorrect determination about their misrepresentation risks. Furthermore, in reality wheat handling decisions are in fact a complex dynamic process because of farmer interaction with respect to testing, individual learning about testing and information feedback on testing. To pursue economic efficiency in this situation, the elevator handlers would need to continuously adjust their test strategy for detecting farmers' misrepresentation behavior based on several factors, including newly perceived information.

In reality, the probability of detection is likely influenced by testing location, testing intensity and the accuracy of testing for misrepresentation. Knowing this, the analytic model developed above is useful for developing intuition about the problem, but it cannot possibly reveal the consequences of the dynamics and complexities inherent even in a simple real-world economic situation like a grain supply chain under VED. To get past the limitations of the analytic model, a basic agent-based economic simulation of the VED supply chain is developed in the next chapter. The simulation will help to uncover the effect of bounded rationality on behavior as well as help us to understand how inherent dynamics and complexities affect the strategies chosen by the various players in a VED wheat handling system.

CHAPTER 4

AGENT-BASED SIMULATION OF THE VED SUPPLY CHAIN

4.1 Introduction

The model discussed in Chapter 3 is an analytic one. Its utility is limited by some assumptions and limitations. First, in the analytic model, it is assumed that farmers are homogeneous. Second, the analytic model does not allow for inter-agent interactions, feedback and system dynamics. Third, wheat handlers have complete information about farmer behavior and display perfect economic rationality. In reality, the supply chain is a dynamic system composed of heterogeneous participants who interact with each other and adapt their behaviors continuously over time. Handlers cannot know the exact misrepresentation probability for a farmer due to information asymmetry and also cannot use information perfectly, therefore their testing strategies are not fully rational but boundedly rational, i.e. individuals are limited in their knowledge and their cognitive abilities about their environment and in their computing ability, and thus in the degree to which they are able to optimize their utility (Simon, 1957). Simon (1957) also argued that bounded rationality is a more accurate and more realistic description of human behavior than perfect personality.

To take a more realistic view of the grain supply chain system dynamics and management, the behavior of participants with bounded rationality over a certain time interval should be more realistically described. This objective cannot be reached by using the standard mathematical techniques of algebra and calculus within an analytic model. To capture the dynamic and complexity inherent in the supply chain, a behavioral adaption simulation model is needed. By implementing and optimizing a set of behavioral agent-based simulation models, this study will derive a range of economic insights for the wheat handler's efficient testing strategies while benchmarking essential features of the dynamic economic system of interest.

4.2 Literature Review

Implementing the declaration system promises to have a substantial effect on the wheat handling industry. While there are tangible benefits from moving away from the visual identification system, the declaration system will create additional costs for the wheat handling and marketing system. The extent of these additional costs for the new segregation system is an important issue for the sector and will vary with the handling objectives and with the strategies employed by the sector participants.

There are two prior studies that have examined the impact of a move from KVD to a declaration system. These studies provide a detailed description of what the process would be and circumstantial qualifications of costs and risks along systems. However, these models simplify the complexity of the wheat handling system and thus deviate from the representative experimental conditions used for evaluating the costs and risks of wheat handling under the declaration system.

Furtan et al. (2003) in an unpublished paper, developed a static mathematical model for assessing the costs of implementing a VED system. They examined three different scenarios involving varying degrees of sampling and testing requirements, traceability, blending cargo and new administrative and enforcement activity costs. The three scenarios are: (1) besides a vessel test, no other test in the upstream supply chain; (2) random testing occurs at specific critical points along the supply chain; (3) tests are distributed strategically among farmers based on their delivery performance. For any of these, if there is any problem detected by testing, there would be a trace-back process implemented to locate the exact source of the problem. In order for a VED system to work, the authors suggest there should be a required penalty and enforcement procedure. The estimation results show that the third scenario has the lowest costs. But the adoption of this scenario requests a system of trust built up between the farmer, grain handler, and, at the time, the Canadian Wheat Board (CWB).

The Furtan study was not focused on developing efficient testing strategies, and in fact testing strategies considered for cost evaluation are exogenously given (i.e. arbitrarily given test rates for farmer's delivery and for railcars). The authors do not state whether such testing strategies are efficient or not. When discussing actual contamination problems, they make assumptions

about the volume of contaminated grain and do not explain how the contamination occurs and gets disseminated, or how serious the contamination can be. Both the contaminated grain volume used in cost evaluation as well as the value for traceability cost are included without further explanation as to why these values are fixed rather than variable. Generally, the model simplifies uncertainties in the system, so the calculated costs for three scenarios can only allow for three special cases and are not a representative assessment of risks in the grain handling system under the VED system.

Wilson and Dahl (2006) conducted a study evaluating the costs and risks of a dual marketing system with GM/Non-GM wheat segregation. A stochastic optimization model is developed to determine optimal testing strategy and quantify the costs and risks of the system. Sensitivity analysis was done to evaluate impacts of risk attitudes of policy makers, variety declaration, grower truth-telling, price discount (penalty), test accuracy, and tolerances. Their numerical simulation results pointed to optimal testing strategies and provided estimates of the additional costs of testing and rejection for the system. These results are suggestive of risk mitigation strategies that could be adopted in the wheat marketing system. Ultimately, they concluded that a supply chain based on testing and segregation can efficiently control the costs and risks for uncertainties within the system.

There are several simplifying assumptions made in Wilson's model. First, they assumed all growers are homogeneous with respect to the probability of truth-telling that reflects their own uncertainty whether the content of grain delivered includes GM varieties. Second, the model does not allow for any interaction or feedback between participants, meaning there is no adaptive behavior among the participants as might be expected in reality. As a result the optimal testing strategies are fixed throughout the simulation. These assumptions render their model only weakly representative of the basic economic and social environment of participants in the grain handling system. Finally, their model does not allow for traceability (i.e. identifying exactly where wheat comes from), but as we shall see, a grain handling system facing commingling risks can function more efficiently if traceability is possible.

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4.3 An Agent-based Modeling (ABM) Approach

As discussed in Chapter 3, the development of optimal testing strategies in this situation can be thought of as a variant of mechanism design, an optimization procedure that has been used to solve economic incentive problems under incomplete information. In economics, mechanism design concerns the problem of designing a protocol or contract that helps implement a desired objective, despite the possibility of divergent self-interest among individuals (Parkes, 2001).

In designing a testing strategy mechanism in the context of this research question, we first needed to specify an agent's objective and then define the set of behavioral strategies. Here, it is assumed that the wheat handlers' objective is to minimize their handling costs, including testing costs and contamination losses. Outcomes of testing strategies in this case must coincide with a desirable overall objective. But with respect to designing a realistic and sustainable testing mechanism in this supply chain composed of heterogeneous and dynamically interacting agents, one will need to turn to an agent-based modeling (ABM) approach.

This study differs from prior research in that this particular grain supply chain is modeled as a type of complex system, a system that is not readily amenable to analytic solution. By definition, a complex system is characterized by non-linear relationships between participants along with an out of equilibrium dynamic (Durlauf, 1998). In the grain supply chain system modeled here, it is assumed that participants behave independently and are heterogeneous, while their aggregate activity is inherently nonlinear (i.e. not derivable from the summations of the activity of individual components). In addition, individuals may also behave irrationally or out of equilibrium, making the system pass through unsteady states. Nonlinearities and out of equilibrium behavior require algorithms capturing how individuals in a system react to each other (feedback) and how they adjust continually to the overall situation they together create (recursion). Traditional mathematical techniques of modelling, which work best for static, homogenous and equilibrating situations, are typically very limited in their ability to deal with nonlinearities, disequilibrium or heterogeneous individuals (Forrester and Senge, 1996). Given the current state of computing power and software, it is now possible to model complex problems using more realistic assumptions to better capture the nonlinearity of participants' behavior with an agent-based modeling (ABM) approach (Li et al., 2010).

The supply chain modeled here falls within the paradigm of a complex adaptive system. The specified system is composed of boundedly rational participants who repeatedly interact with each other over time, including learning from interactions. Those individuals are limited in their cognitive abilities, as well as knowledge about their environment, and thus the degree to which they are able to optimize their individual utility. Farmers are boundedly rational in making decisions on taking risk control efforts. Similarly, handlers' testing strategies are not fully rational but boundedly rational instead. The latter cannot know the exact misrepresentation probability for a farmer due to information asymmetry and also cannot integrate perceived information in their decision making perfectly.

To take a more realistic view of the grain supply chain system dynamic and its complexity, the behaviors and incentives under bounded rationality over a certain time interval must be developed. ABM allows the researcher to create boundedly rational agents and directly represent their interactions, adaption and learning, none of which is easy to do with other modeling approaches (Gilbert, 2007). By implementing and optimizing a set of behavioral agent-based simulation models, this study will derive a range of economic insights for the bounded rational behaviors while maintaining essential features of the complex economic system of interest.

Formally, ABM is a computational framework for creating, analyzing and experimenting with models composed of agents that interact within an environment (Gilbert, 2007). For a complex system, an agent-based approach, which emphasizes autonomous actions and flexible interactions, is a natural computational model (Jennings and Bussmann, 2003). In this context, economic applications using ABM require building economic systems that can be mapped as computer programs. The computer program itself represents the processes that are thought to exist in the actual world (Macy and Willer, 2002). ABM creates a simplified representation of economic and social reality that serves to express as clearly as possible the way in which one believes that reality operates, capturing system dynamics and consequences out of the reach of analytic or mathematical methods. In the context of this problem, Labarthe et al. (2007) stated that the ABM simulation approach is the only one allowing an observation of the behavior of each supply chain actor through time, as well as the dynamics of the supply chain stemming from their interactions. ABM has become an important tool for understanding supply chain

behavior and can yield the information necessary to make informed decisions regarding supply chain design and management (Nolan et al., 2009; Schmit and Rounsevell, 2006).

Since the mid-1990s, ABM has been more widely used to analyze a variety of complex social, business and economic problems including supply chain management (Li et al., 2010; Chatfield et al. 2007; Labarthe et al. 2007), natural resource management (Carpenter et al., 1999; Barreteau et al., 2004), structural change in agricultural activities (Parker et al., 2004; Schmit et al., 2006), finance (Takahashi, 2003), labour markets (Neugart, 2006), urban sprawl (Brown et al., 2005), city growth (Zhang, 2003), electricity markets (Bunn and Oliveira, 2003, 2007), among others. In these economic ABM applications, the system of interest is simulated by modeling the behavior of individual agents and their interconnections. The targeted system is modeled as a collection of autonomous decision-making entities called agents. Each agent individually assesses its situation and makes decisions on the basis of a set of rules. Rather than focusing on stable states, ABM considers a system's robustness, providing a natural framework for harnessing the complexity of the agents: their diversity, connectedness, and level of interactions.

4.4 Model Logic and Description

First, to develop an appropriate agent-based simulation model, the wheat handling procedures involved in this study must be carefully defined. As indicated in Chapter 3, there are several possible testing points for grain quality - (1) a truck test before unloading wheat into primary elevator bins; (2) a primary elevator bin test before loading wheat into railcars; (3) a railcar test before loading wheat into the terminal elevator bins. There are two points where the traceability mechanism can be useful; (1) contaminations detected at the test point 2; (2) contaminations detected at the test point 3. Once again, for tractability, segregation issues that arise after the terminal elevator are not included in this study.

In this model, supply chain participants are represented as autonomous agents that interact with each other as well as with their environment through a set of rules that govern their actions, decisions, and interactions with other agents. These agents exhibit individual behaviors through the actions they perform and interactions they have with each other. Even though very little optimizing behavior at the agent level is assumed, examining the simulated aggregate of the

individual behaviors provides an analytic tool for understanding how the system performs as a whole.

4.4.1 Model Structure and Behavioral Assumptions

Like all modeled representations of reality, one must rely upon a set of simplifying assumptions and a set of realistic behavioral algorithms to render the simulation tractable. Considering the issue as described (except Assumption 9), all other assumptions made in Section 3.2.3 are applied to this model. In this simulation, it is assumed handlers have imperfect information about a farmer's misrepresentation behavior and they can only perceive a farmer's misrepresentation probability through testing. In addition, there is an assumption about the capacity of the primary elevator bins involved in this model: all storage bins in a primary elevator have the same capacity[11].

Of course, the modeled misrepresentation situation and testing regime in this study does not fully represent the current Canadian wheat handling system. Although a declaration system is already in place, at present there appear to be few misrepresentation cases and truck testing and bin testing for variety identification have not yet been implemented. Officers at the CGC (2012) are already aware that commingling risks from visually indistinguishable varieties can unexpectedly occur any time and safety threats could be serious in the future. They have also indicated that stringent testing regimes will be implemented if there are significant contamination threats from farmer misrepresentation. Allowing for this, at the time of this writing, my research in fact models a situation that is likely to occur in the wheat handling system of the foreseeable future. In turn, the results will help to develop strategies under VED to efficiently mitigate these risks before they can undermine the handling system functionality and integrity.

The next sections detail the key components of my simulation model of grain segregation and testing, as well as provide a description of the overall logic of the simulation. Due to the novelty of this aspect of the research, many of my assumptions or algorithms have been created using

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[11] In the prairie region, a typical primary elevator contains several storage bins with various capacities ranging from tens of tons to thousands of tons. The homogeneity assumption about the bin capacity helps reduce the complexity of other handling strategies rather than testing strategies which are the focus of this study. As a result, this model is not concerned with wheat receiving strategies, e.g. unloading wheat from a "high risk" client's delivery into a smaller bin.

related literature in agent-based simulation modeling or alternatively what is considered to be best grain industry practice regarding a particular situation.

4.4.2 Farmer Behavior

Consider a number of farmers located on a defined space. In the initial state of this simulation, farmers are randomly generated farming on a grid. The primary elevator's location is given on the space. Every location has explicit coordinates in an imaginary coordinate system, determining the distance between farmers and the distance from each farmer to the primary elevator. The magnitude of distances determines transportation costs when delivering wheat and also helps define the relationship between farmers.

Each farmer is endowed with an amount of land, labour and capital which yield a certain production capacity to produce wheat (No.1 CWRS, 13.5% protein). Farmers deliver their products to the primary elevator at the call for CWRS. It is assumed that each farmer delivers 1 truck of wheat at each delivery and makes 9 deliveries each year[12]. Just as before, it is assumed that each farmer could potentially misrepresent deliveries and this probability is determined by the amount of the risk control effort plus the level of risk control technology. A farmer is endowed with a certain level of risk control effort and a certain capacity of risk control technology and both of them evolve over time. Risk control effort is essentially a measure of the resources a farmer puts into avoiding possible misrepresentation, while the technology is a measure of the knowledge, management and agronomic capacity of a farmer to control the risk of misrepresentation. Similar as in Chapter 3, an individual farmer j's misrepresentation rate α is defined as a function of the risk control effort c_e and risk control technology k,

$$\alpha_j^T = e^{-\eta \frac{c_{ej}^T}{k_j^T}}$$
(4-1)

where $\alpha \in [0,1]$, the time (year) $T=0, 1, 2, 3...(N-1)$, $j=1, 2, 3...n$, and η is an exogenous parameter common to all agents used for the purpose of scaling. Note that higher value of c indicates a higher level of effort and a lower value of k indicates a higher level of technology. When $\frac{c}{k} \to 0$, $a \to 1$; when $\frac{c}{k} \to \infty$, $a \to 0$.

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[12] This represents about one delivery per month during the shipping season.

It is assumed that agents are boundedly rational but purposeful. They look about them, gather information and act in the next time period on the basis of that information. As discussed in Chapter 3, there are potential moral hazard problems with a farmer's effort if deliveries are not completely tested. Adapting to their environment through information, a farmer adjusts efforts to control misrepresentation risks based on perceived information. Potential profit loss from misrepresentation is assumed to be an effective deterrence to farmers who may potentially misrepresent their deliveries. How a farmer makes an effort at behavioral adjustment is determined in this model by two factors. The first factor is how the farmer was treated by the primary elevator. The second factor comprises information on how farmers adjacent to an individual were treated by the primary elevator.

First, if a farmer misrepresents a delivery and is detected, he or she will suffer a penalty. The penalty imposed is assumed to be a strong motivation to expend additional effort and thus mitigate moral hazard. If a farmer is tested but is in fact correctly represented, such a testing can serve as a warning mechanism to the farmer to take more care in the delivery, again reducing the moral hazard problem. If a farmer is not tested within the standard time frame (one year), it is assumed that he or she will reduce the diligence towards misrepresentation just a little and drop efforts at risk control in the following year, potentially worsening the moral hazard problem.

Second, there are interactions between farmers within the geographic landscape. Each farmer's opportunities and constraints for interaction are determined by geographic location. Historically, spatial and social situations have been determined primarily by geographic distance (Dibble, 2006). More recently, opportunities for social and economic interaction are driven by networks of transportation or communication spatial technologies (Couclelis, 1994). Considering that a farmer can more easily contact or develop collaborations with neighboring farmers than with those located far from him or her, the physical distances between farmers play a determining role on defining the interaction network. For simplicity, it is assumed that farmers within certain physical space exchange information with each other and react to this information. For example, if a neighbor was tested or detected in a given year, this affects the farmer and causes him or her to be a little more cautious with his or her own deliveries in the future. Conversely, if a neighbor has been not tested for some time, the farmer might start behaving in a risk-taking manner and may gradually relax diligence on misrepresentation risk. Doing so most certainly exposes this

individual to being detected with a higher probability in the future. So the behavior of a farmer's immediate neighbors influences the evolution of individual risk control effort, possibly either reducing or worsening the moral hazard problem.

To measure this interactive influence of neighbors, this simulation assumes that what one can call "social" distance is proportional to physical distance which is represented by kilometers. This assumption is based on the concept of "distance decay", which is the usual geographic term reflecting a diminished effect or degree of interaction with respect to greater distance (Dibble, 2006). $d(i, j)$ represents the shortest distance between farmer j and his or her neighbour i. Farmer j's neighbors are defined as farmers adjacent to him or her within a radius of 30 kilometers. Of course, when $i=j$, $d(i, j) =0$. For neighbors located beyond such a radius, their influences are neglected. The reciprocal of the distance value acts as a weight for the influence of different neighbors, so the farther a neighbor is located from the farmer j, the lower the neighbor's influence on the farmer j's behavior.

Figure 4.1 shows a defined spatial landscape with a 100(km)×100(km) space. The locations of 48 farmers and 1 primary elevator for grain deliveries are distributed on the landscape in a manner similar to the simulations used in this study. The red circle at the left bottom shows farmer #29 and the 14 neighbors within a 30 km radius.
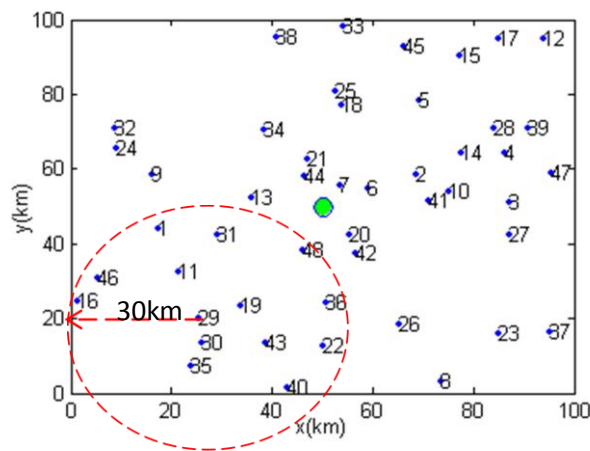
Figure 4.1 Farmers and the Primary Elevator's Locations in a Landscape

Farmer j's risk control effort, and its evolution is algebraically defined as,

$$c_j^{T+1} = c_j^T + D_{ji}[\lambda_1 \sum_{i=1}^{n} \frac{F_i^T}{d(i,j)+1} + \lambda_2 \sum_{i=1}^{n} \frac{D_i^T}{d(i,j)+1} - \lambda_3 \sum_{i=1}^{n} \frac{(1-D_i^T)}{d(i,j)+1}] \tag{4-2}$$

where $T = 1, 2, 3…N$, i or $j=1, 2, 3…n$, λ_1, λ_2 and λ_3 are free parameters in this study. F_i represents the units of farmer i's loss due to detected misrepresentation (a thousand of dollars per unit). The Ds are indicator variables. If the distance between farmer i and farmer j is within 30 kilometers, $D_{ji} =1$; otherwise, $D_{ji} =0$. If farmer i's delivery was tested or traced within the year T, $D_i^T =1$; otherwise, $D_i^T =0$. As before, $d(i,j)$ indicates the physical distance between farmer j and farmer i.

A farmer can also improve risk control technology by learning from his or her own experiences or from his or her neighbor's experiences on personal on-farm practices. Learning behavior is now studied frequently in the social sciences. Vriend (2000) states that there are two levels of learning for computational agents: individual-level learning and population-level learning. An agent is said to employ individual-level learning when it learns from its own past experiences, and to employ population-level learning when it learns from other agents. It is assumed that these two forms of learning play roles on a farmer's technology improvement in this model: a farmer's technology advances after he or she or the neighbors suffer failures in delivering eligible wheat. Such logic stems from the view that accumulated experiences can improve skills in on-farm production processes. The technology evolution of k is defined as,

$$k_j^T = k_j^{T-1} - D_{ji}\omega_1 \sum_{i=1}^{n} \frac{D_{1i}^T}{d(i,j)+1} \tag{4-3}$$

Where $T=1, 2, 3…N$, i or $j=1, 2, 3…n$, and $\omega_1 > 0$. $D_{1i}^T =1$ if the delivery of farmer i was detected within the year T; otherwise, $D_{1i}^T =0$.

4.4.3 Primary Elevator Behavior

There is one primary elevator operating in this basic simulation model. The handling procedures are similar to those described in Chapter 3. For example, it is assumed that the primary elevator

calls for CWRS from farmers 9 times each year and subsequently delivers collected wheat to the primary elevator 9 times each year. Movement of grain through the handling and transportation system is accompanied by documentation and with samples taken and retained at every link in the supply chain where accountability shifts from one party to another. If there is bin contamination or railcar contamination detected, traceability mechanisms will be activated to identify the contamination source. When there are detected farmer's misrepresented deliveries, the primary elevator is responsible for finding alternative markets for them. Of course, farmers with those delivers will be paid discounted prices.

As a key component of the primary elevator's risk mitigation long-run behavior, testing both on trucks at test point 1 and on elevator bins at test point 2, is driven by the pursuit of efficiency. It is assumed that the primary elevator's testing strategy choices are not entirely deterministic and predictable, but may be limited by bounded rationality. Moreover, there are random perturbations in the environment. The presence of perturbations implies that the evolutionary dynamic in testing strategies never settles down completely but is always in flux instead.

Due to the assumed heterogeneity of the farmer misrepresentation performance, it may be not efficient to homogenously distribute tests among farmers over time (Ge et al., 2011, 2012). A farmer with a higher probability of misrepresentation is optimally given a tighter test regimen than a farmer with a lower probability of misrepresentation, where the probability of misrepresentation by a farmer is calculated according to the perceived farmer's performance in the delivery history.

This simulation assumes that a farmer randomly misrepresents the deliveries with a predetermined misrepresented rate over a year. Risk control efforts and technology for a farmer evolves from one year to the next, meaning that the misrepresentation probability changes from year to year. To compensate, the primary elevator handlers in the model reset the test rate for all farmers at the beginning of each year. From the perspective of the elevator, a farmer's delivery performance should be considered when designing a testing strategy for that farmer. A farmer with misrepresentation in the delivery history will be offered a higher testing rate than another farmer with no misrepresentation. The more the misrepresented deliveries a farmer delivered in the past, the higher the test intensity one will face at the first delivery within a year.

Since handlers initially have little information about an individual farmer's probability of misrepresentation, handlers will try to establish a risk indicator system between farmers and themselves. Such a system must approximate the level of misrepresentation risk for a farmer. Obviously, this can only be developed by perceiving the performance of each farmer through delivery history. Such information accumulation takes time and is costly.

Due to farmer behavioral evolution, the perception of their misrepresentation probability involves information value decay over time. Perceptions far from the current period may only weakly indicate a farmer's current misrepresentation status. An exponential weighted moving average (EWMA)[13] of misrepresentation rate over the whole delivery history is used as a proxy for a farmer reputation and is arguable more accurate than a simple average of misrepresentation rate over any period of time. When using EWMA, weighting for each older data point decreases exponentially. In this case, with a given degree of weighting decrease equals 0.222, EWMA gives significantly more weights to recent perceptions. For example, the weighting factors from past 1 to 8 years are set at 0.222, 0.178, 0.134, 0.105, 0.081, 0.063, 0.049 and 0.038, and the total weight for the past 8 years data is 0.866.

In the early years of the simulation, random testing dominates the testing strategy because there is limited information about individual misrepresentation. After more information has been embedded in the simulated testing strategy, testing gradually concentrates on farmers with a history of problems. The test rate for the first delivery in the first year is initialized due to a lack of information. From the second year of the simulation, the test rate for a farmer's first delivery within a year ($T+1$) (i.e. the $(9T+1)^{\text{th}}$ delivery) is,

$$\beta_j^{9T+1} = \phi_1 \vec{\alpha}_f^{9T} + \phi_2 \vec{\alpha}_j^{9T} \tag{4-4}$$

where $T=1, 2, 3\ldots N$, $j=1, 2, 3\ldots n$, ϕ_1 and ϕ_2 are constants to be determined through parameter optimization, $\vec{\alpha}_f$ is the exponential weighted moving average of the general misrepresentation

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[13] Exponential weighted moving average applies weighting factors which decrease exponentially. The weighting for each older data point decreases exponentially but never reaches zero, giving much more importance to recent observations while still not discarding older observations entirely. Please refer to Appendix D for more information about EWMA.

rate of all n farmers in the simulation over the past years, and $\vec{\alpha}_j$ is the exponential weighted moving average of individual farmer j's misrepresentation rate over the past years[14].

This specification means that testing strategies are sensitive to a farmer's misrepresentation conditions over the past years. If the farmer's misrepresentation situation is serious on a continuous basis, the offered test rates will be greater, preventing eligible wheat from contamination by undesirable wheat. Alternatively, if misrepresentation rarely occurs, the test rate will be maintained at a low level, reducing the testing costs without compromising test efficiency. Finally, the test rates offered to farmers in the model are heterogeneous, and farmers with different performances in their delivery histories will be given different test rates.

After the first delivery in a given year, the primary elevator handlers adjust their test rate from delivery to delivery based on new information such as truck misrepresentation and railcar misrepresentation conditions. Furthermore, if a farmer's delivery has been tested or traced sometime during the year but is proven eligible, the remaining deliveries in the year will not be tested. If the farmer's delivery is proven to be misrepresented, then all of that farmer's deliveries will be tested for the rest of that year. Such a strategy is founded on the assumption that a farmer's production is identical within a year as well as the assumption that the test precision is perfect (Assumptions 1 and 4 in Section 4.4.1). This means:

$$\beta_j^{9(T-1)+g+1} = \begin{cases} 1\text{-if detected previously} \\ \\ 0\text{-if tested or traced previously but not detected} \end{cases} \tag{4-5}$$

where $T= 1, 2, 3…N$, $g= 1~8$.

If misrepresented deliveries are unloaded into primary elevator bins without detection, ineligible wheat will then commingle with eligible wheat and result in some level of contamination. Given the nature of testing in the simulated supply chain, railcars loaded from contaminated bins will be misrepresented. Misrepresented railcars may also be detected at the terminal elevator. When there are misrepresented railcars detected in a delivery, the primary elevator handlers will consider the need to maintain a certain level of testing intensity for those farmers who to that

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[14] The probability of misrepresentation for each farmer is initialized at the beginning of the simulation.

point have not been tested or traced. For farmers who have been tested or traced within the year, as mentioned above, they will be treated in two ways for the rest of in the remaining time left in the year, they will be tested or will be left alone. From the second delivery within a given year, all untested or untraced farmers will face testing as defined,

$$\beta_i^{9(T-1)+g+1} = D^{9(T-1)+g} (\varphi_1 \beta_i^{9(T-1)+g} + \varphi_2 \alpha_{tr}^{9(T-1)+g})(1-\theta_1^{9(T-1)+g})(1-\theta_2^{9(T-1)+g}) \tag{4-6}$$

where $T=1, 2, 3\ldots N$, i or $j=1, 2, 3\ldots n$, $g=1\sim 8$, φ_1 and φ_2 are constants, α_{tr} is the perceived misrepresentation rate of farmers through tracing, and θ_1 is the probability that a farmer's misrepresented delivery is identified through bin tracing, while θ_2 is the probability that a farmer's misrepresented delivery is identified through railcar tracing. In fact, θ_1 just equals the primary elevator's bin test rate. Just as shown in Chapter 3, θ_2 is no less than the terminal elevator's test rate for railcars. Thus, at the gth delivery within the year T, if there are no misrepresented railcars, $D^{9(T-1)+g} = 0$; otherwise, $D^{9(T-1)+g} = 1$.

As discussed in Section 3.3.6, if the terminal elevator does not perform complete testing on railcars, handler testing efforts are affected by moral hazard which lowers their incentives for testing. If there are no detected misrepresented railcars for a specific delivery, the primary elevator handlers will regard the current testing strategy as appropriate, although there may be some farmer misrepresented deliveries left undetected. In this context, they will only test the farmers who were revealed to have misrepresented within the year and will not test other farmers' deliveries until misrepresented railcars are detected. If there are misrepresented railcars detected at the terminal elevator sometime in a year, from that moment on, all untested or untraced farmers will be subject to more intensive testing. The intensity of the new tests is determined by anticipation about undetected misrepresented trucks. The anticipation is based on information such as the primary elevator's previous test rate for bins, the terminal elevator's prior test rate for railcars, as well as the misrepresentation rate of railcars at the terminal elevator. The level of this new test rate allows flexibility around potential costs and potential benefits from using alternative testing strategies.

The intensity of bin and railcar testing affects anticipation on undetected misrepresented trucks. If the test rate on primary elevator bins or railcars is high, there will be less contamination left

undetected and fewer misrepresented trucks left untraced. In the simulation, when there are contaminated bins or railcars detected, there will be an economic incentive to activate the traceability mechanism. By referring to delivery documents and testing retention samples, handlers can identify the source of contamination with low traceability costs. Here, the potential penalty amount collected from identified offenders is much greater than traceability costs.

Before loading wheat into railcars, the primary elevator is allowed to test some bins to monitor if there is a contamination problem. For the adjustment of the test rate at the bin, more information is available for consideration. Not only is information available about the truck and railcar misrepresentation in the previous delivery, but the general test rate on farmers and detected farmer's misrepresentation for the current delivery affects handlers' bin testing strategy. For example, if most of a farmer's deliveries were tested and there are few misrepresentations, the overall risk of bin contamination will be small and thus a lower test rate on bins will be the best response. So for the first delivery within year T, the primary elevator's test rates for bins are defined as:

$$\beta_{bi}^{9T+1} = (\mu_1 \vec{\alpha}_f^{9T} + \mu_2 \alpha_f^{9T+1} + \mu_3 P_i^{9T+1})(1 - \gamma_i^{9T+1}) \tag{4-7}$$

where β_{bi} is the test rate for bin i, μ_1 and μ_2 are constants, $\vec{\alpha}_f$ is an exponential weighted moving average of the perceived misrepresentation rates for all farmers over the past years, α_f is a variable reflecting the general misrepresentation rate of all farmers, γ_i is the ratio of deliveries tested before unloading into the bin i, and P_i represents the sum of perceived misrepresentation probabilities of farmers whose deliveries are unloaded in bin i without being tested. The value of P_i can indicate the magnitude of the contamination risk of bin i.

After taking into account this updated information, the handlers can adjust their bin test strategies more effectively to meet the specific situation at each first delivery. Testing is distributed heterogeneously among bins, whereby a bin believed to have high contamination risk will be tested more than a bin believed to possess low contamination risk.

The changes in test rates for farmers influence bin testing strategy. The higher the test rate on farmer delivery, the lower the primary bin test rate. At any time, if all the farmers' deliveries

were tested before being unloaded into bins, misrepresented ones would all be detected and thus all wheat entering bins would be eligible. Under such a condition, there will be no need to test any bin under the assumption of no other contamination sources other than farmer's misrepresentation during wheat handling (Assumption 3 in 4.4.1).

In addition, railcar test rates and results from previous deliveries affect these bin test rates. A high prior railcar test rate implies a low current bin test rate. If all railcars were tested at the terminal elevator in the nth delivery that year, all the misrepresented railcars will be detected and all the contaminated primary elevator bins will be identified through tracing. Through testing retained samples, the primary elevator handlers will finally find all farmers who misrepresented their deliveries. Those farmers who were detected will be continuously tested in the subsequent deliveries within the year. In such a situation, wheat entering primary elevator bins will be acceptable and thus bin testing becomes unnecessary from the nth delivery in that year. If there is no detected railcar contamination at the terminal, the handlers will test no bins at the next delivery until there is detected railcar contamination. Based on this logic, from the second delivery for each farmer, there are adjustments on the bin test necessary to meet this new environment. The model defines the bin test rate from the second delivery as:

$$\beta_{bi}^{9(T-1)+g+1} = D^{9(T-1)+g}(\upsilon_1\alpha_f^{9(T-1)+g+1} + \upsilon_2 P_i^{9(T-1)+g+1})(1-\theta_2^{9(T-1)+g})(1-\gamma_i^{9(T-1)+g+1}) \qquad (4\text{-}8)$$

where $T= 1, 2, 3…N$, $g= 1\sim8$, υ_1 and υ_2 are constants, β_{bi} is the test rate for bin i, θ_2 is the probability that a misrepresented delivery can be identified by traceability after detection in the railcar, γ_i is the ratio of deliveries which were tested before unloading into the bin i, and D is a dummy variable with the following interpretation: if there are detected contaminated railcars at the terminal elevator at the previous delivery in year T, $D=1$; otherwise, $D=0$.

Based on equation 4-8, the bin test rate is positively related to contamination risks to which the bin is exposed, and negatively related with the truck test rate at current delivery and railcar test rate at last delivery. Specifically, if there is no detected railcar contamination at the terminal, then the handlers would not prefer to test any bin at the next delivery until railcar contamination is detected. For a situation where the farmer's misrepresentation situation is a problem but the truck tests are not complete, the bin test acts as a buffer against risks to avoid further quality loss.

4.4.4 Terminal Elevator Behavior

The terminal elevator handlers receive wheat deliveries from the primary elevator and test deliveries before unloading them. It is assumed that testing will be done randomly on railcars with a specified probability. Any delivery in which undesirable classes of wheat exceeds the specified tolerance will be downgraded to feed. In this portion of the model, there is a trade-off between the terminal elevator's test rate for railcars and the penalty imposed on the primary elevator if misrepresented railcars are detected. Of course, the terminal elevator's test rate and test results will influence the adjustment of the primary elevator's handling strategies. However, all other factors involved with the terminal elevator's wheat handling are beyond the scope of the simulation model.

4.4.5 Cost Functions

In the simulation, attention must be paid to changes in the risk management costs of each supply chain participant. The cost levels measured through time provide a foundation for comparing efficiencies between different testing strategies. And only variable costs are considered in this research. Thus, a farmer's cost in this sense includes revenue (or price) loss due to misrepresentation plus a contamination penalty:

$$C_j^T = (p_1 - p_0 + f_j)q_j^T \tag{4-9}$$

where p_1 is the eligible wheat price provided by the primary elevator, p_0 is the feed price, f_j is the fine for per unit of misrepresented wheat, and q_j is the volume of discovered misrepresented wheat.

The primary elevator's handling cost function is composed of the following components, which translate into equation (4-10):

$$\left\{ \begin{array}{l} \text{+sampling and sample retention cost} \\ \text{+test costs (testing and tracing)} \\ \text{+ losses due to bin contamination} \\ \text{- retrieved losses from testing and tracing} \\ \text{ (collected penalty)} \end{array} \right.$$

$$C_p^T = c_1 S_1^T + c_2 S_2^T + c_1 S_3^T + c_4 S_4^T + (p_2 - p_0)Q_1^T + (p_2 - p_0 + f_t)Q_2^T - \sum_{j=1}^{n} C_j^T \qquad \text{(4-10)}$$

Where c_1 is the unit sample retention cost, c_2 is the unit sample test cost of each truck delivery, c_3 is the test cost of a bin sample, S_1 is the number of retained samples of farmer truck deliveries, S_2 is the number of tested truck samples, S_3 is the number of retained samples of bins, S_4 is the number of tested bin samples, p_2 is the eligible wheat price provided by the terminal elevator, Q_1 is the total amount of contaminated wheat detected via bin testing, Q_2 represents the total amount of contaminated wheat detected at railcar testing, and f_t is the monetary penalty per unit volume for railcar misrepresentation.

4.4.6 Model Control Diagram

Farmer behavior is influenced by both primary elevator handling strategies and the behavior of the neighbor. The primary elevator handlers actively respond to the terminal handling strategy and perceived misrepresentation situation and subsequently adjust their handling strategies to meet changing conditions.

Agents in the model interact with each other and the system is dynamic and evolutionary. Existing literature attempts to generate insights through a static model of homogenous agents. Unfortunately, the gap between a complex decision-making environment and these models is significant because those models are applied in a static situation with simplistic assumptions. An agent-based model takes into account the inherent system dynamics as realistically as possible in order to help address the limitations of static models. While the idea of using software agents for understanding, modeling and operating the dynamic of the supply chain is novel, they can provide valuable information for the transition from static supply chain modeling to dynamic supply chain modeling.

Figure 4.2 shows a simple control diagram of simulation. The thick lines indicate the main stream of the handling system dynamics while the dotted lines indicate the interactions between participants in the systematic environment. A more detailed description of the control diagram is in Appendix E.
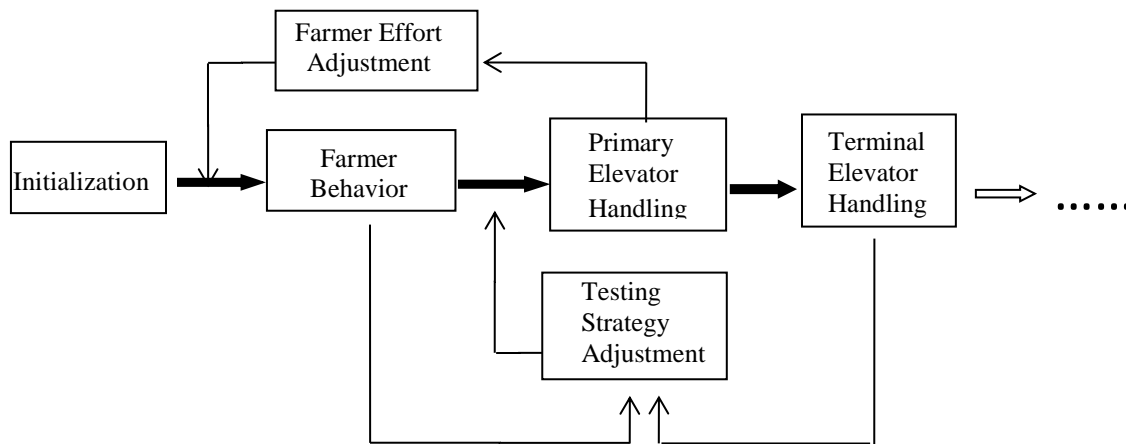
Figure 4.2 Simulation Control Diagram

4.5 Parameters Variables and Data

Variables as well as their assumed values in the simulation are listed below:

Table 4. 1 Parameters, Variables and Their Values

Variables	Values
Years for delivery (N)	30
Farmer number (n)	48
Initial risk control effort distribution	$U[0.15, 1]$[15]
Initial technology index distribution	$U[1.8, 2.0]$[16]
Exogenous parameter η in equation 4-1	10
Misrepresentation probability distribution	$U[0.0039, 0.4724]$
Mean of misrepresentation probability	0.10[17]
Production capacity per farmer	360 tonnes
Yearly deliveries for a farmer	9 (1 truck each time)

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[15] Here 0 is no effort to control risk, and 1 is a full effort to control risk, which makes a farmer's misrepresentation probability approach zero if the farmer risk control technology is also high.
[16] The highest risk control technology a farmer can approach is 1. As defined previously, a lower value in technology proxy indicates a higher level of technology.
[17] Refer to Appendix F for the calculation of the mean of initial misrepresentation probability.

Yearly delivery for the primary elevator	9
Total deliveries for a farmer or the primary elevator	270
Truck loading capacity	40 tonnes
Cost of truck sample test with 100% accuracy	$400/sample
Primary elevator bins used	8
Bin capacity	240 tonnes
Cost of bin sample test with 100% accuracy	$600/sample
Railcars used	32
Railcar capacity	60tonnes
Price of eligible No.1 CWRS 13.5 protein	$10/bushel
Price of feed	$6/bushel
Initial primary test rate for farmers	100%
Initial primary test rate for bins	0%
Railcar test rate	80%
Test accuracy	100%
Effort cost of the farmer	$500/unit[18]

Source: Author

If detected, contaminated wheat in bins and railcars is downgraded to feed wheat due to the high level of undesirable components in it.[19] For misrepresenting farmers detected at the truck test point, there is no additional penalty imposed on them other than a price decrease. For any misrepresented farmer detected with the tracing procedure, he or she will suffer greater penalties due to the contamination losses resulting from misrepresentation.

In this study, supply chain participants share the contamination losses in the following manner. Generally, the farmer with misrepresentation absorbs 40% of the total contamination loss (after the reduction of price loss undertaken by the farmer), while the remaining portion (60%) of the

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[18] It is assumed that farmer's risk control effort, e.g. time, labour, carefulness, and resource allocation and utilization, can be measured by unit and each unit is convertible to a monetary equivalent.

[19] In this study, at most six deliveries share one bin. If one of them is misrepresented, the bin will be commingled with 16.7% undesired wheat at a minimum. According to the CGC (2011) (Official Grain Grading), if a Canadian Western wheat variety contains undesired varieties at over 5%, the wheat would be downgraded to feed.

loss is absorbed by the primary elevator[20]. Based on the Canadian Grain Act (2012), the maximum value of the penalty for an individual farmer in a delivery is eighteen thousand dollars. If the calculated penalty amount for a farmer exceeds such a maximum value, the farmer will only pay eighteen thousand dollars and the primary elevator will bear the rest.

Parameters defining the evolution of farmer's efforts or technology are given starting values as listed in Table 4.2. These values determine the pace of risk control effort and technology defined in equations 4-2 and 4-3. Although both capturing and testing arouse farmer efforts, deterrence stemming from the former (with marginal effect of λ_1) is much greater that from the latter (with marginal effect λ_2).

Table 4.2 Parameters Involved in the Evolution of Efforts or Technology

Parameters	Application	Values
λ_1	Risk Control Effort	0.005
λ_2	Risk Control Effort	0.001
λ_3	Risk Control Effort	0.001
ω_1	Technology	0.01

Source: Author

Note: The values of λ_1, λ_2 and λ_3 help determine the pace of risk effort for farmers. In turn, the value of ω_1 helps determine the pace of technology improvement that results from experience and learning.

To start, a random search was used for testing strategy parameter optimization. In MATLAB®, a routine was designed to check a number of combinations of parameters involved in developing testing strategies to identify the best. Each combination of parameter values is simulated for 100 iterations to collect objective values (handling costs). The minimum objective value from this set

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[20] There are no laws and regulations to control the exact share of damage a related party should bear in the case of contamination. The eligibility declaration (CGC, 2012) (Appendix A) states a producer "will be liable to the Grain Handling Company and/or Grain Buyer for all claims, damages, losses and costs (including legal fees) that may result from such false and/or negligent representation", while the Canadian Grain Act (2012) clarifies the primary elevator "shall exercise reasonable care and diligence to prevent any grain in the elevator from suffering damage or from deteriorating or going out of condition". Allowing for this, it is assumed that the primary elevator and the farmer commonly share contamination losses in this case.

yields the best parameter values for shaping the most efficient testing strategies across time. These parameters and iterated "best" values are shown in Table 2.

Table 4.3 Parameters Involved in Handling Strategy Development
and Their Best Values

Parameters	Application	Values
ϕ_1	Testing at point 1 for 1st delivery	30.0
ϕ_2	Testing at point 1 for 1st delivery	60.0
φ_1	Testing at point 1 for deliveries after the 1st	8.0
φ_2	Testing at point 1 for deliveries after the 1st	16.0
μ_1	Testing at point 2 for 1st delivery	30.0
μ_2	Testing at point 2 for 1st delivery	75.0
μ_3	Testing at point 2 for 1st delivery	90.0
ν_1	Testing at point 2 for deliveries after the 1st	8.0
ν_2	Testing at point 2 for deliveries after the 1st	20.0

Source: Author
Note: The values of ϕ and φ are associated with developing the test rates for farmers. The values of μ and ν are associated with developing the primary elevator's test rate for bins.

There is some intuition in these optimal parameter values. We can see that to pursue testing efficiency, handlers use perceived farmers' misrepresentation information in different ways based on the characteristics of information. To highlight the heterogeneity inherent in farmers' behavior, handlers give more weight to individual information (φ_2, μ_3 and ν_2) than to general information (ϕ_1, μ_1, μ_2 and ν_1) when designing testing strategies. In the meantime, to allow for the variation of misrepresentation probability across time, handlers consider newly perceived information in the current year (φ_2 and μ_2) as more important than old information perceived in the past years (φ_1 and μ_1).

4.6 Simulation Method – MATLAB[®]

As a mathematical tool and a high-level programming language extensively used to solve engineering and scientific problems, MATLAB[®] is also becoming a standard software tool used

by economists to solve a large array of numerical optimization problems (Nolan et al., 2009). It integrates computation, visualization, and programming in an easy-to-use environment where problem and solutions are expressed in familiar mathematical notation (MathWorks, 2001).

The MATLAB® language supports the vector and matrix operations that are fundamental to for large-scale agent-based modeling and testing. Specifically, the sparse matrix functions allow storage and manipulation of large matrices in memory. This function helps manage and operate with the tremendous amounts of data generated in this simulation. MATLAB® enables one to perform computationally intensive tasks faster than with traditional programming languages such as C, C++, and Fortran. As a result, one line of MATLAB® code can often replace several lines of C or C++ code. This allows the researcher to focus on applications rather than on programming details. At the same time, MATLAB® provides all the features of a traditional programming language, including arithmetic operators, flow control, data structures, data, input/output, object-oriented programming, and debugging features. These features provide a block of diagram tools for modeling, simulating and prototyping dynamical systems.

4.7   Simulation and Results

All simulation results discussed here were obtained using 500 iterations of the simulation model[21]. Due to random elements in the model, simulation results differ from one run to another, thus summarized or averaged results from multiple runs are more representative of system operation. The histograms summarize values for 500 model iterations and display how the handling system operates under the aforementioned predetermined rules governing participant behavior.

Farmers interact with the environment and their risk control effort and technology evolves across time. Each farmer's misrepresentation probability may dramatically change from the initial time to the end of the time. Figure 3(a) and 3(b) shows the distribution of farmer's actual misrepresentation rate at the initial and at the end year of delivery.

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[21] The Matlab code for this simulation is available upon request from the author.
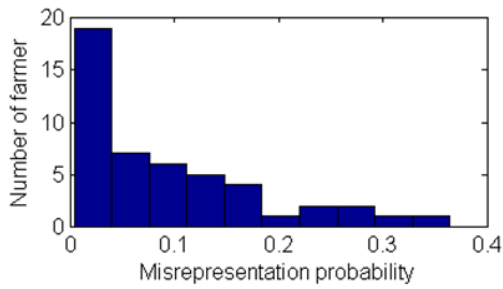
Figure 4.3(a) Distribution of Actual
Misrepresentation Probability in the Initial Time
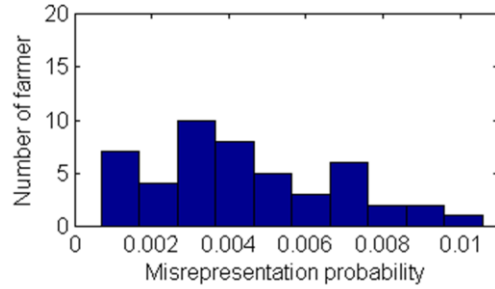
Figure 4.3(b) Distribution of Actual
Misrepresentation Probability in the 30th Year

Handlers rely on a moving average of perceptions to determine an individual farmer's misrepresentation status for any specific time period. The efficiency of testing greatly depends on how exactly the moving average misrepresentation probability can represent the actual misrepresentation probability a farmer applies in a specific year. The moving average function levels out the year to year misrepresentation fluctuations, meaning that testing strategy cannot overreact to any accidentally occurring misrepresentation. Generally, the robustness of the moving average grows with time and so does the efficiency of testing based on this misrepresentation risk indication system. To this end, Figure 4(b) shows the distribution of perceived farmer's misrepresentation probability at the 15th year of the simulation. Note how well it approximates the distribution of actual misrepresentation shown in Figure 4(a).
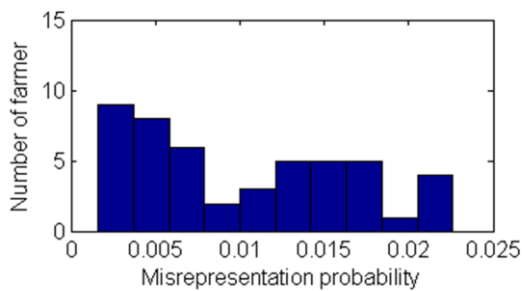
Figure 4.4(a) Distribution of Actual
Misrepresentation Probability in the 15th Year
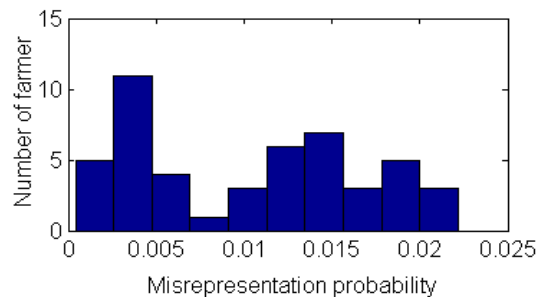
Figure 4.4(b) Distribution of Perceived
Misrepresentation Probability in the 15th Year

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Using the model to generate data for this supply chain, we start by showing how the simulation works with the truck testing procedure. Figure 4.5 shows the effects of the previously described test strategies on farmer deliveries over time (test point 1), while Figure 4.6 shows the test results: the number of misrepresented trucks detected in the simulation. Note that these figures do not include the tested or detected amounts in the traceability procedures, as these will be shown subsequently. Figure 4.5 indicates the testing intensity as it corresponds to the misrepresentation condition: when a farmer's misrepresentation situation is serious, it is efficient to test all or most of the first deliveries of farmers, and when farmers rarely misrepresent their deliveries, a low testing rate is more applicable for monitoring purposes.
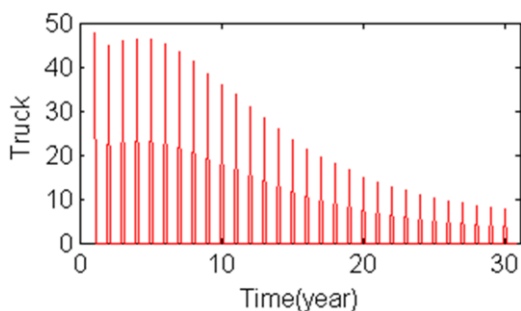
Figure 4.5 Number of Tested Trucks
Figure 4.6 Number of Detected Trucks
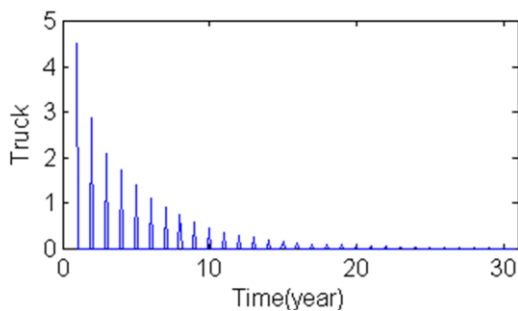
This simulation assumes each farmer's deliveries are consistent through a year and there is no cheating behavior (Assumption 5 in Section 4.4.1). If a farmer knows his or her wheat production is ineligible, he or she will not deliver it again at the call for CWRS. Farmers who were tested but proven non-misrepresented will not be tested again this year. After all misrepresented deliveries are identified at sometime in a given year, there is no misrepresentation from that time on in the year.

Actually, as shall be shown later, almost all misrepresented deliveries are in fact identified just after every first delivery is finished in a year. That explains why the tested number of trucks (and also the tested number of bins subsequently) mostly drops to zero from the second delivery in each year. When the farmers' misrepresentation situation is serious (in the first few years shown in the Figure 4.5), the testing strategy used in the simulation model tests all or most of the first deliveries of farmers. As a result, a large volume of misrepresented wheat never enters the grain handling system and thus extensive contamination is avoided. Conversely, when the farmer's

misrepresentation was not that severe, there were fewer trucks tested in the first delivery within a given year. For example, as shown in Figure 4.5, after the 15th year, less than half of 48 trucks in the sample were tested in the first delivery.

In the model, handlers receive feedback from the truck test, the primary bin test and then the terminal test, adjusting its testing strategy to meet the eventual misrepresentation situation. It is suggested for the most part that not all trucks are tested at the first delivery within a given year. Thus, there exists some probability that undetected and misrepresented wheat enters the primary elevator and results in contamination. The goal of the bin test is to detect contaminated wheat early enough to prevent it from moving to the terminal elevator.

Figure 4.7 shows the bin testing and results over time (testing point 2 in the supply chain) and Figure 4.8 shows the traceability enacted by detected bin contaminations. In Figure 4.7, the number of tested bins (red lines) and the number of bins found to be contaminated (blue lines) for each delivery are indicated. The structure of the simulation means that bin tests only occur in the mid to late time frame in the delivery history. This is due to the fact that all or most of misrepresented trucks are detected before unloading in the first 10 years, minimizing the need for a bin test during this period. Even if there is bin testing, the testing intensity is in low levels. One reason is that testing at the previous test point has prevented most of misrepresented wheat from entering primary elevator bins and there are few contaminations occurring at the bin level. In this situation, intensive bin testing is not efficient. The other reason is that this model excludes any potential penalty from the terminal elevator contamination resulting from misrepresented railcars, lowering the primary elevator handlers' incentive to test bins.
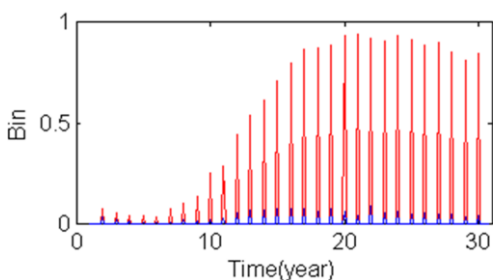
Figure 4.7 Number of Tested Bins and Number of Proven Contaminated
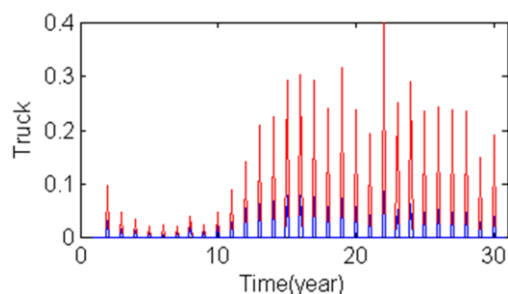
Figure 4.8 Number of Tested Farmers and Number of Detected Farmers at the Tracing

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If there is bin testing necessary in a year, it mostly occurred in the first delivery of the year. The reason is the same as mentioned before: almost all misrepresented deliveries are identified just after the first delivery is finished. So there is almost no need to take a bin test from the second delivery within a year. Any time when there are contaminated bins detected, there is an economic incentive to trigger out traceability mechanism in each of those contamination cases (traceability 1). At given testing cost for samples and penalty level for offences, the potential penalty amount collected from identified offenders is much greater than traceability costs in each case. By testing the reserved truck samples, the primary elevator traces the particular farmer who misrepresented the delivery. Figure 4.8 shows the traced (red line) and detected (blue line) number of trucks. Mostly, but not all the retention samples related to a contaminated bin need to be tested in the tracing procedure. The reason is that some trucks get tested and identified before unloading into the bin, so there is no need to test them again. It has been assumed that normally, each bin contains 6 trucks of wheat, so sometimes the average number of traced trucks is less than 6 for 1 contaminated bin.

To pursue testing efficiency, the handlers testing strategies are adjusted according to misrepresentation conditions. In some years, the truck testing cannot be complete. Thus it is possible that undetected misrepresented deliveries are unloaded into primary bins and are commingled with other eligible wheat. If contaminated bins are left undetected, wheat from those bins will then be loaded in railcars and delivered to the terminal elevator. Those railcars loaded with contaminated wheat will be misrepresented at the terminal elevator and exposed to terminal testing.

As the final stage of the supply chain, Figure 4.9 shows the railcar test result at the terminal elevator (test point 3). Ultimately, not all the misrepresented railcars were detected because the terminal elevator's test rate for railcars in the simulation is fixed at 0.8. Thus, the number of detected railcars is less than the actual number of misrepresented railcars.
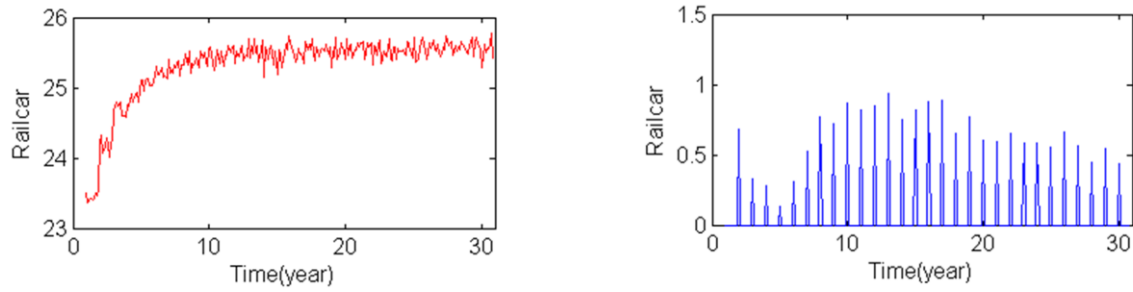
Figure 4.9 Number of Tested Railcars (Left) and Number of Detected Railcars (Right)

Once a misrepresented railcar is detected, a traceability mechanism will be enacted to find the offenders along the upstream of the supply chain (called traceability 2). By referring to the railcar loading records, the handlers can trace the corresponding contaminated bin from which the misrepresented railcar was loaded. Any detected misrepresented railcar provides enough information to target a contaminated bin from which the railcar was loaded. In most of the simulations, the probability of successfully tracing a contaminated bin is greater than the railcar test rate. For example, if the railcar test rate is 0.8, the probability of successfully tracing a contaminated bin is about 0.998.[22] This is the reason why not all the misrepresented railcars could be detected at the terminal elevator, but almost all the contaminated bins were traced and found at the first delivery each year.

In the simulated supply chain, each identified misrepresented railcar corresponds to a contaminated bin and each contaminated bin indicates the need for sample tests for farmers whose deliveries were unloaded in this bin. Finally, after targeting the contaminated bin, the handlers can trace the misrepresented farmers through related truck sample testing.

Figure 4.10 shows the number of traced bins associated with the traceability procedure. Figure 4.11 shows the associated number of test deliveries and the number of detected farmers. The simulation shows that a well arranged tracing procedure can save costs for the wheat handlers. To start, it is not necessary to test each truck sample related to a contaminated bin. If a farmer

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[22] Assumed that there are a bins and each bin can load b railcars. If h railcars are randomly tested at the terminal elevator, a contaminated bin will be identified with a probability $(1 - \dfrac{C_{(a-1)b}^{h}}{C_{ab}^{h}})$.

has proven to have honestly represented sometime within a year, either through testing or tracing, then retention samples of his or her deliveries should not be tested again in tracing. Only truck samples that have never been tested or traced within the year needed to be tested to identify the offender. As figure 4.11 shows, the number of traced farmers is mostly less than the total number of farmers whose deliveries were unloaded in the contaminated bins in each delivery. In the example, at the first delivery in the 8th year, there are only 2 farmers in average who are traced to identify the offender for one contaminated bin.
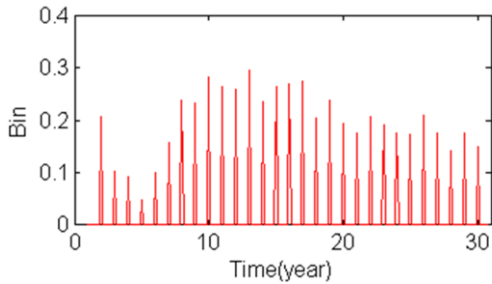
Figure 4.10 Number of Traced Bins
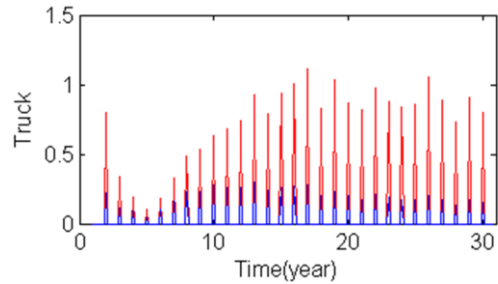
Figure 4.11 Number of Tested and Detected Farmers

From the farmer perspective, Figures 4.12, 4.13 and 4.14 respectively illustrate the evolution of the farmer's average risk control effort, technology, and the resulting misrepresentation probability through the simulation.
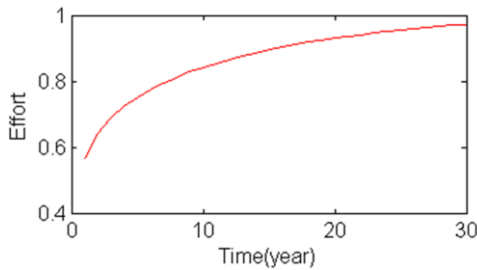
Figure 4.12 Farmer's Effort
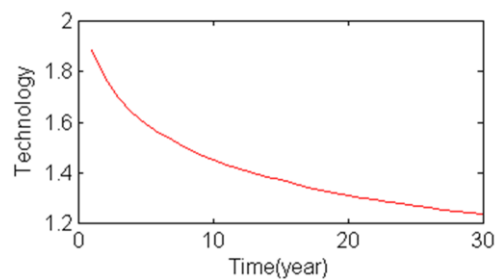
Figure 4.13 Farmer's Technology Index

Generally speaking, it is found that farmer risk control effort increases over time. The motivation of testing and penalty dominates the evolution of effort and helps to reduce moral hazard issues over time. In this case, the value of effort is initialized at a medium level 0.57 and ends at a high

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level 0.97, where 0 is no effort and 1 is a full effort. Note as well that the technology improves over time while the value in technology proxy goes down gradually, with the technology spanning from 1.88 to 1.24 units.

Accordingly, shown in Figure 4.14, the farmer's misrepresentation rate goes down from a relatively high value of 0.095 to a final of value 0.005. This means the farmers in the simulation are being detected when they misrepresent and corrective steps enacted within the supply chain to trace and penalize them seem to push incentives in the correct direction.
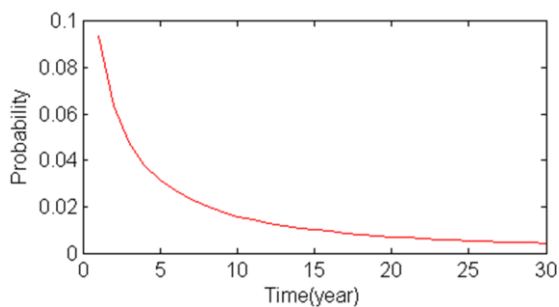
Figure 4.14 Farmer's Misrepresentation Probability

Next, there are relative costs for supply chain participants. These costs include the primary elevator's handling costs, the farmer's economic loss from misrepresentation, and the farmer's costs to undertake risk control efforts. Figure 4.15 shows the primary elevator's handling costs as they evolve over time. In the simulation, higher handling costs occurred in those delivery periods when there were serious misrepresentations which incurred high test costs. Handling costs were also high in those periods when contaminations were severe. Although in the contamination cases all the misrepresented trucks resulting in contaminations were ultimately traced, the misrepresentations already resulted in contamination and thus revenue reductions in the system. And as was assumed, although the detected offenders were able to cover part of their ultimate revenue shortfall, the primary elevator also shared some of this shortfall. So any bin contamination adds costs for the primary elevator handlers.

Figure 4.16 shows the collective farmer's economic loss from misrepresentation. If a farmer's misrepresented delivery is detected at an early stage (test point 1), he only suffers a price drop. If a misrepresented delivery is identified at a later stage (i.e. test point 2 or test point 3), loss will be

greater because the farmer suffers both a price reduction and a contamination penalty. Figure 4.17 tracks the cost of farmer's efforts over time. In the simulation it is assumed that cost for per unit effort is fixed, so the farmer's effort costs linearly increase with efforts. Figure 4.18 shows the summation of the listed three types of costs over time, and illustrates the total costs of maintaining a trustworthy grain supply chain for the participants involved in this simulation.
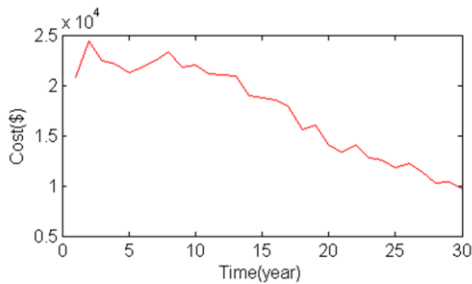
Figure 4.15 Elevator's Handling Costs
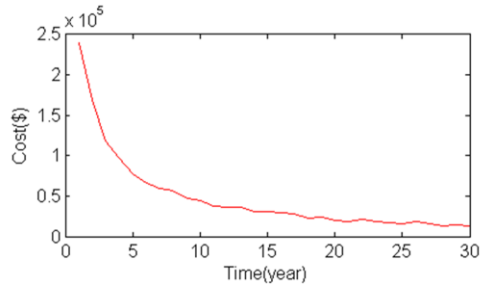
Figure 4.16 Farmers' Loss from Misrepresentation
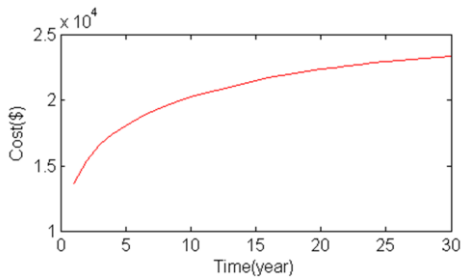
Figure 4.17 Farmer's Effort Costs
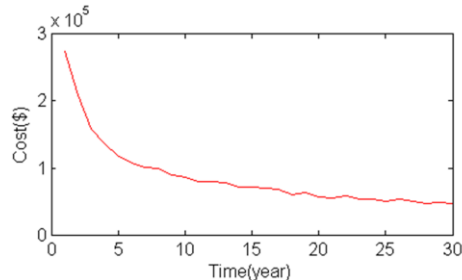
Figure 4.18 Total Costs

4.8 Cost Analysis

In order to compare the simulated "best" testing regime against reasonable alternative regimes, relative costs generated by the simulation results are compared with costs generated using alternative test strategies that may offer potential efficiencies. The alternatives considered for comparison are:

Model 1 (base model): Test strategies used in the above simulation. As shown previously, there are 3 testing points along the handling system and the testing strategies at the testing point 1 and point 2 are conditioned on perceived information (testing at the point 3 is fixed at 80%). Those strategies are continuously adjusted according to updated farmer's misrepresentation data over time.

Model 2 (truck 100%): 100% testing of trucks before unloading. This model has two possibilities to add efficiency to wheat handling: First, there are no other strategies better than this one to ensure grain consistency. This testing strategy can exclude any misrepresented deliveries from entering the supply chain; second, there is no need to take any bin testing. Whether this model is better than Model 1 depends on whether benefits from avoided contamination and bin testing cost savings can cover the increase in costs for truck testing.

Model 3 (bin 100%): 0% testing of trucks before unloading, but 100% testing of the elevator bins before loading. Compared with Model 1, this model enjoys advantages. First, handlers can save costs of truck testing. As shown in Model 1, truck testing costs significantly more than the bin test costs in Model 1. Next, contamination sources are all identified at bin test point and there is no contaminated wheat moving farther to the terminal elevator. Can those benefits surpass the bin contamination losses resulting from the absence of truck testing? Model 3 can answer this question.

Model 4 (truck 50% plus bin 50%): 50% testing of trucks and 50% testing of bins. This strategy is a representative random testing without allowing for misrepresentation situations across time.

Model 5 (traceability only): There is no truck testing or bin testing but there is a full testing of railcars. Thus, the system relies solely on traceability to identify offenders in cases of contamination. Simulations in Model 1 shows most truck and bin tests catch nothing. If there is no testing at those test points, testing costs can be reduced. This model can provide a comparison as to whether these reduced testing costs lead to large contamination losses.

To produce large sample results, each model was run for 500 iterations to obtain cost values. The average values from the simulations are shown in Figure 4.19. To facilitate comparison, each cost value in Model 1 (the base model) is normalized to unity.

As expected, Model 1 (the base model) generates the lowest primary elevator handling costs. In contrast, no contamination occurs in Model 2 (truck 100%), but the testing cost is very high, raising the overall handling costs. And although Model 5 (traceability only) saves test costs, contamination loss is the highest among the models. It is also worth noting that high test costs and significant contamination losses occur in both Model 3 (bin 100%) and Model 4 (truck 50%, plus bin 50%). Interestingly, farmer losses from misrepresentation are lowest in Model 2 (truck 100%). This occurs because all the misrepresented deliveries are detected at an early stage of supply chain. If misrepresented wheat enters the handling system and moves farther along the chain, large contamination losses will ultimately result. This helps explain why farmers' losses are so high in Model 3 (bin 100%), Model 4 (truck 50% plus bin 50%) and Model 5 (traceability only). Finally, the difference between farmer's effort costs in the five models is not significant. However, Model 1 (base model) and Model 2 (truck 100%) enjoy generate lower farmer effort costs. This stems from the fact that in these scenarios, farmers suffer less misrepresentation losses, so their motivation to improve efforts are not as strong as in the other models. In summary, the aggregation of farmer and elevator costs in Model 1 (base model) is the lowest among all the models/scenarios, so it is concluded that from either the handlers' or a social welfare perspective, Model 1 represents the most efficient testing regime.
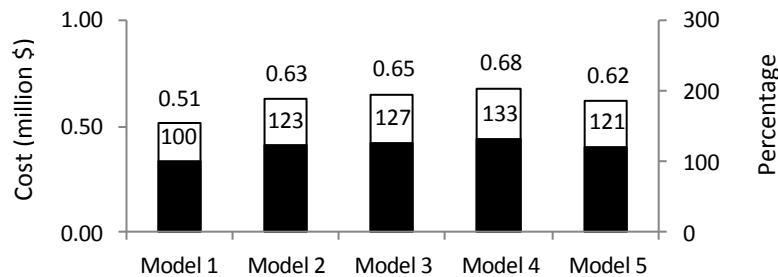
(a) Primary Elevator's Handling Costs
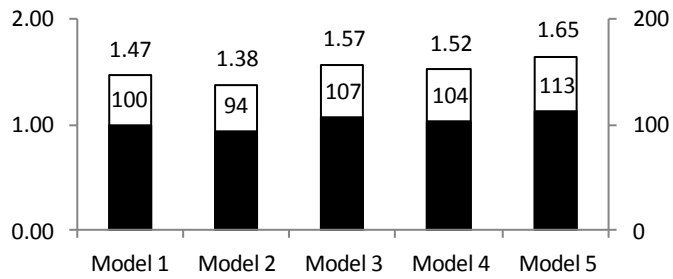
(b) Farmers' Losses from Misrepresentation
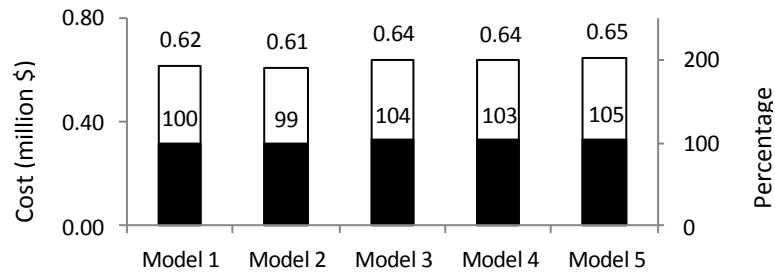
(c) Farmer's Effort Costs
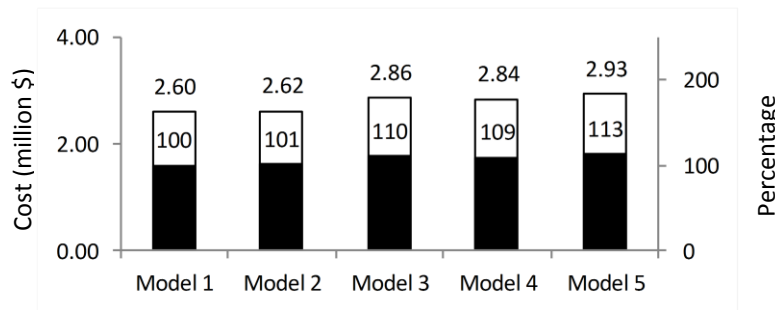
(d) Total Costs

Figure 4.19 Relative Costs in Different Models

4.9 Summary

Mirroring reality, in this chapter grain supply chain participants are represented as autonomous agents exhibiting a degree of heterogeneous behavior. The agents interact with each other as well

as with their operating environment via a set of heuristic rules governing their actions and decisions. The operation of a hypothetical grain handling system under VED including sampling, testing, misrepresentation, contamination and traceability is simulated from the individual farm level up through the supply chain to the elevator. Integrating information flow and feedback into decision-making allows the developed testing strategies to better coincide with different misrepresentation situations. These preliminary results suggest contamination testing strategies under VED will be more efficient when they can be continually adjusted with respect to testing location within this dynamic operational environment.

Simulation results indicate the testing strategies are also very sensitive to the particular misrepresentation situation. When the farmer's misrepresentation condition is severe (here severe is assumed to be over a 2% misrepresentation rate), the simulation indicates that it is cost efficient to test all or most farmer's deliveries at the first delivery (at the truck stage) for each year. When the misrepresentation condition is less severe (0.005%-2% misrepresentation rate), testing intensity will need to shift from farmer's trucks to elevator bins to maintain cost efficiency.

The adoption of a traceability mechanism under VED in the agent based simulation contributes to the trust and cost efficiency of the overall handling system. Simulation results suggest that it is efficient to enact traceability when there are contaminated bins detected or misrepresented railcars detected. The main reason for this is that under the misrepresentation situation assumed in the simulation, the possible penalty from the offence is higher than traceability cost. A handling system operating under traceability has the potential to save the entire system much more than a system without traceability. Based on delivery documentation and retention samples, it is relatively straightforward to figure out tracing steps in order to swiftly identify where the contamination occurred. Traceability cost is low in each tracing case assumed here because only truck or bin samples related to detected contamination need to be tested. Furthermore, successful traceability gives a strong deterrence to misrepresentation behavior and thus helps motivates farmers to put more effort on controlling production risks, reducing potential moral hazard problems and further contributing to the risk and cost reduction of the supply chain system.

Moral hazard problems under VED add complexity to the development of handling strategies. Testing helps alleviate these moral hazard problems and the success of a handling regime even if tests cannot catch any misrepresentation. The aim of such testing is to create an incentive for farmers to put efforts into production activities to reduce the likelihood of misrepresentation. This is especially true if the testing is designed with a higher level of test intensity for those farmers who have a higher likelihood to misrepresent their deliveries than others. The effect of testing is to reduce moral hazard over time as participants react rationally to the costs of being tested. Under the defined regulations governing individual reactions in the simulation, the results show that cost efficient testing is possible for wheat handling under VED.

A grain handling system under VED with carefully considered testing strategies can mitigate contamination risks while keeping handling costs relatively low. As shown in the latter parts of the chapter, the simulation provides a foundation on which to compare testing strategies that may be thought useful in a specific operating environment or alternatively to evaluate the efficiency of a predetermined test strategy. Given the current policy environment, this research is timely and can provides input into potential unforeseen consequences of implementing VED within the grain supply chain.

In the simulation, the rules that govern participants' actions, decisions, and interactions with other agents are rested on specific assumptions regarding functional forms and parameter values. Any change in these rules can change the simulation results. The degree of rationality inherent in these forms and values determines the extent to which the simulated environment matches reality. Overall, the approach used in this study contributes to the methodology of risk forecasting and assessment under VED as well as moral hazard situations in modern agriculture.

CHAPTER 5

MODEL COMPARISONS: TESTING STRATEGIES

5.1 Introduction

Chapter 4 characterized a set of testing strategies for a handling system under VED with three test points in a supply chain. In fact, the handlers enjoy considerable freedom for selecting test points. This raises some other interesting questions: Can the efficiency of testing strategies be improved if fewer test points are chosen for testing? Can handling efficiency be ensured if it depends only on testing without traceability? What are the influences of an initial misrepresentation condition on developing testing strategies? We attempt to answer these questions as part of the study on developing better handling strategies under VED.

Analysis in Chapter 3 showed us that when test points are predetermined, various testing strategies could reduce contamination, but at possibly different costs to the system or to certain participants. To this end, the effects of different strategies on handling system costs are evaluated by examining simulation models with different combinations of test points under different levels of misrepresentation. Recall that the comparative simulation model in Chapter 4 used what were considered to be three logical test points in the wheat supply chain: (1) a truck test before unloading wheat into primary elevator bins (test point 1). (2) A primary elevator bin test done before loading wheat into railcars (test point 2). (3) A railcar test before loading wheat into the terminal elevator bins (test point 3). Due to this, there are two points where the traceability mechanism can be activated: (1) when there are contaminations detected at test point 2; and (2) when there are contaminations detected at test point 3. When developing these new models for comparison, it is firstly needed to decide which test points to use in each model and then develop appropriate testing and trace strategies for the predetermined test points in each model.

This thinking led to the development of the following five models. They are considered for this portion of the study because it is believed they represent the best variety of combinations of testing possibilities throughout each step of the wheat supply chain and offer the potential to contribute to wheat handling efficiency:

Model A (*truck, bin and railcar*): In this model, there are 3 test points - truck, bin and railcar. Samples for all truck deliveries are retained. If there is detected contamination at test point 2 or test point 3, traceability will be triggered. Note that this model is similar to the one developed in Chapter 4, but different assumptions on initial misrepresentation rates will be applied. In this manner, one can check whether testing strategies developed in Model 1 in Chapter 4 still work well under different misrepresentation conditions.

Model B (*truck and railcar*): In this model, there is a truck test (test point 1) and a railcar test (test point 3). If contamination is detected at test point 3, traceability will be triggered. Results from Chapter 4 suggested the test point 2 (bin test) can be neglected when the misrepresentation rate is extremely low or extremely high. This model will examine whether the omission of test point 2 can generate additional efficiency to wheat handling.

Model C (*bin and railcar*): In this model, there is a bin test (test point 2) and a railcar test (test point 3). Traceability will be triggered if there is any contamination detected at those two test points. If test point 1 is available in the supply chain, most testing occurs at this test point and accordingly, testing costs at test point 1 generate a considerable share of the total costs of wheat handling. This model checks whether the absence of testing at point 1 contributes to the efficiency of wheat handling.

Model D (*railcar only*): In this model, only a railcar test (test point 3) is used and traceability is available for offending cases. Interestingly, this strategy is openly preferred by managers in Viterra (2007) and the CWB (2008). These participants believe a well-established traceability mechanism will provide incentives to supply chain participants for segregation efforts. Through this model, one can check whether the testing costs saved at test point 1 and test point 2 can cover the increased contamination costs due to testing omissions.

Model E (*no traceability*): There are 3 test points in this model, but samples for truck deliveries are not retained. So traceability is not available even if contamination is detected at test point 2 or test point 3. Through this model one can examine whether costs saved from eliminating sample retaining and traceability processing outweigh the relative contamination cost increases from misrepresentation under these different misrepresentation conditions.

When test points are chosen, the procedure for determining efficient testing and tracing strategy is complicated due to the factors involved in the strategy design. For example, a farmer's reaction to testing, tracing and penalty, or a handler test strategy adjustments are made according to perceived misrepresentation information. Many parameters might be considered in the evolution of testing strategies. Any change in these parameter values in such a complex system, even those that might seem insignificant, can influence the simulation results significantly. The procedure used to assess best parameter values is the same as that developed in Chapter 4. By examining numerous parameter value combinations, the most successful parameter values for handling and cost minimization can be identified.

Handling costs are closely related to a farmer's misrepresentation rate. Under different assumptions on a farmer's initial misrepresentation rate, each model generates a set of different testing strategies resulting in varying handling costs. For doing this, two different base assumptions on the farmer's initial misrepresentation rate are considered: a high misrepresentation rate and a low misrepresentation rate.

First, this part of the study starts the simulation under the assumption of a high misrepresentation rate. Then a low initial misrepresentation rate is introduced as an alternative and the simulation results are compared with those obtained under a high initial misrepresentation rate assumption. All other assumptions about the grain handling system are the same as those used in Sections 4-4.3.1.

5.2 Wheat Handling under a High Initial Misrepresentation Rate Condition

Here, the simulation identifies efficient testing and tracing strategies for each model under the assumption that a farmer's initial misrepresentation situation is serious. After that, the reaction

by the farmer via risk control effort and risk control technology under those strategies will be shown. Finally, by calculating handling costs and farmer losses and making comparisons, we conduct a scenario analysis on the effects and efficiencies of handling strategies within each model.

These five comparative models are all affected by the evolution of participant behavior over time. For the same model, simulation results will vary from iteration to iteration due to randomness and uncertainties along the supply chain during handling. By way of example, farmers randomly misrepresent their deliveries over time and are also randomly detected at different testing points and those situations will almost never be the same in two different simulation runs. And farmer effort and technology can evolve in different ways depending on the frequency of being detected, the test point used for detection and the time detected, and this will differ across iterations. Further, contamination from misrepresentation can occur in different ways. It can occur in a way that two misrepresented truck deliveries contaminate one bin or one misrepresented truck delivery contaminates two different bins. Finally, a railcar can also be randomly loaded with wheat from the same bin, either clean or contaminated, or loaded wheat from two different bins, one that is clean and the other that is contaminated, while handlers' testing strategies are different from iteration to iteration since the handling environment is never consistent in different runs - and so on. As a result, individual simulation runs can generate very different outcomes. Simulation results from any single model run are not representative of the system operation in that model. To reduce the effects of this variability and generate large sample results, the averaged simulation results obtained from 500 iterations of each model are illustrated in this study.

5.2.1 Test Strategies and Trace Strategies

Under the first assumption of high initial misrepresentation probability, the initial farmer's effort is set at a randomly generated low value interval [0.0934, 0.4173] and the average effort value is set at a low level of 0.2441. The initial farmer technology is in a randomly generated interval [1.8295, 1.9980] with an average value of 1.8874. Based on equation 4-4.1 (with $\eta=10$), the initial farmer's misrepresentation rate is distributed in the range [0.0940, 0.6489] with an average value of 0.3152. Such a high initial level of misrepresentation probability is clearly hypothetical.

But modeling such a specific situation can provide insight into those extreme cases which may rarely be perceived in reality. Once again, the simulated time period is 30 years for each model.

Figures A-G1 to A-G5 in Appendix G illustrate test strategies at each test point as well as tracing strategies for detected contaminations across the 5 base models. These strategies include a testing strategy for trucks, a testing strategy for elevator bins and a testing strategy for railcars. Test results include the number of detected misrepresented grain trucks, detected contaminated bins and detected misrepresented railcars at each test point and in the trace procedure.

All models include test point 3, the railcar test at the terminal. It is further assumed that the terminal elevator handlers test 80 percent of railcars delivered by the primary elevator, so the railcar test does factor in strategy design. If traceability is possible, all contamination sources can be identified with a probability 0.998 (refer to Appendix C for more information). This implies almost all misrepresentation will be detected if not detected already at each previous test point.

For those models including the first test point (models A, B and E), intensive truck testing is suggested. The logic behind such a test strategy is that it should effectively prevent misrepresented wheat varieties from entering the supply chain in early stages. If misrepresented wheat enters in the supply chain and moves farther along, greater losses will result. When most of the misrepresented deliveries are detected at the truck testing stage, the necessity and efficiency of primary bin testing is reduced (models A and E).

When there is no testing at point 1 (models C and D) in this grain handling system, grain movement along the supply chain will be under threat of contamination from misrepresented deliveries. In this situation, if test point 2 is available (as in Model C), a high bin test rate is assumed. Doing so helps avoid a situation where the misrepresented contaminated wheat is moved to and results in misrepresentation at the terminal elevator.

Ultimately while costly, the truck test and the primary elevator bin test help prevent misrepresented wheat from moving farther into the supply chain. Without these test points, in fact contamination from misrepresented deliveries can be severe, leading to high costs. Among the five models, serious contamination occurred in Models C (bin and railcar) and D (railcar only). In Model C, because there is no test point number 1, wheat from misrepresented deliveries

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was loaded into primary elevator bins and contaminated other eligible wheat. Although part of the contamination losses are compensated by the traced offenders (40 percent of contamination losses or less), the primary elevator still suffers large economic losses (60 percent of contamination losses or more). And in Model D, there are no test points 1 and 2. In this case, contaminated wheat cannot be identified until it arrives at the terminal elevator. Thus, it is found the number of contaminated railcars is much greater than found in the other simulations. For example, contamination losses in Model C are less than those generated in Model D. When a certain amount of contaminated wheat is moved to the terminal elevator, the deliverer will be penalized not only the lower price but also any penalty imposed by the terminal. If contaminated wheat can be detected before it is loaded in railcars, such losses can be discounted.

Model E is the only one without traceability among the five models. Unlike the other models, if there are contaminations detected at the test point 2 or test point 3 at the first delivery within a year, offenders cannot be immediately targeted through traceability. The only way to identify offenders is to enhance testing at a later time within the year, but doing so increases handling costs. Allowing for this situation, the testing at test point 1 is enhanced and most contamination sources in the model were detected at previous test points. The costs for eliminating all contamination sources before test point 3 are too high so that, just as the simulation shows, there remain a few cases in which contaminated railcars are still undetected.

5.2.2 The Evolution of Farmer's Misrepresentation Rate under VED

Testing and tracing strategies influence not only the probability of wheat contamination in this supply chain, but also the evolution of a farmer's misrepresentation condition. As Figure 5.6A-G6 in Appendix G shows, the farmer's effort, technology and misrepresentation rate continuously evolves during simulation runs and their end values at the 30th year are often vastly different from those initial values. For example, in Model A (truck, bin and railcar), the 48 farmers' effort values end in a set [0.4250, 1.2405] with an average value 0.8738 (initial average value 0.2441); their technology values end in [0.8507, 1.5237] with an average value 0.8489 (initial average value 1.8874); finally their misrepresentation rate values end in [0, 0.0676] with an average value 0.0040 (initial average value 0.3152). The average misrepresentation probability in the simulation over 30 years is 0.0279.

Table 5.1 lists the evolution of farmer's total misrepresentation rate across 30 years in each of the five models.

Table 5.1 The Farmer's Misrepresentation Rate Over Time (High Initial Misrepresentation Rate)

Model	Interval over 30 Years	Average over 30 years
Model A	0.3152 – 0.0040	0.0279
Model B	0.3152 – 0.0041	0.0278
Model C	0.3152 – 0.0040	0.0273
Model D	0.3152 – 0.0041	0.0272
Model E	0.3152 – 0.0043	0.0289

The main motivation to drive farmer efforts under the VED regime is the penalty imposed by the system on offenders. Based on the assumption that effort incentives are mainly motivated by penalty deterrence, the penalty imposed on farmers dominates the evolution of their risk control efforts. In Models A to E, all offenders are finally detected by testing or tracing. Simulation results show that in these models, farmers keep increasing risk control efforts over time.

There is no test point 1 in Model C (bin and railcar) and D (railcar only) and in these models, misrepresented truck deliveries cannot be prevented from entering the supply chain. Although eventually identified, all offences generate contamination losses. Due to where they are detected in the supply chain, penalties for those offenders are greater than penalties for offenders detected earlier at test point 1. Note as well that in Model A (truck, bin and railcar) and B (truck and railcar test) most of the offenders are detected at test point 1. Based on the assumption used in Chapter 4 (equation 4-4-2), a farmer's efforts to properly represent their crop grow with the penalty and the testing he or she receives. On one hand, farmers detected in test points 2 and 3 have more motivation to arouse these mitigation efforts than farmers detected attest point 1. On the other hand, the absence of testing at test point 1 clearly lowers a farmer's incentive to put efforts on risk control. In effect, those two effects cancel each other out. Just as shown in Table 5.1, the average misrepresentation level over 30 years in Models C and D is only slightly lower than in Model A (truck, bin and railcar) and B (truck and railcar). We conclude that a VED based

grain handling system without traceability deterrence can increase moral hazard (Section 3.3.5). And as the simulation results demonstrate, the average misrepresentation rate in Model E (with no traceability) is the highest.

5.2.3   Handling Costs, Farmers' Losses and Total Costs

The primary elevator's handling costs comprise costs resulting from wheat contamination due to undetected misrepresented deliveries, including both price reductions and penalties from the terminal, as well as costs resulting from operations associated with assuring supply chain safety (including sampling and sample retention costs), testing costs at each test point and tracing costs associated with the traceability process. Penalties collected from those detected farmers will be used to cover handling costs. Clearly, if a particular design does not allow for traceability, sampling, sample retention and tracing costs will be excluded from the handling costs. Farmers' losses in this case include a price drop due to misrepresentation as well as penalties if misrepresented deliveries are actually detected. The handling costs and farmer losses all form part of the supply chain system costs shared by different participants. From this point of view, the sum of those costs can also be used as a measure of the handling efficiency for a VED supply chain.

Under VED, wheat contamination can occur in the primary elevator bins if misrepresented wheat is loaded in bins and blended. If handlers cannot detect contamination in the bins before loading the wheat in railcars, contaminated wheat will be moved to the terminal elevator and additional economic losses will result. In those models shown here using traceability, when offenders are detected, they will suffer a price drop loss and subsequent penalty from the primary elevator. The penalty amount depends on the contamination losses resulting from their misrepresentation. Conversely, if there is no traceability in the model, e.g. Model E, the primary elevator will completely absorb all the contamination losses. By way of illustration, Figure A-G7 in Appendix G shows the primary elevator's handling costs, farmers' losses and the total costs over time in each simulation, assuming a high initial misrepresentation rate.

One component of handling costs is contamination loss. Contamination losses vary with the level of wheat contamination across time. When there is no wheat contamination, contamination losses are zero. The other component of handling costs are those related to the safe maintenance of the

wheat handling system. These always occur even if there is no wheat contamination. Finally, farmers' losses occur when farmers who misrepresented their deliveries are detected. If there is no farmer misrepresentation, farmers' losses are zero.

The peaks in the values for handler's costs indicate the periods when the misrepresentation situation is severe (Figure A-G7). In those periods, testing intensity at test point 1 for Models A (truck, bin and railcar), B (truck and railcar) and E (no traceability) is very high, generating high testing costs which are the main components of corresponding handling costs. The handling cost value peaks in Models C (bin and railcar) and D (railcar only) and can be attributed to serious contaminations detected at the test point 2 or 3. With respect to values of farmers' losses, thispeaks during the first few years of the simulation when farmers' misrepresentation is severe. Finally, Model E does not include traceability, so wheat handlers alone absorb all contamination losses. Farmers suffer losses only when they are verified as having misrepresented their wheat at test point 1.

To facilitate the comparison of the efficiency of those five models, this study computes the total handling costs and the total farmers' losses over the 30-year delivery history. The values of handling costs are illustrated in Figure 5.1.
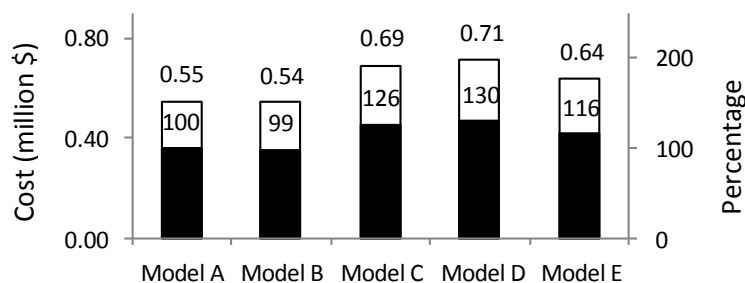
Figure 5.1 Primary Elevator's Handling Costs (High Initial Misrepresentation Rate)

To more readily evaluate the variability of costs from model to model, the value of the handling costs generated by Model A (truck, bin and railcar) is normalized to unity. By comparison, the value of handling costs in Model B (truck and railcar) is 0.99, the lowest among all the models. The handling cost value is at the highest in Model D (railcar only) at 1.30. From the primary elevator handlers' perspective, those handling strategies utilized in Model B are their best choice.

In the same manner as with primary elevator handling costs, the value of farmers' losses in Model A is normalized to unity. And as shown in Figure 5.2, the value of farmer losses in Model E (no traceability) is the lowest. Obviously, farmers will prefer Model E as the set of rules in which they are most likely to minimize their economic losses. The reason is simple: Model E allows the farmer to escape a penalty when there is detected contamination which he or she should be found responsible.
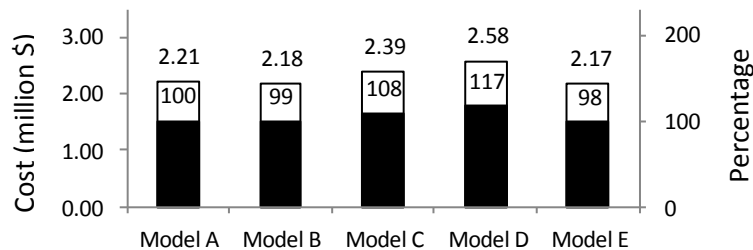
Figure 5.2 Farmers' Losses in the Five Models (High Initial Misrepresentation Rate)

The reader will note that handling costs and farmers' losses are lower both in Model A (truck, bin and railcar) and Model B (truck and railcar) than the other models (except farmers' losses in Model E (no traceability)). This is likely due to the fact that most of the misrepresented deliveries in these models were prevented from contaminating primary elevator bins by the truck test at point 1. When misrepresented wheat can be detected at an early stage of grain supply chain, contamination losses will be lower. In contrast, in Model E, most misrepresented deliveries were also detected at test point 1. However, handling costs are greater because the handlers must absorb the contamination costs alone. Farmers who misrepresented their deliveries and were not detected at test point 1 are not penalized for misrepresentation because there is no traceability in this particular model. This explains why the handling costs and farmers' losses in Model E run in opposite directions. In Models C (bin and railcar) and D (railcar only), contamination from undetected misrepresented deliveries creates more problems than in the other models. Considerable economic losses from contamination in this model are shared by wheat handlers and farmers. This is the main reason why handling costs along with farmers' losses are so great in these two models.

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Figure 5.3 shows the total costs, the summation of the handling costs and the farmers' losses, in each model. The total cost value generated by Model A (truck, bin and railcar) is normalized to unity. In fact, the primary elevator's handling strategies utilized in Model B (truck and railcar) generate the lowest total system costs among five models. The second lowest value is of Model A, whereas the highest value, 1.19, is generated by Model D (railcar only).
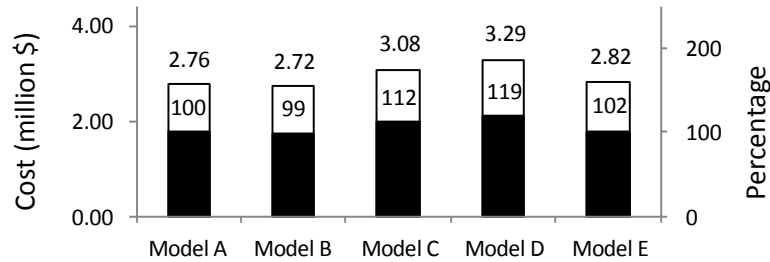
Figure 5.3 Total Costs in the Five Models (High Initial Misrepresentation Rate)

The total costs for both Models C (bin and railcar) and D (railcar only) are considerably higher than those generated by the other models. Once again, the reason is that there is no test point 1 in these two models, so misrepresented deliveries have no way of being detected before being unloaded in primary elevator bins. As a result, the ineligible wheat contaminated wheat in the whole bin in which the misrepresented delivery was unloaded in, degrading wheat quality in this bin. When contaminated wheat is not detected early and is allowed to move farther through the supply chain, the resulting losses can be even greater.

The handling costs and farmers' losses generated through Model A (truck, bin and railcar) are only slightly different from those generated by Model B (truck and railcar). The results indicate test point 2, the primary bin test, is not essential for VED system if test point 1 is available. When the first test point is available in the supply chain, the best test strategy is to test most of deliveries at the first test point at the beginning of each year. In this case, most misrepresented deliveries are detected before being unloaded into the primary elevator bins. In those models using a high truck test rate, a low bin test rate is presumed to be efficient. However, there is little chance that a rare contaminated bin will be detected using such a low bin test rate. Thus, under the given conditions in this study, the bin test contributes little to the efficiency of the testing

process if there is a prior truck test in a given supply chain. The advantage of bin testing is it reduces the volume of contaminated wheat delivered to the terminal elevator and thus prevents further contamination at the terminal level. If the system costs can allow for losses from the terminal contaminations which are not considered in this study, the importance of bin testing will be enhanced.

Compared with Model D (railcar only) which uses only a railcar test, the amount of handling costs in Model C (bin and railcar) is 4 percent less. So although the bin test in Model C detected most of the contaminated bins, the test costs were also relatively high because of my assumption about bin sample testing cost ($600/sample). Ultimately, if contaminated wheat in bins is not detected and delivered to the terminal, the potential losses in the system are greater. But in the simulations, these losses are shared by the primary elevator and the traced offenders. Obviously, those losses shared by the offenders are not significantly higher than bin test costs, lowering the feasibility of bin testing.

The condition of farmers' misrepresentation influences the choice of testing strategies. This situation can be described using a special case. If the farmer's misrepresentation rate stays at a very high level, e.g. greater than 2% in the simulation, then best testing strategies will become relatively simple. The best strategy at the truck test point is to test all the first deliveries of farmers within a given year. Under an assumption of perfect test accuracy, all misrepresented deliveries will be detected at this test stage and no further tests are necessary in the supply chain. This means models including truck test points (e.g. Models A, B, and E) will generate similar results regarding the best testing strategies, and the handling costs of these three models will necessarily be very close to each other, while the same conclusion is applicable to the farmers' losses. The overall total costs in these three models will remain the lowest among the five models under comparison, with the total costs in Model C (bin and railcar) the highest and those in Model D (railcar only) the second highest. For models without a truck test point but with a bin test point (e.g. Model C), the best test strategy is to test all bins upon first delivery within a year if the farmer's misrepresentation rate is over 2%. (please also refer to Figures A-F1 to A-F6 in the Appendix)

5.3 Wheat Handling under a Low Initial Misrepresentation Condition

Figures A-G8 to A-G12 in Appendix G illustrate the results of different testing strategies for the five models under consideration, with the assumption that the farmer's initial misrepresentation rate is low. The testing intensity at each test point is much lower than under the higher initial misrepresentation rate condition due to slight contamination risks. It must be noted again that all results shown in those figures and tables were generated using simulations with 500 iterations.

It is assumed here that the randomly generated farmer's initial misrepresentation rate is low (0.0051). As in the previous section, Figure A-G13 in Appendix G shows the evolution of farmer's effort, technology and corresponding misrepresentation probability. Based on the simulation results, the farmer's misrepresentation rate over time evolves as follows,

Table 5.2 The Farmer's Misrepresentation Rate Over Time
(Low Initial Misrepresentation Rate)

Model	Interval over 30 Years	Average over 30 years
Model A	0.0051 – 0.0024	0.0034
Model B	0.0051 – 0.0023	0.0034
Model C	0.0051 – 0.0024	0.0035
Model D	0.0051 – 0.0023	0.0034
Model E	0.0051 – 0.0024	0.0034

Clearly there is only a rare chance that a farmer will misrepresent his or her deliveries in these simulations. Under this situation, there are fewer chances to detect truck misrepresentation at the truck testing point or bin contaminations at the bin testing point. In fact, intensive testing at either of those two test points is no longer efficient. The need for tests at the two test points becomes negligible. As a result, testing and tracing strategies in the five models under consideration are significantly different from those generated previously under the assumption of high initial misrepresentation. Here, there is need for only minimal testing at the truck and bin test points. The handling system depends instead on traceability to locate the exact contamination source and catch system offenders.

Figure A-G14 in Appendix G shows the flows of costs over time. Once again, the evaluation of the efficiency of each comparative supply chain depends on the relative costs generated by the model, i.e. handling costs, farmers' losses and their combined total.

Figure 5.4 here shows the primary elevator's handling costs under a condition of low initial misrepresentation.
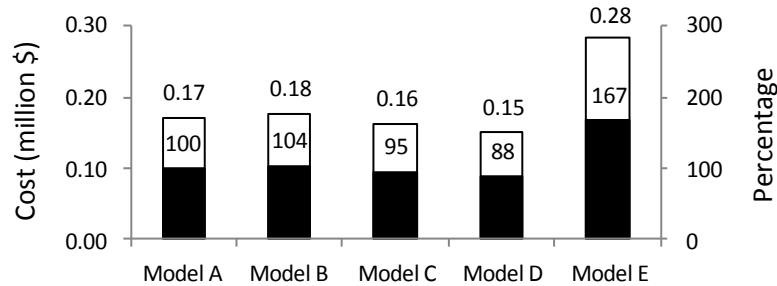
Figure 5.4 Primary Elevator's Handling Costs (Low Initial Misrepresentation Rate)

As above, handling costs in Models C (bin and railcar) and D (railcar only) are now the lowest. This is just the opposite of the results obtained under an assumption of a high initial misrepresentation rate. When there are few misrepresented deliveries, the truck test point and the bin test point are rendered unessential. As a result, most of the time, there are few tests at those two test points in models with those test points available. The absence of a truck test point in Models C and D does not lead to large-scale contamination since there is a low misrepresentation risk. On the contrary, the handling systems in those two models take advantage of savings in testing, resulting in the lowest handling costs.

Handling costs in Model E (no traceability) are now the highest, supporting the need for traceability to provide efficiency to wheat handling. First, traceability helps identify the source of contamination in an efficient way. When there is no traceability, if there are contaminated railcars detected at the railcar testing sometime within a year, the only way to identify the misrepresented farmers is to test more truck deliveries in the later time in the year, costs incurred by misrepresentation identification are far more than those generated by the traceability system establishment (sampling and sample retaining) and traceability application (sample testing). Second, any compensation paid by offenders can partially cover contamination losses. If there is

no traceability, grain handlers have to bear all losses from contamination by themselves. Third, traceability contributes to reducing farmer moral hazard issues and thus reducing potential handling costs. Finally, traceability allows more information to be obtained, information that can be used to improve test strategies with the goal of cost savings.

Figure 5.5 shows farmer losses due to detected misrepresentation. Again, the value of farmer losses in Model E (no traceability) is the lowest. Since there is no traceability applicable in Model E, farmers who misrepresent their deliveries without detection do not share contamination losses resulting from their misrepresentation. Farmer losses are in similar levels in Models A, B, C and D. Here, all contamination sources, misrepresented deliveries, are identified through traceability, and part of any contamination losses are shared by those farmers who misrepresented their deliveries.
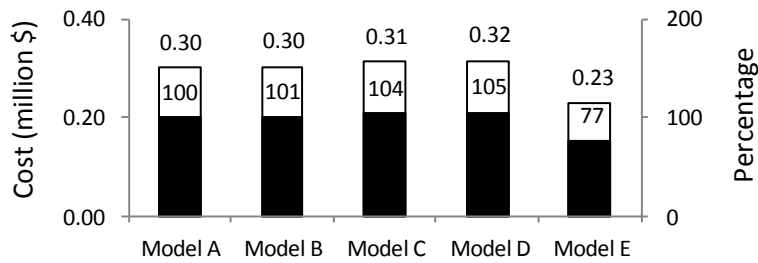
Figure 5.5 Farmers' Losses (Low Initial Misrepresentation Rate)

Figure 5.6 shows total costs as the sum of handing costs and farmer losses. The total costs in Models A to D are very close. The highest total costs occur in Model E (no traceability). The simple reason is that handling costs in this model are much higher than those in the other models.
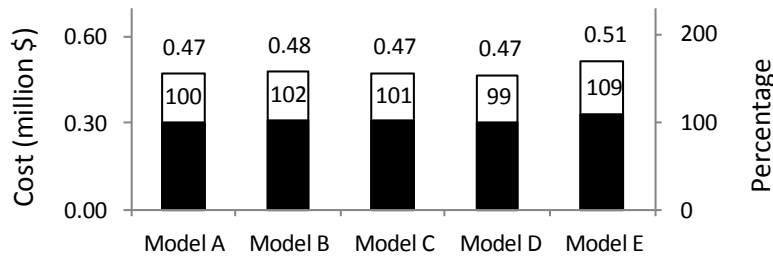
Figure 5.6 Total Costs (Low Initial Misrepresentation Rate)

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5.4 Analytic Solutions vs. Agent-Based Simulation Solutions

Given the need for modeling this supply chain as a complex system using agent based modeling, this section compares the simulated solutions generated in Ch. 4 and this chapter with related analytic solutions solved for in Chapter 3. These comparisons are summarized in Table 5.3.

To generate the table, parameter values used in the simulations were substituted into the general solutions of the cost minimization problems solved in Chapter 3 (recall equations 3-17, 3-37, 3-43, 3-56 and 3-61). This allows us to compute a comparative set of specific analytic solution values for truck or bin test rates, shown in the second column of the table. Next, the corresponding farmer's misrepresentation probability for each related analytic model (column 3) was computed (recall equations 3-24, 3-30, 3-40 and 3-48). By checking this against the simulated results, we can identify specific points where the farmer's misrepresentation probabilities are approximately the same as those computed for the analytic models, along with the perceived misrepresentation probabilities at these points (Column 4).This allows us to verify the corresponding truck or bin test rates at those points as simulated counterparts of the analytic solutions. To facilitate the subsequent analysis, we also illustrate the simulated truck or bin test rates that would be generated if the perceived misrepresentation rates were equal to the computed ones from the analytic model (Column 3).

Table 5.3 Analytic Solutions vs. Simulated Solutions

Model	Analytic/Simulated Solutions for Truck Test β_i and Bin Test β_b)		Computed Mis Rate	Perceived Mis Rate
Two test points: truck and railcar (with traceability)	Analytic (Ch. 3, case 2 (b))	$\beta_i^* = 0.1175$	0.0090	
	Simulated (Ch. 5, Model B)	$\beta_i = 0.4375$		0.0116
		$\beta_i = 0.3750$		if 0.0090
Two test points: bin and railcar (with traceability)	Analytic (Ch. 3, case 3 (b))	$\beta_b^* = 0.5567$	0.0100	
	Simulated (Ch. 5, Model C)	$\beta_b = 0.6025$		0.0128
		$\beta_b = 05350$		if 0.0100
	Analytic (Ch. 3, case 4 (b))	$\beta_i^* = 0.3749$ $\beta_b^* = 0.0477$	0.0110	

Three test points: truck, bin and railcar (with traceability)	Simulated (Ch. 5, Model D)	$\beta_i = 0.6250$ $\beta_b = 0.0539$		0.0140
		$\beta_i = 0.4160$ $\beta_b = 0.0762$		if 0.0110
	Simulated (Ch. 4)	$\beta_i = 0.5833$ $\beta_b = 0.0905$		0.0139
		$\beta_i = 0.3542$ $\beta_b = 0.1025$		if 0.0110
Three test points: truck, bin and railcar (without traceability)	Analytic (Ch.3, case 4 (a))	$\beta_i^* = 1$ $\beta_b^* = 0$	0.0250	
	Simulated (Ch. 5, Model E)	$\beta_i = 1$ $\beta_b = 0$		0.0283
		$\beta_i = 1$ $\beta_b = 0$		if 0.0250

Except for the supply chain model containing three test points without traceability (the final one under consideration in the table), the values of the simulated solutions for test rates are substantially higher than the analytic solutions for the other (three) models used for comparison. While the complexity of the simulation makes it difficult to know exactly why this is the case, the divergence between the iterated solutions from the simulation models and the solved analytic solutions of same seems to stem from the following factors:

1. In the analytic model, farmers are homogenous in their behavior and there is no interaction between them. The farmer's aggregate activity is thus linear in the analytic model and the behavior of the entire system can be solved by adding together the individual behavior of each agent. Such a linear system possesses exact analytic solutions. On the contrary, in the simulation model, farmers are heterogeneous, dynamically interacting through time and space, so their aggregate activity is inherently nonlinear. The behavior of a nonlinear dynamic system is not the mere sum of the behavior of its parts. When considering a nonlinear and complex system, simulations generate approximate solutions of the system but are only rarely as precise or exact as analytic solutions (Hommes, 2006).

2. In my analytic model, handlers are fully rational in making testing decisions. Under the assumption of perfect information, they always make the optimal decision regarding testing. In the simulation model, handlers are goal-oriented and adaptive, but only boundedly rational. Under imperfect information, they are limited in their cognitive ability to arrive at the optimal solutions of testing strategies (Kahneman, 2003).

3. The analytic model does not allow for participants' interaction so as to capture system dynamics on a variety of spatial and temporal scales, while the simulation model does this. The analytic model describes a simple (linear) stable system in which handlers have rational expectations and develop perfect testing strategies only simply allowing for each uniquely given misrepresentation condition. In the simulation model, due to assumed agent nonlinear interactions, agents are necessarily in a path-dependent world, in which early choices determine future possibility (Page, 2006). Any testing strategy at a specific time point will change the farmer's misrepresentation probability distribution after that time and thus influence the testing strategy (and also the handling cost) in subsequent times. The simulated best testing strategy in time conditions on not only the system risk and cost under the current misrepresentation conditions, but also on system risk and cost under the redistributed misrepresentation probability in the subsequent time interval for simulation (30 years in this study). Rationally, testing more at the current time facilitates saving more in the future.

4. The analytic solutions are solved under assumptions of perfect information. This implies handlers have exact knowledge about an individual farmer's personal information, including technology level, and the response pattern to testing, or the chosen effort level. As a result, in the analytic model handlers know an individual farmer's misrepresentation probability exactly and subsequently make their optimized decisions about testing. The simulation model effectively assumes a more realistic situation of information asymmetry, meaning that handlers have little information about an individual farmers' misrepresentation condition. In this case, handlers only perceive and accumulate such information through testing. An enhanced testing intensity helps to better understand the farmer's misrepresentation behavior and thus reduce potential system risk. This partly explains why handlers in the simulation always prefer higher testing rates than the

computed ones in the analytic model. Furthermore, handlers' testing strategies are based on their perception of farmers' misrepresentation probability. As shown in the simulation, handlers are necessarily limited in their information sources and perception errors always exist over time. Any perception errors in this respect can force the testing strategies to deviate from optimality.

5. The simulated solutions only assure local optimization. The simulation programming is designed to find a global optimum and explores check test rate value areas where the best solutions are thought to be most possibly located, however, not all the possible combinations of truck testing and bin testing are examined. Theoretically, there exists a probability that better solutions are ignored by this simulation model.

So although there is divergence across the solutions of the models used in this analysis, examining comparisons between the respective solutions can provide valuable insights into the overall analysis of the issue.

1. As described, testing intensity for a truck or bin in the simulation model is always greater than in the analytic model. One explanation for this finding is that under imperfect information, handlers need additional monitoring efforts to prevent handling risk than those under a perfect information assumption. In other words, imperfect information constrains monitoring efficiency and increases monitoring costs.

2. Solutions in the analytic model support a primary conclusion reached in the simulation models (Chapters 4 and 5) – that is, under the assumption that there are no contamination sources other than farmer's misrepresentation, when the truck test point is available in the supply chain, bin testing is rendered less important.

3. In fact, the analytic solutions for the case of three test points without traceability support the conclusion generated through the simulation - when the misrepresentation situation is severe, i.e. when misrepresentation rate is greater than 2%, the best overall testing strategy is to test all truck deliveries if the truck test point (my test point 1) is available.

4. In all the simulation models, the perceived farmer's misrepresentation probability is generally higher than the actual misrepresentation probability, due in this case to the

downward trend of misrepresentation probability over time and the exponentially weighted moving average used as a proxy for the farmer's misrepresentation probability. This bias or over perception contributes to the higher test rate in the simulation model. As shown in Table 5.3, if handlers in the simulation can uncover the exact misrepresentation probability of each individual farmer as they do in the analytic model, the simulated solution does a better job at approximating the analytic solutions. From this perspective, the analytic solution and the simulation work in the same direction in developing efficient testing strategies.

Clearly there is a trade-off between modeling accuracy and choice. Simulated solutions in these models do not necessarily iterate to globally optimal solutions with respect to testing strategies while analytic solutions yield these by design. Generally, analytic models defy realism (by ignoring heterogeneity, interaction and perception error) while simulation models allow whatever degree of realism of the phenomena is desired by the researcher (Shanthikumar and Sargent, 1983). In this sense, the use of analytic models for solving optimization problems in such systems is preferable if sufficient realism can be maintained in the analytic model assumptions. Unfortunately, the actual dynamic and heterogeneous grain handling supply chain system simulated here is inherently nonlinear and if modelled realistically in an analytic fashion, would not be solvable by those methods. Ultimately, if the researcher wants to obtain solutions for a nonlinear system that is designed to capture greater realism - for example better accounting for spatial interactions and temporal factors in the system - then computer simulations of that system are the only feasible way to realize that objective.

5.6 Summary

In this set of agent based simulations analyzing the efficiency of grain quality testing through a modern supply chain, a testing strategy is characterized by two key components. The first is the choice of testing points, while the second is the choice in testing intensity at each chosen test point. Clearly the best testing strategy from the primary grain handler's perspective is one that minimizes handling costs. The five comparative models simulated in this chapter provide some

insight into handling strategies that could be under consideration by primary elevator handlers under a VED regime.

It is found that the best handling strategies vary with farmer misrepresentation of grain type over time. To perform testing efficiently, results from past time periods need to be updated for current decision making. When farmer misrepresentation is frequent or serious, intensive testing at the earliest possible test point is critical to maintain a least cost yet quality assured handling system. Under this situation, primary elevator handlers will prefer Model A (truck, bin and railcar) or Model B (truck and railcar) in the simulations. When a truck test point is available in the current grain supply chain, bin testing is rendered less important since most of the contamination risks will already have been prevented from occurring.

When farmer misrepresentation is less frequent or rare, truck or bin testing is rendered inefficient because the reduced contamination risks do not merit intensive testing. Under this situation, only infrequent delivery supervision is needed. In a supply chain with traceability, I find that it is more efficient to test later in the system even if doing so could raise contamination chances and moral hazard problems. Thus if misrepresented railcars are detected at the terminal, elevator handlers will use traceability to catch any offenders. Under some circumstances, the testing cost savings from reduced truck or bin tests can be greater than the contamination losses resulting from the absence of testing at point 1 or point 2, as well as the possible increased likelihood of moral hazard. But in this case, efficiency considerations indicate that no testing at the truck test point or bin test point should be conducted and monitoring deterrence can be realized by enacting a traceability mechanism in the supply chain. As a result, Model D (railcar only) of this supply chain becomes the elevator handlers' preferred choice.

The advantage of a supply chain model without traceability (Model E) is that it can save both sample retention costs and costs of realizing tracing procedures. But such cost savings are often less than the amount of contamination losses under defined farmer misrepresentation probabilities as used in this study. And if there is no traceability in the supply chain, handlers will lose the ability to request compensation from offenders for contamination and they will not be able to obtain useful information for test strategy improvements. Furthermore, farmers can underestimate the risks of misrepresentation and subsequently reduce their efforts on risk

control, increasing moral hazard potential. Data generated using the simulation support the notion that traceability is necessary in order to reduce the primary elevator's handling costs. In a high initial misrepresentation rate case, handling costs in Model E (no traceability) are 16 percent higher than those in the Model A (truck, bin and railcar). Conversely, in the low initial misrepresentation rate case, this cost increases to 67 percent. With respect to the structure of grain supply chains as represented by Models C (bin and railcar) and D (railcar only), contamination is more serious than in the other models considered. If no traceability mechanism had been assumed in those two models, contamination losses will grow quickly.

Models in which contamination can be effectively prevented by truck testing, i.e. Models A, B and E, under a high misrepresentation situation are associated with small farmer losses. Models in which there are no truck test points, i.e. Model C and Model D, suffer from a higher likelihood of elevator contamination. And farmers' losses also increase when contamination sources can be traced exactly. I find that the value of farmers' losses in Model E (no traceability) is the lowest because farmers who misrepresent do not share losses for elevator contamination.

Total economic costs are also evaluated within the grain handling supply chain. Assessing the value of total costs is a way to compare the feasibility of wheat handling strategies from a social perspective. Under the principle of minimizing the primary elevator's handling costs, the resulting total costs do not possess the same ranking as found for handling costs. In addition, the handling strategies preferred by the primary elevator handlers do not align with the objective of total cost minimization. The reason is that the primary elevator handlers focus on their own objectives instead of minimizing farmer losses. For example, if the primary elevator tests at the earliest possible testing point, farmers' losses are reduced to their lowest level. But if the gains from testing cannot cover the testing costs, then the primary elevator has little incentive to continue doing this. Therefore, if the welfare of the whole supply chain is taken into consideration, the best testing and tracing strategies may be very different from those developed and simulated here.

It is concluded that a policy of traceability appears to be an efficient way for primary elevator handlers to retrieve contamination losses. From a social welfare perspective, the amount of penalty charged to offenders does not increase the value of the supply chain. But under the

assumption that the imposed penalty can motivate farmer's efforts for delivering eligible wheat, a penalty can contribute to a reduction in moral hazard, supporting the overall reliability of the handling system and likely increasing social welfare.

For any test point combination, efficient testing intensity at each test point can be worked out in more detail through simulations. The primary elevator handlers can identify an efficient test point combination to allow for specific misrepresentation conditions. This type of analysis offers further flexibility for the primary elevator handler concerning their choices of test points as well as the application of test and trace strategies under different situations in a grain handling supply chain.

Within the simulations, the wheat supply chain is modeled as a complex system composed of boundedly rational participants possessing a set of nonlinear relationships. For such a complex system, analytic or globally unique solutions cannot readily be found but simulated solutions can be used to identify the most efficient testing strategies. In fact, the testing strategies identified through simulation in Chapters 4 and 5 are somewhat different from those generated by the analytic solutions derived from the model of Chapter 3. Generally, the simulated solution values are greater than comparable analytic solution values when misrepresentation probability is low. An explanation for this phenomenon is that under an assumption of imperfect information, handlers must increase monitoring efforts in trying to understand a farmer's misrepresentation behaviour. And this research also indicates that compared to analytic solutions, simulated solutions of systems are often only nearly optimal, but simulations can generate very good approximations depending on model circumstances.

CHAPTER 6

SUMMARY AND CONCLUSIONS

The Canadian grain handling industry is an export focused supply chain. While movements are often bulk in nature, the suppliers are concerned with product safety and quality. Grading of wheat for value-added blending has historically been accomplished by a visual identification method known as KVD. KVD was phased out for all primary classes of wheat and replaced by a trust-based declaration system called VED. Essentially, VED relies on individual trust to ensure that farmers will deliver reliably and accurately into the supply chain.

Under the VED system, although wheat varieties put forward for registration have to meet all other registration requirements, they can be similar in appearance to existing wheat classes. If one of these varieties is misrepresented as another type of wheat physically similar to it, using low cost visual inspection methods wheat handlers would not be able to readily distinguish these from each other. As a result, the quality and safety of wheat handling cannot be guaranteed under VED. Given the costs of controlling on-farm commingling risks and implementing a declaration system through the current wheat supply chain, there exists some potential for accidental or opportunistic misrepresentation behavior under a declaration system on the part of Canadian wheat producers.

To manage and optimize wheat safety and quality, the first priority under a VED system is to manage the misrepresentation problem. It is well understood that the long-term solution to wheat misrepresentation lies in the development of rapid and affordable variety identification technology. However, a short to medium-term solution is to develop efficient testing strategies for monitoring visually indistinguishable wheat varieties. In light of this, there will be important operational issues such as determining the best location to test, how intensively to test, appropriate penalty levels for misrepresentation, feasibility of system traceability and how relative costs might be distributed among participants.

This study uses both analytic method and simulation to explore optimal testing strategies for handlers to minimize their handling costs. Under some simple assumptions, a contractual

economic model is developed to explore the economic incentives for farmers to practice risk control and identify optimal handling strategies to mitigate contamination risks. However, this model is found somewhat lacking to capture the subtleties of such a complex system as a grain supply chain. To develop a more realistic description of supply chain dynamics and operations, the study of testing strategies is conducted through an agent-based simulation model.

In the analytic model, objective functions for cost were structured allowing for different test locations with or without a traceability mechanism in the wheat supply chain, from the individual farm level to the terminal elevator. Through solving this minimization problem, some efficient testing strategies using different test locations were identified. While limited in explanatory power, in fact these solutions facilitated the analysis of how related factors affect the set of testing strategies in the simulation.

Under VED, if testing on farmer deliveries is inadequate or the penalty for offenders is below a critical level, there will be moral hazard issues arising in the farmers risk control efforts. The same problems exist in the primary elevator handlers' decision-making if their railcar deliveries are not fully inspected or the penalty for offences is limited. Knowing this, the solution for an individual participant cost minimization may differ from that for the entire system of grain safety and quality assurance. This study suggests that if incentives can be effectively designed to make the relative parties with moral hazard bear fully the consequences of their actions, the moral hazard problem will be mitigated. That is, if a testing mechanism can eventually detect all offenders through either testing or tracing, and the penalty for offenders is exactly equal to the expected damage resulting from their misrepresentation, the moral hazard problems inherent in farmer and handler behaviors can be eliminated. While farmer moral hazard potential adds costs to wheat handling, alleviating them by the strategy of increasing testing intensity is also costly. If the expected cost of inducing the farmer to select an appropriate level of effort is relatively high, cost minimizing handlers will refuse to do that, and instead they will try to motivate some reduced level of effort from the farmer at lower cost, allowing the moral hazard problems to remain.

To address the limitations of the static analytic model of the problem and incorporate more realistic behavior of future supply chain participants under VED, an agent-based simulation model was developed to help model factors such as agent heterogeneity, interaction, adaptation

and dynamics. Mirroring reality, wheat supply chain participants under VED are represented as autonomous agents exhibiting heterogeneous behavior. These agents interact with each other as well as with their environment via a set of rules governing their actions and decisions. Following this construction, Chapter 4 (and Chapter 5) develops supply chain models allowing for different combinations of test points to provide an overall view of handling strategies that can be potentially considered by the primary elevator handlers under VED. Results suggest contamination testing strategies under VED are more efficient when they are adaptable and can be readily adjusted throughout the supply chain.

Testing strategies considered in the simulation allow for a combination of test points in the chain and testing intensities at each test point. As a dynamic simulation, the determination of efficient handling strategies varies with farmer misrepresentation situation over time. To efficiently allocate testing, information from the past needs to be used and updated for current decision making. For example, when individual farmer misrepresentation is frequent or serious, intensive testing at the earliest test point is crucial to help maintain the quality of the handling system and keep handling costs low. Under this situation, the effect of a bin test is rendered insignificant because almost all contamination risk would have been eliminated through testing at the previous test point. Conversely, when farmer misrepresentation is infrequent or rare, intensive testing at the earliest test point is inefficient.

Chapter 5 reaches a conclusion that a VED grain handling system with a functional traceability mechanism further enhances the safety and efficiency of wheat handling. Although sample retention costs and tracing cost can be saved if there is no traceability, in the given misrepresentation environment used in this study, such cost savings are much lower than the benefits forgone. The advantages of traceability are obvious- penalties from uncovered offenders can be used to cover contamination losses, information obtained through traceability can be used for optimizing future testing, and traceability deterrence reduces those moral hazard problems inherent in risk control behaviors.

The latter simulations also generate results about the cost distribution of monitoring among the supply chain participants. These facilitate a comparison of efficiencies between different testing strategies. Due to the diversity in individual objectives, testing strategies that work best for the primary elevator handlers likely will not benefit farmers. In light of this, if the welfare of all

supply chain participants is under consideration by a regulatory body, actual testing strategies may be different from those identified and examined in this study.

However, agent based simulation provides a foundation on which to identify a set of testing strategies that best align with a specific regulatory target. The simulation environment can also help evaluate the economic efficiency of a predetermined test strategy. Given the current uncertain policy environment regarding this issue in Canada, this research is timely and should provide valuable input into possible unforeseen consequences of switching to VED within the grain handling and transportation system. Ultimately, this research should also contribute to the continuation of a sustainable and competitive Canadian agri-food supply chain. While beyond the scope of the current analysis, the methodology could also be extended to other supply chains to help optimize risk management and control costs. Examples include an organic food handling system, genetically modified grain segregation systems as well as other food safety and quality assurance systems.

To date, economists have not embraced agent-based simulation methods in the same manner as other social and physical scientists. More broadly, one can identify economic researchers using various types of computational simulation for economic analysis. But to the knowledge of this author, there are almost no existing studies that have developed a two-tiered modeling approach for such an economic problem, allowing comparisons between the analytic results to the simulated ones. Those comparisons put insight into discussions of developing efficient strategies to mitigate grain handling risks, and, in the meantime, help address some essential economic issues associated with complex grain supply chain systems. While the policy issue of KVD vs. VED may seem somewhat distant to those outside of the grain industry, from the point of view of modeling the problem it is believed that this thesis represents a somewhat unique contribution to the economic literature in this regard.

Specification of complex systems is not an easy task. The simulation is based on assumptions on participant behavior and simple economic logic. In fact, the grain handling system is even more complex than the one described in my models. To more accurately simulate the adaptation of supply chain participant behavior would require incorporating considerably more detail. To really advance the modeling of these sorts of microeconomic issues, more research on farmers

and handling behaviour would be needed to help better understand the boundedly rational nature of their individual decision making.

These models only develop a very stylized grain handling system, with just a single primary elevator in the simple supply chain. In this sense, the model is still quite abstracted from the actual Western Canadian wheat handling system and the complexity within it is reduced when compared to reality. In fact, there are many primary elevators and inland terminal elevators in the Prairie region. Due to spatial competition between them, they also interact to some extent with other elevators with respect to their handling strategies. In this light, models with multiple elevators could better mirror the actual set of decisions within the wheat handling system than this model using a single elevator. In addition, other assumptions were made to simplify both of the kinds of models utilized in this study. For example, this study assumed that all contaminations stem only from farmer misrepresentation, meaning there are no botched operations during elevator handling and wheat transportation. It is also assumed that testing precision is perfect. It is suspected that easing these assumptions could also contribute to a better understanding of a future grain supply chain under VED.

The removal of KVD for registration and the implementation of a VED system created greater uncertainty in the Canadian wheat handling system. The operation of this kind of varietal declaration system could involve collaborative and participatory efforts at a number of levels, and could end up consuming more resources for producers and handlers or costing them more money than currently, whether directly or indirectly. The Canadian regulatory system carries some responsibility to develop appropriate quality assurance programs. It must also allow the grain quality assurance system to adapt to conform to the functional requirement of consistency and uniformity of wheat delivered to customers, while maintaining Canada's reputation as a reliable supplier of quality grain. The cost-risk tradeoff of a switch to VED provides a primary incentive for the regulatory system to invest in the development of innovative handling strategies. There is a need for more research to address the area of risk and uncertainty and a more detailed assessment of costs of operating a new handling system under VED.

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DECLARATION OF ELIGIBILITY FOR DELIVERY OF GRAINS

AND OILSEEDS FORM

I, _____ (print name)

of _____ (print address)

in the Province of _____ .

DO SOLEMNLY DECLARE THAT:

1. I am the undersigned producer and have entered into a contract with the Grain Buyer to deliver grain and/or oilseeds. In the case of a Corporation that has entered into a contract with the Grain Buyer to deliver grain and/or oilseeds, I am an authorized representative of the Corporation and make this Declaration personally and on behalf of the Corporation.

2. Any and all deliveries of wheat made by or on my behalf to the Grain Handling Company and/or the Grain Buyer are eligible varieties for delivery for the class of wheat for which payment is being requested in accordance with the Marketing Freedom for Grain Farmers Act, Canada Grain Act, Seeds Act, and all Regulations and Orders made pursuant to those Acts (collectively, the "Acts") as applicable. Any and all deliveries of other grains and/or oilseeds made by me or on my behalf to the Grain Handling Company and/or the Grain Buyer are eligible varieties for delivery for the commodity type of grain and/or oilseed for which payment is being requested in accordance with the Acts. I understand and agree that in order to be eligible, the variety must be registered by the Canadian Food Inspection Agency as eligible for the commodity type (e.g. wheat, barley, flax,

peas, canola, mustard, etc.). I further understand that, in the case of wheat, the variety must be placed into a wheat class by the Canadian Grain Commission.

3. If I, or anyone on my behalf, deliver(s) to the Grain Handling Company and/or the Grain Buyer grain and/or oilseeds that are not eligible varieties for delivery for the commodity type of grain and/or oilseed for which payment is being requested, I acknowledge and agree that the Grain Handling Company and/or the Grain Buyer may consider the representation I made in paragraphs 1 and 2 above to have been made fraudulently and/or negligently, in which case I will be liable to the Grain Handling Company and/or Grain Buyer for all claims, damages, losses and costs (including legal fees) that may result from such false and/or negligent representation. I further acknowledge and agree that the Grain Handling Company and/or Grain Buyer may consider me to be in default of my delivery contract and, in addition to any other remedies available to the Grain Buyer and/or Grain Handling Company, may cancel any contracts between myself and the Grain Handling Company and/or the Grain Buyer.

4. I acknowledge and agree that the Grain Handling Company and/or Grain Buyer may exchange with each other and the Canadian Grain Commission relevant materials (including producer name, address, delivery sample information, and a portion of the physical sample taken by the Grain Handling Company) relating to suspected deliveries of ineligible varieties of grains and/or oilseeds by me or on my behalf to the Grain Handling Company. I understand that this information will be used as the basis for establishing responsibility, which may result in the imposition of penalties and/or claim for damages on me, as part of evidence given in an arbitration process and/or court proceeding.

5. This Declaration is made and intended to apply to all deliveries of grains and/or oilseeds made by me or on my behalf to the Grain Handling Company from and including the date indicated below until the end of the 2012-2013 crop year, or until this Declaration is replaced or withdrawn by my written notice acknowledged by both the Grain Buyer and the Grain Handling Company. (Source: CGC (2012))

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THE COMPOSITION OF THE PRIMARY ELEVATOR COST FUNCTION FOR CASE 4 (B) IN CHAPTER 3

The objective functions in case 4 (b) are the most complex ones among all the cases in Chapter 3. Functions in other cases only contain parts of the components of the functions in case 4 (b). As described, cost functions in case 4 (b) allow for three test points and according traceability.

The farmer's cost function is composed of,

1. Expected Penalty

    1.1 Expected Penalty from the Testing on the Farmer's Delivery If he or she was detected,

$$f_1 \alpha \beta q_1 \tag{A3-1}$$

    1.2 Expected Penalty from the Tracing Stemming from the Primary Bin Contamination Detected,

$$f_2 \alpha (1-\beta) \beta_b q_1 \tag{A3-2}$$

    1.3 Expected Penalty from the Tracing Stemming from the Railcar Contamination Detected,

$$f_3 \alpha (1-\beta)(1-\beta_b)(n\beta_t) q_1 \tag{A3-3}$$

2. Risk Control Cost,

$$c_e q_1 \tag{A3-4}$$

Totally, the farmer's cost objective function is,

$$\text{Farmers' loss} = \begin{cases} +\text{expected penalty (include price reduction)} \\ +\text{risk control cost} \end{cases}$$

$$J_1 = f_1\alpha\beta q_1 + f_2\alpha(1-\beta)\beta_b q_1 + f_3\alpha(1-\beta)(1-\beta_b)(n\beta_t)q_1 + c_e q_1 \tag{A3-5}$$

The primary elevator's cost function is composed of,

1. Sampling and Sample Retention Cost

$$C_{sr} \tag{A3-6}$$

2. Testing Costs
    2.1 On Farmers' Deliveries,

$$c_1\sum\beta_i q_i \tag{A3-7}$$

    2.2 On Primary Elevator Bins,

$$c_2\beta_b\sum(1-\alpha_i\beta_i)q_i \tag{A3-8}$$

3. Costs due to the primary elevator bin contamination
    3.1 Detected by the Primary Elevator Bin Testing,

$$f_{p2}\beta_b\sum(1-\beta_i)\alpha_i m_i q_i \tag{A3-9}$$

where mq represents the volume of wheat in bin contaminated by misrepresented delivery.

    3.2 Detected by Railcar Testing at the Terminal Elevator,

$$f_{p3}\sum\alpha_i(1-\beta_i)m_i(1-\beta_b)(n_i\beta_t)q_i \tag{A3-10}$$

If a contaminated bin was not detected at the bin test, wheat in it will be delivered to the terminal elevator and misrepresented. It is assumed that wheat in a contaminated bin is loaded in h_i railcars. If one of the h_i railcars is detected, the contaminated bin will be traced. Then all railcars loaded from the contaminated bin will be identified. So the detection probability of a misrepresented railcar is different from β_t. The value of $(n_i \beta_t)$ is used to represent the probability that a contaminated bin is traced or a misrepresented railcar is identified, where n_i is a probability multiplier (to know more by referring to Appendix 3.2).

4. Tracing Costs

   4.1 Tracing Enacted by Bin Testing,

$$c_1 \beta_b \sum (1 - \beta_i) \alpha_i m_i q_i \tag{A3-11}$$

   4.2 Tracing Enacted by Railcar Testing,

$$c_1 \sum (n_i \beta_t)(1 - \beta_b)(1 - \beta_i) \alpha_i m_i q_i \tag{A3-12}$$

5. Retrieved Losses (Benefit) from Testing and Tracing

   5.1 From Testing on Trucks,

$$\sum f_{1i} \alpha_i \beta_i q_i \tag{A3-13}$$

   5.2 From Tracing Enacted by Bin Testing,

$$\sum f_{2i} \alpha_i (1 - \beta_i) \beta_b q_i \tag{A3-14}$$

   5.3 From Tracing Enacted by Railcar Testing,

$$\sum f_{3i} \alpha_i (1 - \beta_i)(1 - \beta_b)(n_i \beta_t) q_i \tag{A3-15}$$

In total, the primary elevator handling costs can be obtained through a summation of components of A1-A16,

Handling costs = $\left\{\begin{array}{l}\text{+sampling and sample retention cost} \\[8pt] \text{+testing costs and tracing costs} \\[8pt] \text{+ costs due to bin contamination} \\[8pt] \text{- retrieved costs from testing and tracing}\end{array}\right.$

That is,

$$\begin{aligned}
J_2 &= C_{sr} + c_1 \sum \beta_i q_i + c_2 \beta_b \sum (1 - \alpha_i \beta_i) q_i + f_{p2} \beta_b \sum (1 - \beta_i) \alpha_i m_i q_i \\
&+ f_{p3} \sum \alpha_i (1 - \beta_i) m_i (1 - \beta_b)(n_i \beta_t) q_i + c_1 \beta_b \sum (1 - \beta_i) \alpha_i m_i q_i \\
&+ c_1 \sum (n_i \beta_t)(1 - \beta_b)(1 - \beta_i) \alpha_i m_i q_i - \sum f_{1i} \alpha_i \beta_i q_i \\
&- \sum f_{2i} \alpha_i (1 - \beta_i) \beta_b q_i - \sum f_{3i} \alpha_i (1 - \beta_i)(1 - \beta_b)(n_i \beta_t) q_i
\end{aligned} \qquad \text{(A3-16)}$$

THE PROBABILITY OF IDENTIFYING A CONTAMINATED BIN THROUGH TRACEABILITY

If there are a bins and each bin can load b railcars. The total number of railcars that can be loaded is ab. If h railcars are randomly tested at the terminal elevator, the test rate for railcars will be $\dfrac{h}{ab}$. I assume the primary elevator handlers have all loading and unloading information recorded and the terminal elevator can obtain information concerning the exact bin from which a railcar was loaded. So if a misrepresented railcar was tested and detected, the corresponding contaminated bin will be traced and all other misrepresented railcars loaded from this bin will be identified. If there is traceability, the farmer who misrepresented the deliveries and resulted in the contamination will be detected.

When h railcars are tested, the total combination of railcars is C_{ab}^{h}. If there is a contaminated bin from which b railcars loaded, the probability that there is at least one railcar from this contaminated bin among all tested railcars is $\left(1 - \dfrac{C_{(a-1)b}^{h}}{C_{ab}^{h}} \right)$. Such a probability is just the one that the contaminated bin will be identified or the one that the farmer responsible for the contamination will be traced and detected. Then the probability multiplier will be:

$$ n = \left(1 - \frac{C_{(a-1)b}^{h}}{C_{ab}^{h}} \right) \times \left(\frac{ab}{h} \right) $$

For example, say there are 20 bins and each bin can load 6 railcars. There was 1 farmer that misrepresented the delivery without being detected. This misrepresented delivery resulted in contamination in the bin in which the misrepresented were unloaded. If there are 60 railcars tested at the terminal elevator, the terminal elevator's test rate is 0.50. The probability that the

contaminated bin can be identified is $\left(1 - \dfrac{C_{114}^{50}}{C_{120}^{50}}\right) = 0.96$, much greater than the test rate 0.50. That

is, all misrepresented railcars from the same contaminated bin will be detected with a probability 0.96. The farmer who misrepresented the delivery and resulted in contamination can be detected at the same probability 0.96. Under these conditions, the probability multiplier n is 1.92. In this study, there are about 32 railcars used for each delivery. When the railcar test rate is 0.80, a contaminated bin or a misrepresented farmer's delivery can be identified with a probability $\left(1 - \dfrac{C_{28}^{26}}{C_{32}^{26}}\right) = 0.998$. The probability multiplier n is 1.25.

EXPONENTIALLY WEIGHTED MOVING AVERAGES

An exponentially weighted moving average (EWMA) applies weighting factors which decrease exponentially. The weighting for each older data point decreases exponentially, giving much more importance to recent perceptions while still not discarding older perceptions entirely. In this study, EWMA is used to assess the misrepresentation situation when the test strategy for farmers and for the primary elevator bin for the first delivery within a year is developed.

The degree of weighting decrease is expressed as a constant smoothing factor η, a number between 0 and 1. A higher η discounts older observations faster. Alternatively, η may be expressed in terms of N time periods, where $\eta = \dfrac{2}{N+1}$. For example, N=8 is equivalent to $\eta = 0.222$.

The observation at a time period T is designated Y_T, and the value of the EWMA at any time period T is designated S_T (S_1 is undefined). S_2 may be initialized in a number of different ways, but is done more frequently by setting S_2 to Y_1. However, other techniques exist, such as setting S_2 to an average of the first 4 or 5 observations. The prominence of the S_2 initialization's effect on the computed moving average depends on η, where smaller η values make the choice of S_2 relatively more important than larger η values, because a higher η discounts older observations faster.

The formula for calculating the EMA at time periods $T > 2$ is

$$S_T = \eta \times Y_{T-1} + (1-\eta) \times S_{T-1}$$

This formulation is based on the work of Hunter (1986). By repeated application of this formula we can eventually write S_T as a weighted sum of the data points Y_T, thus,

$$S_T = \eta \times (Y_{T-1} + (1-\eta) \times Y_{T-2} + (1-\eta)^2 \times Y_{T-3} + (1-\eta)^3 \times Y_{T-4} + ...(1-\eta)^k \times Y_{T-(k+1)})$$

for any suitable $k = 1, 2, 3...$, and the weight of the general data point Y_{T-i} is $\eta(1-\eta)^{i-1}$.

In those models, the EWMA uses $N=8$. In this way, the EWMA gives significant more weights to recent observations. For example, the calculated weights from the past 1 to 8 years are 0.222, 0.178, 0.134, 0.105, 0.081, 0.063, 0.049 and 0.038 respectively. The total weight for the past 8 years data is 0.866 and the rest of the years account for 0.134. Figure A-D1 shows the weight distribution among past 20 years.
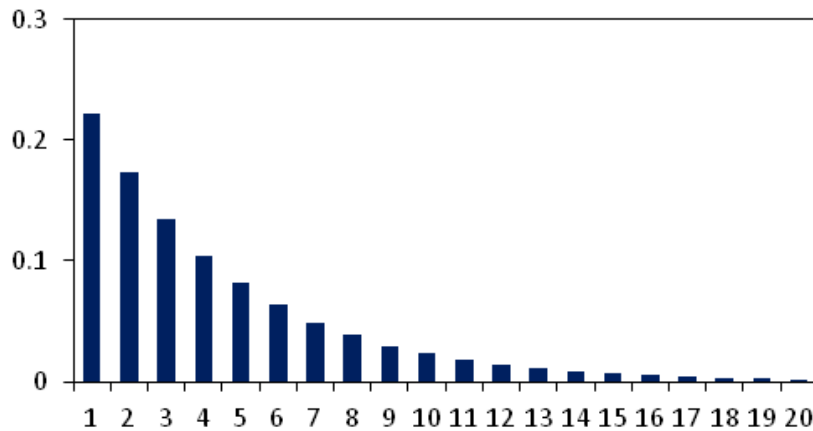
Note: EWMA Weights $N=8$

Figure A-D1 Weight Distribution of an EWMA Over 20 Years

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APPENDIX E: CONTROL FLOW DIAGRAM OF THE SIMULATION

Absorb Loss	Effort Adjustment

No

Trace Back — Yes

Be Penalized

Yes

Yes

No — Detected — Yes

No — Detected

Yes

Yes

Railcar Test ← Bin test ← No — Truck Test ← Delivery ← Farmer

No

Yes

No — Contaminated

Yes

Trace Back — Yes

No

Absorb Loss

Terminal Elevator → Test Rate for Bin Adjustment

Terminal Elevator → Test Rate for Farmer Adjustment

start
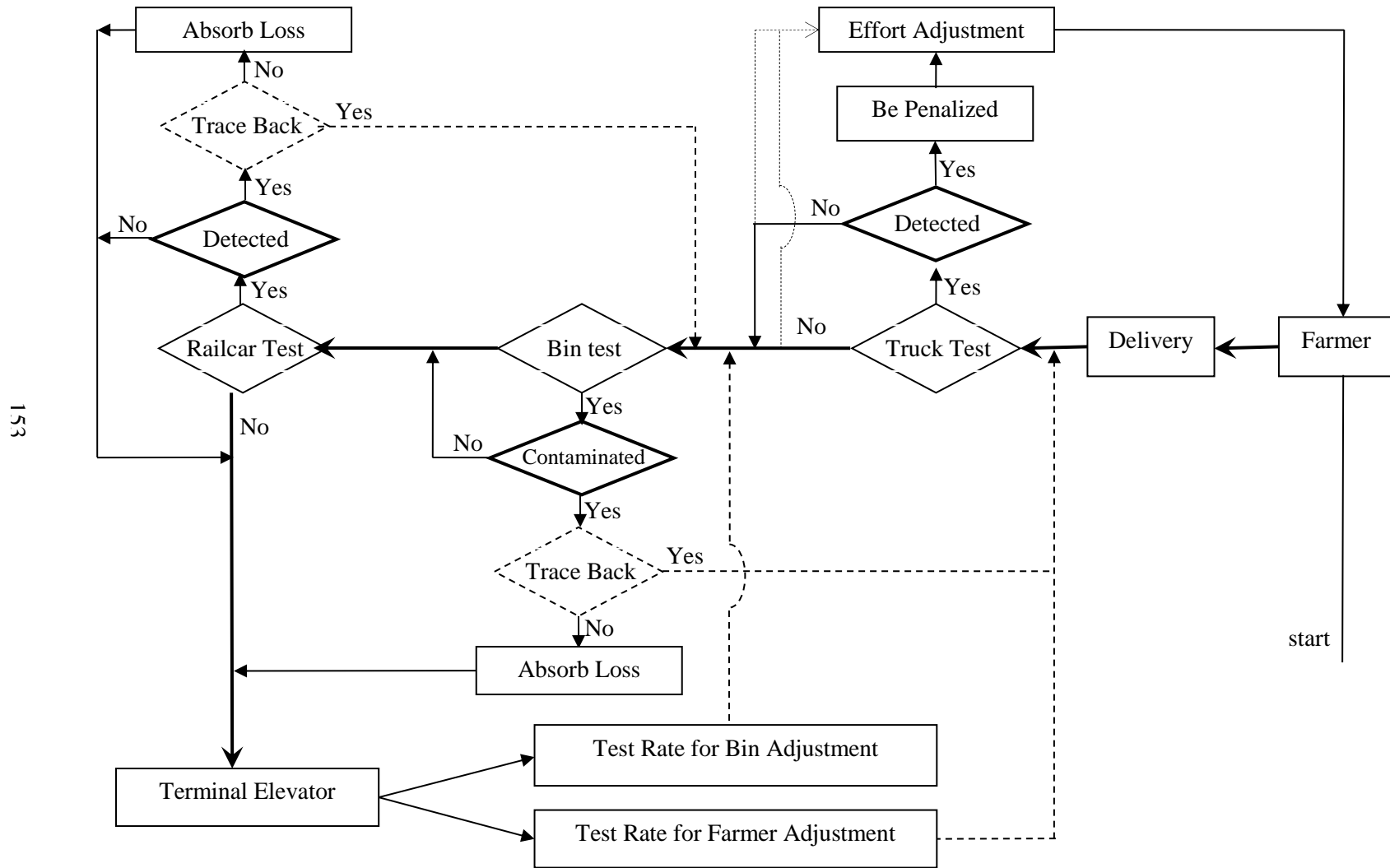
APPENDIX F

THE DENSITY FUNCTION AND
THE MEAN OF THE MISREPRESENTATION PROBABILITY

The farmer's misrepresentation probability function is,

$$\alpha_j^T = e^{-\eta \frac{c_j^T}{k_j^T}}$$

Under the assumption $c \in [b1, b2]$, the density function for c is,

$$f(c) = \frac{1}{b2 - b1}$$

The property of the misrepresentation probability function indicates,

$$f(c)dc = g(\alpha)d\alpha$$

where $g(\alpha)$ is the density function of α.

Then,

$$g(\alpha) = \frac{f_c(c)}{\frac{d\alpha}{dc}} = \frac{1}{b2 - b1} \times \frac{k}{\eta e^{-\eta \frac{c}{k}}} = \frac{k}{\eta(b2 - b1)\alpha}$$

The mean of α is,

$$\bar{\alpha} = \int \alpha g(\alpha)d\alpha = \frac{k}{\eta(b2 - b1)}\alpha \Big|_{e^{-\frac{b2}{k}}}^{e^{-\frac{b1}{k}}} = \frac{k}{\eta(b2 - b1)}(e^{-\eta \frac{b1}{k}} - e^{-\eta \frac{b2}{k}})$$

When $\eta=10$, $b1=0.15$, $b2=1$, $k=1.9$, one gets that,
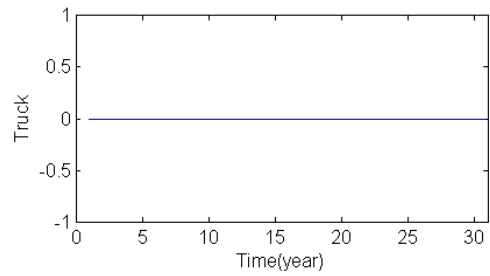
$$\bar{\alpha} = 0.100343$$
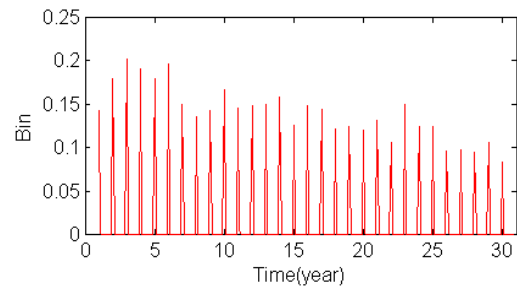
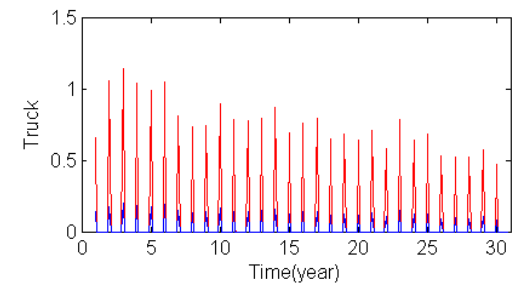(a1) Test Point 1: Truck Test (a2) Test Point 2: Bin Test (a3) Test Point 3: Railcar Test
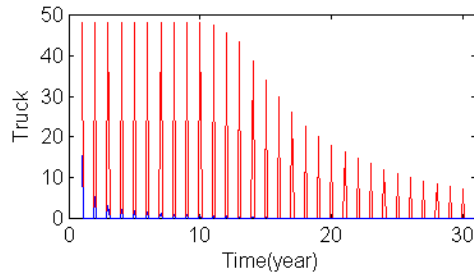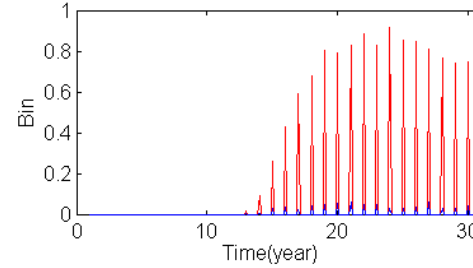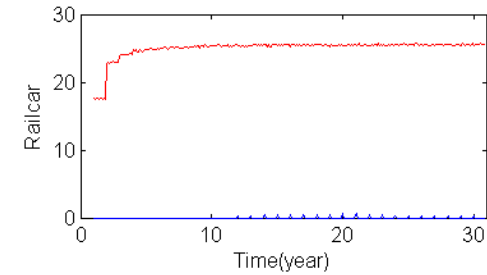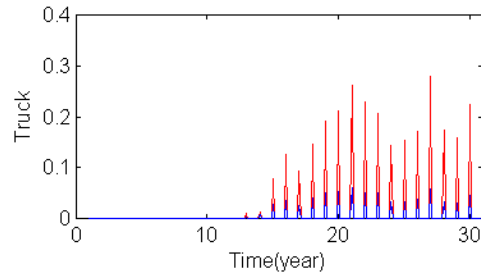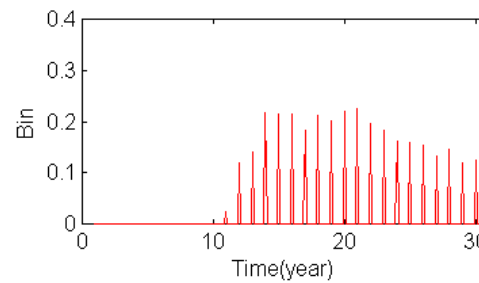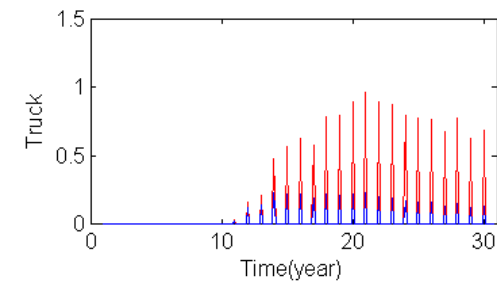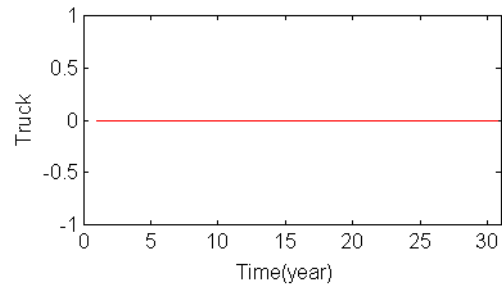
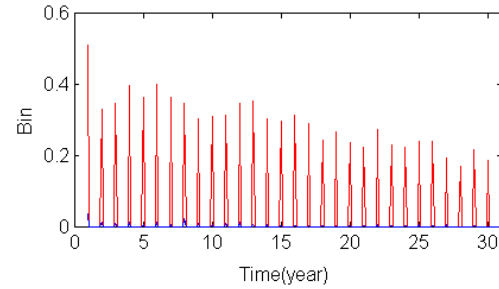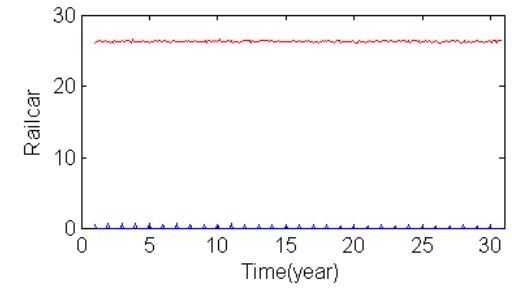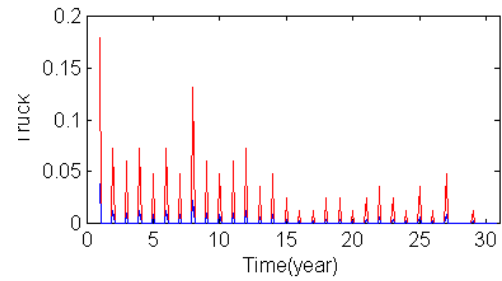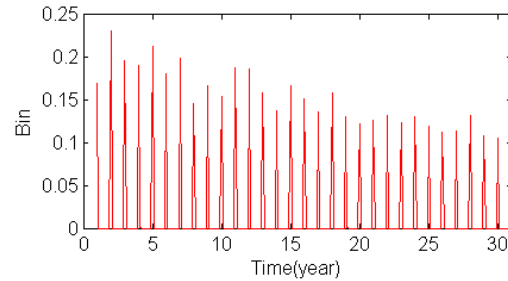(a4) Traceability 1: Bin to Farmer (a5) Traceability 2: Railcar to Bin (a6) Traceability 2: Bin to Farmer

Figure A-G1 Model A - Elevator's Testing and Tracing Strategies and Results (High Initial Misrepresentation Rate)

Figures in row 1: testing strategies (there are three test points in model A, test points 1, 2 and 3)
Figure 5.1(a1): The number of tested trucks (red line) and the number of detected trucks (blue line) at test point 1
Figure 5.1(a2): The number of tested primary elevator bins (red) and the number of bins proven contaminated (blue) at test point 2
Figure 5.1(a3): The number of tested railcars (red) and the number of detected railcars (blue) at test point 3

Figures in row 2: tracing strategies
Figure 5.1(a4): The number of tested trucks (red) and the number of detected trucks (blue) in the first tracing triggered by detected contaminated primary elevator bin.
Figure 5.1(a5): The number of tested primary elevator bins in the second tracing triggered by detected misrepresented railcars
Figure 5.1(a6): The number of tested trucks (red) and the number of detected trucks (blue) in the second tracing.
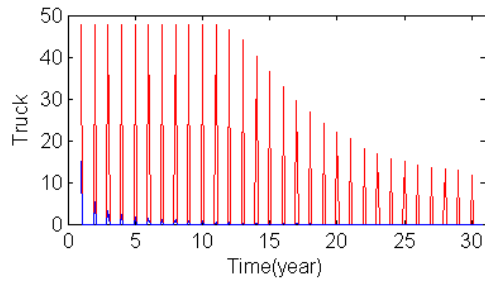
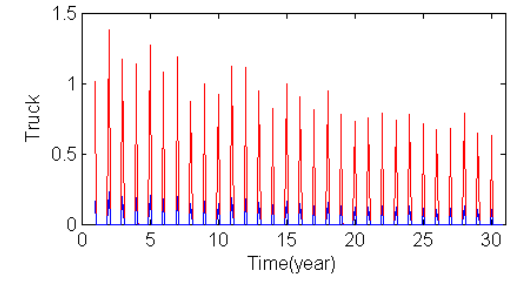(b1) Test Point 1: Truck Test   (b2) Test Point 2: Bin Test   (b3) Test Point 3: Railcar Test
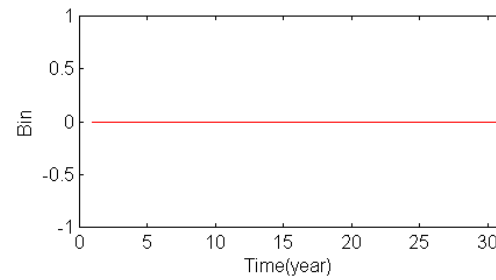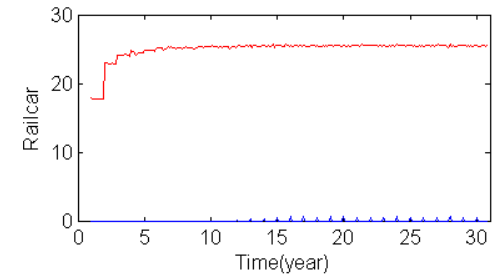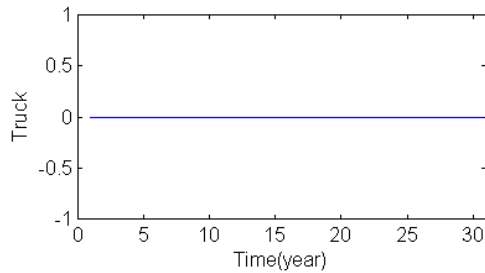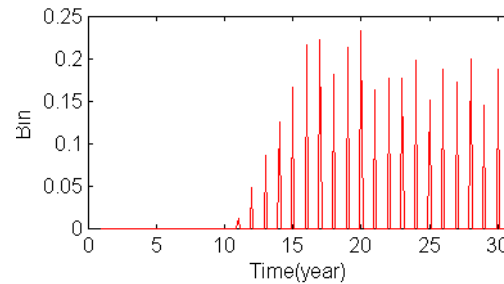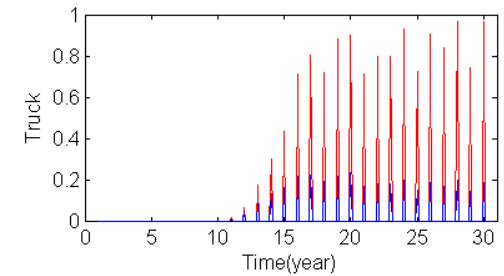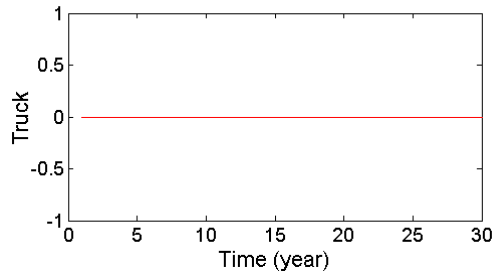
(b4) Traceability 1: Bin to Farmer   (b5) Traceability 2: Railcar to Bin   (b6) Traceability 2: Bin to Farmer
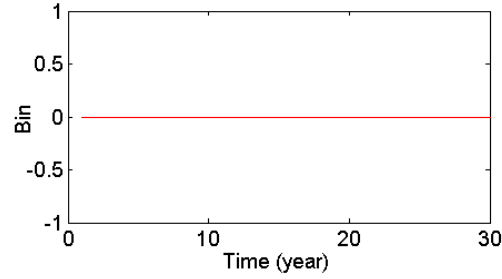
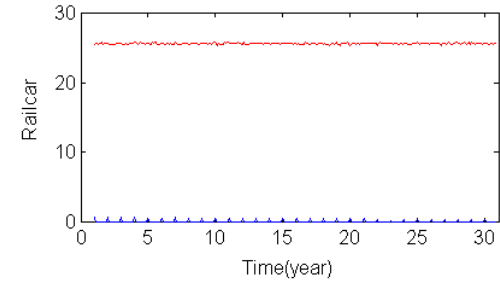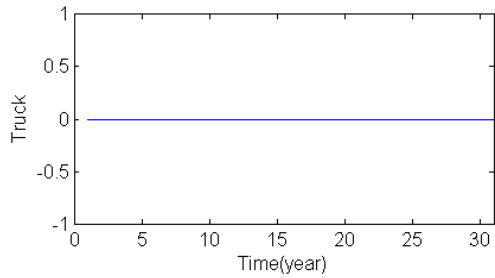Figure A-G2 Model B - Elevator's Testing and Tracing Strategies and Results (High Initial Misrepresentation Rate)

Figures in row 1: testing strategy (there are two test points in model B, test points 1 and 3)
Figure 5.2(b1): The number of tested trucks (red line) and the number of detected trucks (blue line) at test point 1
Figure 5.2(b2): There is no test at test point 2 in this model
Figure 5.2(b3): The number of tested railcars (red) and the number of detected railcars (blue) at test point 3

Figures in row 2: tracing strategy
Figure 5.2(b4): There is no traceability involved at test point 2
Figure 5.2(b5): The number of tested primary elevator bins in the second tracing triggered by detected misrepresented railcars
Figure 5.2(b6): The number of tested trucks (red) and the number of detected trucks (blue) in the second tracing
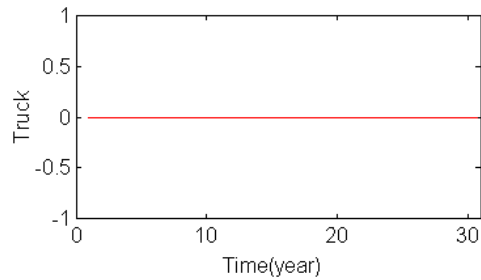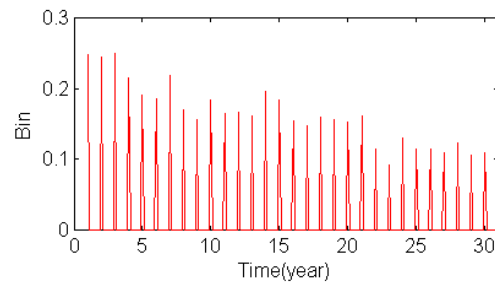
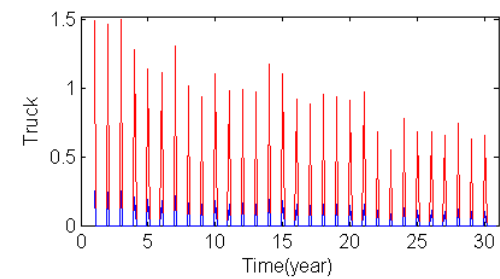(c1) Test Point 1: Truck Test   (c2) Test Point 2: Bin Test   (c3) Test Point 3: Railcar Test
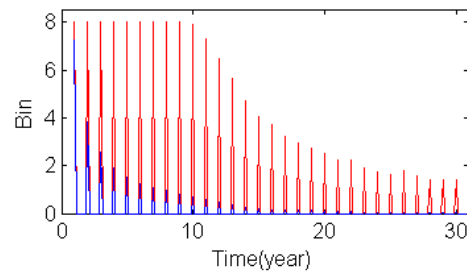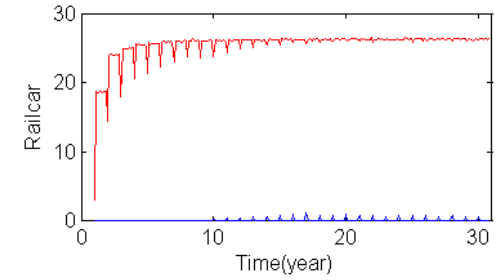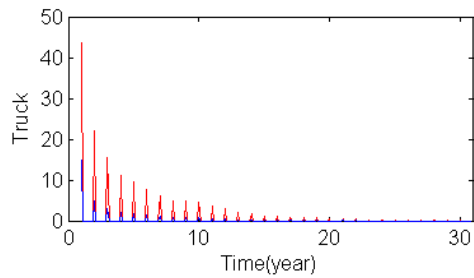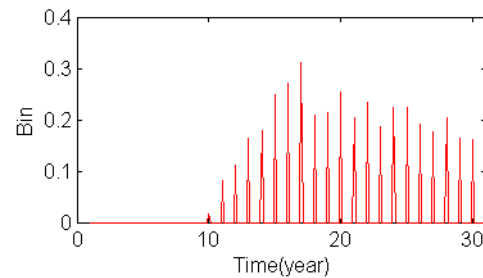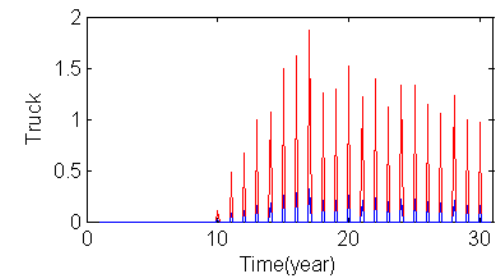
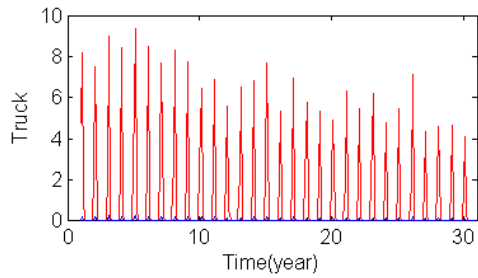(c4) Traceability 1: Bin to Farmer   (c5) Traceability 2: Railcar to Bin   (c6) Traceability 2: Bin to Farmer
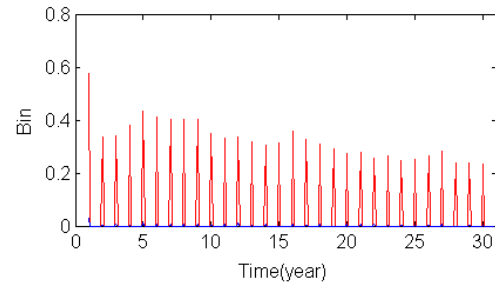
Figure A-G3 Model C - Elevator's Testing and Tracing Strategies and Results (High Initial Misrepresentation Rate)

Figures in row 1: testing strategies (there are two test points in model C, test points 1 and 2)

Figure 5.3(c1): There is no test at test point 1.

Figure 5.3(c2): The number of tested primary elevator bins (red) and proven contaminated (blue) at test point 2

Figure 5.3(c3): The number of tested railcars (red) and detected railcars (blue) at test point 3

Figures in row 2: tracing strategies

Figure 5.3(c4): The number of tested trucks (red) and detected trucks (blue) in the first tracing triggered by detected contaminated primary elevator bin

Figure 5.3(c5): The number of tested primary elevator bins in the second tracing triggered by detected misrepresented railcars

Figure 5.3(c6): The number of tested trucks (red) and the number of detected trucks (blue) in the second tracing
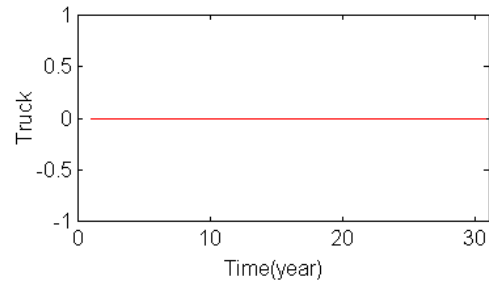
(d1) Test Point 1: Truck Test   (d2) Test Point 2: Bin Test   (d3) Test Point 3: Railcar Test
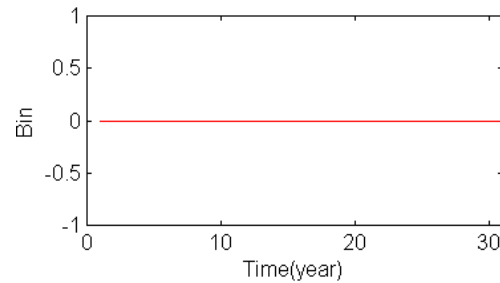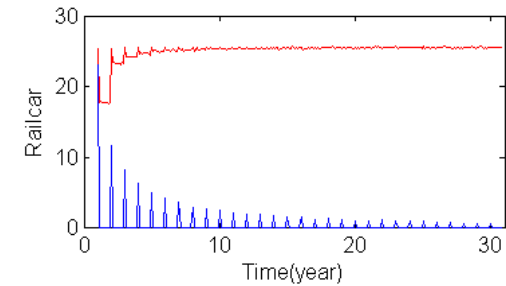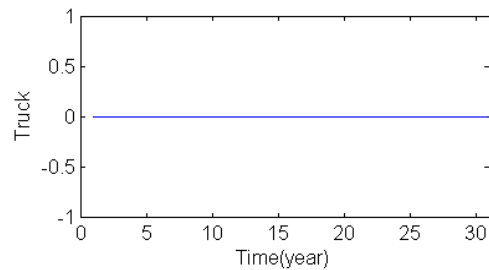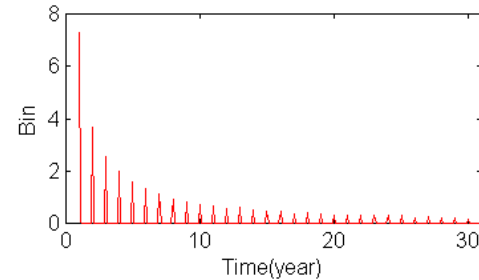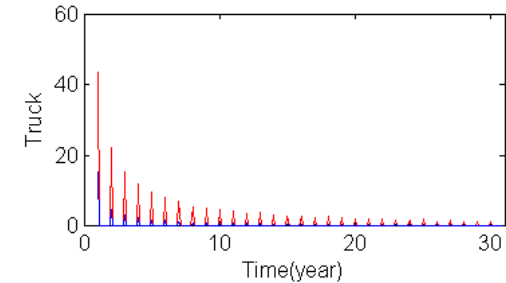

(d4) Traceability 1: Bin to Farmer   (d5) Traceability 2: Railcar to Bin   (d6) Traceability 2: Bin to Farmer

Figure A-G4 Model D - Elevator's Testing and Tracing Strategies and Results (High Initial Misrepresentation Rate)

Figures in row 1: testing strategy (there is one test point in model D, test point 3)

Figure 5.4(d1): There is no test at test point 1.

Figure 5.4(d2): There is no test at test point 2

Figure 5.4(d3): The number of tested railcars (red) and detected railcars (blue) at test point 3

Figures in row 2: tracing strategy

Figure 5.4(d4): There is no traceability involved at test point 2.

Figure 5.4(d5): The number of tested primary elevator bins in the second tracing triggered by detected misrepresented railcars

Figure 5.4(d6): The number of tested trucks (red) and the number of detected trucks (blue) in the second tracing
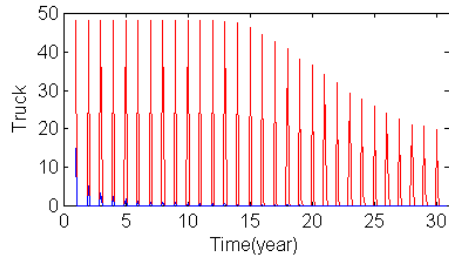
(e1) Test Point 1: Truck Test   (e2) Test Point 2: Bin Test   (e3) Test Point 3: Railcar Test
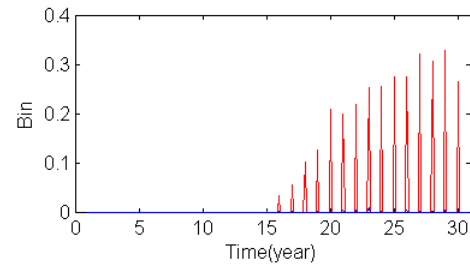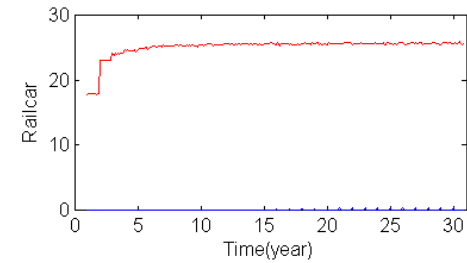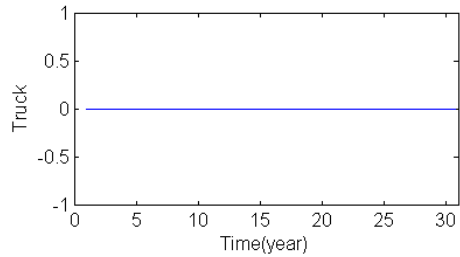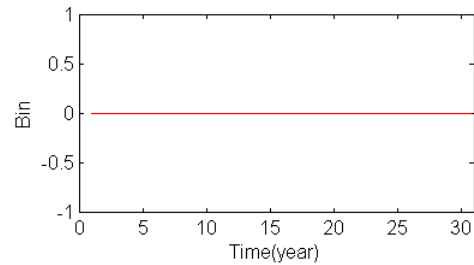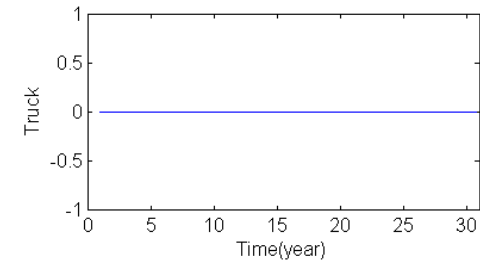
(e4) Traceability 1: Bin to Farmer   (e5) Traceability 2: Railcar to Bin   (e6) Traceability 2: Bin to Farmer

Figure A-G5 Model E - Elevator's Testing and Tracing Strategies and Results (High Initial Misrepresentation Rate)

Figures in row 1: testing strategy (there are three test points in model 5, test points 1, 2 and 3)

Figure 5.5(e1): The number of tested trucks (red line) and the number of detected trucks (blue line) at test point 1

Figure 5.5(e2): The number of tested primary elevator bins (red) and the number of bins proven contaminated (blue) at test point 2

Figure 5.5(e3): The number of tested railcars (red) and detected railcars (blue) at test point 3. Railcars are completely tested by the terminal.

Figures in row 2: tracing strategy (there is no traceability in model E)
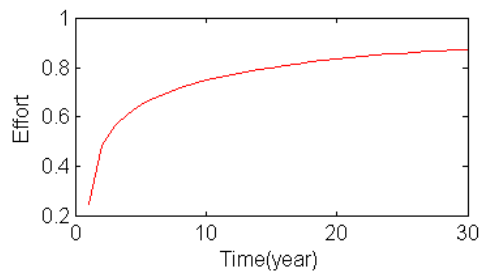
(a1) Model A: Effort   (a2) Model A: Technology   (a3) Model A: Misrepresentation Rate
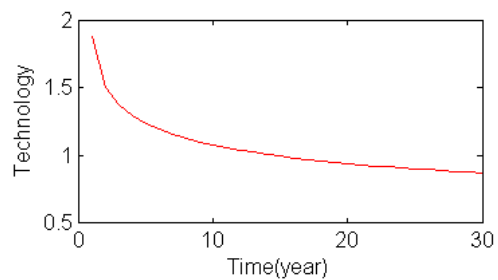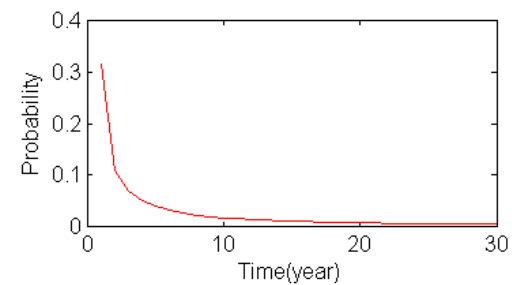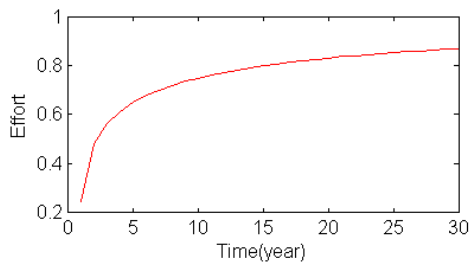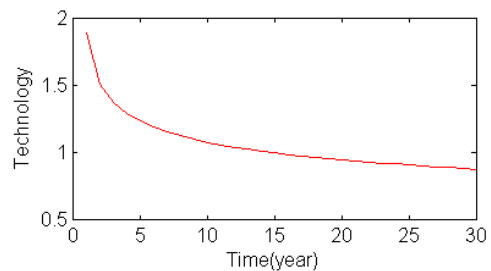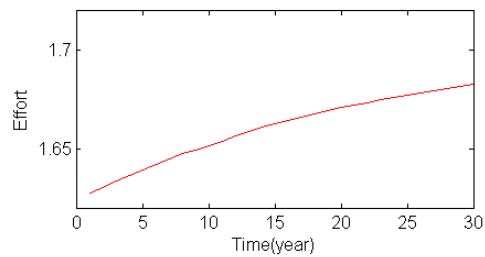
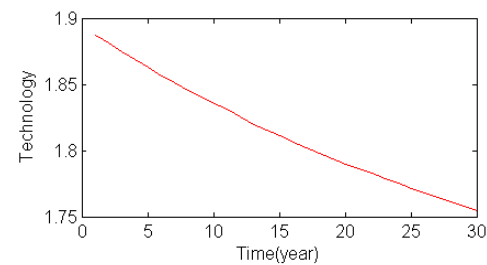(b1) Model B: Effort   (b2) Model B: Technology   (b3) Model B: Misrepresentation Rate
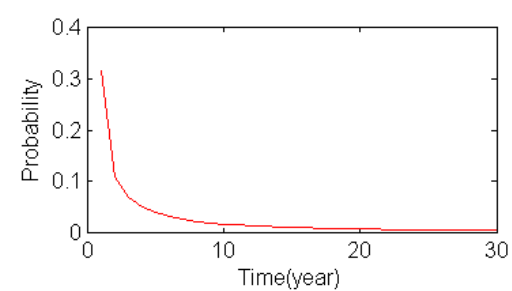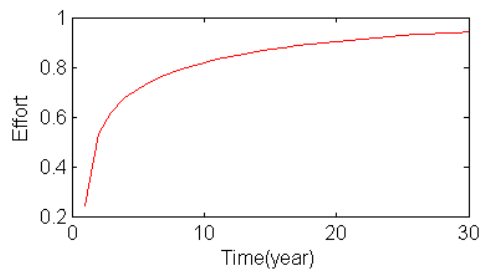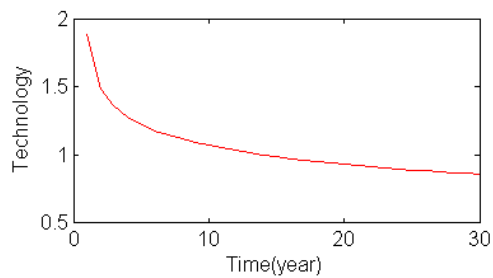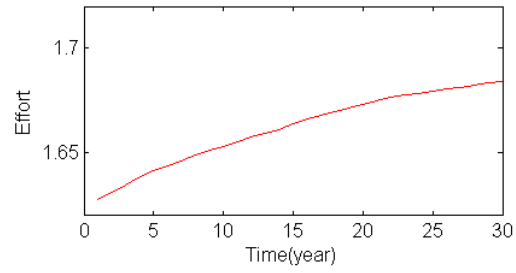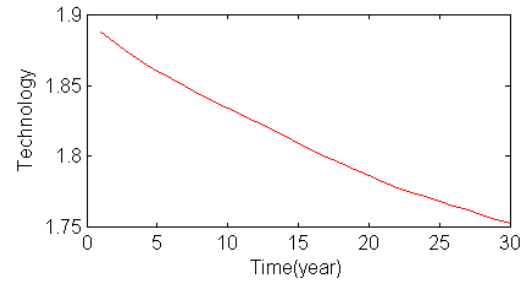
(c1) Model C: Effort   (c2) Model C: Technology   (c3) Model C: Misrepresentation Rate
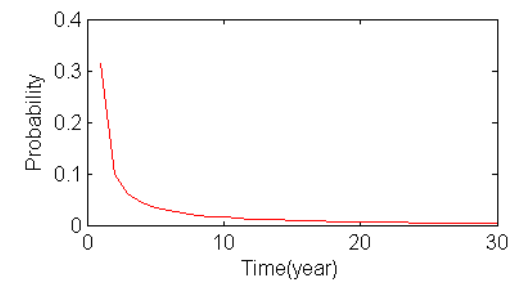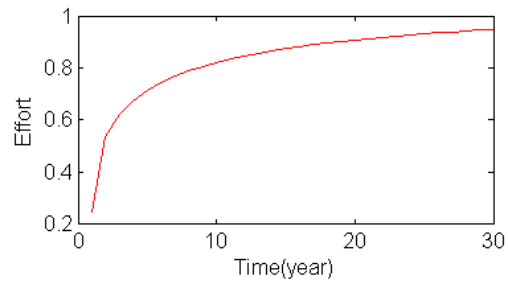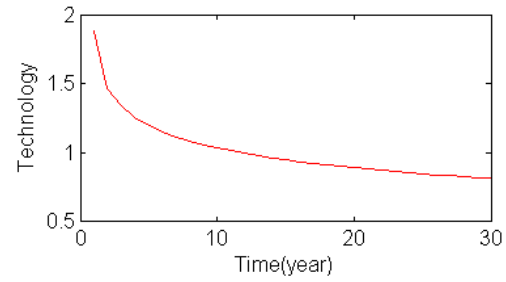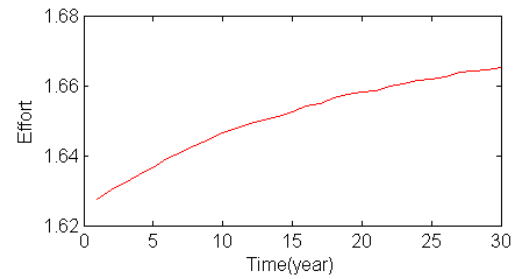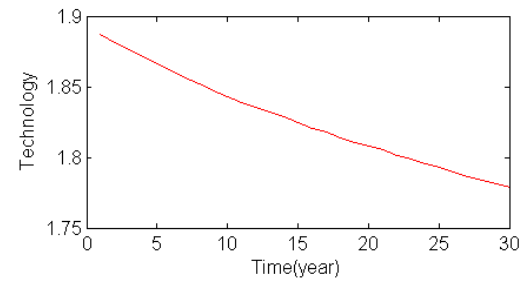
(d1) Model D: Effort　　　　　　　(d2) Model D: Technology　　　　　(d3) Model D: Misrepresentation Rate
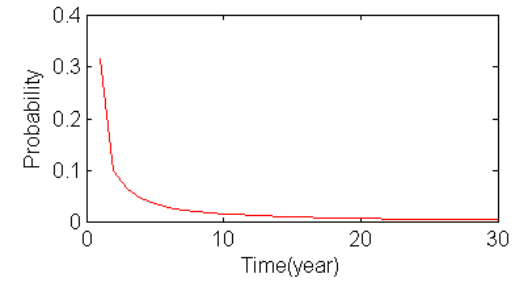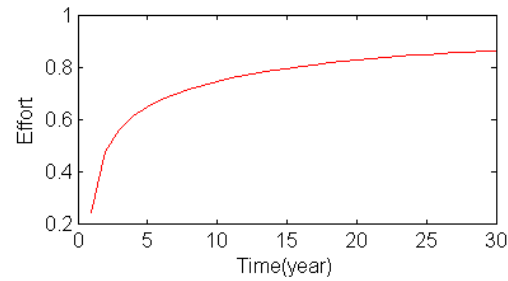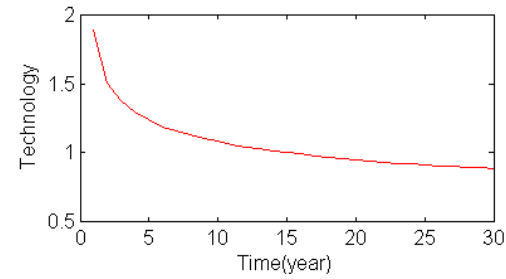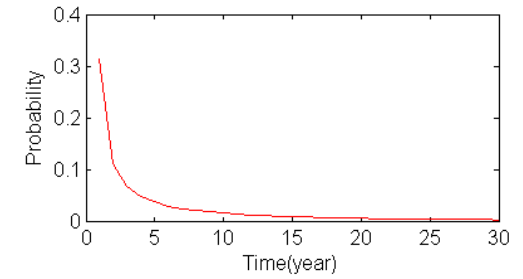
(e1) Model E: Effort　　　　　　　(e2) Model E: Technology　　　　　(e3) Model E: Misrepresentation Rate

Figure A-G6 Evolution on Farmer's Efforts on Risk Control, Technology Efficiency and Misrepresentation Rate
(High Initial Misrepresentation Rate)
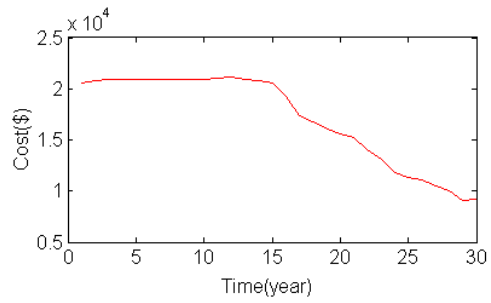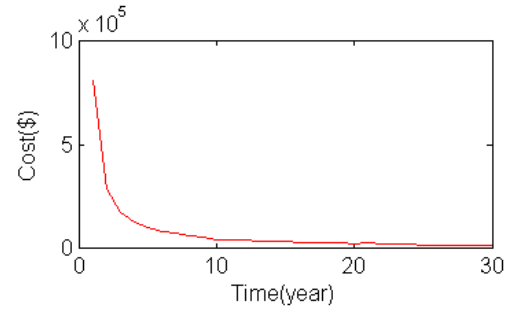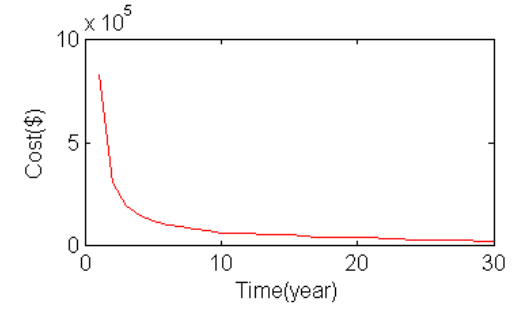
(a1) Model A: Handling Costs (a2) Model A: Farmers' Losses (a3) Model A: Total Costs
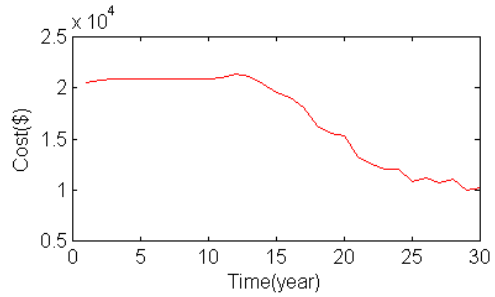
(b1) Model B: Handling Costs (b2) Model B: Farmers' Losses (b3) Model B: Total Costs
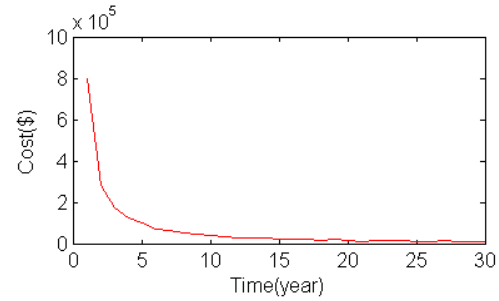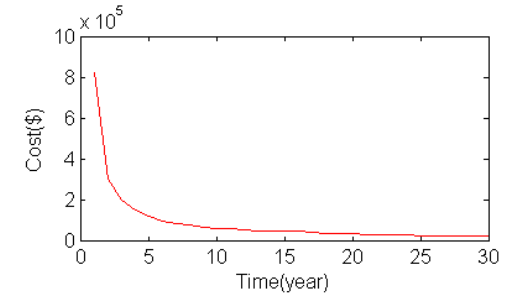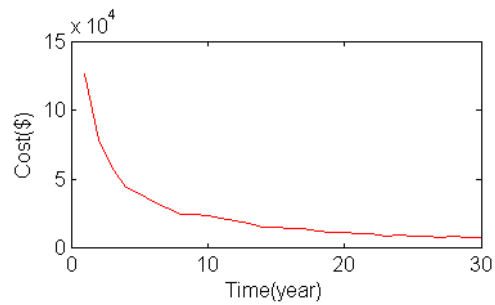
(c1) Model C: Handling Costs (c2) Model C: Farmers' Losses (c3) Model C: Total Costs
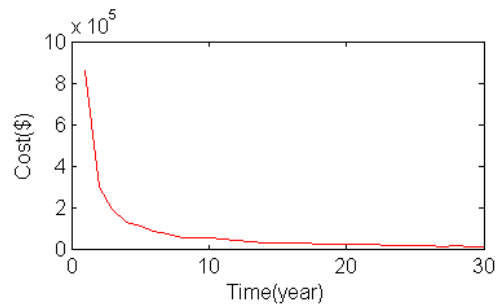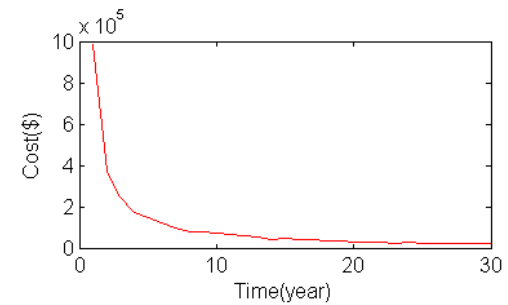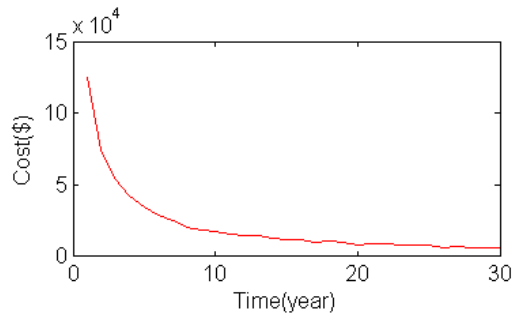
(d1) Model D: Handling Costs   (d2) Model D: Farmers' Losses   (d3) Model D: Total Costs
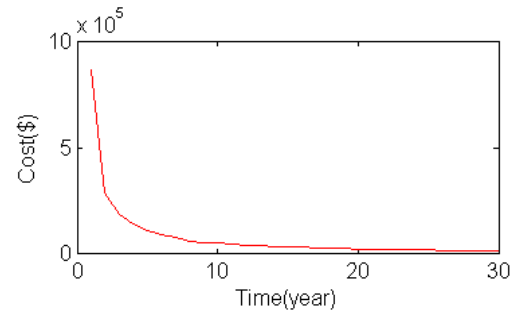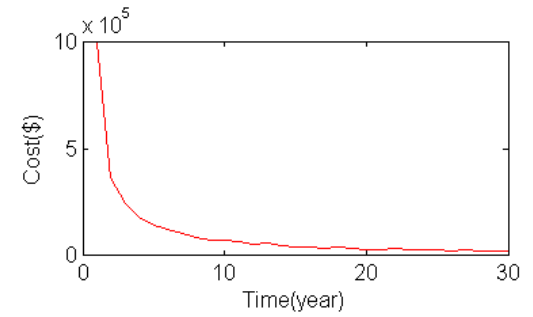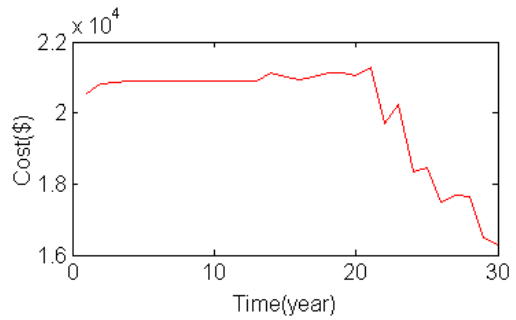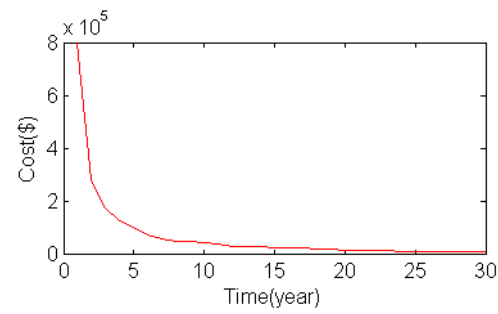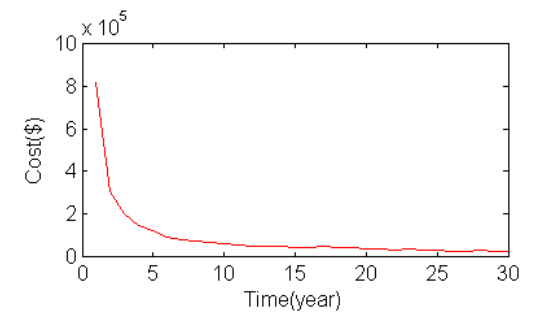
(e1) Model E: Handling Costs   (e2) Model E: Farmers' Losses   (e3) Model E: Total Costs

Figure A-G7 Handling Costs, Farmers' Losses and Total Costs (High Initial Misrepresentation Rate)
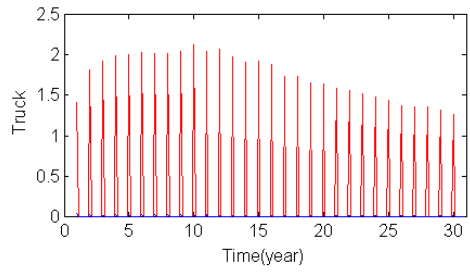
(a1) Test Point 1: Truck Test   (a2) Test Point 2: Bin Test   (a3) Test Point 3: Railcar Test
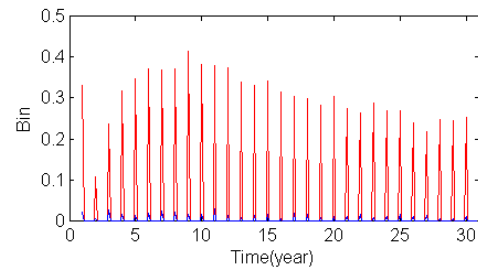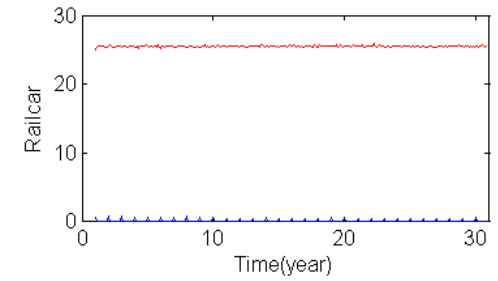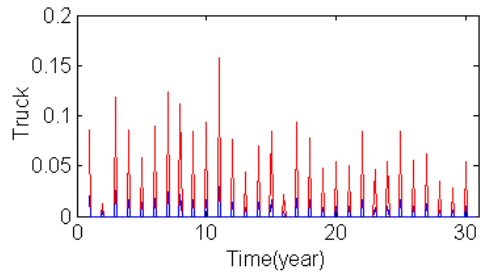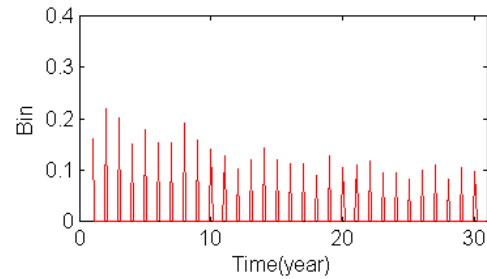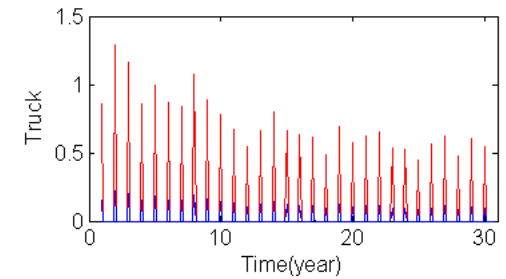
(a4) Traceability 1: Bin to Farmer   (a5) Traceability 2: Railcar to Bin   (a6) Traceability 2: Bin to Farmer

Figure A-G8 Model A- Elevator's Testing and Tracing Strategies and Results (Low Initial Misrepresentation Rate)
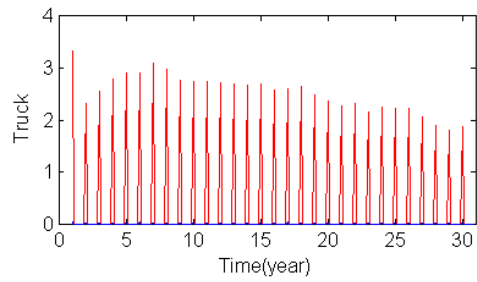
(b1) Test Point 1: Truck Test   (b2) Test Point 2: Bin Test   (b3) Test Point 3: Railcar Test
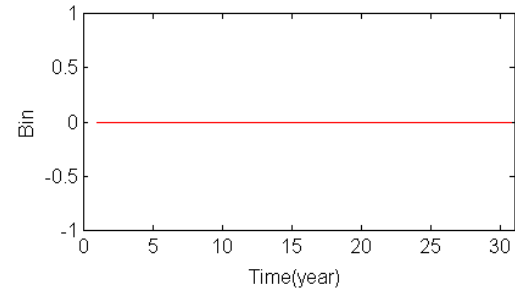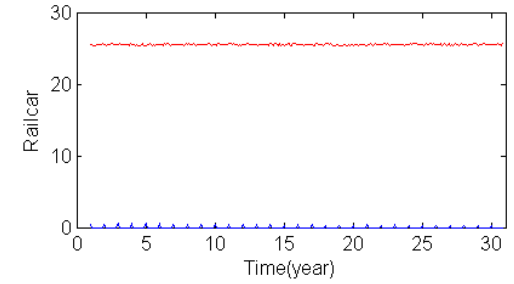
(b4) Traceability 1: Bin to Farmer   (b5) Traceability 2: Railcar to Bin   (b6) Traceability 2: Bin to Farmer

Figure A-G9 Model B - Elevator's Testing and Tracing Strategies and Results (Low Initial Misrepresentation Rate)

(c1) Test Point 1: Truck Test   (c2) Test Point 2: Bin Test   (c3) Test Point 3: Railcar Test

(c4) Traceability 1: Bin to Farmer   (c5) Traceability 2: Railcar to Bin   (c6) Traceability 2: Bin to Farmer

Figure A-G10 Model C - Elevator's Testing and Tracing Strategies and Results (Low Initial Misrepresentation Rate)

(d1) Test Point 1: Truck Test

(d2) Test Point 2: Bin Test

(d3) Test Point 3: Railcar Test

(d4) Traceability 1: Bin to Farmer

(d5) Traceability 2: Railcar to Bin

(d6) Traceability 2: Bin to Farmer

Figure A-G11 Model D - Elevator's Testing and Tracing Strategies and Results (Low Initial Misrepresentation Rate)

(e1) Test Point 1: Truck Test   (e2) Test Point 2: Bin Test   (e3) Test Point 3: Railcar Test
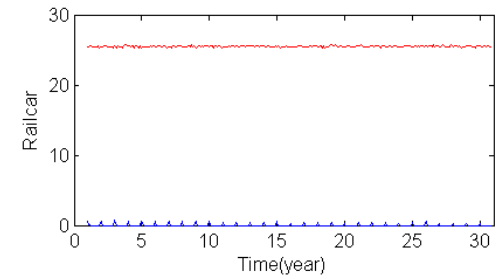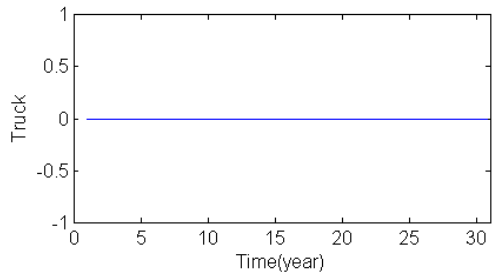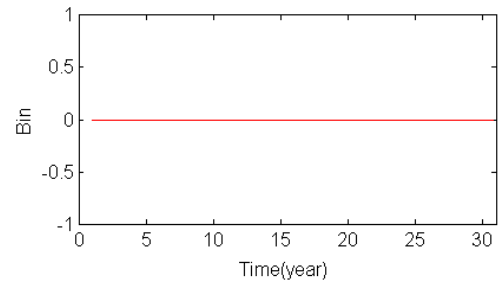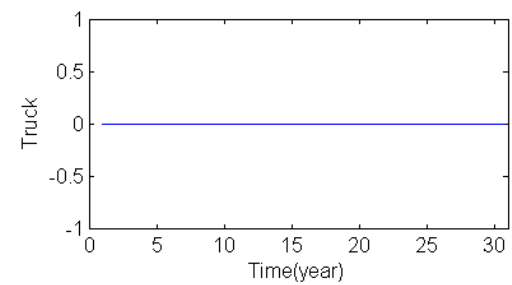
(e4) Traceability 1: Bin to Farmer   (e5) Traceability 2: Railcar to Bin   (e6) Traceability 2: Bin to Farmer

Figure A-G12 Model E - Elevator's Testing and Tracing Strategies and Results (Low Initial Misrepresentation Rate)
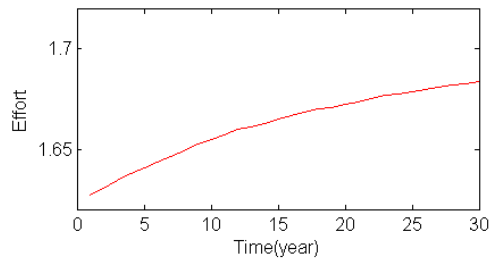
(a1) Model A: Effort (a2) Model A: Technology (a3) Model A: Misrepresentation Rate
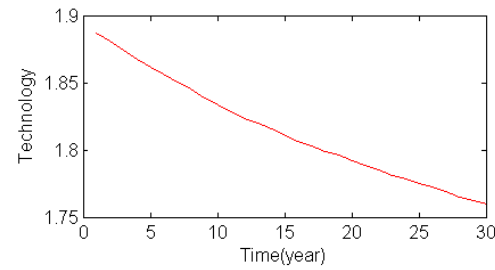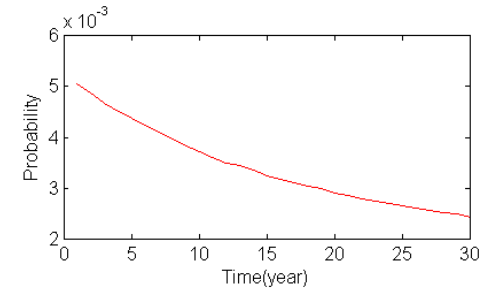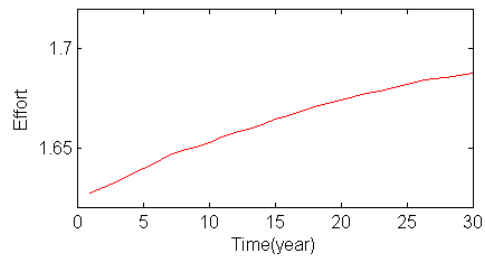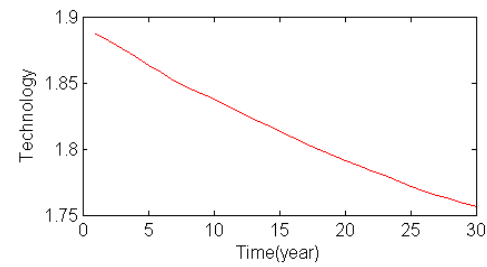
(b1) Model B: Effort (b2) Model B: Technology (b3) Model B: Misrepresentation Rate
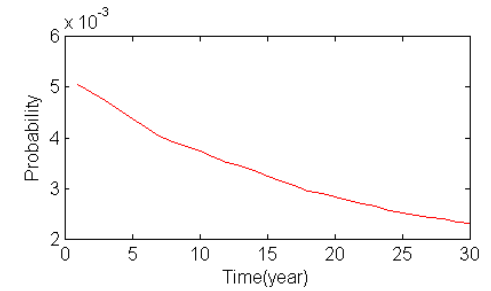
(c1) Model C: Effort (c2) Model C: Technology (c3) Model C: Misrepresentation Rate
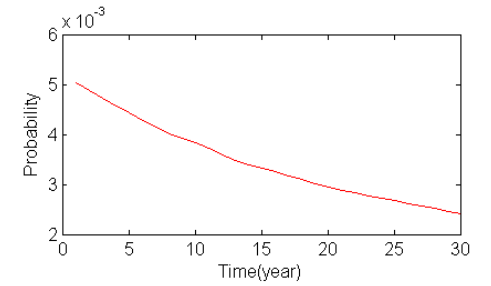
(d1) Model D: Effort   (d2) Model D: Technology   (d3) Model D: Misrepresentation Rate
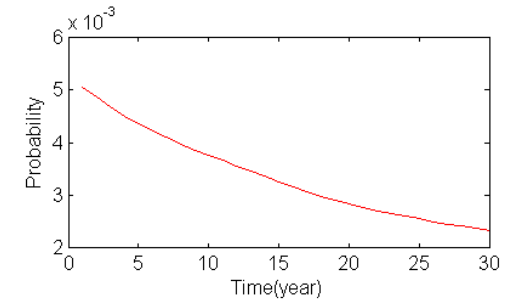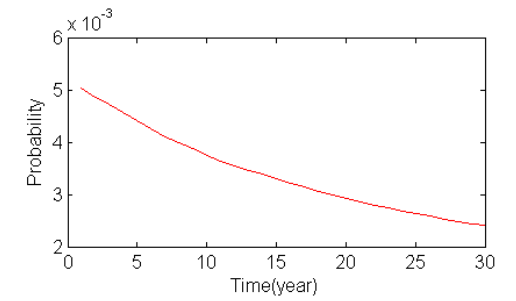
(e1) Model E: Effort   (e2) Model E: Technology   (e3) Model E: Misrepresentation Rate

Figure A-G13 Farmer's Efforts on Risk Control, Technology Efficiency and Misrepresentation Rate
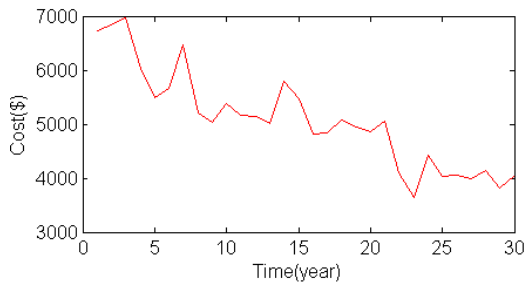(Low Initial Misrepresentation Rate)
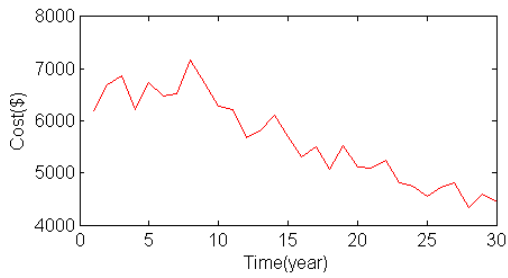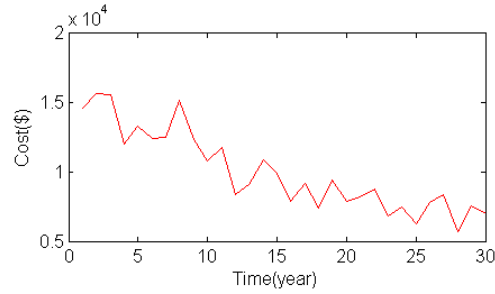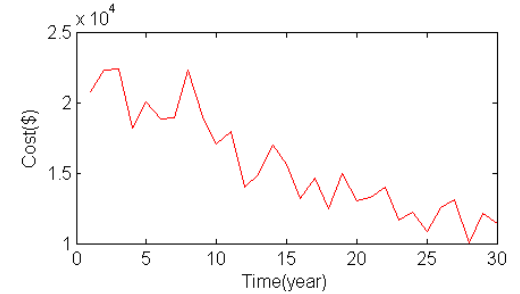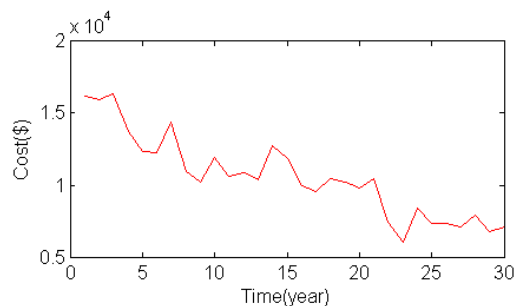
(a1) Model A: Handling Costs

(a2) Model A: Farmers' Losses

(a3) Model A: Total Costs
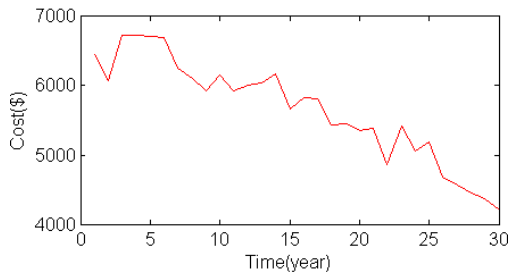
(b1) Model B: Handling Costs
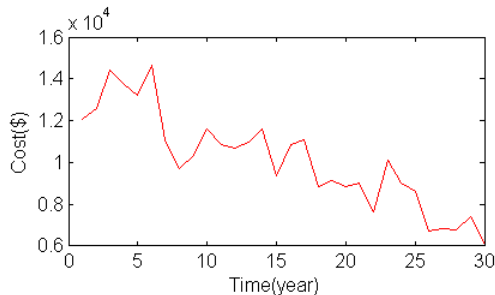
(b2) Model B: Farmers' Losses
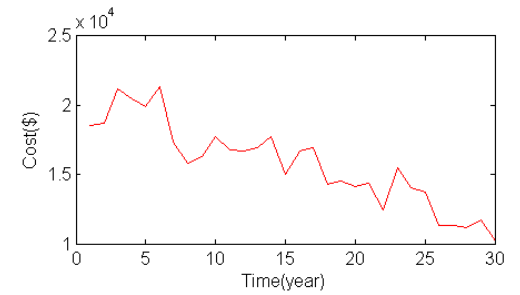
(b3) Model B: Total Costs
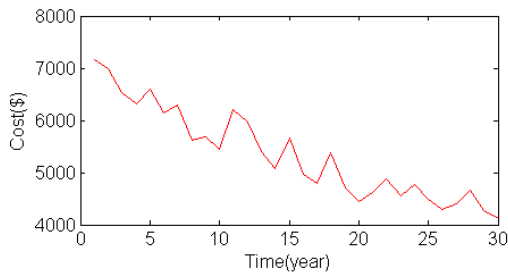
(c1) Model C: Handling Costs
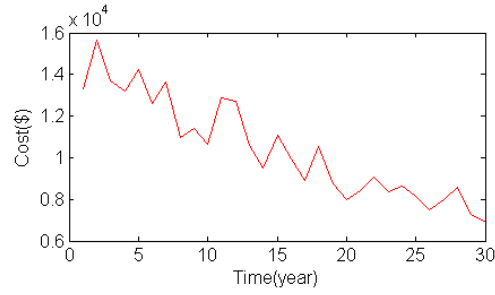
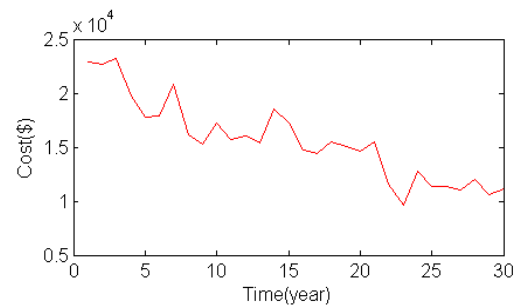(c2) Model C: Farmers' Losses
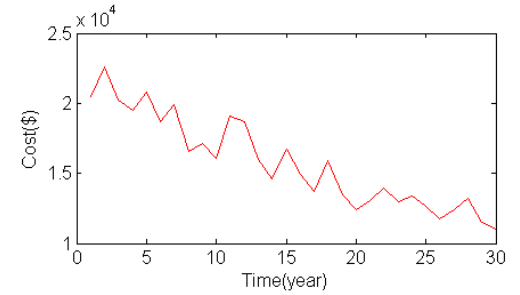
(c3) Model C: Total Costs
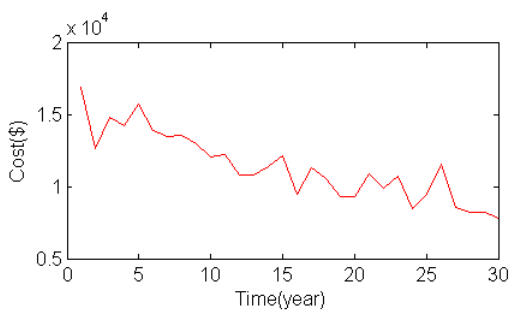
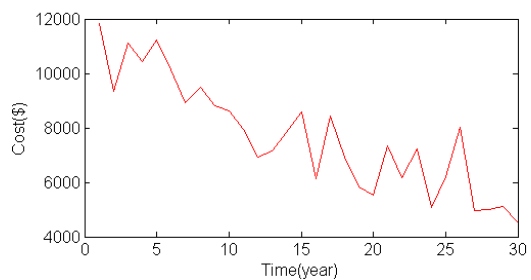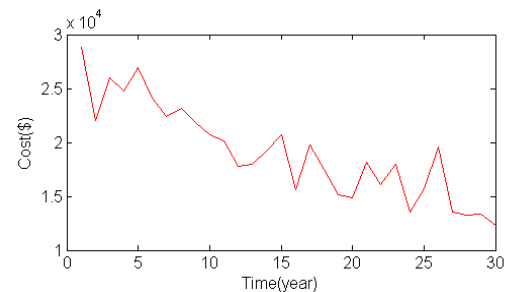(d1) Model D: Handling Costs   (d2) Model D: Farmers' Losses   (d3) Model D: Total Costs

(e1) Model E: Handling Costs   (e2) Model E: Farmers' Losses   (e3) Model E: Total Costs

Figure A-G14 Handling Costs, Farmers' Losses and Total Costs (Low Initial Misrepresentation Rate)

APPENDIX H

TOLERANCE LEVEL FOR OTHER CLASSES/

VARIETIES OF WHEAT IN CWRS

Grade name	Wheat of other classes or varieties	
	Contrasting classes %	Total %
No.1 CWRS	0.5	1.5
No.2 CWRS	1.5	3
No.3 CWRS	2.5	5
No.4 CWRS	2.5	5
CW Feed	No limit – but not more than 10% amber durum	

Source: Official Grain Guide, CGC 2012.

APPENDIX I

RECENT PRICES OF CWRS 13.5% PROTEIN, BY GRADE

Year	No.1 CWRS 13.5% protein, Thunder Bay CWB delivery price, CD$/bushel	No.2 CWRS 13.5% protein, CWB export price, CD$/bushel	Wheat feed, Thunder Bay cash, CD$/bushel
Final average 2011	8.41	10.29	6.92
Final average 2010	N/A	11.81	6.64
Final average 2009	N/A	8.79	4.84

Source: Agriculture and Agri-Food Canada, 2012.