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Supply chain complexity and risk mitigation – A hybrid optimization–simulation model

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ABSTRACT

With food safety a growing concern in agriculture, the structure and management of agricultural supply chains has become a significant policy issue. In turn, agricultural supply chains are often analytically complex, characterized by feedback and time sensitive, often random parameters. Modern commodity chains such as wheat handling in Canada are no exception. Recently, the Canadian government classes of wheat, replacing it by a new wheat segregation system that relies on trust and self-declaration of wheat type by individual farmers. To maintain food safety as well as operate cost-effectively in this new trust-based system, wheat handlers may be forced to develop a set of contamination testing strategies to maintain historical wheat quality and consistency. In contrast to much of the extant literature, this research builds a hybrid optimization-simulation model representing the new Canadian wheat supply chain, with the goal of identifying cost efficient varietal testing strategies. After solving for a base scenario, sensitivity analysis is conducted on key variables that influence wheat quality testing strategies. Our results validate the utility of currently employed wheat quality testing strategies in the Canadian supply chain.

1. Introduction

With worldwide food safety and quality emerging as a major policy issue, public and business interest in the sustainability of food supply chains has increased, and the structure of agricultural supply chains has grown in importance. Wheat is an essential staple food for much of the world's population. Canada's historically strong export position has been buttressed by its reputation for high quality and consistent wheat exports. But recently a series of policy changes have been implemented that potentially negatively impact both the quality and integrity of the Canadian wheat handling system. These changes could generate new wheat quality risks that would jeopardize the export position of this industry. Due to this on-going situation, growing attention has been given to the need for analyzing reactive strategies to mitigate potential wheat handling risks and maintain the safety of the Canadian wheat quality assurance system (Blomquist, 2015; Skinner, 2015; Vanneste, 2012). This research will highlight uncertainties inherent in agricultural supply chains and support the analysis of

strategic decisions in these kinds of systems (Musshoff and Hirschauer, 2007; Tanure et al., 2013).

While research and analysis on wheat handling strategies is relatively well developed using numerical simulation methods (Ge et al., 2015a, 2015b; Wilson and Dahl, 2006, 2008), studies modeling risk mitigation using more formal optimization methods have been limited. While the inherent uncertainty and complex structural dynamics of these supply chains often drive researchers to use simulation methods to generate solutions, the nature and characteristics of the Canadian wheat handling system actually facilitates the use of optimization models. This gap in the risk mitigation literature offers us the chance to explore the utility of optimization models to help generate new handling strategies in the evolving Canadian wheat handling system.

The Canadian grain or wheat handling system is a very large and continuously evolving supply chain. Most of the supply chain is effectively an economic pyramid, with thousands of dispersed farmers delivering wheat to dozens of elevators for storage and blending, which ship grain by rail car to just a handful of Canadian ocean ports. One of the historic objectives of this agricultural supply chain has been to ensure that different types or classes of wheat are blended in an accurate and transparent manner so as to meet agronomic specifications in wheat export contracts. The method in Canada used to facilitate wheat blending has been the

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so-called "kernel visual distinguishability" (KVD) of wheat segregation. Essentially, for many years Canadian wheat has been deliberately bred to contain specific visual characteristics that allow rapid visual identification by a trained wheat grader.

While KVD enabled rapid, dependable, and low-cost segregation of wheat into functionally different classes or quality types, it also limited the development of novel traits in wheat. In the KVD system, wheat breeders had to incorporate KVD characteristics in their varietal selection process. As such, the KVD requirements represented a significant constraint for wheat breeders that impeded progress in variety development and slowed the rate of productivity growth for the wheat sector. Due to on-going breeding costs or losses associated with this visual identification system, interest grew to replace it by an alternative wheat segregation system known as VED (Variety Eligibility Declaration). Such a system relies not on visual distinctions of wheat type, but rather is incentive or trust based, relying on self-declarations of wheat type as delivered by individual farmers. While reducing potentially costly breeding restrictions for wheat, VED can also lead to either accidental or opportunistic wheat misrepresentation, a situation that can affect blending accuracy for all system participants. If a variety is misrepresented as another that is visually indistinguishable, wheat handlers would not be able to distinguish the varieties from one another without performing physical testing on a sample. Undetected mixing or contamination in this manner will necessarily reduce wheat value and performance for downstream users.

To identify visually indistinguishable wheat varieties, identification testing is required. Current technology is costly and requires a laboratory setting (Bowler, 2015; Canadian Grain Commission (CGC), 2009; Zhou, 2015). Considering this, complete testing on wheat deliveries may be not economically viable over the foreseeable future. But if elevators and blenders do not perform full testing on commodity deliveries, potential contaminations can occur and will result in system losses. Thus, there is an essential tradeoff in this evolving supply chain between testing costs and contamination costs. To pursue cost effectiveness, industry participants need to work out a set of effective risk management solutions to determine the optimal balance between these two factors (Fraser and Monteiro, 2009).

At present, the consequences of these policy changes within the Canadian wheat handling system are only weakly understood. Although the industry is aware of the potential importance of the contamination issue, to date few comprehensive studies have been done to assess any supply chain contamination risks. As such, to our knowledge there is no contamination testing currently being conducted along the wheat supply chain, nor is anyone trying to quantify the costs of implementing variety testing regimes under foreseeable but potentially severe contamination situations. What is clear is that the latter kind of information will be needed to inform careful logistics decisions, and would be most effective to have well before any actual contamination undermines the sustainability of the Canadian wheat supply chain.

In this light, the primary objective of this study is to identify a set of wheat varietal testing strategies that minimize handling costs within this new Canadian wheat supply chain. First, we build an optimization model that incorporates the economic incentives inherent in the new supply chain. Operation of a portion of the wheat handling system is modeled in this manner, transitioning from the individual farm up through wheat movements for export. Subsequently, we identify supply chain participants' cost functions and then solve the cost minimization problem associated with behavioral strategies in the supply chain. Then, sensitivity analysis of system parameters or variables is conducted to identify how these optimal testing strategies may be affected by supply chain participants' future decision making. The paper ends with a brief conclusion.

2. Optimization vs. simulation: comparing and contrasting the approaches

Evaluating performance and dependability in modern economic systems has become a challenging problem due to the inherent complexity found in such systems (Tuffin et al., 2007). As two of the most commonly used solution approaches, both optimization methods as well as numerical simulation analyses are each associated with specific strengths. Numerical simulation analysis offers advantages in modeling actual systems and further permits the researcher to perform counterfactual experiments in order to better understand the behavior of the system or to further assess various functions of the system (Akanle and Zhang, 2008; Zizka, 2005). But simulation models do not always rely on exact functional relationships between variables of interest and thus are not as precise as equivalent optimization solutions (Lewis, 2013). In contrast to simulation analyses, optimization models almost always yield a solution that permits a larger design space to be explored (Gries et al., 2004). Considering its specific strengths, we are interested in pursuing an optimization approach to examine what seems to be the relatively complex system that is the Canadian wheat supply chain.

There are limitations in the ability of optimization models to mathematically represent economic systems of interest. One commonly recognized problem with optimization methods is their frequent use of simplifying assumptions which can dilute uncertainties and realism contained in the system of interest (Hung et al., 2006). Abstracting from important details limits the use of mathematical formalisms for the research goals of interest, so the overall simplicity of a typical optimization model comes at the expense of generality. When more realistic phenomena are incorporated into an optimization model, the model becomes more general but also more difficult to solve (Lewis, 2013). To prevent simplicity from weakening the predictive strength of an optimization model, here we seek a balance between simplicity and generality when performing this optimization exercise.

Difficulties can also be encountered when attempting to include more sources of uncertainty in an optimization model because model solutions become more complex as the model grows more detailed. In turn, this could generate very complicated relationships that have very little practical application (Gries et al., 2003). Ideally, a good optimization model should be broadly applicable and yet easy to use and understand. In this study we exert effort in integrating as much detail as possible while avoiding excessive complexity. Characterizing and quantifying uncertainties within the system and converting these characteristics into mathematical representations are important processes for building an optimization model of what seems to be a complex system. In fact, some mathematical constructs are inherently very difficult to solve. Directly imbedding such elements into this kind of analysis can render the model unsolvable. To avoid this, here we replace certain mathematical formulations of a function with results from an equivalent simulation exercise, in cases where those results appear to be dependable and concise. In fact, it is good scientific practice that optimization and simulation perspectives are deeply complementary. In the future, we expect to see emergent modeling approaches in supply chain analysis that combine the beneficial features of both simulation and optimizations for general modeling applications.

3. Building a supply chain – model assumptions

Assumptions used in our model are based mainly on prior literature (Wilson and Dahl, 2002, 2006, 2008), as well as interviews and discussions with experts (Skinner, 2015; Steinke, 2011;

Vanneste, 2012) and finally, adaptation of pre-existing related models (Ge, 2013; Ge et al., 2015a, 2015b). Of course several of these assumptions are due to the particulars of the problem being studied, but in general most are implemented to avoid including certain functional relationships that might overcomplicate the model. Our basic assumptions are as follows:

1. A farmer's wheat production and deliveries are consistent throughout a year, i.e., they are either eligible Canadian Western Red Spring (CWRS) wheat or non-CWRS (CWRS is the most common type of wheat grown in Canada and is used as the base variety here).
2. Test accuracy is 100%.
3. There are no contamination sources other than farmer's misrepresentation.
4. There is no intentional misrepresentation.[1] Farmers make declarations based on their honest, sometimes incorrect, perception of the variety being grown and delivered.
5. A penalty system will be applied in the case of an offence and the penalty can be perfectly enforced.
6. When computing costs, the model does not allow for a farmer or a handler's insurance obtained against loss or damage from misrepresentation.

For our study, due to the time lag between variety registration and adoption, we anticipate 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. At present, there is anecdotal evidence of a few misrepresentation cases in Canada but policies like truck testing and wheat bin testing for variety identification have not yet been implemented. In the long run, a conflict may be unavoidable if newly registered visually indistinguishable varieties are allowed to flourish. Together with the visually indistinguishable non-registered varieties, this increases the likelihood of mix-ups between wheat classes and thus challenges the function of the wheat quality control system in western Canada.

Interviews with officials in Canada, including the Canadian Grain Commission (Bowler, 2015; Vanneste, 2012), the Canadian Wheat Board (CWB) (Steinke, 2011) and other experts in wheat marketing (Blomquist, 2015; Skinner, 2015) highlight that commingling among visually indistinguishable varieties can unexpectedly occur at any time and that future quality threats could in turn be sudden and serious. These individuals also indicated that stringent testing regimes would very likely be implemented if there are significant contamination threats from farmer misrepresentation. We remind the reader that this research describes a likely situation within the Canadian wheat handling system of the foreseeable future. To efficiently mitigate these risks before they can undermine the handling system functionality and integrity, the development of wheat quality assurance programs will almost certainly gain strategic emphasis within the supply chain.

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[1] In reality most grain farmers only have 3–6 grain buyers within a reasonable delivery radius. The elevator managers have memory so the farmer's reputation will impact their future ability to negotiate price within the repeated selling environment. A farmer's honest reputation within their community is valuable both economically and socially. There have also been unlicensed varieties of wheat available to Canadian farmers for several decades, which yield more but are of a lower quality than licensed varieties. While minor misrepresentations have been made, and despite the long term opportunity to misrepresent, this has never been a large issue. We submit that this experience along with the other anecdotal evidence suggests that intentional misrepresentation is not a problem that needs to be incorporated into the model.

4. Model specification

The following notation is introduced for an optimization model of the wheat supply chain in Canada:

- Variables

  α Farmer's misrepresentation rate (FMR hereafter), $0 \le \alpha \le 1$
  β_1 Truck test rate at test point 1, $0 \le \beta_1 \le 1$
  β_2 Bin test rate at test point 2, $0 \le \beta_2 \le 1$
  β_3 Railcar test rate4at test point 3, $0 \le \beta_3 \le 1$
  β_4 Terminal elevator test rate at test point 4, $0 \le \beta_4 \le 1$
  m_1, m_2, m_3 Contamination multipliers

- Parameters

  q Volume of wheat for a delivery from a farmer, bushels
  f_{p2} Primary elevator's profit loss due to contamination detected at test point 2, dollars/bushel
  f_{p3} Primary elevator's profit loss due to contamination detected at test point 3, dollars/bushel
  f_{p4} Primary elevator's profit loss due to contamination detected at test point 4, dollars/bushel
  f_1 Penalty for farmer's misrepresentation if detected at test point 1, dollars/bushel
  f_2 Penalty for farmer's misrepresentation if detected through traceability 1, dollars/bushel
  f_3 Penalty for farmer's misrepresentation if detected through traceability 2, dollars/bushel
  f_4 Penalty for farmer's misrepresentation if detected through traceability 3, dollars/bushel
  c_e Farmer's risk control effort cost, dollars/bushel
  c_1, c_2, c_3, c_4 Sample test cost for truck, primary elevator bin, railcar and terminal elevator bin, dollars/sample.

4.1. Wheat handling system under study

The wheat handling situation considered here is a stylized rendition of the Canadian wheat supply chain, starting at the farm level and ending at the point of export. To start this supply chain, individual farmers are assumed to load and transport full truckloads of CWRS wheat to a primary elevator. With the existence of visually indistinguishable wheat varieties farmers could inadvertently deliver a non-CWRS variety. The likelihood of this is determined by farmers' individual risk control effort exerted, and the level of risk control technology. Risk control effort is essentially a measure of the resources an individual farmer puts into avoiding possible misrepresentation. Risk control technology is a signal of the capacity a farmer has to control their risks of misrepresentation. Using an exponential functional form for misrepresentation probability (Ge et al., 2015a, 2015b), an individual farmer's misrepresentation rate is defined as a function of his risk control effort c_e and risk control technology k in the following manner;

$$\alpha = e^{-\frac{c_e}{k}} \tag{1}$$

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. Given the chosen functional form, Eq. (1) implies diminishing marginal effect of risk control effort on the probability of misrepresentation at all effort levels. In particular, when $c_e/k \to 0$, $\alpha \to 1$; and when $c_e/k \to \infty$, $\alpha \to 0$. Next we detail the key components of our model of wheat segregation and testing in the supply chain.

When wheat is delivered to the primary elevator, several events occur in a prescribed but realistic sequence as described in Fig. 1.
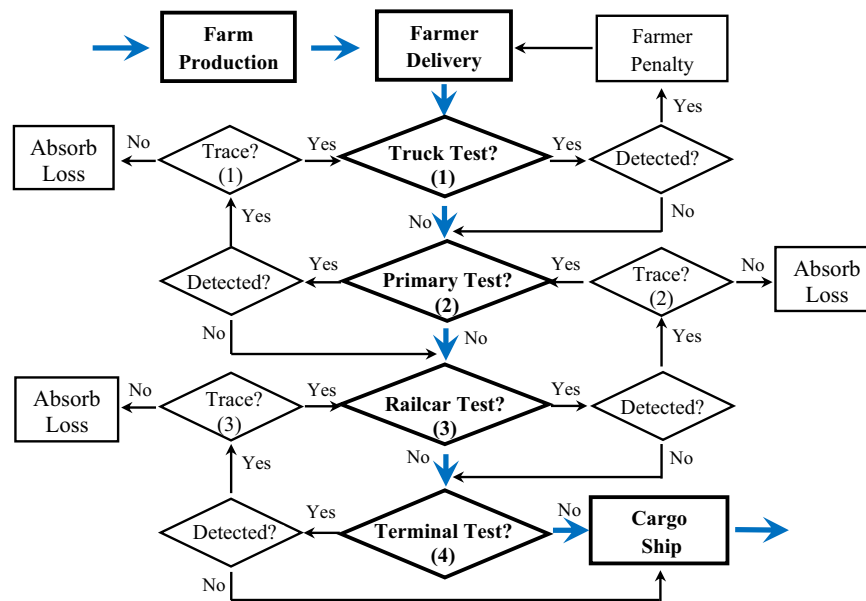
Fig. 1. Representation of wheat movement in the Canadian supply chain.

Based on known logistics considerations as well as prior work on this topic (Furtan et al., 2003; Johnson and Lin, 2005; Wilson and Dahl, 2002, 2006), we assume that there are four potential test points available in the system. These are: (1) a test of wheat on the truck while unloading into primary elevators; (2) a primary elevator bin test before loading wheat onto railcars; (3) a test of wheat on the rail car while unloading into terminal; and (4) a terminal elevator test before loading wheat into the cargo ship. In addition to these assumed testing points, we also assume that there are three other places in the supply chain where a traceability mechanism using retained samples could be implemented to identify sources of contamination. As shown in Fig. 1, tracing opportunities emerge when contamination is detected at (1) test point 2 (traceability 1); (2) test point 3 (traceability 2); (3) test point 4 (traceability 3). The economic argument for adopting a so-called traceability mechanism is two-fold. First, it allows for the tracking of affected products in the event of a contamination problem so as to minimize the system costs of contamination. Second, it also facilitates allocation of any liability, further improving incentives to maintain wheat quality (Banterle and Stranieri, 2008; Starbird, 2005).

4.2. Supply chain participants' cost functions

In this analysis, a commingling rate is the ratio of undesired (or contaminated) wheat contained in a wheat variety or sample. According to the Canadian Grain Act (Ministry of Justice, 2015), if the commingling rate of any wheat variety is less than 5%, it is deemed eligible. But if the commingling rate is greater than 5%, the sample is considered to be contaminated. If contamination is detected at any test point in the chain, we assume this contaminated wheat will be downgraded to feed wheat (i.e. a less valuable variety) and diverted from the supply chain. However, if a contaminated sample is not detected the sample moves further into the system and will contaminate more formerly eligible wheat.

The physical movement of wheat in our stylized supply chain is quantified and described in Table 1. Each component (marked from E_1 to E_{18}) can generate costs and these components will ultimately interact with supply chain participants' cost functions, as we shall see later.

To facilitate an efficiency comparison between alternative testing strategies, we consider only variable costs in both the farmer and elevator's cost functions, which also implicitly assumes that fixed costs are equal across testing regimes. To start, the elevator's cost function is composed of the following components:

Table 1
Wheat contamination, testing and tracing in the supply chain.

Location	Process	Quantity tested	Quantity contaminated	Con. detected	Quantity traced (Tr.1/Tr.2/Tr.3)	Quantity remained
Truck	Test 1 (β_1)	$E_1 = \beta_1 q$	$E_2 = \alpha q$	$E_3 = \alpha\beta_1 q$	/	$q - E_3$
Pri. Bin	Con.(m_1)	/	$E_4 = (1 - \beta_1)E_2 m_1$	/	/	$q - E_3$
Pri. Bin	Test 2 (β_2)	$E_5 = \beta_2(q - E_3)$	E_4	$E_6 = \beta_2 E_4$	Tr.1: $E_7 = E_6$ Tr.2: $E_8 = E_{13}/m_2$ Tr.3: $E_9 = E_{14}/m_2$	$q - E_3 - E_6$
RC	Con.(m_2)	/	$E_{10} = (1 - \beta_2)E_4 m_2$	/	/	$q - E_3 - E_6$
RC	Test 3 (β_3)	$E_{11} = \beta_3(q - E_3 - E_6)$	E_{10}	$E_{12} = \beta_3 E_{10}$	Tr.2: $E_{13} = E_{12}$ Tr.3: $E_{14} = E_{18}/m_3$	$q - E_3 - E_6 - E_{12}$
Ter. Bin	Con.(m_3)	/	$E_{15} = (1 - \beta_3)E_{10} m_3$	/	/	$q - E_3 - E_6 - E_{12}$
Ter. Bin	Test 4 (β_4)	$E_{16} = \beta_4(q - E_3 - E_6 - E_{12})$	E_{15}	$E_{17} = \beta_4 E_{15}$	Tr.3: $E_{18} = E_{17}$	$q - E_3 - E_6 - E_{12} - E_{17}$

RC = railcar, Pri. = primary elevator, Ter. = terminal elevator, Tr. = traceability, Con. = contamination.

Table 2
Model variables, parameters and values.

Variables or parameters	Values	Data sources
Farmer number	180	Assumed
Truck loading capacity	40 t (1470 bushels)[a,b,c]	Assumed
Primary bin number	30	Calculated
Primary bin capacity	250 tonnes	Assumed
Railcar number	120[d]	Calculated
Railcar capacity	60 tonnes[c]	Assumed
Terminal bin number	15	Calculated
Primary bin capacity	500 tonnes	Assumed
Sample test cost	$400/truck, $1200/primary bin, $500/railcar, $1600/terminal bin	UC Davis (2015)
Terminal test rate	60%	Assumed
Price reduction	$4/bushel	AAFC (2015)
Contamination tolerance	5%	CGC (2015)
Penalty limit for a farmer	$ 18,000	Ministry of Justice (2015)
Contamination multiplier	dependable	Calculated
Technology k	0.05[e]	Assumed

[a] Bushel equivalents per tonne are 36.74 (Alberta Agriculture and Forestry, 2015).

[b] This is the quantity contained in a one time delivery for a farmer. However, a farmer may deliver many times during the season.

[c] This represents the loading capacity of grain trucks or railcars which are commonly used for grain transportation in the Canadian Prairies.

[d] This represents an economical and efficient way to ship wheat for a single railcar shipment.

[e] Under given penalty levels and possible testing regimes, this technology parameter value renders the FMR range from 1% to 0.3% (refer to Eq. (3)). While understanding that such a FMR interval may overestimate current FMR in Western Canada, we believe it represents an appropriate misrepresentation level interval and allows us to examine how the testing regimes examined in this study perform. If the k value is set too low (for example at 0.01), this means FMR ranges from 0.1% to 0.06%, at which point testing becomes trivial: there will be no testing on truck deliveries or bins or railcars.

(i) test costs at test points 1, 2, 3 and 4; (ii) losses at test points 2, 3 and 4 due to detected primary and terminal bin contamination; (iii) tracing costs (retained sample testing) from traceability; and (iv) recovered losses (collected misrepresentation penalties) from traceability. In sum, these processes generate the following cost function (also refer to Table 2 for a listing of components):

$$
\begin{aligned}
j_1 = & \underbrace{\frac{c_1 \times E_1 + c_2 \times E_5 + c_3 \times E_{11} + c_4 \times E_{16}}{(i)}} \\
& + \underbrace{\frac{f_{p2} \times E_6 + f_{P3} \times E_{12} + f_{p4} \times E_{17}}{(ii)}} \\
& + \underbrace{\frac{c_1 \times (E_7 + E_8 + E_9) + c_2 \times (E_{13} + E_{14}) + c_3 \times E_{18}}{(iii)}} \\
& - \underbrace{\frac{(f_2 \times E_6 + f_3 \times E_{12} + f_4 \times E_{17})}{(iv)}}
\end{aligned}
\tag{2}
$$

Next, a farmer's cost includes (i) revenue (or price) loss at test point 1; (ii) a contamination penalty due to identified misrepresentation through traceability; (iii) risk control effort costs. This generates the following individual farmer cost function:

$$
J_2 = \underbrace{\frac{f_1 \times E_3}{(i)}} + \underbrace{\frac{f_2 \times E_6 + f_3 \times E_{12} + f_4 \times E_{17}}{(ii)}} + \underbrace{\frac{c_e q}{(iii)}}
\tag{3}
$$

In this model, for tractability the optimization problems applicable to both Eqs. (2) and (3) are subject to the following constraints[2]:

$$
f_2 m_1 q \leq \$18,000^2; \quad f_3 m_1 m_2 q \leq \$18,000^2; \quad f_4 m_1 m_2 m_3 q \leq \$18,000^2; \tag{c-1}
$$

$$
0 \leq \alpha \leq 1; \quad 0 \leq \beta_1 \leq 1; \quad 0 \leq \beta_1 \leq 1; \quad 0 \leq \beta_3 \leq 1; \quad 0 \leq \beta_4 \leq 1 \tag{c-2}
$$

Our assumed diminishing marginal effect of risk control effort means that completely eliminating misrepresentation risks incurs high effort costs. Allowing for this, any rational farmer prefers a finite level of effort which in turn exposes her/him to a certain level of misrepresentation risk. The farmer's optimal misrepresentation level can be found by minimizing the objective function defined by Eq. (3). Eq. (2) indicates $c_e = -k \ln \alpha$. After replacing c_e into Eq. (3) and then taking the first order condition with respect to α, one yields:

$$
\alpha = \frac{k}{\begin{aligned} & f_1 \beta_1 + f_2 (1 - \beta_1) m_1 \beta_2 + f_3 (1 - \beta_1)(1 - \beta_2) m_1 m_2 \beta_3 \\ & + f_4 (1 - \beta_1)(1 - \beta_2)(1 - \beta_3) m_1 m_2 m_3 \beta_4 \end{aligned}}
\tag{4}
$$

Implications of this solution are consistent with the arguments of Pouliot and Sumner (2008), Starbird (2000), and Starbird and Amanor-Boadu (2006) that the costs associated with potentially being caught under misrepresentation constitute a potential deterrent to farmers and should provide enough incentive for them to produce and deliver into the supply chain accurately represented and eligible products.

We replace Eq. (4) into Eq. (2). With the exogenously given handling system structure, penalty mechanism, sample testing cost and elevator testing regime on terminal bins, this leaves three control variables that the elevator handlers can choose for minimizing their handling costs. These are the testing rates for trucks at test point 1, testing rates for primary bins at test point 2, and test rates for rail cars at test point 3. The cost optimization problem can be solved with assumed values of interest with respect to the variables and parameters in Eq. (2). The optimal solutions will be shown later in Sections 5 and 6.

4.3. Parameters, variables and values

Listed in Table 2 are all of the variables, parameters as well as assumed values (as well as the source of the assumed value, if applicable) used to solve the model.

4.4. Contamination multipliers

To appropriately model the future Canadian wheat handling system and formulate the research problem, it is essential to integrate the wheat contamination dynamics into the system cost function. The challenge is how to quantify contamination at each wheat transfer point after misrepresented wheat gets unloaded into the primary bins and/or moves into the handling system.

First, we need to identify the contamination patterns occurring if misrepresented wheat enters the supply chain. As prior work by Ge (2013) has described, contamination from misrepresentation can manifest in different ways. Contamination can occur in such a way that, for example, two or more misrepresented truck deliveries contaminate just one bin or conversely that one misrepresented truck delivery contaminates two different bins. In turn, a railcar might be loaded with wheat from the same bin, either clean or contaminated, or loaded with wheat from two different bins, one clean and the other contaminated. In the latter cases, additional uncontaminated wheat will become contaminated. In the same way contaminated wheat loaded into a railcar might be unloaded into two different terminal bins or conversely contaminated wheat from two or more different railcars might be unloaded into one terminal bin. Thus with different contamination patterns, contamination can spread in a nonlinear

Table 3
Contamination multipliers.

Stage	Contamination source	Quantity contaminated	Contamination multiplier
Primary bin	$(1 - \beta_1)\alpha q$	$(1 - \beta_1)\alpha q m_1$ (i.e., E_4 in Table 1)	m_1
Railcar	$(1 - \beta_2)(1 - \beta_1)\alpha q m_1$	$(1 - \beta_2)(1 - \beta_1)\alpha q m_1 m_2$ (i.e., E_{10} in Table 1)	m_2
Terminal bin	$(1 - \beta_3)(1 - \beta_2)(1 - \beta_1)\alpha q m_1 m_2$	$(1 - \beta_3)(1 - \beta_2)(1 - \beta_1)\alpha q m_1 m_2 m_3$ (i.e., E_{15} in Table 1)	m_3

way, meaning that the same quantity of contaminated source wheat can generate different contamination levels at any of the primary bin, railcar or terminal storage stage, with commingling rates of contaminated wheat being different from case to case.

Simply put, contaminated wheat located at one stage will become contaminated source wheat at the next stage of the supply chain if it is allowed to move farther into the handling system undetected. Normally, the volume of contaminated wheat will not be less than that of the contamination source. To quantify this effect, we introduce a contamination multiplier (see Table 3). The contamination multiplier value m represents the ratio of the volume of contaminated wheat in the system to the volume of contaminated source wheat, i.e., contamination at each stage will render the total contaminated volume of wheat in the system be m times as much as the volume of contamination source.

With conditions predetermined by variable and parameter values as shown in Table 2, when a certain amount of misrepresented wheat enters the supply chain system, we assume wheat contamination will follow set patterns, rendering the contamination expansion quantifiable. Due to the complexity of the contamination patterns, quantifying m directly through a mathematical derivation would make the model very difficult to solve analytically. Thus we develop a virtual wheat supply chain system with the structure and characteristics consistent to those we clarified in this section and obtain operational data using numerical simulations and then use these data to estimate our contamination multiplier functions.

For the same volume, wheat with a higher commingling rate can potentially contaminate more eligible wheat than one with a lower commingling rate. We assume that the commingling rates of misrepresented trucks in the system are homogenous at 100%. The commingling rate of contaminated wheat at the primary elevator bins will differ due to either varying quantity of contaminated sourced wheat or through different contamination patterns. Such commingling rate heterogeneity adds difficulty for quantifying the contamination effects at the sequent railcar and terminal elevator stages.

With respect to our contamination multiplier regression estimates, we recognize that the soundness of this analysis will be improved if the commingling rate of the contamination source can be incorporated as an additional explanatory variable, together with the quantity of the contamination source wheat. But the complexity of the contamination patterns render mathematical representation of commingling rates essentially unobtainable in cases of contamination through the system. In such a situation, there is no way to integrate the commingling rate into the model. So for simplicity, in the contamination multiplier functions (regressions) we consider the quantity of contamination source wheat as the only explanatory variable. In fact, the quantity of contaminated wheat performs well in explaining contamination effects in our regressions.

For m_1 and m_2, we assume the value of the contamination multiplier has a linear relationship with the quantity of contamination source wheat. For m_3, we chose a polynomial functional form to better approximate the pattern of simulated data:

$$\hat{m}_1 = a_1 + b_1 \times (1 - \beta_1)\alpha q m_1 \tag{5}$$

$$\hat{m}_2 = a_2 + b_2 \times (1 - \beta_2)(1 - \beta_1)\alpha q m_1 \tag{6}$$

$$\hat{m}_3 = a_3 + b_3^1 \times (1 - \beta_3)(1 - \beta_2)(1 - \beta_1)\alpha q m_1 m_2$$
$$+ b_3^2 \times \left[(1 - \beta_3)(1 - \beta_2)(1 - \beta_1)\alpha q m_1 m_2 \right]^2 \tag{7}$$

The simulation is designed to monitor the contamination multiplier effects if a varying volume of misrepresented wheat enters the system. The possible volume of misrepresented deliveries ranges from 1 to 10 truckloads, so that contamination sources beyond 10 truckloads are not considered in this simulation. If the number of misrepresented truckloads is more than 10 (i.e., a misrepresentation rate $> 6.1\%$ with 180 farmers in the model), the elevator is assumed to take complete testing at the first test point (Ge, 2013). In this case, there is no chance for any misrepresented wheat to enter the supply chain system.

We set the simulation for 10 individual cases where an original contamination source of 1–10 truckloads enters the system respectively. Subsequently we assumed the testing rate for primary elevator bins (test 2) starts from 0% and increases by 2% each time until the value reaches 100% in each case. These 50 differently assumed test rates let varying levels of contaminated wheat with different levels of commingling rates get loaded on railcars from primary elevator bins and then get unloaded into terminal elevator bins without testing (i.e. assuming railcar test rate equal to zero in each case). Totally 50 data samples are generated by the simulation for each case. These 10 cases allow for 500 data samples that can be used to estimate each of the three multiplier functions.

To reduce variation and generate large sample results, the simulation results reported here were averaged from 10,000 iterations of the computational execution. The wheat contamination simulation was coded and compiled using Matlab, while execution was performed on a High Performance Computing System (20 cores/2.84 GHz CPU/256GB RAM per server) and took almost 12 hours.

4.5. Generating contamination multipliers using simulated data

First, we illustrate the simulated contamination situation at the primary elevator stage. As shown in Fig. 2, the 50 simulated data points almost overlap with each other in each of 10 cases. As a result, the value of contamination multiplier has a perfect negative relationship with contamination source wheat. This phenomena stems from both the homogeneity of contamination source wheat in each case (wheat unloaded into primary elevator bins from
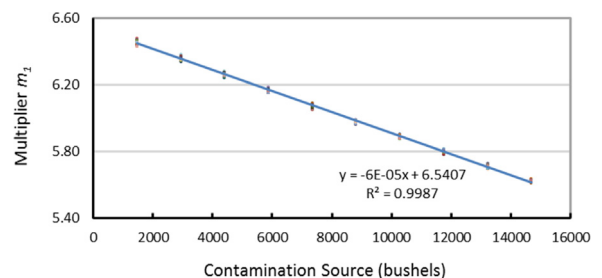
y = -6E-05x + 6.5407
R² = 0.9987

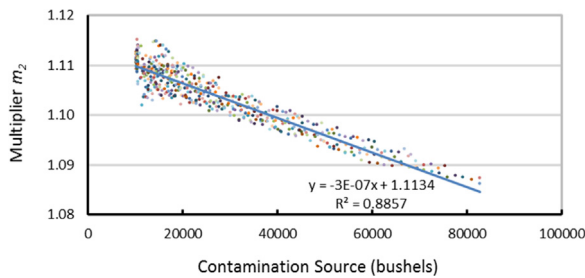**Fig. 2.** Regression for Simulated m_1.

Fig. 3. Regression for Simulated m_2.

misrepresented trucks without being tested) and the commingling rate (100%) of the contamination source wheat in these cases. The total volume of contaminated wheat increases with the contamination source but in a decreasing rate, indicated by the value m_1. An explanation for this result is that when two or more misrepresented trucks enter the supply chain, it is possible several misrepresented trucks are assigned to the same bin, thus reducing the contamination magnitude.

At the railcar level, it is entirely possible that wheat loaded from a contaminated bin could contaminate other eligible wheat. The contamination situation at the railcar stage is slightly different from that at the primary elevator stage. As shown in Fig. 3, the varying bin test rates in each case of the simulation generate varying magnitude of contamination of source wheat at the railcar stage. In addition, there are differing commingling rates of contamination source wheat with differing levels of contamination effects across cases. These factors jointly lead to a divergence in the simulated data. Similar to the situation with m_1, the value of the multiplier m_2 decreases with the volume of the contamination sources. The reason for this is that the number of clean bins decreases when more bins are contaminated. Under this situation, the chance is lowered that contaminated wheat in a bin will be loaded on the same railcar together with clean wheat from another, thereby reducing the contamination effect.

Normally, the farther contaminated wheat moves in the supply chain, the more wheat will be contaminated. If contaminated wheat in primary bins is loaded on railcars and moved to a terminal elevator and then unloaded into terminal bins, contamination will magnify. If wheat in railcars loaded from a contaminated primary bin is unloaded to one terminal bin or two different terminal bins, it can readily contaminate other eligible wheat. As shown in Fig. 4, the heterogeneous commingling rates of contamination source wheat create somewhat diverse patterns in the simulated data. Even so, the consistent negative relationship between the multiplier value and the volume of contamination source wheat is noteworthy.

Based on our simulated data regarding the quantity of contaminated source wheat and contaminated wheat, we develop regression relationships for our contamination multipliers. The results indicate that the quantity of contaminated source wheat (independent variable) explains the magnitude of contamination
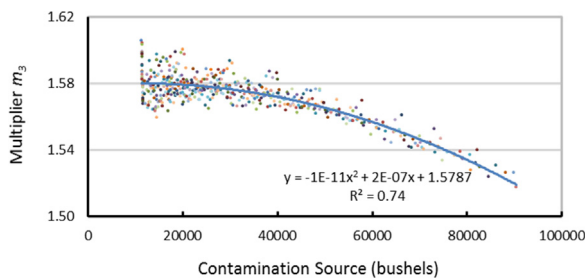
multiplier (dependent variable) very well. These regressions are shown in Table 4.

5. Model solutions and findings

Now we can place the three multiplier functions for m_1, m_2 and m_3 into Eq. (2). These functions integrate into the model varying contamination effects resulting from undetected and misrepresented wheat at each stage of the supply chain. Given certain values of interest with respect to the variables and parameters as shown in Table 2, this cost optimization problem is solvable. For simplicity, we plot values of the cost function for all possible combinations of truck test rates and primary bin test rates, helping us to identify the minimum value of the cost function. For this situation, the global solution we find is unique – the handlers should test primary bins at a rate of approximately 4%, and to ensure minimum handling costs, handlers should conduct no additional testing at either the truck (i.e., $\beta_1 = 0$) or railcar test point (i.e., $\beta_3 = 0$). Fig. 5(a)–(c) illustrates the varying responses of the elevator's handling costs to the changes of the other two test rates while one test rate is fixed at its optimal value, along with the corresponding range of FMR values. As indicated by the red dots marked in each frame of Fig. 5, the total costs attributed to elevator handlers are $53,964 and the corresponding optimal FMR is 0.66% under the optimal test regime.

As mentioned above, the optimal testing solutions shown here are derived within an operational context for the foreseeable future of the wheat handling system. The FMR applied in the model is likely greater than the one applicable to the current situation, so the solved testing regimes are not necessarily applicable to current wheat handling system. If actual FMR is at a lower level approximating what we believe to be current FMR levels, for example an FMR of less than 0.5%, in fact we find that no testing should be performed at any of the three test points. These findings support current wheat variety testing strategies in the Canadian wheat supply chain system. At the moment, visually indistinguishable wheat varieties have not yet entered the system in large volumes and as of this writing there are few reported misrepresentation cases. Considering what must be an extremely low FMR, elevator handlers thus undertake no truck testing nor bin testing for variety identification in the current wheat handling system (Blomquist, 2015; Skinner, 2015).

The solutions shown are subject to specific values of variables chosen for the elevator and farmer's objective functions. But since agriculture is undergoing dramatic change, it is very likely that economic and operational environments described here are evolving through time. Any changes in these values will reshape the optimal testing protocols for misrepresentation or contamination detection. Exploring the response of testing strategies to a range of possible variable values is the focus of the next section.

6. Sensitivity analysis

We next conduct sensitivity analysis for certain key parameters or variables germane to formulating optimal test strategies, including price reductions, changes in testing costs, as well as changes in commingling tolerance and misrepresentation penalties. Sensitivity analysis will allow ones to better understand the full range of testing regimes' responses to changes in environmental conditions.

In the sensitivity cases we examine here, it turns out that railcar test rates are always zero under all assumed conditions in the analysis. This is not surprising. Under the assumption that there are no wheat contamination sources other than farmer

Fig. 4. Regression for Simulated m_3.

Table 4
Regressions for contamination multipliers.

Dependent variables	Independent variables	Coefficients	t Stat	P-value	F	R^2
Multiplier m_1	Intercept	6.541	7020	0	381366	0.999
	X	$-6.310E-5$	-617	0		
Multiplier m_2	Intercept	1.113	5876	0	3859	0.885
	X	$-3.486E-7$	-62	1.1E-236		
Multiplier m_3	Intercept	1.579	1266	0	707	0.740
	X	2.146E-7	3.02	0.003		
	X^2	$-9.7E-12$	-11.82	1.41E-28		

misrepresentation, when either truck or primary elevator testing points are available in the supply chain, railcar testing is rendered cost ineffective since the vast majority of contamination will have already been prevented or caught. Due to this, railcar test rates are not included in the following figures illustrating model sensitivities.

6.1. Price margins

The prices of food eligible wheat and downgraded (i.e., feed) wheat fluctuate over time. As a result, the price margin between food eligible wheat and feed wheat also varies with time. The changes in price margin play a significant role in reshaping optimal testing strategies.

As shown in Fig. 6, when the price margin between food and feed wheat is at a low level, i.e., from 0 to $3.85, no testing is suggested for either the test points. An increase in these price margins widens the potential loss for both farmers and elevators, so that the elevator's testing incentives increase with the magnitude of price margins. When the price margins increase to a level more than $3.85, proportional testing at the second test point is optimal. When the price margin is greater than $7.35, testing will switch to full testing of truck deliveries at the first test point. In the latter case, to avoid the high cost of downgrading via contamination, it is best to detect all original misrepresented deliveries before they enter the supply chain.

6.2. Testing costs

While current variety identification methods are accurate and replicable, they are laboratory based, require skilled technicians and to date, are not widely available. They are relatively expensive and take time to yield results. 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. If this technology proves successful, it would constitute a major step forward for reducing test costs and hence could influence testing strategies along the wheat supply chain.

Allowing for the potential test cost reduction in the future, we consider a value interval for truck testing cost [0, $400]/sample, or [0, $0.27] /bushel. We further assume that the primary elevator bin and terminal elevator bin sample testing cost changes remain in our original proportions of 1:3:1.25:4 (refer to Table 2) as related to truck testing costs, where the truck test cost is normalized to unity.

A high test cost weakens handlers' economic incentive to test. Just as Fig. 7 shows, when the test cost is higher than $0.29/bushel, no testing is conducted. The incentive to test increases with the reduction in testing cost. When the total test cost falls from $0.29/bushel to $0.11/bushel, the primary bin test rate increases from 0 to 0.88 while in the meantime, the truck testing rate remains

zero. When the overall test cost is lower than $0.11/bushel, the testing strategy switches to testing all the trucks. In this way, testing strategies continue to seek a balance between testing costs and contamination detection. The elevator's test costs and contamination losses decrease when the testing cost falls. In light of this, it is clear that a rapid and affordable variety identification technology for testing will improve the functional performance and efficiency of this supply chain.

6.3. Contamination tolerance levels

If detected, any wheat delivery in which undesirable classes exceed specified tolerance will be downgraded to feed, resulting in losses for supply chain participants. The contamination issue could become even more important in the presence of non-registered genetically modified (GM) varieties. Although no GM wheat has been approved in Canada and the U.S. for commercial planting and sale, eligible wheat could become contaminated with GM wheat illegally grown or grown in testing fields. A notable example is the GM wheat contamination that occurred in Oregon in 2013 which greatly harmed the reputation and customer trust of U.S. production and threatened U.S exports. As is well known, the international food safety threshold for GM wheat contamination has been kept very strict. As an example, the EU operates using a 0.001 threshold of GM contamination. Only recently has the European Commission issued a proposal to drop the policy of zero tolerance for unapproved and untested GMOs in food.

Here we examine how testing strategies respond to more stringent tolerances for undesired wheat. Results are shown in Fig. 8. When contamination tolerance becomes more stringent, the values of the contamination multipliers grow, i.e., for a given quantity of contamination source wheat, more wheat could meet the contamination threshold and be downgraded to feed wheat in the case of contamination. This motivates additional efforts of wheat handlers to enhance contamination testing. Our findings suggest that the testing intensity for primary elevator bins increases when the contamination tolerance becomes stricter. And here, when the tolerance is less than 0.003, complete testing on primary elevators is considered optimal.

6.4. Penalty levels

We propose there are two methods that could be used to deter misrepresentation behavior and thus reduce contamination risks. These are a penalty system and a liability system. By definition, a penalty system would make handlers share the losses from farmer misrepresentation, while a liability system would force losses to be unconditionally covered by offenders. We note that handlers have no economic incentive to prevent farmer misrepresentation at all in a liability system. Thus, a penalty system should be preferred to a liability system for supporting quality assurance in the new
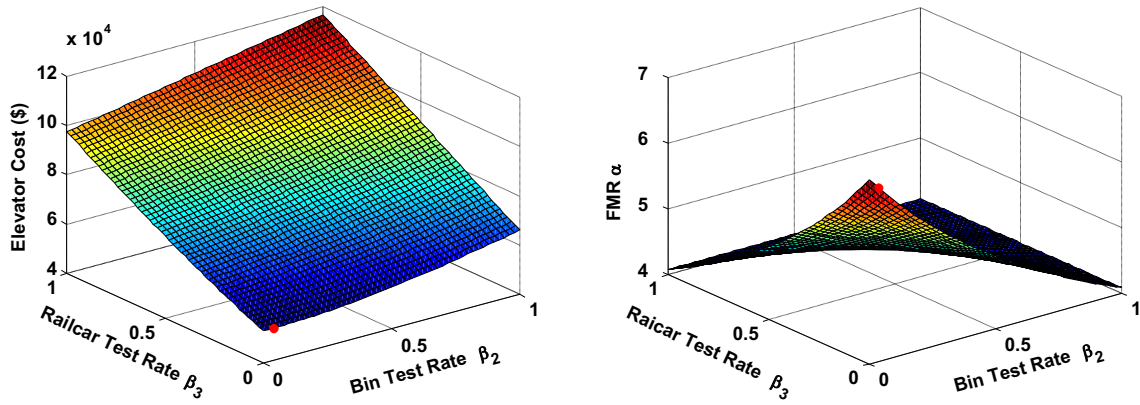
(a) When truck test rate $\beta_1 = 0$.
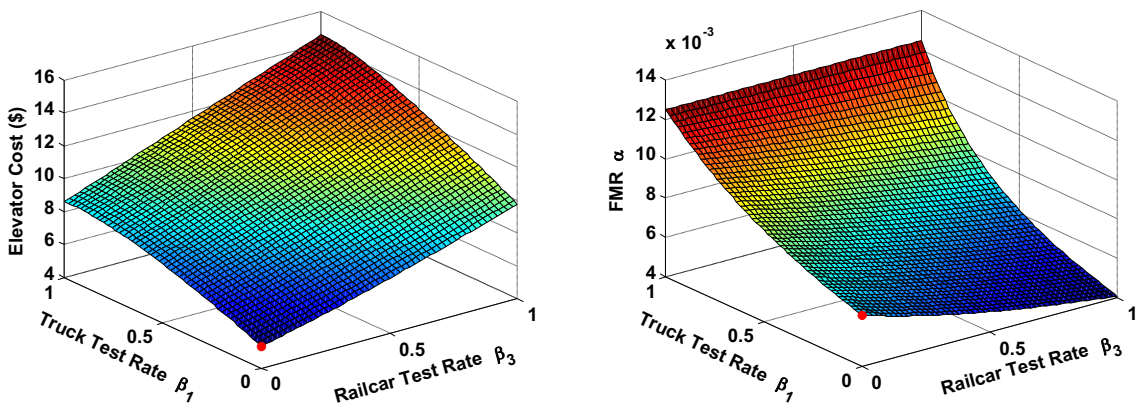
(b) When primary bin test rate $\beta_2 = 0.04$.
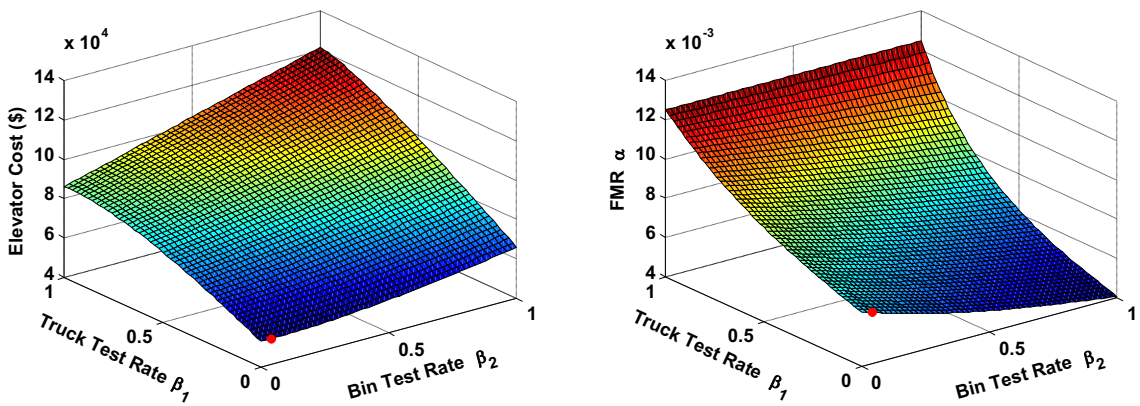
(c) When primary bin test rate $\beta_3 = 0$.

Fig. 5. Optimal solution for test rates and corresponding FMR.

wheat supply chain.

Under a penalty system, the amount of the penalty cannot be unbounded, but would need to be carefully regulated. Note that if handlers are free to set a 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 food risk control, in a manner similar to the liability system.

Under given levels of a misrepresentation penalty, a handler's testing strategies change the distribution of risk sharing between the farmer and the primary elevator. As shown in Fig. 9 for our model, when the penalty limit is at a low level, e.g. 0–9961, complete testing on the truck is necessary due to the high FMR resulting from the low misrepresentation penalty. When the penalty limit increases from $9962 to $19,682, a proportional test on the primary elevator bin is proposed, while the test intensity
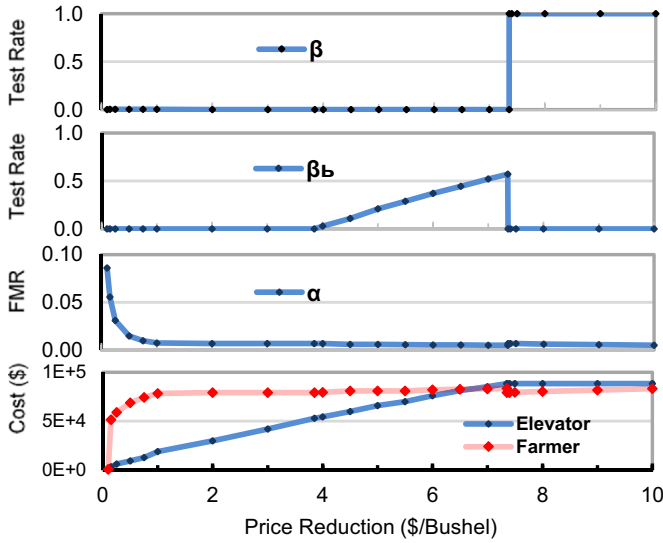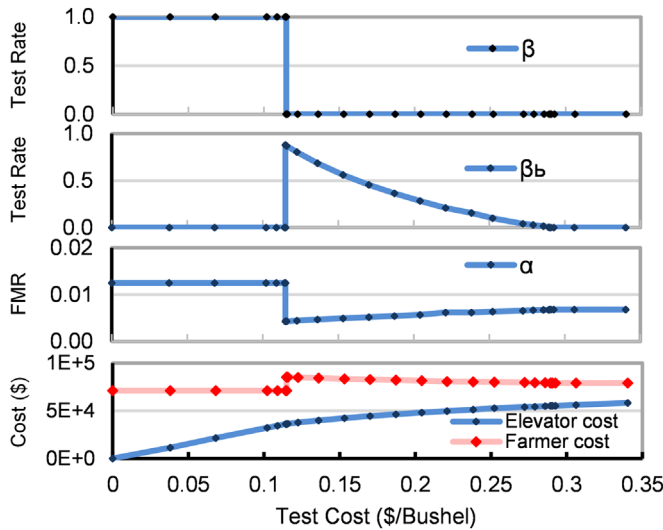
Fig. 6. Sensitivity analysis-Price margins.

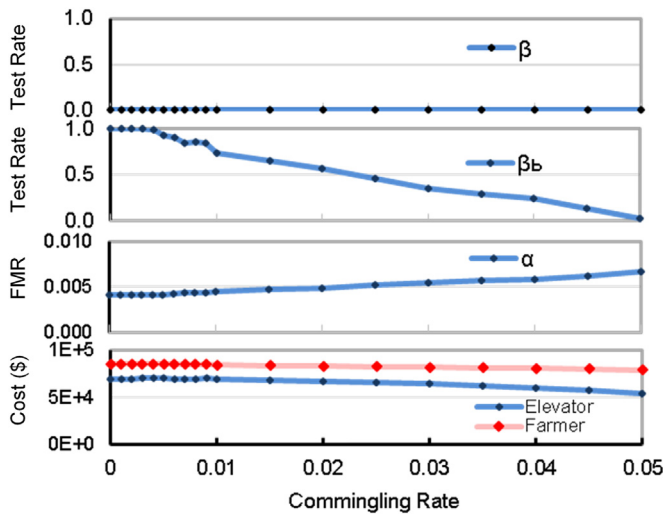Fig. 7. Sensitivity analysis – Test cost.

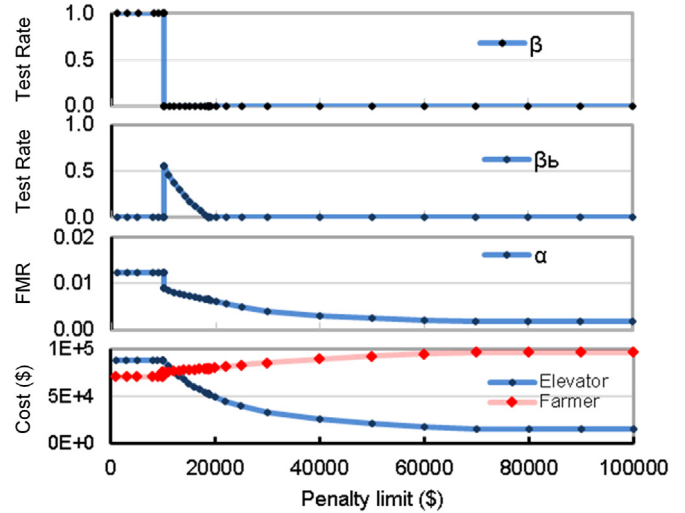Fig. 8. Sensitivity analysis – Contamination tolerance.

Fig. 9. Sensitivity analysis – Penalty levels.

decreases with the value of penalty. The elevator's potential losses from contamination decrease as the penalty limit increases, discouraging handlers' testing efforts. When the penalty limit is greater than $19,682, as mentioned the optimal handling strategy is no testing.

Handling costs decrease sharply when the limit increases through the $10,000–$40,000 interval. The FMR markedly decreases and the farmer's cost increases in this interval. In reality, the current maximum penalty for an individual farmer is set at $18,000. This is not high (by our measure) and is in fact located in the middle of the interval. We conclude that a slight increase in the current penalty level can improve overall system efficiency. As shown in Fig. 9, when the penalty limit is over $70,000, the elevator's cost function becomes very flat, while the FMR and the farmer's cost function become flat as well. We also observe that there are few benefits associated with a penalty increase for reducing the misrepresentation rate and handling costs when the penalty limit is set beyond $70,000.

Although a penalty and enforcement system for wheat quality surely represents an attempt to guard against certain undesirable system outcomes, ideally any economic system should avoid the tendency to overkill with an excess of rules and procedures in a quest to ensure that those undesirable outcomes can never occur. Not surprisingly, we find once again that there needs to be a balance struck in this new wheat handling system between bearing risks and inducing regulatory overload.

7. Conclusions

Considering the changes in wheat varietal testing that have recently been enacted in the Canadian wheat handling system, sustained and imaginative modeling efforts are needed to understand the consequences of these policy changes as well as to identify effective handling strategies and policies to maintain the historical integrity of the supply chain. To date, few comprehensive studies have been done to address potential risks associated with these policy changes, or explore risk mitigation strategies in the new trust system. In this work, after characterizing the basic analytics of the problem motivating the analysis, we explicitly model the Canadian wheat supply chain in a realistic manner and then develop testing strategies that most efficiently balance the tradeoff between testing costs and contamination risks.

The specification of appropriate wheat handling strategies in the supply chain can be formulated as system optimization

problems. In contrast to much of the extant literature, we develop a unique hybrid optimization-simulation model and find global solutions to the potential wheat contamination problem. Numerical simulation is used as a complementary tool to integrate complex characteristics of the system into the optimization model. Simulated model output is used to generate realistic wheat contamination data under various scenarios, enabling the development of key functional forms for our contamination multipliers, all helping to better quantify contamination effects and dynamics in the Canadian wheat supply chain.

The analysis generates a set of testing strategies to minimize the risks and costs of contamination to participants under foreseeable wheat handling scenarios. Testing locations and intensity are determined by the level of contamination risks from wheat misrepresentation. In essence, the more serious the contamination risks, the earlier the test point that must be chosen for testing. Comparatively, this means truck and primary bin test points have more important roles in minimizing contamination losses in the supply chain than the railcar test point. The structure of the supply chain matters - the assumed availability of these two test points renders the railcar test point unnecessary. While high testing costs and a low penalty for farmer misrepresentation weaken the wheat handler's incentives to test for contamination along the supply chain, alternatively tight commingling thresholds and high price margins between eligible wheat and (downgraded) feed wheat encourage more contamination testing. These findings have direct implications for the optimal testing strategy for risk mitigation under certain operational conditions.

In addition to the model's policy implications and methodological contribution, this study also addresses a historical policy issue about wheat quality within the Canadian wheat industry. But similar issues related to food safety and supply chains will develop across many countries and commodities. These could include other wheat sectors across the globe (including the EU and Australia), while this very issue seems to be an emerging problem for soybeans in the United States. We believe the policy issue addressed in this study as related to food safety and quality will essentially be "re-discovered" for other crops and regions of the globe. Hence, our framework can be expected to retain its influence as researchers in the future look to address similar supply chain and food safety problems elsewhere.

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