Essays in Agricultural Business Risk Management

by

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We acknowledge with respect the Lekwungen peoples on whose traditional territory the university stands and the Songhees, Esquimalt and W̱SÁNEĆ peoples whose historical relationships with the land continue to this day.

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ABSTRACT

Insurance has been considered as a useful tool for farmers to mitigate income volatility. However, there remain concerns that insurance may distort crop production decisions. Positive mathematical programming (PMP) models of farmers' cropping decisions can be applied to study the effect of agricultural business risk management (BRM) policies on farmers' decisions on land use and their incomes. Before being used to examine agricultural producer responses to policy changes under the expected utility framework, the models must first be calibrated to obtain the values of the risk aversion coefficient and the cost function parameters. In chapter 2, three calibration approaches are compared for disentangling the risk parameter from the parameters of the cost function. Then, in chapter 3, to investigate the impacts on production incentives of changes in Canada's AgriStability program, farm management models are calibrated for farms with different cost structures for three different Alberta regions. Results indicate that farmers' observed attitudes towards risk vary with cost structure. After joining the program, all farmers alter their land allocations to some extent. The introduction of a reference margin limit (RML) in the AgriStability program under Growing Forward 2 (2013-2018), which was retained in the replacement legislation until 2020, has the most negative impact on farmers with the lowest costs. The removal of RML significantly increases the benefits to low-cost farmers.

Traditional insurance products provide financial support to farmers. However, for fruit farmers, the products' quality can be greatly affected by the weather conditions during the stage of fruit development and ripening, which may lead to quality downgrade and a significant loss in revenue with little impacts on yields. Hence, chapters 4 and 5 investigate the conceptual feasibility of using weather-indexed insurance (WII) to hedge against non-catastrophic, but quality-impacting weather conditions to complement existing traditional insurance.

Prospect theory is applied to analyze a farmer's demand for WII. The theoretical model demonstrates that an increase in the volatility of total revenue and the revenue proportion from blueberries increases the possibility of farmers' participation in WII. On the other hand, the increase in the value loss aversion coefficient and WII's basis risk leads to less demand for WII.

To design a WII product for blueberry growers to hedge against quality risk, a quality index must be constructed and the relationship between key weather conditions, such as cumulative maximum temperature and cumulative excess rainfall, and the quality index should be quantified. The results from a partial least squares structural equation modeling (PLS-SEM) show that the above goals are achievable. Further, rainfall and temperature can be modelled via a time-series model and statistical distributions, respectively, to provide reasonable estimates for calculating insurance premia.

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DEDICATION

To my father and my husband who have been patiently waiting to celebrate the end of my never-ending student life.

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First, I'm extremely grateful to my supervisor, Dr. G. Cornelis van Kooten, for the opportunity to work with him. I will forever be grateful for his guidance, encouragement and support. I will do my best to let others to have similar positive experience as I had if I will get the chance to mentor others.

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Finally, I cannot begin to my express to my husband. Without his support, this dream cannot come true.

CHAPTER 1

INTRODUCTION AND BACKGROUND LITERATURE REVIEW

1.1 Introduction

Farmers are always exposed to a variety of risks. Among them, two main sources of risks are distinct from those in other economic sectors. First, a long interval exists between making production decisions and selling products, which causes high uncertainty in output prices and the corresponding market-related risks. Second, nature-related uncertainty is inherent in the production process, but exogenous to farmers. During the production phase, farmers must accept the price risk of input markets and decide what and how much inputs they plan to apply to production before the states of nature, primarily precipitation and growing-season heat units, are revealed. Hence, agricultural business risk management has been and will continue to be one of the key components of agricultural development.

Many governments have implemented different income stabilization policies with the intention of helping crop farmers mitigate income volatility. However, results show that some policies have undesirable impacts on farmers' land allocation decisions. For example, agricultural policies in rich countries, such as the EU, U.S. and Canada, originally protected producers with a price floor, provided insurance against production risk (e.g., low crop yields), and/or set production quotas, with tariff and non-tariff trade barriers put in place as needed to prevent imports (Barichello 1995; Schmitz et al. 2010). Output restrictions using quotas were implemented in the dairy and poultry sectors, thereby raising prices with import restrictions to protect the domestic price while limiting the sectors' abilities to export. Farmers in the crop sector, mainly grains, were supported through a variety of programs, which eventually evolved into subsidized business-risk management (BRM) programs (van Kooten 2021). Early programs led to increasing production, with products disposed of through low domestic prices, export subsidies, and/or storage programs, with only the cost to the public purse varying according to available foreign demand and how programs were implemented. Despite acreage reduction programs and conservation compliance provisions requiring farmers to meet certain environmental standards to be eligible for program payments, government intervention through direct support prices changed farmers' behavior, at least partially canceling out the stabilization effect of the policies.

Since the 1990s, government intervention has relied on BRM rather than direct subsidies to crop producers. Past agricultural support programs had incentivized production at the expense of the environment as farmers no longer needed to rely on mixed crop-livestock enterprises to protect against income variability, but instead concentrated on crop production only (Aguilar et al. 2015; Hedley 2015; Johnson n.d.). Such monoculture provided higher expected returns but with higher variability, which created a demand for BRM options. Nonetheless, BRM programs continue to distort the allocation of land and other inputs. Therefore, discussions are ongoing about how to provide business risk management tools without distorting farmers' production incentives, something known as "decoupling".

Given this background, the study focuses on the following questions: (1) How do we incorporate crop farmers' risk attitudes into a model that studies their economic decisions related to production and changes in government programs? (2) How do crop farmers' different attitudes toward risk affect their production and the financial outcomes of Canadian BRM programs? (3) Will index-based weather derivatives (e.g., forward contracts and options) or indexed insurance products be effective and attractive to farmers as a complement or substitute for current Canadian BRM programs for mitigating fruit farmers' financial risks?

Chapters 2 and 3 will address the first and second questions. To better understand the impacts of different BRM programs on farmers' production decisions and the environment, we construct farm management models that incorporate farmers' risk attitudes and the strategies implemented by farmers, such as a diversified crop portfolio. Specifically, we assume that a producer varies land uses or crop activities to maximize expected utility, which means that they take into account not only net returns (gross margins), but also their perception of risk and the volatility of returns. Before farm management models can be used to investigate farmers' responses to policies, they need to be calibrated so that the model's parameters replicate farmers' observed crop allocations. Positive mathematical programming (PMP) is currently the preferred approach for calibrating farm management models. However, it is challenging to calibrate models that maximize expected utility (EU) rather than expected gross margins, because the procedures for simultaneously calibrating farmers' risk attitudes and the cost function remain unsettled in the literature.

In Chapter 2, three positive mathematical programming (PMP) approaches for simultaneously calibrating the risk aversion coefficient and cost function parameters are compared. The differences among these three approaches are discussed, and region (county/municipal) level data for Alberta are used to assess the performance of these approaches. Then in Chapter 3, we choose the empirically practical model based on the above assessments and introduce current agricultural programs into the model to study the effectiveness and impacts of policies. To be specific, we investigate how the changes in the AgriStability program in Canada affect the land allocation decisions and the financial outcomes of crop farmers.

Chapters 4 and 5 address the third question. The main objective is to study the conceptual feasibility of using a weather-indexed insurance (WII) product to address the risk associated with adverse weather conditions. we will use blueberry farms in British Columbia as the focus group.

The study region is chosen because BC is the largest blueberry producer in Canada with most blueberries grown in the lower Fraser River Valley. Chapter 4 sets up a theoretical model using third-generation prospect theory (PT3) to analyze the demand for a WII product. we also discuss the results of one survey that targets blueberry producers about farmers' openness to purchase a WII product and their willingness to pay, especially whether the results are consistent with the conclusions drawn from the theoretical model.

In Chapter 5, we examine the feasibility of developing a WII product from the supply side by discussing the key elements of WII. A regression model will be used to construct an index representing blueberry quality, to identify the key weather factors (e.g., temperature, precipitation and timing of rainfall) affecting blueberry quality and to quantify the impacts of weather conditions on quality. Then a time series model will be used to model temperature, and a two-step stochastic process will be applied to model rainfall.

Finally, in Chapter 6, we summarize how the studies address the overall hypothesis and the research questions while identifying the limitations of the studies and future research directions.

1.2 Background Literature Review

As indicated above, risk is inherent to the farm business and acts as a major thread running through the dissertation. Hence, we review the literature regarding the characteristics of risk in agriculture, including its sources and types of risks, measurement and relationships among different risks. Agricultural risk management strategies are also touched upon. The literature related to research methods and modelling approaches will be reviewed in corresponding chapters.

The interpretation of risk is always related to uncertainty. Researchers have discussed the definition of risk and uncertainty and the distinction between them in various ways, but the root of the discussion about the difference between the two terms (risk and uncertainty) is the assessment and interpretation of probabilities (Chavas 2004). Usually, risk refers to situations where people have knowledge about possible outcomes and their probabilities. Uncertainty describes situations where the possible outcomes and/or the corresponding probabilities are not completely ascertained (Knight 1921; Harwood et al. 1999; Hardaker et al. 2015). This dissertation focuses on risks, assuming that possible outcomes and their probabilities can be discovered.

1.2.1 Sources and types of agricultural risks

Identifying sources of risk helps to categorize risks and corresponding risk management tools and strategies, which will be further discussed later. In the literature, risks are categorized in different ways. Rasmussen (2011) takes both positive and negative variations into consideration and uses a graph to show the sources of risks during the production and marketing phases, assuming input and output prices are stochastic and a farmer makes production-related decisions to maximize his expected utility. As indicated in Figure 1.1, only the amount and the timing of inputs at the production phase are controllable by farmers; other factors, such as the state of nature and market prices of crops at harvest time, are uncontrollable; accordingly, results are uncertain across all phases of production and sales. Hence, for farmers, the question is how actively to respond to risks and even make good use of the potential opportunities related to risks by adjusting allocations of resources, such as land, water and fertilizer.

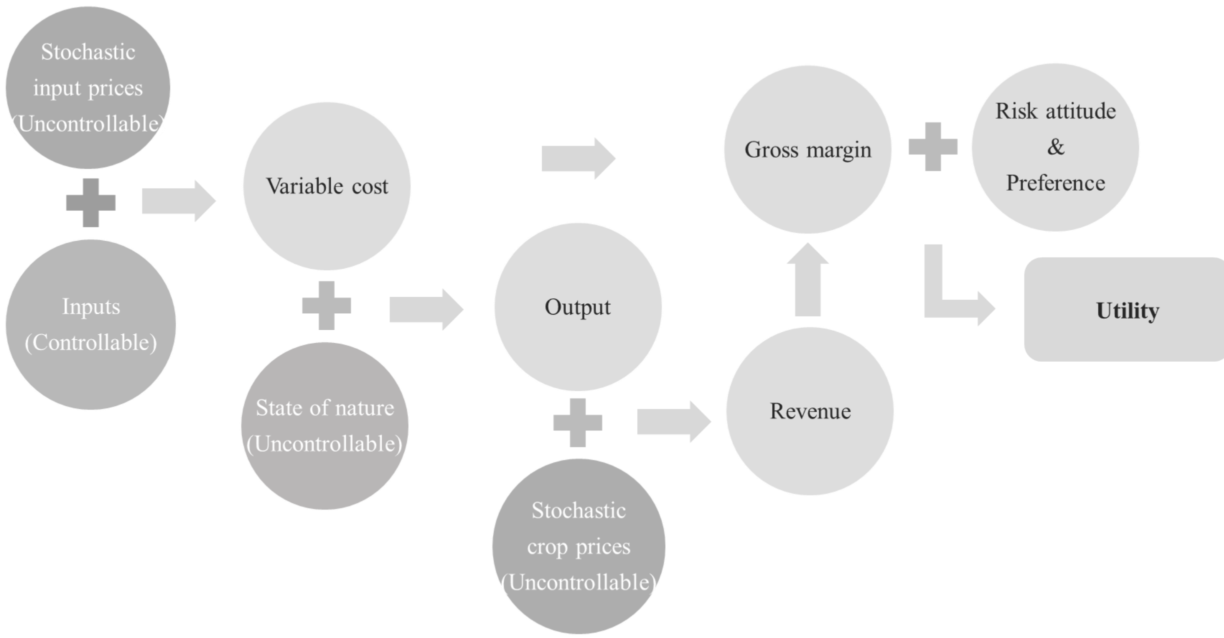

Figure 1.1 Production, utility, and risk
Source: Adapted from Rasmussen (2011)

Governments and non-profit organizations tend to emphasize negative variations as these harm agricultural producers. The OECD (2011) defines three layers of risks: normal, market/insurable, and catastrophic. Normal risks with limited damage happen frequently and can be better managed by producers, much like in other businesses. Normal risk includes small variations in input prices and yields at the farm level.

Price and weather-related production risks, along with other marketable risks, are insurable. Losses related to risks are often significant enough severely to affect farmers' consumption, while the probability of a loss is computable and the cost for farmers to transfer the risk to others is reasonable. This type of risk can be dealt with using insurance or other financial instruments (futures contracts, options, indexed financial derivatives).

The occurrence of catastrophic risk is unpredictable and many farmers will suffer great losses at the same time. An example might be a disease outbreak among livestock. In this case, government intervention is required to protect farmers.

The OECD (2009) proposes to use two sets of criteria to group agriculture-related risks: four types or sources of risk and the scale of risks' impacts (see Table 1.1). The risks presented in Table 1.1 cover the items discussed by most researchers. The risks considered in this dissertation are insurable risks, reflected by variations in farmers' incomes, which may be caused by a variety of risks at the same time.

Table 1.1: Types of risks

Type of risk	Scale of Impact		
	Micro (Household)	**Community (Groups)**	**Macro (Region or nation)**
Market		Changes in land price, etc.	Changes in market conditions, e.g. trade policy
Production	Non-contagious disease, personal risks (e.g. health)	Pollution, rainfall, etc.	Contagious disease, droughts, technology, etc.
Financial	Income from other sources (off-farm income)		Changes in interest rates or access to credit
Institutional		Changes in local policy or regulations	Changes in agricultural policy, environmental law

Source: Adapted from OECD (2009, Chapter 2)

1.2.2 Correlation among risks

Risks that lead to variations in farmers' incomes come from many sources. The correlations among different factors causing risks are worth exploring because the overall impact on farms is not the simple sum of individual risks. A negative correlation or lack of perfect positive correlation among risks helps to mitigate diversifiable risk exposure to reduce farmers' income variability. Hence, diversification has been a major risk management strategy in all countries that has proven effective in reducing income risk in most cases, especially for arable farms (Kimura, Antón and LeThi 2010; OECD 2011).

For arable farms, the literature usually identifies three correlations: the negative correlation between yield and output price (in most cases), the positive correlation among yields of different crops and/or regions, and the positive correlation among crop prices. These types of correlations have repeatedly been addressed using farm-level and aggregate data (Harwood et al. 1999; Kimura et al. 2010; OECD 2011).

Figure 1.2 shows the values of the correlation coefficients between yields and the prices of wheat in seven countries at the farm and aggregate levels. The left panel in the graph presents the numbers at the aggregate level. Compared with the numbers at the farm level, the coefficients of correlation are bigger at the aggregate level because market prices fluctuate only when the aggregate yield changes. For example, the correlation coefficient is -0.88 at aggregate level in Australia but drops to -0.24 when measured at the farm level. Meanwhile, correlation tends to be negative and has a larger absolute value in a big country that can affect world prices, such as Germany, while the value is more likely to be positive and smaller in absolute terms in a small country or region with isolated markets, like Estonia (OECD 2011).

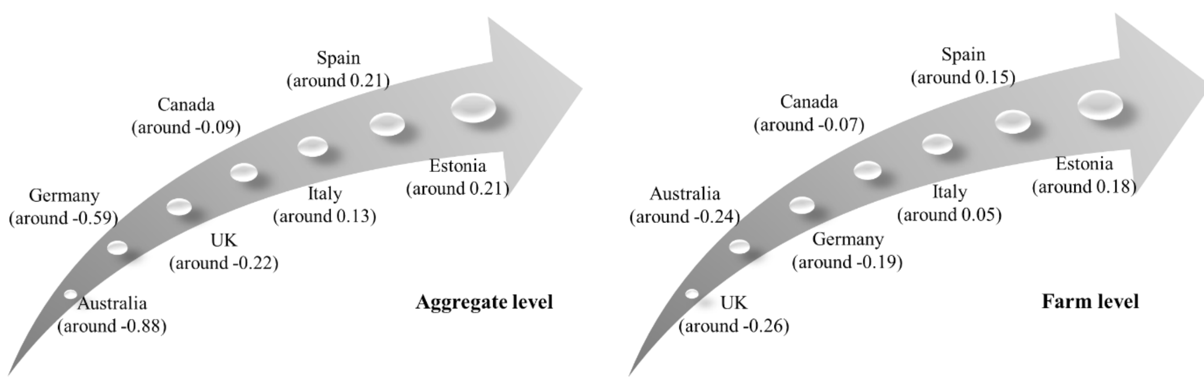

Figure 1.2 Yield-price correlations for wheat
Source: OECD (2011, Chapter 3)

Both the correlation of yields among crops and the correlation of prices across crops are positive and imperfect (OECD 2011). Price movements are more correlated with each other than with yields. Similar to the situation in the yield-price relationship, the coefficients of correlation are higher at the aggregate level than the farm level, but the difference between the two levels is larger with yields than with prices. Overall, the above results support diversifying the product mix to reduce the variability of whole farm income, particularly at the farm level.

1.2.3 Risk management strategies

How does the above discussion impact agricultural business risk management? First, the interaction and trade-offs among all risks and strategies must be taken into account when analyzing the impact of any particular strategy. Accordingly, a holistic approach is required to research about farmers' behavior and the effect on agricultural policies. Second, differentiated strategies should be designed for different risks (OECD 2011).

Risk management instruments and strategies can be labelled as ex ante (before the risk occurs) or ex post (after the risk occurs). Ex ante strategies include risk reduction actions that focus on reducing the probability of the occurrence of the risk, while risk mitigation strategies aim to decrease the potential impact. Ex post refers to risk coping and emphasizes relieving the actual impact and smoothing consumption.

Meanwhile, strategies are carried out by different actors: farmer or farm household, community, market-based institutions, and governments (Holzmann and Jørgensen 2001; OECD 2009). Hence, the main risk management instruments and strategies can be put into twelve groups as indicated in Table 1.2. Not all the strategies mentioned in the table will be available to farmers in all countries because of different conditions related to institutional structures and the availability of markets and information. When it comes to agricultural policies, different countries have distinct approaches.

Table 1.2: Agricultural risk management strategies

		Farm/household	Community	Market	Government
Ex ante	Risk Reduction	Technology		Training on risk management	Disaster prevention (e.g., flood control, prevention of animal diseases) Macroeconomic policies
	Risk Mitigation	Diversification in production Savings Off-farm income	Crop sharing	Production/marketing contracts Diversified financial investments Vertical Integration Futures and options Insurance	Counter-cyclical programs Border and other measures for contagious disease outbreaks
Ex post	Risk Coping	Borrowing from neighbours/family	Intra-community charity	Selling financial assets Saving/borrowing from financial institutions	Disaster relief Social assistance and other agricultural support programs

Source: Adapted from OECD (2009); Cervantes-Godoy, Kimura and Antón (2013)

In Canada, income stabilization has always been a common goal of all kinds of agricultural support policies, but the instruments used to stabilize farmers' incomes have changed over time. Before the mid-1980s, various agricultural policies were implemented to stabilize farmers' incomes and ensure an adequate supply of food for domestic use and export by setting product prices directly or controlling imports and production. After that, the goals of policies have been gradually expanded to include competitiveness and economic and environmental sustainability; accordingly, the instruments have become more market-oriented to encourage farmers to make production decisions based on market conditions, instead of adjusting their production mainly based on government programs. Meanwhile, more and more programs were coordinated between the federal and provincial/territorial governments to lessen disputes among regions (Hedley 2015; van Kooten 2021).

In March 2008, a new suite of business risk management (BRM) programs, known as Growing Forward (GF), came into effect to replace the old programs, including the Net Income Stabilization Account (NISA), crop insurance and the Canadian Agricultural Income Stabilization (CAIS) program, which used to be offered under different policy frameworks (Barichello 1995;

Stogstad 2011). The relationship and the function of five BRM programs are briefly explained in Table 1.3.

Table 1.3: BRM programs in Canada

Business Risk Management (BRM)				
Protection against losses				Supports for risk research (Ex ante)
Normal risks (Ex ante)	Marketable risks (Ex ante)		Catastrophic risks (Ex post)	
AgriInvest (A producer savings account with government matching contributions)	AgriStability (A whole-farm gross margin support program)	AgriInsurance (A support program targeting the production losses due to natural hazards)	AgriRecovery (A disaster relief framework to help producers recover from natural disasters)	AgriRisk Initiatives (A program for supporting risk investigation and risk management tool development and implementation)

When GF expired on March 31, 2013, it was replaced by Growing Forward 2 (GF2), which left much of GF intact with the exception of AgriInvest and AgriStability. With regard to the former, producer contributions were raised and the size of savings accounts that farmers could hold greatly increased. The major change of relevance to the current research concerned AgriStability, where the margin necessary to trigger a payout changed from 85% of the reference margin to 70%, and the method for calculating the reference margin was revised so that farmers could choose the lesser of the historic average program margin (as in GF) or a margin based on the historical average of allowable expenses (determined for the same three years used to calculate the reference margin). This change was implemented so that AgriStability would qualify as a green box program under Annex 2 of the Agreement on Agriculture (WTO Legal Texts 2015).

When GF2 expired on March 31, 2018, it was replaced by the Canadian Agricultural Partnership (CAP), which came into effect April 1, 2018. For the AgriStability program, there are two changes: the adjustment of the reference margin limit (RML) and the introduction of late participation (AAFC 2017); both will be explained in Chapter 3. Subsequently, the RML was removed in 2021 to provide better support to farmers (Agriculture and Agri-Food Canada 2021).

In Chapter 3, we will investigate the impacts of changes in Canada's AgriStability program on production and farmers' incomes via a farm management model that assumes expected utility maximization. The comparison of the key features of the AgriStability program under GF, GF2 and CAP will be covered in that chapter.

As the previous discussion about risk in agriculture shows, agricultural producers cannot control natural outcomes or effectively control for this type of risk. Hence, a main concern of farmers is how to mitigate the adverse impacts of weather risk on production and finance. In Canada, producers will buy price insurance and multiple-peril crop insurance products (e.g., AgriInsurance) that provide direct coverage for yield losses, as well as a specific, privately-provided product such as hail insurance, to deal with weather risk. Other programs, such as AgriStability, provide farmers some compensation when they suffer a major loss in incomes, whether due to low yields or adverse prices, or both. In this sense, Canada's BRM suite of programs provides farmers financial support when they face weather risk. Program payments are based on each farm's own operational outcomes, such as gross margins or yields. Alternatively, index-based weather derivatives (WD) or weather-indexed insurance (WII) are financial products that provide farmers some contingent payments that are determined by pre-defined underlying common weather outcomes, such as accumulated rainfall or the number of degree days over a period of time within one particular area.

In the literature, the benefits and the problems of using weather derivatives and insurance as risk management tools have been thoroughly discussed (e.g., Alexandridis and Zapranis 2013; Erhardt and Smith 2014; Richards, Manfredo and Sanders 2004; The World Bank, 2011). The main points can be summarized as follows.

a) With traditional insurance, individual risk assessments, loss investigations and adjustments lead to expensive monitoring and administrative costs plus long wait times before payment – the transaction costs are high. With WD and WII, payments are simply based on the difference between the value of the underlying weather index and the corresponding pre-determined strike value. The calculation is straightforward and no individual investigation is needed. Hence, at least in theory, the operational and transaction costs of using weather derivatives and insurance to hedge risks in terms of both time and money can be quite low compared to traditional insurance.

b) With crop insurance, there are problems with adverse selection and moral hazard that may cause market failure and push up premiums along with the high level of administration expenses. In contrast, WD and WII pay out according to some objective measure so they potentially can be more cost-effective than traditional insurance for farmers interested in hedging weather risk. Problems of adverse selection and moral hazard are avoided because neither participation rates nor farmers' actions can influence the outcome.

c) Farmers can possibly get more personalized hedges using over-the-counter (OTC) weather derivatives since they can negotiate contracts tailored to their specific requirements. However, the cost of customized contracts could be high, thereby discouraging farmers to participate. If farmers buy standard futures or options contracts from some derivatives market, they have the choice to close some or all of their positions before the expiration of those contracts on the derivatives market. But farmers need to deal with basis risk in this case. Basis risk refers to the situation where the payment from a derivatives product is different from the loss that a grower intends to cover – no payment is made when losses occur, or a payment is received when no loss is indicated. Basis risk usually comes from two sources: (i) product basis risk, which refers to the imperfect correlation between the underlying weather index and the hedging interest of farmers caused by the nonlinear relationship between yields (or quality) and weather conditions (e.g., temperature and rainfall); and (ii) spatial or geographic difference, which is due to the fact that the reference weather index is measured at a location different from the actual location of interest (Manfredo and Richards 2009).

d) The design of WD and WII is technically challenging due to the complexity of valuing a contract based on weather measurements. First, a weather index should be constructed based on a weather variable that affects the output variable, and that can be observed and measured every day. This ensures that the index will be objective, representative and observable (Turvey 2001). After a weather measure is defined, the remaining challenge is to price the index and value contracts based on the index; this is needed to determine the premium that agricultural producers would need to pay. Neither no-arbitrage models for derivatives pricing nor the well-known pricing model for options (viz., the Black–Scholes model) are applicable in the weather derivatives market. Different methods should be used, which will be discussed in Chapter 5.

From a research point of view, index-based weather derivatives and insurance are similar to each other except for regulatory rules, so the discussion in Chapters 4 and 5 is based on weather-index insurance.

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CHAPTER 2
CALIBRATION OF AGRICULTURAL RISK PROGRAMMING MODELS USING POSITIVE MATHEMATICAL PROGRAMMING

2.1 Introduction

Many mathematical programming, equilibrium and agent-based farm models have been developed to study the efficacy of agricultural business risk management (BRM) policies in reducing farmers' exposure to risk, and the effect that BRM programs have on land and other input use, outputs, and incomes. In a recent survey of 202 studies that developed and used farm models in policy analysis, Reidsma et al. (2018) found that nearly 70% used a mathematical programming (MP) approach and an increasing portion of these applied positive mathematical programming to calibrate the model parameters. Many farm management MP models assume that a producer varies land uses or crop activities to maximize her expected utility (EU), where utility is represented by the certainty equivalent (CE) because maximizing EU is equivalent to maximizing CE under some assumptions (Levy and Markowitz 1979). CE is defined as the expected gross margin (= revenue – variable costs) minus the variance of the gross margin multiplied by a risk aversion parameter (denoted φ).[1] In such models, φ is important for investigating farmers' economic decisions and evaluating the effectiveness of agricultural support programs. Given its importance in such models, the parameter φ must be calibrated along with the parameters of the cost function so that the MP replicates the observed land allocation before one can use the model to examine the impacts of a new policy (e.g., Howitt 1995, 2005; Paris 2011).

It has been challenging, however, to calibrate models that maximize expected utility (EU) rather than expected gross margins. The reason is that the means for calibrating φ along with the

[1] Gross margin is the term used in Canada's BRM programs and is defined as revenue minus certain but not all variable costs. For example, some programs do not allow one to subtract hired labor. More generally, net revenue would be used in lieu of gross margin.

cost function parameters remain unsettled in the literature. Several approaches that calibrate both the risk coefficient and cost function parameters have been proposed by different researchers (Petsakos and Rozakis 2011, 2015; Cortignani and Severini 2012; Louhichi et al. 2018). By examining and comparing these calibration methods, it is possible to identify their strengths and shortcomings, which can further contribute to the improvement of empirical analyses related to policy decisions.

In this chapter, therefore, we compare several calibration methods, focusing on their strengths and weaknesses, and evaluating their performance in recovering the values of the cost function parameters and the risk aversion parameter φ. We begin in the next section by briefly reviewing methods of model calibration and recent efforts to calibrate the risk aversion coefficient in farm BRM models using positive mathematical programming. In section 2.3, we provide a detailed discussion of three models for calibrating the risk aversion coefficient. We compare differences in model specification, approaches to calibration and where they are applicable. Then, in section 2.4, we apply our models to arable farms with mixed crop portfolios, using sensitivity analysis to test the performance of the methods and determine their robustness. Our application is to arable farms in Vulcan County in the province of Alberta, Canada. Finally, we provide some conclusions in section 2.5.

2.2 Calibrating Agricultural Business Risk Management Models: Background

A major challenge of agricultural BRM modelling relates to calibration. One early approach to calibration is referred to as the historical crop-mix approach, which is used primarily for aggregate- or sector-level analysis (McCarl 1982; Önal and McCarl 1989, 1991). It does not find the explicit economic cost functions but assumes that observed past crop choices are optimal; thus, it constrains farmers' crop allocations so they resemble past choices – the historical mixes. The procedure assumes that observed farmers' choices are extreme points or corners on the convex constraint set (viz., a simplex algorithm for solving LP problems). It is argued that the optimal solution for crops at the aggregate level is a weighted average of extreme points at the farm level representing individual farms' optimal plans. That is, farmers' risk attitudes are implicitly addressed because the observed optimal crop portfolio chosen by farmers does not consist solely of a single crop – the one with the largest gross margin. To employ this approach for policy analysis, the aggregated MP model would need to determine the weights associated with each farm to obtain the crop choices at the aggregate level; the sum of the weights is constrained to equal 1.

One shortcoming of this approach is that future choices are constrained by the historical ranges. As a solution to this issue, Chen and Önal (2012) suggest that is possible to include new crops that have not previously been planted by adding synthetic (or simulated) mixes of the decision variables to the historical mixes. The optimization procedure then chooses the weights, which are again constrained so the sum of the historical plus synthetic weights equals 1.

Positive mathematical programming (PMP) is now the preferred approach for calibrating farm management models because PMP can be used to estimate crop-specific marginal cost functions and, thereby, exactly replicate farmers' observed crop allocations (Mérel and Bucaram 2010; Mérel et al. 2011). PMP was first developed by Howitt (1995) (hereafter referred to as 'standard PMP') to address land-use allocation problems in agriculture (e.g., Röhm and Dabbert 2003), although PMP has increasingly been adapted for use in trade modeling and other resource management settings (Weintraub et al. 2007; Paris et al. 2011; Heckelei et al. 2012; Mérel and Howitt 2014; Johnston and van Kooten 2017).

While the calibration of crop-specific cost functions using PMP is generally considered to be straightforward, significant challenges remain (Heckelei and Wolff 2003; Heckelei et al. 2012). The standard PMP as introduced by Howitt (1995) requires specification of a strictly diagonal quadratic cost matrix, implying that there are no substitutionary or complementary effects among crops. Gradually, the PMP method has been extended by employing external information, such as supply elasticities, and the principle of maximum entropy (ME) to obtain parameter estimates for the entire cost matrix (Paris and Howitt 1998).

Moreover, Heckelei and Wolff (2003) argue that the estimates of the parameters obtained by following the standard PMP procedure can be inconsistent because the first-order conditions imposed in the first step with linear cost functions and in the last step with non-linear cost functions are generally not compatible. Hence, they propose to directly estimate the parameters of the desired mathematical programming model by a generalized maximum entropy (GME) approach that relies on the first-order conditions (FOCs) to the MP. Prior information can also be included to influence the estimation results even in situations with limited data while ensuring computational stability.

One important challenge with agricultural BRM models relates to their calibration when risk attitudes are to be explicitly included in the analysis – when expected utility rather than net revenue (gross margin) is to be maximized. The challenge is to estimate the risk aversion coefficient and cost function parameters simultaneously within the PMP calibration framework. Several approaches are used in the literature for the calibration of φ; these can be categorized into two groups based on different assumptions about the utility function (Louhichi et al. 2010; Jeder, Sghaier and Louhichi 2011; Jeder et al. 2014; Petsakos and Rozakis 2011, 2015; Cortignani and Severini 2012; Louhichi et al. 2018).

The first assumes that wealth W is normally distributed and that the utility function is a negative exponential function of W as follows: $U(W)=1–e^{-\varphi W}$. For this functional form, the constant absolute risk aversion coefficient (CARA) can simply be derived as $\varphi = –U''(W)/U'(W)$ (McCarl and Spreen 2003). Then, maximizing the expectation of the negative exponential utility function is equivalent to maximizing the certainty equivalent (CE) subject to technical constraints, where CE = $\mu - ½\ [U''(W)/U'(W)]\ \sigma^2 = \mu - ½\ \varphi\sigma^2$, where μ and σ^2 are the mean and variance of the distribution of wealth. The second option assumes a logarithmic utility function: $U(W) = \ln(W)$. Its absolute risk aversion coefficient is decreasing with wealth: $\varphi = -(-W^{-2}) / (W^{-1}) = 1/W$ and the corresponding relative risk aversion coefficient is 1 (= $W \times \varphi$).

The majority of studies that maximize expected utility employ an exponential utility function, which implicitly assumes CARA. Cortignani and Severini (2012) extend an ME approach proposed by Heckelei and Wolff (2003) to estimate simultaneously all the parameters for a farm-level model within a PMP framework, including the parameters of the quadratic cost functions and the CARA coefficient. The objective is to maximize expected utility subject to resource constraints. The authors estimate the model's parameters using time series data from a single farm, with the error terms expressed as the deviation between the observed and optimal land allocations. Meanwhile, the expected values of the own- and cross-land supply elasticities for all crops are required to obtain the decision set. We do not consider their approach here because we lack a suite of supply price elasticities of land in crops for Alberta (or even Canada).

The EU's Farm System SIMulator (FSSIM) employs another method for deriving the risk aversion parameter. The approach is to vary φ in an iterative fashion until the simulated land allocation comes closest to duplicating the observed crop allocation. If the calibration in the first step is not exact (which is the common result because risk attitudes alone cannot fully explain crop choices), the value of φ determined in the first step is assumed fixed, with the cost function parameters then calibrated in a second step in the same way as the standard PMP method with elasticity adjustment (Louhichi et al. 2010; Jeder et al. 2014). However, because the marginal crop from the expected utility perspective may not be the least profitable crop in the standard PMP framework, directly applying this method cannot guarantee perfect recovery of the observed land allocation (Liu et al. 2018). Hence, calibration of the cost function parameters must be modified to achieve perfect recovery.

With the availability of farm-level data and the increasing demand to assess the impacts of policies on different farms simultaneously for accommodating heteroskedasticity, the Individual Farm Model for the EU's Common Agricultural Policy (IFM-CAP) was developed. The first version of the IFM-CAP model was used for policy assessments in 2018 (see the technical report by Louhichi et al. 2018). One feature distinguishing the model from the others discussed in the paper is that the IFM-CAP model is built on the EU's Farm Accountancy Data Network (FADN), with all farms in the 2012 dataset individually modelled. To calibrate all parameters, IFM-CAP employs data from the 2007-2012 farm-level FADN, official statistics, and datasets from other models, such as the Common Agricultural Policy Regional Impact. Due to the lack of such data in Canada and the different levels of model complexity, the IFM-CAP model is not considered for further comparison here.

Arata et al. (2014, 2017) propose to make use of the primal and dual specifications of the farmer's expected utility maximization problem (hereafter referred to as *Arata CARA*). They combine the 1st and 2nd steps of the standard PMP approach to derive the calibrated objective function and constraints. Instead of ME estimation, their procedure includes a least squares estimator that is based on the errors on the marginal cost functions. Then they simultaneously calibrate the CARA coefficient, shadow prices of land, and the parameters of the cost functions. This is explained further in the next section [see equations (2.11) through (2.15) below].

In contrast to approaches that seek to estimate a CARA coefficient, Petsakos and Rozakis (2011, 2015) assume linear cost functions and a logarithmic utility function, which leads to a decreasing absolute risk aversion (DARA) parameter that is a convex function of wealth. They then apply an ME method within the PMP framework to recover the parameters. One drawback is that the method requires a choice of an appropriate level of initial wealth. If the initial wealth is too small, the DARA coefficient is highly sensitive to the farmer's cropping choice, which leads to situations where the observed land allocation cannot be recovered. Their approach based on a logarithmic utility function (thus DARA) is discussed in detail at the beginning of the next section.

2.3 Agricultural Business Risk Management Modeling

In this section, we describe in more detail three approaches for modelling risk aversion on the part of agricultural decision makers, and compare the results from these models. We classify the models into two groups based on their assumptions about the utility function and risk attitude.

2.3.1 Logarithmic utility function and DARA

The method proposed by Petsakos and Rozakis (2011, 2015) begins by assuming a logarithmic utility function defined as:

$$U(W) = \ln\left[W^0 + \mathrm{E}\left(\sum_{k=1}^{K} R_k\right)\right], \tag{2.1}$$

where W^0 denotes the (representative) farmer's initial wealth, E is the expectation operator, R_k represents the total gross margin from crop k, and the farmer can choose from K crops. $U(W)$ has the DARA property because the risk aversion coefficient is derived as:

$$\varphi = \frac{-U''(W)}{U'(W)} = \frac{1}{W^0 + \mathrm{E}\left[\sum_{k=1}^{K} R_k\right]}. \tag{2.2}$$

Petsakos and Rozakis (hereafter P&R) also assume separate linear cost functions at the farm level for each crop for simplicity, so they do not need to calibrate the parameters of a nonlinear cost function.

P&R's intuition is that, when we use regional-level prices, yields, accounting costs and the related variance-covariance matrix of gross margins to solve a farmer's optimization problem, the derived optimal land allocation deviates from the observed farm-level land allocation. To replicate the observed land choices, the unobservable farm-level values of the above parameters must be recovered. Hence, to calibrate the DARA model, we need to solve algebraically the nonlinear expected utility maximization problem twice to derive two sets of the FOCs using observed farm-level land allocations. The first problem is defined by equations (2.3) through (2.6) below, and solved using the observed *regional-level* values of prices, yields, accounting costs, and the related variance-covariance (VC) matrix of the gross margin. The second problem is defined by equations (2.7) through (2.9), but it requires the unobserved *farm-level* values of prices, yields and the corresponding VC matrix. The FOCs associated with the above two MPs are equal to zero at the observed farm-level land allocations because the observed allocations are assumed to be optimal, as evident from equation (2.10). The calibration process described later will use equation (2.10) as a key constraint to derive farm-level values of prices, yields, costs and the VC matrix.

The first problem using the regional-level data can be approximated by the following MP:

Maximize $$CE = W^{f,o} + \mathrm{E}\left[\sum_{k=1}^{K} r_k^R x_k^f\right] - \frac{1}{2}\frac{\sum_{k=1}^{K}\sum_{i=1}^{K}\left[x_k^f \times S_{k,i}^R \times x_i^f\right]}{W^{f,o} + \mathrm{E}\left[\sum_{k=1}^{K} r_k^R x_k^f\right]} \tag{2.3}$$

Subject to: $$\sum_{k=1}^{K} x_k^f \leq \bar{X} \quad [\psi] \tag{2.4}$$

$$x_k^f \leq x_k^{f,o} + \varepsilon_k \quad [\lambda_k],\ \forall k, \tag{2.5}$$

$$x_k^f \geq 0,\ \forall k. \tag{2.6}$$

The superscript R indicates regional-level data, while f refers to data at the farm level; $W^{f,o}$ represents the farmer's initial level of wealth. The term $\mathrm{E}[r_k^R]$ is the expected regional-level gross margin ($/ac) from planting crop k, x_k^f denotes the number of acres at the farm level allocated to crop k, and $\bar{X}$ represents the total area (acres) the farmer allocates to crop production. The non-risk component of the CE can be written as: $\mathrm{E}\left[\sum_{k=1}^{K}(r_k^R x_k^f)\right]=\mathrm{E}\left[\sum_{k=1}^{K}(p_k^R y_k^R - c_k^R)x_k^f\right]$. In the equation, p_k^R and y_k^R represent, respectively, the regional output price and yield for crop k; c_k^R is the observed per-unit-area variable cost of producing crop k. As to the risk component, $S_{k,i}^R$ in equation (2.3) refers to the elements of the regional variance-covariance matrix of the realized per-acre gross margins related to crops k and i. The optimal allocation of land to crops is endogenously determined.

The shadow prices associated with the constraints are indicated in square brackets in equations (2.4) and (2.5). Constraint (2.4) restricts the farmer's cultivated area to that available. Equations (2.5) constitute the calibration constraints and are needed to derive the shadow values (prices) of the various crops, λ_k, which are then used in equation (2.10) below to recover farm-level values. In the calibration constraints (2.5), $x_k^{f,o}$ is the observed number of acres planted to crop k, while ε_k is added to each of the calibration constraints to prevent degeneracy that could occur because constraints (2.5) are related to the land constraint (2.4).

The corresponding farm-level MP for the expected utility maximization problem is defined as:

Maximize $$CE = W^{f,0} + \mathrm{E}\left[\sum_{k=1}^{K} r_k^f x_k^f\right] - \frac{1}{2}\frac{\sum_{k=1}^{K}\sum_{i=1}^{K}\left[x_k^f \times S_{k,i}^f \times x_i^f\right]}{W^0 + \mathrm{E}\left[\sum_{k=1}^{K} r_k^f x_k^f\right]} \quad (2.7)$$

Subject to: $$\sum_{k=1}^{K} x_k^f \leq \bar{X} \ [\psi^f] \quad (2.8)$$

$$x_k^f \geq 0, \ \forall k. \quad (2.9)$$

The definitions of the parameters and variables are the same as before except: (i) everything is at the farm level (e.g., $r_k^f = p_k^f y_k^f - c_k^f$); and (ii) $c_k^f = c_k^R + q_k^f$, where c_k^R and q_k^f represent, respectively, the explicit and implicit marginal costs of producing crop *k*, which are equal to the average costs as the cost function is assumed to be linear. In this way, q_k^f is defined as the differences between the farm-level real costs, c_k^f ($/ac), and the observed regional accounting costs, c_k^R ($/ac).

One can then equate the two sets of FOCs from the above two models with each other as follows (P&R 2015, p.539):

$$E(p_k^R y_k^R - c_k^R) - \frac{\sum_{i=1}^{K}\left[S_{k,i}^R \times x_i^{f,o}\right]}{W^{f,0} + \mathrm{E}\left[(p_k^R y_k^R - c_k) x_k^{f,o}\right]} + \frac{1}{2}\frac{\left\{\sum_{k=1}^{K}\sum_{i=1}^{K}\left[x_k^{f,o} \times S_{k,i}^R \times x_i^{f,o}\right]\right\} \times \mathrm{E}(p_k^R y_k^R - c_k^R)}{\left\{W^{f,0} + \mathrm{E}\left[(p_k^R y_k^R - c_k) x_k^{f,o}\right]\right\}^2} - \lambda_k =$$

$$\mathrm{E}(p_k^f y_k^f - c_k^f) - \frac{\sum_{i=1}^{K}\left[S_{k,i}^f \times x_i^{f,o}\right]}{W^{f,0} + \mathrm{E}\left[(p_k^f y_k^f - c_k^f) x_k^{f,o}\right]} + \frac{1}{2}\frac{\left\{\sum_{k=1}^{K}\sum_{i=1}^{K}\left[x_k^{f,o} \times S_{k,i}^f \times x_i^{f,o}\right]\right\} \times \mathrm{E}(p_k^f y_k^f - c_k^f)}{\left\{W^{f,0} + \mathrm{E}\left[(p_k^f y_k^f - c_k^f) x_k^{f,o}\right]\right\}^2}, \forall k \qquad (2.10)$$

As described by P&R (2011, 2015), a maximum entropy (ME) approach can then be applied to obtain the values of the farm-level prices, yields, variance-covariance matrix ($\boldsymbol{S}^f$), and hidden or implicit marginal costs ($\boldsymbol{q}^f$) for one representative farm in the region. For their ME process, it is necessary to have information on the initial wealth of the farm, time series data on regional-level prices and yields, along with the constant accounting variable costs and a regional-level variance-covariance matrix of gross margins across time. Meanwhile, the farm's technology and land allocations are also assumed constant during the period used for calibration. It is not possible to use cross-sectional data from multiple farms unless farms (i) face different prices and yields while (ii) using the same technology, (iii) have the same land constraint, and (iv) allocate land across crops in exactly the same way.

2.3.2 Exponential utility and CARA

<u>Dual approach</u>

The key features of the method proposed by Arata et al. (2014, 2017) include: (1) The parameters of the cost functions, the risk aversion coefficients of more than one farm, and the shadow prices for total land and land in various crops are all simultaneously calibrated in one step. (2) The farm-level cost functions are defined in quadratic form with symmetric full matrices. (3) Farmers are assumed to have different risk attitudes; their cost functions share the same cost matrix but have different intercepts. Hence, cross-sectional data containing the base-year information for a group of farmers who share the same technology are required. Time-series data are not suitable because no farmer is supposed to change her risk attitude over time nor do the intercept terms on the crop cost functions change from year to year.

The mathematical programming model used to calibrate the parameters is as follows:

Minimize

$$\sum_{f=1}^{F} \psi_f \bar{X}_f + \sum_{f=1}^{F} \sum_{k=1}^{K} \left[\frac{1}{2} \alpha_{f,k}^2 + c_{f,k} y_{f,k} x_{f,k}^o + \lambda_{f,k} \left(y_{f,k} x_{f,k}^o + \varepsilon_{f,k} \right) + \varphi_f \sum_{i=1}^{K} \left(x_{f,k}^o \times S_{k,i} \times x_{f,i}^o \right) - p_{f,k} y_{f,k} x_{f,k}^o \right] \quad (2.11)$$

subject to

$$\boldsymbol{c}_f + \varphi_f \boldsymbol{S} \boldsymbol{x}_f^o + \psi_f \boldsymbol{J} + \boldsymbol{\lambda}_f \geq \boldsymbol{p}_f \quad (2.12)$$

$$\boldsymbol{c}_f + \boldsymbol{\lambda}_f = \boldsymbol{Q} \boldsymbol{x}_f^o + \boldsymbol{\alpha}_f \quad (2.13)$$

$$\boldsymbol{Q} = \boldsymbol{L}\,\boldsymbol{D}\,\boldsymbol{L}' \quad (2.14)$$

$$\Psi_f,\ \varphi_f,\ \boldsymbol{\lambda}_f \geq 0 \quad (2.15)$$

The objective function is developed from the mathematical problem in the first step of the standard PMP and its corresponding dual problem. Constraint (2.12) represents the condition that marginal cost in terms of utility is greater than or equal to price with the optimal choice. Equations (2.11) and (2.12) differ slightly from those in Arata et al. (2017); as discussed below, our notation and definitions of the parameters and variables differ somewhat from those used by these authors. Constraint (2.13) is a combination of the FOCs from the first- and second-step standard PMP equations; it shows the relationship between the linear cost and the quadratic cost for each crop.

The parameters for the F farms are calibrated via the above model. The subscript f represents the f^{th} farm; $\boldsymbol{L}$ and $\boldsymbol{D}$ are Cholesky decomposition matrices of $\boldsymbol{Q}$ – the quadratic component of the cost functions; Ψ_f represents the land shadow price for the f^{th} farm. The vectors $\boldsymbol{J}$, $\boldsymbol{\lambda}_f$, $\boldsymbol{p}_f$ and $\boldsymbol{\alpha}_f$ are all K×1; the elements of $\boldsymbol{J}$ are all 1; and the other vectors represent the shadow prices, the expected product prices and the intercepts of the cost functions for K crops on the f^{th} farm, respectively. Other variables and parameters are defined as previously. $\boldsymbol{Q}$, Ψ_f, φ_f, $\boldsymbol{\lambda}_f$ and $\boldsymbol{\alpha}_f$ are to be simultaneously calibrated. Then estimated parameters for each farm are implemented using the farm risk management model defined below by equations (2.16) through (2.18) individually for policy analysis.

In the model described by Arata et al. (2017), the VC matrix $\boldsymbol{S}$ is based on farm-level prices, and x_k represents the total yield of the k^{th} crop, which equals the crop yield per acre times the number of acres. The implication is that a farmer can choose each crop's output level. For comparison purposes, we adjust the model used here and define $\boldsymbol{S}$ as the VC matrix based on gross margins per acre. Hence, a farmer chooses how to allocate land to maximize her utility as represented by the following MP:

$$\text{Maximize: } CE = \mathrm{E}\left[\sum_{k=1}^{K}\left(p_k y_k \text{-} \alpha_k\right) x_k - \frac{1}{2}\sum_{k=1}^{K}\sum_{i=1}^{K}\left(x_k \times Q_{k,i} \times x_i\right)\right] - \frac{\varphi}{2}\sum_{k=1}^{K}\sum_{i=1}^{K}\left(x_k \times S_{k,i} \times x_i\right) \quad (2.16)$$

$$\text{Subject to: } \sum_{k=1}^{K} x_k \leq \bar{X} \ [\psi] \quad (2.17)$$

$$x_k \geq 0, \ \forall k. \quad (2.18)$$

<u>FSSIM ME approach</u>

The farmer is assumed to maximize her expected utility as defined by the MP represented by equations (2.16)-(2.18),[2] but with one exception: the quadratic terms on the cost functions constitute a diagonal matrix with positive diagonal elements. (A diagonal matrix, instead of a full matrix, is assumed because the calibration results would tend to be inconsistent with one observation and lack of information regarding the range of the matrix's elements.) We first calibrate the risk aversion coefficient φ by iteratively varying φ until the simulated land allocation comes closest to duplicating the observed crop allocation using historical cost data. Then the following ME problem is constructed to calibrate the parameters of the cost functions:

$$\text{Maximize } H = -\sum_{k=1}^{K}\sum_{z=1}^{Z}\pi_{k,z}^{\alpha_k}\ln\left(\pi_{k,z}^{\alpha_k}\right) - \sum_{k=1}^{K}\sum_{z=1}^{Z}\pi_{k,z}^{Q_{kk}}\ln\left(\pi_{k,z}^{Q_{kk}}\right) \tag{2.19}$$

subject to

$$p_k y_k - \sum_{z=1}^{Z} z_{k,z}^{\alpha_k}\pi_{k,z}^{\alpha_k} - \sum_{z=1}^{Z} z_{k,z}^{Q_{kk}}\pi_{k,z}^{Q_{kk}} \times x_k^o - \psi - \varphi \times \sum_{i=1}^{K} S_{k,i} \times x_i^o = 0,\ \forall k \tag{2.20}$$

$$c_k + \lambda_k = \sum_{z=1}^{Z} z_{k,z}^{\alpha_k}\pi_{k,z}^{\alpha_k} + \sum_{z=1}^{Z} z_{k,z}^{Q_{kk}}\pi_{k,z}^{Q_{kk}} \times x_k^o,\ \forall k \tag{2.21}$$

$$\sum_{z=1}^{Z} z_{k,z}^{\alpha_k} = 1,\ \sum_{z=1}^{Z} z_{k,z}^{Q_{kk}} = 1 \tag{2.22}$$

$$z_{k,z}^{\alpha_k},\ z_{k,z}^{Q_{kk}},\ \Psi,\ \varphi \geq 0;\ \sum_{z=1}^{Z} z_{k,z}^{Q_{kk}}\pi_{k,z}^{Q_{kk}} \geq 0 \tag{2.23}$$

The superscripts α_k and Q_{kk} indicate the intercepts and the diagonal elements of the matrix of the cost functions, respectively, while λ_k represents the crop shadow prices. Following the steps of the

[2] ME is a special case of generalized maximum entropy (GME), which can be used to derive the values of the parameters. If there is prior information on the range of the targeted parameters, the prior information is specified in the form of support values and a related discrete uniform probability distribution. Then, to estimate the parameters, the objective is to maximize the Shannon entropy [equation (2.19)] subject to the known constraints [equations (2.20) and (2.21)] and the available data for calculating the probabilities. Where prior information is available, the expected values of estimates of parameters are used (e.g., for α_k, Q_{kk} and λ_k); but parameters such as Ψ and φ are simply determined upon solving the MP.

standard ME method, for each crop we define discrete support vectors $\boldsymbol{z}_k^{\alpha_k}$ and $\boldsymbol{z}_k^{Q_{kk}}$ for α_k and $Q_{k,k}$. Accordingly, $z_{k,z}^{\alpha_k}$ and $z_{k,z}^{Q_{kk}}$ are the z^{th} elements of their respective support vectors, whose values are based on the gross margins and accounting variable costs for the crops; $\pi_{k,z}^{\alpha_k}$ and $\pi_{k,z}^{Q_{kk}}$ are the endogenous z^{th} elements of the corresponding discrete probability distributions for the above support vectors. The values of p_k, y_k, c_k and x_k^o are from the pre-defined base-case data. Constraints (2.20) and (2.21) are derived from the FOCs of the Lagrange functions for the first and second steps of the PMP approach. Once the values of all $\pi_{k,z}^{\alpha_k}$ and $\pi_{k,z}^{Q_{kk}}$ are obtained, $\sum_{z=1}^{Z} z_{k,z}^{\alpha_k}\pi_{k,z}^{\alpha_k}$ and $\sum_{z=1}^{Z} z_{k,z}^{Q_{kk}}\pi_{k,z}^{Q_{kk}}$ are calculated as the expected estimation of α_k and Q_{kk}.

2.4 Calibration and Performance Assessment of Agricultural BRM Models

To assess the performance and robustness of the three approaches discussed in section 3, we first check their ability to calibrate the 'true' (recovered or implied) values of the unobserved parameters, and then conduct sensitivity analyses to investigate whether the optimal land allocations are sensitive to slight changes in the values of the unobserved parameters.

2.4.1 Methodology

Initially, we assume that the true values of all unobserved parameters, including the cost-function parameters and the risk aversion coefficient, are known for each approach. Then we obtain three sets of optimal land allocations separately using the true values of the unobserved parameters and the observed farm level values for the exogenous parameters, including expected prices, yields and the variance-covariance matrix **S**. Then, for each approach, we use the derived optimal land allocation in the previous step and the observed exogenous parameters to calibrate the cost function parameters and the risk aversion coefficient(s). Finally, we compare the calibrated parameters with the true values to check the ability of the various calibration approaches to recover the true parameter values.

For the sensitivity analyses, we focus on the impacts of the changes in prices and yields on land allocation, because the expected prices and yields are comparable across different approaches since we use the same data source. But the values of φ and the cost function parameters are different with each approach due to their different assumptions about the utility function and cost functions, which makes the outputs less comparable. As an illustration, we assume a policy, such as the introduction of a support price, that would increase the revenue from each crop by ten percent, with a step size of one percent, while holding the other parameters constant; we also consider a potential decrease in revenue. We obtain an optimal land allocation under each scenario, and compare and discuss the pattern of the changes. Large revenue changes, such as a 50% increase, are not considered because it is not reasonable to hold other parameters constant when expected revenue undergoes such large changes.

To facilitate the presentation and discussion, we refer to Petsakos and Rozakis's (2011, 2015) approach as *P&R-DARA* and Arata et al.'s approach as *Arata-CARA*, as noted earlier, and our proposed approach as *FSSIM-ME-CARA*.

2.4.2 Data

For our analysis and to obtain the values of the exogenous parameters, we choose arable grain farms in Vulcan County located in South Central Alberta (Figure 2.1). There are 70 municipalities in Alberta with cropland, but we focus on Vulcan County, which is located in the dark brown soil zone, consists of 608 farms, 1.067 million acres of cropland, and a population of 3,984 (Government of Alberta, 2017a). Of the 70 municipalities, Vulcan has the largest area of cropland, the second largest number of cropland acres per person, and the third largest average acres per farm. Farmers in the county produce mainly barley, canola, peas, wheat and durum wheat, which are also the most important crops in Alberta.

Figure 2.1 Map of Alberta: Vulcan County is shaded

For the *P&R-DARA* model, we identify a representative arable farm in Vulcan County that is of average size and allocates land to crops on the basis of the average cropping pattern in the county, where the distribution of farm sizes and cropping patterns are provided by the Government of Alberta (2017a, 2017b). The same is true for the *FSSIM-ME-CARA* model. For the *Arata-CARA* model, however, we employ 16 representative (average) farms based on data from 16 townships within Vulcan county and calibrate the parameters for these farms in one step. Because cross-sectional, farm-level data are not available, no other economic, financial or environmental characteristics are considered.

For calibration, although different datasets are applied to different models, the following types of data are required: product prices, yields, variable costs of production, land allocations, and the variance-covariance matrix of gross margins per acre among crops. Total variable costs of production ($/ac) are obtained from Alberta Agriculture & Forestry (2014) and assumed constant across time and across farms. Yearly crop prices in Alberta are obtained by taking the average of monthly crop prices available from Statistics Canada (2017). Alberta's Agricultural Financial Services Corporation (AFSC) provided municipal-level data on average yields, the number of farms and total insured acres of cropland, which are used to calculate yields per acre and the land allocations for all crops for each year.

Table 2.1 provides the base-case information for the *P&R-DARA* and *FSSIM-ME-CARA* models. The prices and yields are the Olympic averages of the data in Table A.1 in chapter Appendix A—the average after the two highest and two lowest values are removed. Further, for the *P&R-DARA* model, the value of the initial wealth level W^0 is set at the average 2015 net worth for farms in the study region, namely $3,490,636 (Statistic Canada 2017b). Table A.1 provides the time-series data of prices and yields for the period 2008 through 2016 for the *P&R-DARA* model. Table A.2 in the Appendix A provides the data for calibrating the *Arata-CARA* model. Because durum is counted under wheat and not listed separately at the township level, weighted price and production costs calculated according to the land allocations of durum and wheat are used. The assumed true values for the unobserved parameters are reported with the calibration results for comparison in the next subsection.

Table 2.1: Base-case information regarding the representative farm

Item	Barley	Canola	Durum	Peas	Wheat
Price ($/bushel)	4.18	11.06	7.54	7.72	6.46
Yield (bushel/acre)	65.65	38.74	45.71	41.52	45.52
Variable cost ($/acre)	110.49	172.70	138.15	135.63	138.15
Gross margin ($/acre)	163.67	255.88	206.36	184.80	155.96
Land (%)	17.7%	24.9%	11.0%	14.9%	31.6%
Land (acre)	311.2	436.6	192.6	261.2	554.4
Farm size (acre)			1,756		
Region			South Central		
Soil Zone			Dark Brown		

2.5 Results and Analysis

For each model, we report the true values and the corresponding calibrated values for the parameters of φ and the cost functions, followed by the results of sensitivity analysis regarding land allocation. For the *P&R-DARA* model, we also report the true values and the calibration results of the elements of the farm-level variance-covariance matrix **S** because this matrix needs to be calibrated under P&R's approach.

P&R-DARA: In this model, φ is not a constant number. Because the farmer's initial wealth is $3.49 million and the gross margin is around $0.3 million, the value of φ is about 2.62E-07, which is primarily dependent on the assumed initial wealth. The true and calibrated values of farm-level prices, yields, the VC matrix **S**, and $\boldsymbol{q}$ – the term that represents the farm's implicit production costs – are found in Table 2.2. The *P&R-DARA* model recovers the true values with small differences.

Table 2.2: The true values and calibration results, P&R-DARA model

True values						Calibrated values					
φ =	2.66E-07					φ =	2.67E-07				
	Barley	Canola	Durum	Peas	Wheat		Barley	Canola	Durum	Peas	Wheat
Price	4.19	11.07	7.55	7.74	6.50	Price	4.19	11.07	7.55	7.74	6.50
Yield	67.30	38.82	46.11	42.17	47.00	Yield	67.30	38.81	46.11	42.17	46.99
q	14.88	99.94	53.90	33.34	10.80	q	14.93	99.95	53.92	33.38	10.79
True S						Calibrated S					
	Barley	Canola	Durum	Peas	Wheat		Barley	Canola	Durum	Peas	Wheat
Barley	6855	6276	3909	6955	4734	Barley	6868	6277	3913	6963	4733
Canola	6276	7664	2289	7447	4583	Canola	6277	7656	2288	7444	4574
Durum	3909	2289	6974	3752	3387	Durum	3913	2288	6975	3754	3385
Peas	6955	7447	3752	9677	5628	Peas	6963	7444	3754	9681	5624
Wheat	4734	4583	3387	5628	4179	Wheat	4733	4574	3385	5624	4168

The sensitivity analysis indicates the optimal land allocation changes in the *P&R-DARA* model, even with one percent change in revenue. This outcome is not realistic. The changes in land allocation under the scenarios of increasing revenue are provided in Figure 2.2. The numbers on the horizontal axis represent the revenue level compared to the base case (e.g., 1.0 represents the base-case scenario with 1.05 implying a revenue increase of five percent). Each stacked bar shows the portions of the land used for each crop for one scenario. When the revenue increases by one percent from the base case, only canola and durum are planted. All land is used to produce canola once the revenue increases by one more percent and no other crops are planted beyond a 2% increase in revenue. Contrariwise, when revenue declines by 1%, only barley and wheat are produced. If the revenue decreases by 3% compared to the base case, all land is allocated to barley production. The potential reason for the large discrete changes is the inflexibility associated with linear cost functions. P&R (2015) state that they use linear cost functions for simplicity. Because they fail to provide technical specifications regarding the calibration process if non-linear cost functions are used, it is not possible to test the ability of the model to recover the parameters' true values and conduct sensitivity analysis with a quadratic matrix in the *P&R-DARA* specification.

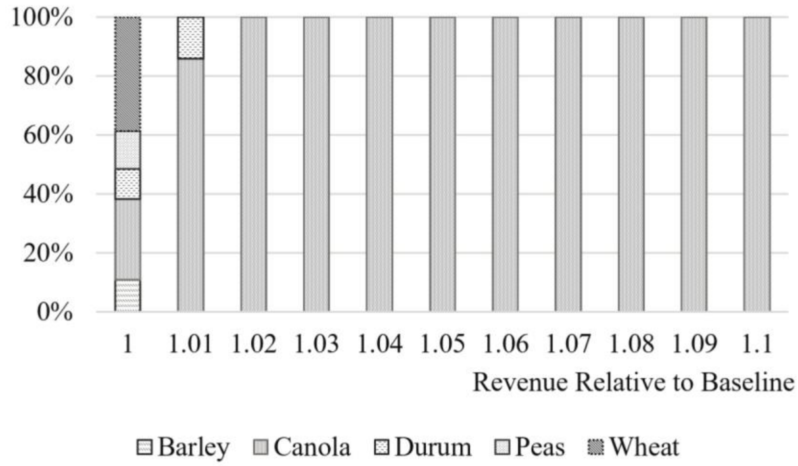

Figure 2.2 Impact of Increases in Crop Revenues on Land Allocation, P&R-DARA Model

Arata-CARA: For the risk aversion coefficients, the calibrated values resulting from the *Arata-CARA* model are close to the true values. Except for the parameters of the cost functions, the biases of the estimates are large in some cases, especially for the quadratic cost term Q (see Tables 2.3 and 2.4). One potential reason for the discrepancies is that $\hat{Q}$ is sensitive to the values of the elements of the decomposition matrices, while no reliable rules exist for the choice of those values in the calibration process.

As to sensitivity, we find the changes in land allocations are reasonable. The land allocations for sixteen farms under two scenarios are provided in Figure 2.3 on a crop-by-crop basis for the base case and the case where the revenue from each crop increases by 10%. The bars in light grey with dashed borders represent the acres of the crops in the base case. With higher revenues, all farms increase the land allocated to canola by 22.75 acres on average (about 5.4% of the land allocated to canola in the base case), because planting canola increases revenue the most in absolute terms even though all crops' revenues increase by the same amount in relative terms.

Table 2.3: The true values and the calibration results, Arata-CARA model

	True values					Calibrated values				
		Alpha					Alpha			
Farm	φ	Barley	Canola	Peas	Wheat	φ	Barley	Canola	Peas	Wheat
1	0.00E+00	-6.27	52.31	-9.81	2.21	0.00E+00	-4.50	53.22	-9.35	3.53
2	6.69E-07	26.40	-2.58	34.23	-58.05	6.40E-07	26.58	-2.52	33.56	-57.62
3	0.00E+00	3.81	202.75	-50.83	31.76	0.00E+00	5.68	203.57	-50.24	32.66
4	0.00E+00	39.42	17.60	-27.29	-29.73	0.00E+00	39.50	17.66	-27.70	-29.45
5	3.03E-05	-18.81	-238.17	82.22	97.49	3.05E-05	-18.27	-237.21	81.52	96.95
6	0.00E+00	-5.28	8.37	-72.14	69.06	0.00E+00	-3.53	8.14	-72.73	68.12
7	2.17E-05	26.83	18.12	50.43	111.54	2.17E-05	29.10	19.18	50.71	112.13
8	0.00E+00	-31.29	59.39	86.11	68.95	0.00E+00	-29.46	60.26	86.49	69.73
9	0.00E+00	-15.65	11.70	64.19	81.32	0.00E+00	-14.02	12.72	64.51	81.99
10	0.00E+00	43.58	32.73	8.59	-84.91	0.00E+00	43.84	32.71	7.99	-84.53
11	0.00E+00	-35.46	145.96	46.48	102.70	0.00E+00	-49.85	130.08	66.57	86.77
12	3.40E-05	-39.07	-73.82	45.95	36.05	3.42E-05	-38.27	-73.23	45.05	35.75
13	0.00E+00	-11.68	52.70	-34.49	30.89	0.00E+00	-9.92	53.52	-33.95	31.53
14	0.00E+00	33.34	27.83	-15.84	-3.61	0.00E+00	34.34	28.54	-15.34	-2.66
15	1.09E-05	77.78	5.31	-84.59	1.50	1.09E-05	78.13	5.33	-84.97	1.51
16	9.81E-06	-12.25	-12.77	106.78	-81.76	1.00E-05	-11.19	-12.54	105.48	-81.74

Table 2.4: Q matrix for Arata-CARA model

True **Q** matrix					Calibrated **Q** matrix				
	Barley	Canola	Peas	Wheat		Barley	Canola	Peas	Wheat
Barley	1.647	0.014	-0.992	-0.164	Barley	0.799	-0.274	0.924	-0.952
Canola	0.014	0.742	0.111	0.080	Canola	-0.274	1.567	-1.122	0.774
Peas	-0.992	0.111	1.444	-0.133	Peas	0.924	-1.122	1.828	-1.201
Wheat	-0.164	0.080	-0.133	0.488	Wheat	-0.952	0.774	-1.201	1.650

Most farms also reduce their production of barley and peas. The change in revenues has the most diverse impacts on the land allocated to wheat: four farms slightly increase the land planted to wheat, but farm 6 reallocates 24.15 acres from wheat to canola, even though this farm allocated the least amount of land (267.7 acres in the base case) to wheat compared to other farms and other crops produced by this farm.

When the revenue from each crop falls by 10%, all farms reduce the production of canola while farmers' allocations of land to other crops differ greatly (see Table A.3 in the Appendix). For example, seven farms decide to reduce wheat plantings, while the other five farms increase plantings of wheat. Four farms even choose to idle part of their land to reduce the production of all crops.

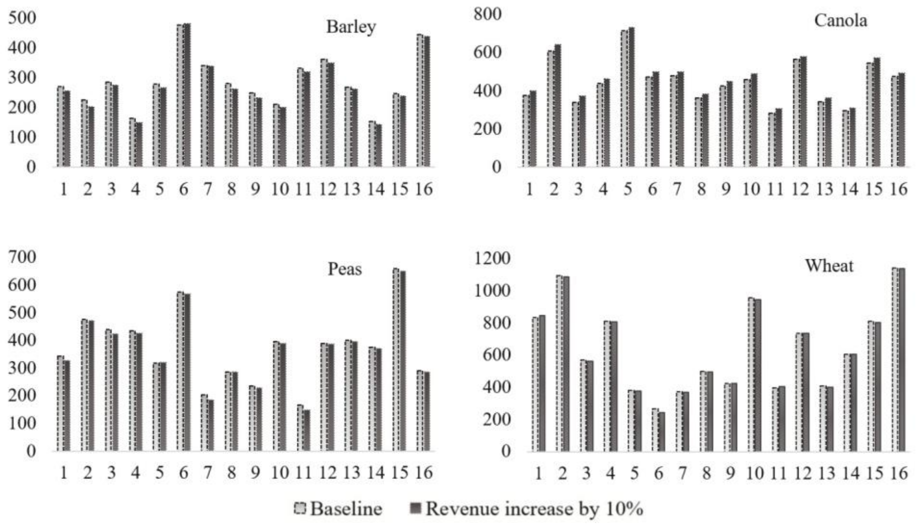

Figure 2.3 Impact of Increases in Crop Revenues on Land Allocation, Arata-CARA Model (Farm Identifier Number on the Horizontal Axis)

FSSIM-ME-CARA: With the *FSSIM-ME-CARA* model, the calibrated values of all parameters are very close to their true values, with the exception of the intercept (alpha) of the cost function for peas (see Table 2.5). For peas, the absolute value of alpha and the ratio of alpha over Q^{kk} (the quadratic term) are both small, indicating that the difference between the true and the calibrated cost function is acceptable.

Similar to Figure 2.2, the horizontal axis in Figure 2.4 shows the revenue levels compared to the base case. The acres allocated to each crop (rather than proportions) are provided on the vertical axis. As crop revenue increases, more land is allocated to canola while less is allocated to barley and wheat. Meanwhile, more durum and less peas are produced, but the changes are small.

For example, if revenue increases by 10%, the land allocations to canola and durum are increased by 13.13 and 1.91 acres, respectively, while the land allocated to barley, peas and wheat decreases by 8.24, 0.59 and 6.22 acres, respectively. When revenue decreases, the impacts are just the opposite and all land continues to be allocated to crop production.

Table 2.5: The true values and the calibration results, FSSIM-ME-CARA model

True values						Calibrated values					
$\varphi =$	5.10E-06					$\varphi =$	5.10E-06				
	Barley	Canola	Durum	Peas	Wheat		Barley	Canola	Durum	Peas	Wheat
Alpha	-16.89	-13.50	50.72	0.55	-73.05	Alpha	-16.79	-13.54	50.37	0.73	-72.53
Q^{kk}	0.62	0.78	1.06	0.83	0.49	Q^{kk}	0.62	0.78	1.06	0.83	0.49

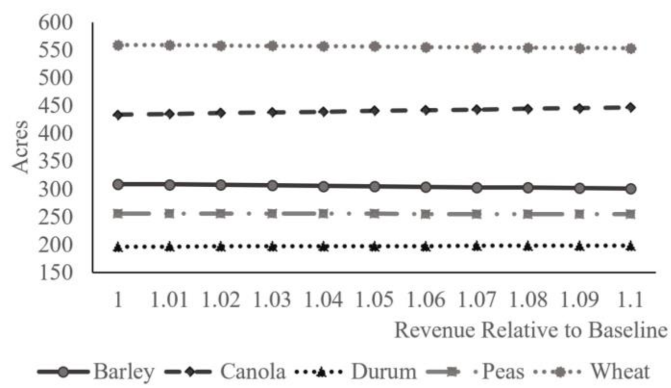

Figure 2.4 Impact of Increases in Crop Revenues on Land Allocation, FSSIM-ME-CARA Model

2.6 Discussion and Conclusions

Agricultural economists frequently construct mathematical programming models to investigate the effects of various policy levers on farm management decisions. Instead of maximizing the expected net returns (or gross margins), economists tend to maximize the expected utility of net returns because farmers are also concerned about the variance of returns when making crop allocation decisions. Given the focus on crop allocation decisions, in this study we examined a simplified version of a farm management MP that leaves aside biophysical and other constraints that might impact farmers' crop choices. Where such constraints can be identified, they can simply be carried along in the various stages of the calibration without changing the results presented here. However, when these biophysical constraints are not included, the calibrated cost function and risk aversion parameters reflect the impact that such considerations would have on crop allocations. Thus, the PMP calibration procedure itself takes into account, for example, the need of farmers to plant crops in rotation to manage pathogens and other pests.

Mathematical programming models must be calibrated before they can be used to analyze the effects of new policy initiatives. Hence, the ability to calibrate the needed risk aversion and cost function parameters, and the reliability of the calibration results, are key elements for assessing calibration approaches. In this study, three approaches for explicitly calibrating the risk aversion coefficients for an agricultural business risk management model were compared using an application from a grain-producing region in western Canada.

Given a logarithmic utility function, linear crop-specific cost functions and unobserved farm-level values, the *P&R-DARA* model uses a maximum entropy procedure that is able to recover the hidden marginal crop production cost (q_k) for a representative farm, along with the farm-level prices, yields and the variance-covariance matrix. However, a sensitivity analysis determined that very small changes in the calibrated parameters can lead to big changes in land allocation. Therefore, concerns are raised about the use of linear cost functions, as required by this calibration approach. It will be necessary in the future to assess the model's performance with non-linear cost functions, once the related technical specifications become available.

The *Arata-CARA* model employs a primal/dual approach and assumes an exponential utility function and quadratic cost functions with a full variance-covariance matrix. While the *P&R-DARA* model uses regional-level time-series data to calibrate parameters for one farm, the *Arata-CARA* model relies on farm-level, cross-sectional data to calibrate parameters for more than one farm simultaneously. As a result, *Arata-CARA* leads to different calibrated values of the CARA coefficient and the intercept component of the cost functions for each of the ‘observed’ farms even though they share the same technology. The main drawback of this approach is that it cannot recover the true values of the parameters, especially for the quadratic terms (Q) of the cost function. The imprecision in the estimates is mainly due to the high sensitivity of the estimates to the decomposition of the Q matrix and the lack of a rule to eliminate unreasonable estimates. One potential improvement is to obtain and incorporate prior information regarding the range of the parameters into the calibration process.

Finally, the *FSSIM-ME-CARA* model starts with an iteration process to find the value of the risk aversion coefficient. Then it uses a maximum entropy method to estimate the parameters of a quadratic cost function with a diagonal matrix for a single representative farm. In this regard, the *P&R-DARA* and *Arata-CARA* models have one advantage in that they use information from multiple data points in the calibration process. The *FSSIM-ME-CARA* model relies on only one observation. We can improve the reliability of the calibration results by taking an average of the calibrated estimates as the parameter values, and use that for policy purposes, if farm-level data for more than one farm with similar size and crop mix are available.

In summary, due to the high sensitivity of land allocation to the changes in parameters, the use of the *P&R-DARA* model for policy analysis is not empirically practical. The *Arata-CARA* model can be employed, but only after prior information about the range of the parameter values is incorporated into the calibration process to ensure an appropriate level of accuracy and precision of the estimates. At present, the *FSSIM-ME-CARA* approach is perhaps the most practicable to use for policy purposes. One must conclude, however, that more research on this topic is required.

Appendix A: Supplemental Data and Results

Table A.1: Time series data for prices and yields, 2008-2016

	Price ($/bushel)					Yield (bushel/acre)				
Year	Barley	Canola	Durum	Peas	Wheat	Barley	Canola	Durum	Peas	Wheat
2008	4.34	11.18	11.03	8.53	7.95	58.76	35.27	43.78	35.79	41.45
2009	3.33	9.93	6.69	6.16	5.97	43.85	28.63	34.43	21.68	31.39
2010	3.01	9.46	5.11	5.36	5.51	67.05	42.14	47.39	49.64	47.70
2011	3.80	12.02	6.49	7.74	6.38	71.21	40.78	48.33	51.76	46.35
2012	4.66	12.81	7.45	8.65	6.99	65.42	33.24	48.80	47.15	45.60
2013	5.21	13.03	6.85	8.30	7.38	80.04	42.80	55.13	54.68	56.17
2014	3.78	10.02	6.68	6.49	5.66	64.22	35.12	45.94	40.75	44.40
2015	4.76	10.40	9.48	8.36	6.06	68.06	40.34	45.83	36.93	47.76
2016	4.70	10.71	8.05	9.87	6.25	72.21	50.35	41.79	35.31	48.85

Table A.2: Township-level data of yields and land allocations in Vulcan County, 2016

	Yield (bushel/acre)				Land allocation (%)				Farm
No.	Barley	Canola	Peas	Wheat	Barley	Canola	Peas	Wheat	size (acre)
1	70.71	51.96	39.29	58.59	14.8%	20.6%	18.8%	45.7%	1828
2	38.37	53.53	33.52	38.57	9.4%	25.3%	19.8%	45.5%	2407
3	36.42	47.75	18.43	28.36	17.5%	20.7%	26.9%	34.9%	1635
4	60.54	50.94	37.56	47.66	8.9%	23.7%	23.5%	43.9%	1850
5	66.06	47.87	45.89	50.00	16.5%	42.2%	18.8%	22.5%	1696
6	105.18	59.62	49.13	51.31	26.6%	26.3%	32.1%	14.9%	1792
7	81.31	50.99	34.20	50.52	24.5%	34.2%	14.6%	26.7%	1396
8	70.61	52.99	50.97	57.72	19.7%	25.3%	20.0%	34.9%	1426
9	75.73	56.13	48.09	59.69	18.7%	31.9%	17.6%	31.7%	1334
10	73.65	56.61	43.47	49.30	10.5%	22.8%	19.5%	47.2%	2024
11	92.52	60.45	48.21	69.01	27.0%	23.4%	18.0%	31.6%	1183
12	88.90	51.92	54.46	66.47	17.6%	27.6%	19.0%	35.8%	2053
13	77.75	52.10	43.86	50.77	19.0%	24.0%	28.3%	28.7%	1420
14	68.62	43.74	41.70	50.07	10.7%	20.7%	26.3%	42.4%	1430
15	81.32	55.99	43.28	53.01	10.9%	24.1%	29.1%	35.8%	2266
16	83.80	48.07	46.82	54.00	18.9%	20.2%	12.3%	48.6%	2356
Price	4.18	11.06	7.72	6.74	($/bushel)				
Cost	110.49	172.70	138.15	135.63	($/acre)				

Table A.3: Land allocation changes with decreased revenue, Arata-CARA model

Farm	Barley			Canola			Peas			Wheat			Land used for production		
	Base case	10% decrease	Differ-ence	Base case	10% decrease	Differ-ence	Base case	10% decrease	Differ-ence	Base case	10% decrease	Differ-ence	Base case	10% decrease	Differ-ence
1	270.6	285.5	14.9	377.1	355.6	-21.6	344.1	359.7	15.6	836.2	827.2	-9.0	1828	1828	0
2	225.9	223.9	-2.1	609.3	562.5	-46.8	476.3	451.0	-25.3	1095.4	1055.0	-40.4	2407	2292	-114.58
3	285.9	263.8	-22.1	339.1	287.7	-51.5	439.5	415.9	-23.6	570.5	515.2	-55.3	1635	1482	-152.51
4	165.1	179.7	14.6	438.7	413.7	-25.0	434.9	443.4	8.5	811.2	813.1	1.9	1850	1850	0
5	279.9	259.0	-20.9	715.2	668.1	-47.1	319.3	274.5	-44.8	381.6	317.9	-63.7	1696	1519	-176.53
6	477.0	471.5	-5.5	471.9	445.7	-26.2	575.4	582.9	7.5	267.7	291.9	24.2	1792	1792	0
7	341.6	343.0	1.4	477.8	456.4	-21.4	204.0	222.2	18.2	372.5	374.3	1.8	1396	1396	0
8	281.0	300.4	19.4	361.2	340.8	-20.4	285.6	285.4	-0.2	498.3	499.6	1.3	1426	1426	0
9	250.0	266.8	16.8	425.7	402.5	-23.2	235.2	242.1	6.9	423.1	422.6	-0.5	1334	1334	0
10	212.2	223.0	10.8	460.6	432.7	-27.9	395.2	401.4	6.2	956.0	966.9	10.9	2024	2024	0
11	333.1	345.3	12.1	283.8	260.4	-23.3	167.0	184.6	17.6	399.0	392.6	-6.4	1183	1183	0
12	362.0	334.0	-28.0	566.2	517.0	-49.2	390.3	343.0	-47.3	734.5	651.5	-83.0	2053	1846	-207.49
13	269.7	277.6	7.9	341.2	318.9	-22.3	401.5	407.6	6.1	407.6	415.9	8.3	1420	1420	0
14	152.9	163.4	10.5	295.4	280.2	-15.3	375.7	379.8	4.1	606.0	606.7	0.7	1430	1430	0
15	246.8	254.3	7.4	547.2	522.6	-24.6	660.4	670.3	9.9	811.6	818.9	7.3	2266	2266	0
16	445.8	451.6	5.8	475.5	459.9	-15.6	290.2	294.3	4.1	1144.4	1150.0	5.6	2356	2356	0

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CHAPTER 3
THE IMPACT OF CHANGES IN THE AGRISTABILITY PROGRAM ON CROP ACTIVITIES: A FARM MODELING APPROACH

3.1 Introduction

The main sources of agricultural risks relate to production and price. Based on input prices of seeds, chemicals, fuel and equipment (rental rates), and some notion of the output price at harvest, agricultural producers decide the mix of inputs and how much of each crop to plant well before the states of nature are revealed. Hence, an important component of agricultural business risk management is to mitigate the volatility of farmers' income caused by exogenous factors, like output prices, possible hail or heavy frost, potential risk of disease and insect pests, and the amount and timing of precipitation and temperatures (heating) throughout the growing season.

In Canada, income stabilization programs provided by the federal and provincial/territorial governments have been changing. As introduced in Chapter 1, Growing Forward (GF) policy framework was implemented in March 2008, replacing previous farm programs. That is, Canada abandoned all programs that rely on direct support payments and went entirely to business risk management as the means to support farmers. In this sense, Canadian agricultural programs are decoupled from production. When GF expired in 2013, it was replaced by Growing Forward 2 (GF2), which was then replaced by the Canadian Agricultural Partnership (CAP) in 2018. Much of the programs were left intact since GF, but the AgriStability program has been adjusted three times in order to attract greater participation. In Table 3.1, we compare key features of the AgriStability program under GF, GF2 and CAP.

The AgriStability program is a whole farm insurance product, similar to the Whole-Farm Revenue Protection (WFRP) offered in the United States (U.S. Department of Agriculture 2019). However, there are differences in the two programs. For example, both AgriStability and WFRP require participants to file income tax returns, but the WFRP offers an extra premium subsidy to farms with two or more commodities to encourage diversity. The range of allowable expenses that is used to calculate reference margins differs across the two programs. For example, custom (contract) work and repairs and maintenance are allowable expenses under WFRP, but not under AgriStability (Government of Canada 2018; U.S. Department of Agriculture 2019). Canada has a stricter definition of allowable expense and applied a reference margin limit in an attempt to mitigate moral hazard (see Table 3.1 for details). But some rules either significantly decrease the benefits (see section 3.4 for an example) or lead to a larger difference between the amount of payments that farmers expect to receive based on their losses and what they actually receive—this results in basis risk that discourages participation in AgriStability. Hence, increasing the transparency of payment calculation and reducing basis risk are important for enhancing participation in AgriStability.

The purpose of the current chapter is to investigate the effects of changes in the AgriStability program on crop allocations and farmers' incomes. To demonstrate the explicit impact of risk attitudes, our farm management model maximizes a farmer's expected utility (EU) rather than expected gross margin. The *FSSIM-ME-CARA* approach that is explained in Chapter 2 will be employed in this study.

In the next section, the models used in the current application are discussed. The application to arable farms in Alberta is provided in sections 3.3 and 3.4, with the former describing the data and the latter providing our results. Some conclusions follow in section 3.5.

Table 3.1: Key features of the AgriStability program under different policy frameworks

	Growing Forward	Growing Forward 2	Canadian Agricultural Partnership (CAP)
Reference margin (RM)	Five-year Olympic average of gross margin (GM) (=allowable income-allowable expenses)	Same as GF	Same as GF
Reference margin limit (RML)	N/A	The lower of the RM and the average of allowable expenses for the corresponding years used to calculate RM	Similar to GF2, but RML is set to no less than 70% of the RM (until 2020) RML was removed in 2021
Trigger	Less than 85% of the RM	Less than 70% of the RM or RML (if applicable)	Same as GF2
Payment (coverage)	multi-tier: 70% of margin decline when the realized GM is between 70% to 85% of RM; 80% of margin decline between 0% to 70% of RM; 60% of negative margin	70% of margin decline when the realized GM is below the trigger	Same as GF2
Late participation	N/A	N/A	Provincial and territorial governments can trigger; benefits will be reduced by 20%
Fee paid by a farmer	85%×0.0045× contribution RM + $55 (administrative cost share)	70%×0.0045× contribution RM (RML not applied) + $55	Same as GF2

3.2 Farm Risk Management Modelling

3.2.1 Calibration model

As explained in Chapter 2, a farmer is assumed to maximize her utility, which is a negative exponential function of wealth. The following mathematical programming (MP) model represents the farmer's optimization problem:

$$\text{Maximize} \quad CE = E\left[\sum_{k=1}^{K}\left(p_k y_k x_k - \alpha_k x_k - \frac{1}{2}\beta_k x_k^2\right)\right] - \frac{1}{2}\varphi \sum_{k=1}^{K}\sum_{i=1}^{K}\left(x_k \times S_{k,i} \times x_i\right) \qquad (3.1)$$

Subject to: $\sum_{k=1}^{K} x_k \leq \overline{X}$ [ψ], and $x_k \geq 0$, ∀k. (3.2)

where K crops are available to be planted; x_k denotes the number of acres allocated to crop k that will be endogenously determined, and $\overline{X}$ represents the total area (acres) the farmer allocates to crop production. The shadow price associated with the constraint is indicated in square brackets. Meanwhile, p_k and y_k represent the output price and yield for crop k, respectively; α_k and β_k are the parameters of the quadratic cost function for crop k; and $S_{k,i}$ represents the (k,i) element of the VC matrix based on gross margins per acre.

We first calibrate the risk aversion coefficient φ by iteratively varying φ until the simulated land allocation comes closest to duplicating the observed crop allocation. Then we implement the maximum entropy (ME) method to calibrate the values of the cost function parameters.

3.2.2 Extensions for policy analysis

After the calibration process, we modify the model given by equations (3.1) and (3.2) to reflect the rules of the AgriStability program. Now a farmer needs to solve the following MP problem:

Maximize

$$\mathrm{EU} = \mathrm{E[R]} - \frac{1}{2}\varphi\sigma^2 \tag{3.3}$$

Subject to:

$$\mathrm{E[R]} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}} R_t \tag{3.4}$$

$$\mathrm{GM_t} = \sum_{\mathrm{k}=1}^{\mathrm{K}} \left(\mathrm{p_{k,t}y_{k,t}x_k} - \alpha_\mathrm{k}\mathrm{x_k} - \frac{1}{2}\beta_\mathrm{k}\mathrm{x_k^2}\right) \tag{3.5}$$

$$\mathrm{RM} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t}=1}^{\mathrm{T}} GM_\mathrm{t} \tag{3.6}$$

$$R_\mathrm{t} = GM_\mathrm{t} + \mathrm{Max}\{0,\ \mathrm{coverage}\times[\mathrm{trigger}\times\mathrm{RM} - \mathrm{GM_t}]\} - contrib \tag{3.7}$$

$$contrib = 0.0045\times\mathrm{RM}\times\mathrm{trigger}+55 \tag{3.8}$$

$$\sigma^2 = \sum_{\mathrm{k}=1}^{\mathrm{K}} \sum_{\mathrm{i}=1}^{\mathrm{K}} \mathrm{x_k}\times\mathrm{S_{k,i}}\times \mathrm{x_i} \tag{3.9}$$

R_t is the gross margin in the state of nature t and E[R] represents the expected whole farm gross margin, including the effects of the AgriStability program. GM_t is the gross margin in the state of nature t without participating in the program, which implies no program payments and no need to pay participant contribution. Monte Carlo simulation is used to generate T sets of prices and yields, and thus gross margins, for each crop and representative farm; these represent the scenarios a farmer with a given risk attitude and crop cost functions may face. The simulation process is described in detail in the section 3.3. *RM* represents the reference margin calculated from the farm's gross margin; the average of T scenarios represents the expected value. *RM* is replaced by RML in constraint (3.7) under GF2 and CAP when the conditions defined in Table 3.1 are met. Under CAP, constraints (3.7) and (3.8) are also modified to mimic the late participation, which assumes farmers only pay the participant contribution (denoted *contrib*) in the years they will get a payment, but the benefits will be reduced by 20% accordingly.

3.3 Alberta Application

To illustrate the effects of the program changes, we apply the model to three representative arable grain farms located in Alberta (see Figure 3.1), considering geographic locations, soil types and crop portfolios. The data for calibrating the model and for policy analysis are described below, followed by the presentation of results and discussion.

The base-case information about the representative farms used for the model calibration are provided in Tables 3.2 and 3.3. Crop prices are obtained by taking the Olympic average of crop prices for years 2008 through 2017 that are available from Statistics Canada (2017). Alberta's Agricultural Financial Services Corporation (AFSC 2016) provided county-level data on average yields and total insured acres of cropland for the period 2008 through 2016. The data are used to calculate the Olympic average of yields and the land allocations for all crops. Total variable costs of production per acre are an Olympic average of costs that are adjusted to match AgriStability's (Agriculture and Agri-Food Canada 2013) rules for allowable expenses for the period 2008-2018, where expenses are obtained from Alberta Agriculture and Forestry (2018a; 2018b).

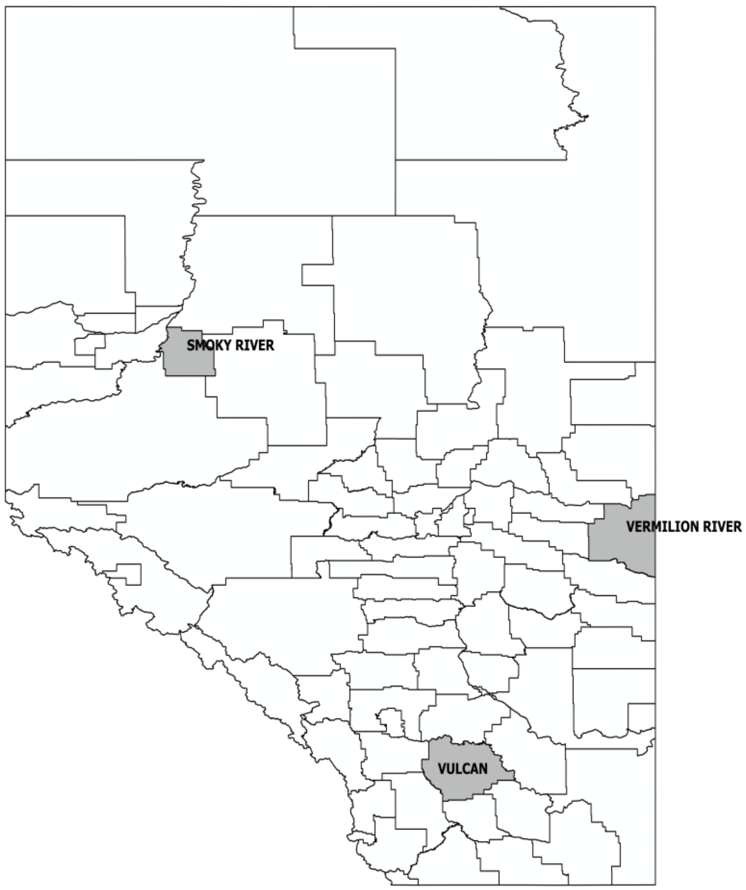


Figure 3.1 Map of Alberta: The three counties with representative farms are shaded – Smoky River, Vermilion River and Vulcan.

Table 3.2: Soil types and land allocation for the representative farms

County	Region	Soil Zone	Farm Size (acres)	Crop Land Allocation				
				Barley	Canola	Durum	Peas	Wheat
Smoky River	North	Dark Gray	1763	2%	53%		3%	42%
Vermilion River	East	Black	722	15%	43%		5%	38%
Vulcan	South	Dark Brown	1756	19%	28%	7%	15%	31%
Average of Alberta			608	14%	33%	8%	10%	35%

Table 3.3: Summary of returns and costs for three representative farms

Item	County	Barley	Canola	Durum	Peas	Wheat
Mean Price ($/bu)		4.2	11.0	7.4	7.7	6.4
Yields (bu/acre)	Smoky River	64.8	34.3		38.9	53.3
	Vermilion River	65.5	39.8		41.7	55.6
	Vulcan	65.0	37.4	43.0	42.2	44.9
Costs ($/acre)	Smoky River	138.0	164.7		131.1	153.7
	Vermilion River	146.2	211.5		157.0	163.3
	Vulcan	133.5	186.8	149.8	127.9	132.4
Gross Margin ($/acre)	Smoky River	125.1	178.9		145.5	178.3
	Vermilion River	124.0	226.5		165.7	191.7
	Vulcan	139.2	228.4	167.7	198.8	154.1

For policy analysis, simulated data are used to represent the potential outcomes a farmer may face. The literature has repeatedly pointed out the need to include the correlation between yield and output price, the correlations among yields of different crops, and the correlations among crop prices (Harwood et al. 1999; Kimura et al. 2010; OECD 2011). However, as discussed in Chapter 1, the coefficients of correlation are higher at the aggregate level than the farm level, and the difference between the two levels is larger with the yield-price relationship than with yields or with prices. Hence, we first calculate three types of correlations using adjusted historical data on prices and yields for all crops for 1995-2016; the yield data are detrended and the price data are adjusted using grain price index available from Statistics Canada (Statistics Canada 2018). Then, we decrease the estimated values of the correlation coefficients between yield and output price, the coefficients among crop yields, and the coefficients among crop prices by 30%, 20% and 10%, respectively, to reflect that the correlations are weaker at the farm level. The correlation coefficients used for simulation for the Vulcan representative farm are provided in Table 3.4.

Lastly, we assume that the prices and yields come from a multivariate normal distribution whose mean vector is formed using the base-case price and yield data, and its variance-covariance matrix is derived from the historical data and multiplied by 1.1 to reflect that the price and yield variability is higher at the farm level than at the aggregate level.

Table 3.4: The correlations among detrended yields and adjusted prices for Vulcan

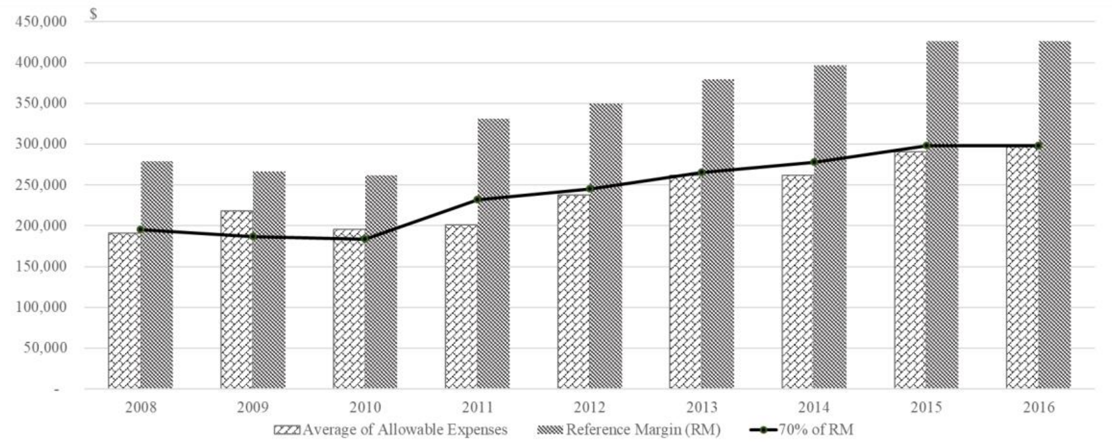
		Yield					**Price**				
		Barley	Canola	Durum	Peas	Wheat	Barley	Canola	Durum	Peas	Wheat
Yield	Barley	1.00	0.03	-0.08	0.63	-0.56	-0.01	-0.04	-0.10	-0.09	0.00
	Canola	0.03	1.00	-0.24	0.34	0.03	0.23	0.32	0.27	0.35	0.25
	Durum	-0.08	-0.24	1.00	0.06	-0.16	-0.14	-0.16	-0.23	-0.23	-0.16
	Peas	0.63	0.34	0.06	1.00	-0.46	0.14	0.24	-0.05	0.01	0.11
	Wheat	-0.56	0.03	-0.16	-0.46	1.00	0.16	0.14	0.36	0.25	0.24
Price	Barley	-0.01	0.23	-0.14	0.14	0.16	1.00	0.65	0.60	0.71	0.76
	Canola	-0.04	0.32	-0.16	0.24	0.14	0.65	1.00	0.55	0.58	0.66
	Durum	-0.10	0.27	-0.23	-0.05	0.36	0.60	0.55	1.00	0.69	0.70
	Peas	-0.09	0.35	-0.23	0.01	0.25	0.71	0.58	0.69	1.00	0.72
	Wheat	0.00	0.25	-0.16	0.11	0.24	0.76	0.66	0.70	0.72	1.00

To show the effects of the AgriStability program on farmers with different costs, for each representative farm three groups of data are generated to reflect three types of farms and each group has 1,000 samples. First, assuming a farm has the cost structure indicated in the base case (shown hereafter as ‘medium cost’), samples are generated to represent the situation that the farmer’s cost is less than her reference margin (RM) but greater than 70% of the RM (see Figure 3.2(c) for an example). Then RML will be applied under GF2 and CAP, but will be further adjusted under CAP. Second, we suppose a producer faces a high-cost structure and that cost equals the average cost plus one standard deviation (based on historical costs for 2004-2018 for that representative farm). In this case, the farmer’s cost is greater than her RM, which means RML will not be trigged (Figure 3.2(b)). Lastly, we assume a farm has low cost if it equals the average cost minus one standard deviation. In this case, the farmer's cost is less than 70% of her RM and RML will be applied under GF2 and CAP, while being adjusted up to 70% of RM under CAP (Figure 3.2(a)).

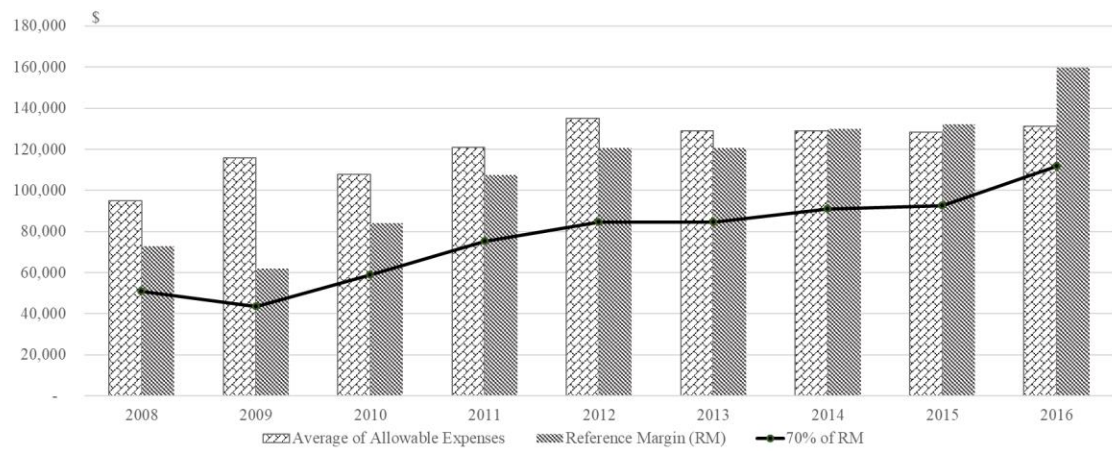
3.4 Results

Table 3.5 reports the changes to our representative farmers' land use and the related expected annual financial outcomes under different scenarios. First, the calibration results show that the low-cost farmers are most risk averse, while the high-cost farmers are least risk averse. A possible explanation for this is as follows: Since the value of outputs is uncontrollable under the simulation framework in this study, farmers who are more risk averse would choose to lower their production costs. Thus, for example, Sulewski et al. (2020) found that farmers with high risk aversion are more likely to decrease on-farm employment to control the costs. Overall, however, there is little information in the literature regarding the relation between an agricultural producer's farm-cost structure and risk attitudes; further research is required to determine how risk attitudes might influence farmers' input choices.

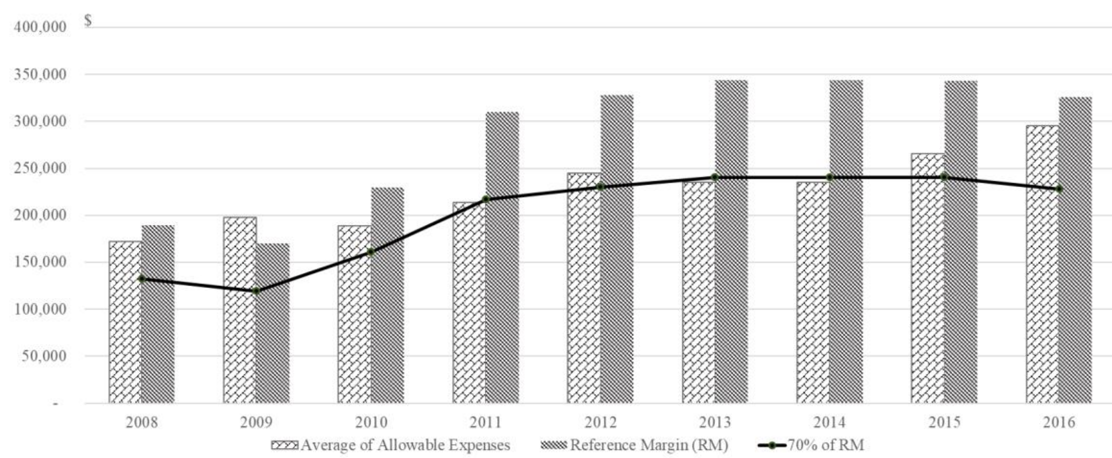
Second, after joining the AgriStability program, all types of farmers make changes to their crop mix to maximize their expected utility. For example, in the Smoky River and Vermilion River counties, farmers allocate less land to barley, while in Vulcan they significantly allocate more land to barley and wheat. Farmers make different changes because they are face different marginal cost structures. Figure 3.3 shows the marginal production costs for the medium-cost farmers. Then the earlier Table 3.4 indicates the reduction in coverage from GF to GF2, and the introduction of RML, further alter farmers' land allocations; however, the changes from GF2 to CAP and the removal of RML in year 2021 have little further impacts on most farmers' land allocation decisions.



(a) Smoky River



(b) Vermilion River



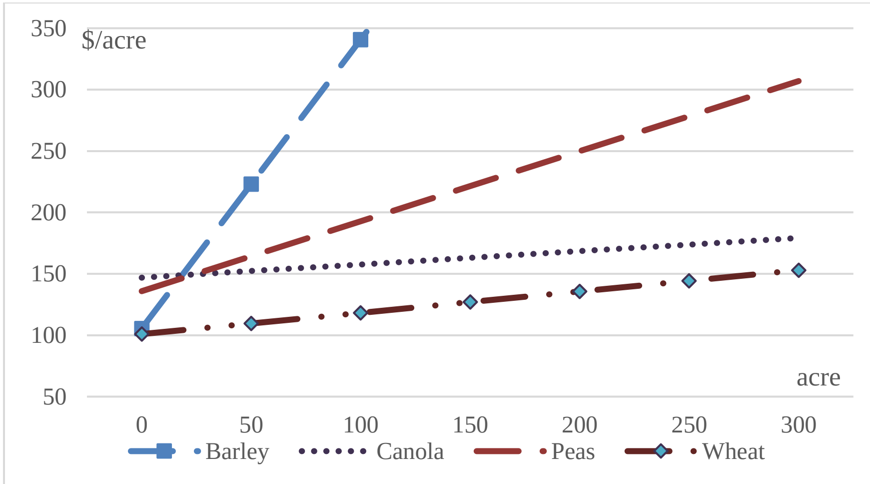
(c) Vulcan

Figure 3.2 Relationship between the reference margin and the allowable expense of a representative farm, 2008-2016

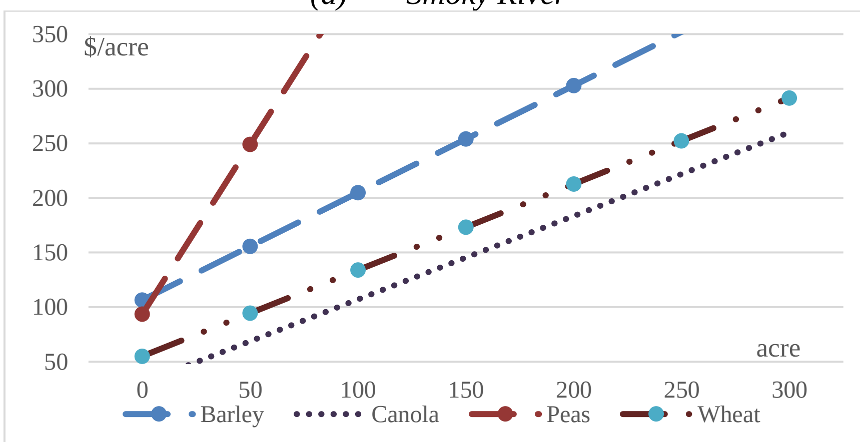
Third, with the shift from GF to GF2, farmers with low costs get the biggest hit because of the introduction of RML and the changes in the coverage level and trigger. The number of payments and the expected payouts decrease by more than 90% across three counties, while they pay more participant contributions than medium- and high-cost farmers due to their higher reference margins. Overall, farmers with low costs are worse off by participating in GF2 because their contributions are higher than their potential payouts. Farmers with high costs are not affected by the RML. However, the number of payments and the expected payouts decrease by around 40% and 55% across counties, respectively, due to the reduction of coverage and trigger. Both high-cost and medium-cost farmers are still better off by participating in GF2 but the benefits are much less than those under GF.

Fourth, if farmers with low costs enroll late in AgriStability and have an adjustment to RML under CAP, they achieve a higher expected gross profit (increase by 0.4% to 1.6%) even after foregoing 20% of benefits for choosing late participation because they contribute much less (-97% to 99%), and their RML increases (0.3% to 60%). For the high-cost farmers, their payouts from the program decrease by around 20% with late participation, the reduction in participant contributions does not outweigh the loss in benefits, and the adjustment to RML does not apply in their situation. Therefore, it is better for these farmers to participate in the program every year to obtain higher expected gross profits.

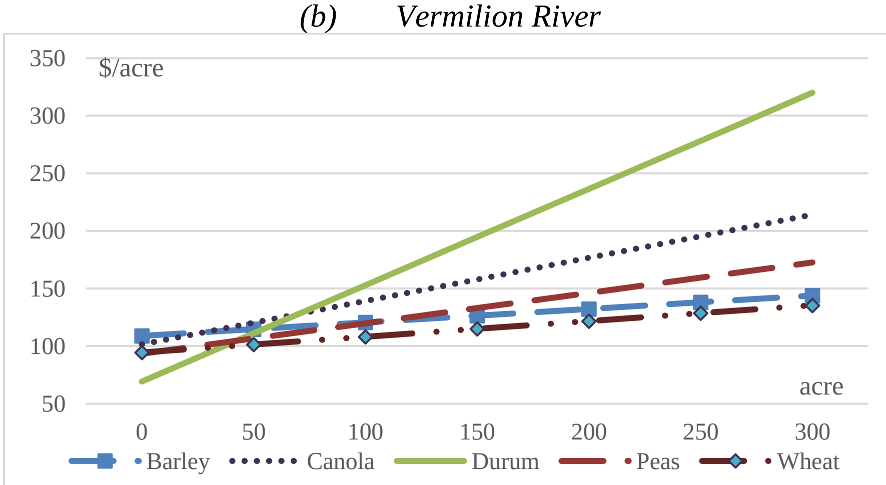
Lastly, the removal of RML in 2021 greatly increases the benefits to the low-cost farmers. The number of payments and their amount increase by no less than 370% and 500%, respectively, compared to those under CAP with RML. The benefits to the medium-cost farmers in Vermilion River and Vulcan also increase.



(a) Smoky River



(b) Vermilion River



(c) Vulcan

Figure 3.3 Marginal production costs of farms with medium costs

Table 3.5: Farms' optimal choices and financial outcomes

(a) Smoky River

		Base case	Medium costs				Higher costs				Lower costs			
			GF	GF2	CAP [c]	CAP21[c]	GF	GF2	CAP [c]	CAP21[c]	GF	GF2	CAP [c]	CAP21[c,d]
Land allocation	Barley	35	25	26	26	26	19	20	20	20	15	18	18	17
	Canola	952	941	936	935	935	946	941	941	941	967	961	961	965
	Peas	71	115	120	121	121	110	113	113	113	130	136	136	134
	Wheat	705	681	682	682	682	689	689	689	689	650	648	649	647
φ			1.540E-05				1.660E-05				2.100E-05			
Reference margin ($)		308,270	308,462	308,435	308,435	259,108	258,838	258,812	271,171	371,958	371,837	372,044	371,972	
Reference margin limit ($)		N/A	308,462	308,435	N/A	N/A	258,838	258,812	N/A	N/A	259,619	260,431	N/A	
Numbers of payments [a]		310	138	138	138	339	197	196	196	259	14	14	103	
Amount of payments [b] ($)		13,037	4,245	3,394	3,394	15,644	6,438	5,149	5,149	11,091	323	262	2,346	
Expected gross profit ($)		320,063	312,439	311,689	311,689	273,712	264,404	263,789	263,789	381,563	366,365	372,289	374,300	
Farmer contribution ($)		1,235	1,026	142	142	1,046	870	171	171	1,479	1,226	17	17	

(b) Vermilion River

		Base case	Medium costs				Higher costs				Lower costs			
			GF	GF2	CAP [c]	CAP21[c]	GF	GF2	CAP [c]	CAP21[c]	GF	GF2	CAP [c]	CAP21[c,d]
Land allocation	Barley	90	85	83	85	89	85	87	88	88	86	91	92	90
	Canola	316	324	324	321	318	323	319	317	317	322	313	312	315
	Peas	41	42	39	39	41	41	41	41	41	41	38	39	39
	Wheat	274	271	276	276	274	272	275	276	276	273	279	279	277
φ			1.300E-05				9.000E-06				1.440E-05			
Reference margin ($)			143,262	143,206	142,955	143,108	121,992	122,107	122,080	122,080	164,857	164,298	164,501	164,404
Reference margin limit ($)			N/A	132,981	132,424	N/A	N/A	122,107	122,080	N/A	N/A	111,984	115,151	N/A
Numbers of payments [a]			323	150	149	190	368	223	223	223	311	30	34	141
Amount of payments [b] ($)			7,786	2,181	1,708	2,377	8,990	4,083	3,252	3,252	7,174	321	294	1,929
Expected gross profit ($)			150,448	144,882	144,586	145,410	130,452	125,752	127,544	127,544	171,348	164,046	164,778	166,312
Farmer contribution ($)			603	506	76	75	522	439	98	98	685	573	17	20

Table 3.5 (cont.)

(C) Vulcan

		Base case	Medium costs				Higher costs				Lower costs			
			GF	GF2	CAP [c]	CAP21[c]	GF	GF2	CAP [c]	CAP21[c]	GF	GF2	CAP [c]	CAP21[c,d]
Land allocation (acres)	Barley	311	429	447	447	441	398	405	407	407	503	523	521	515
	Canola	437	363	353	351	354	358	346	344	344	349	331	332	337
	Durum	193	161	167	167	164	166	169	170	170	148	152	151	150
	Peas	261	222	188	189	204	213	199	196	196	182	150	154	162
	Wheat	554	581	602	601	594	622	636	639	639	574	600	598	591
φ			1.280E-05				1.140E-05				1.740E-05			
Reference margin ($)			314,542	311,418	311,448	312,692	268,392	266,840	266,482	266,482	385,326	381,015	381,453	382,633
Reference margin limit ($)			N/A	246,518	246,372	N/A	N/A	266,840	266,482	N/A	N/A	169,460	272,496	N/A
Numbers of payments [a]			355	89	89	186	370	235	235	235	300	1	25	133
Amount of payments [b] ($)			17,865	2,397	1,912	5,353	20,870	9,537	7,596	7,596	14740	47	380	2,314
Expected gross profit ($)			1,258	312,779	313,268	317,952	288,192	275,487	273,872	273,872	398,537	379,806	381,832	385,571
Farmer contribution ($)			1,260	1,036	92	93	1,081	895	210	210	1,529	1,255	1	32

[a] This refers to the number of payouts made to a farmer over the 1,000 simulated outcomes.
[b] This represents the expected annual payments to a farmer.
[c] Assumes farmers choose late participation.
[d] CAP21 represents the removal of RML in 2021.

3.5 Concluding Discussion

In this study, we investigated how the changes in the rules of the AgriStability program from GF to GF2 and then to CAP affect the land allocation decisions and the financial outcomes of farmers with low, medium and high costs of production. A farm-level risk management model was developed on the assumption that a farmer chooses her land allocation to maximize her expected utility, rather than expected gross margin. A two-step maximum entropy method was applied to the Alberta data on arable grain farms to calibrate the parameters of the risk aversion coefficient and the cost function. We then analyzed the impacts of the policy changes using simulated outcomes based on the statistical characteristics of the historical data; thereby, the results represent potential situations for each farm type, rather than the limited observed outcomes. The results indicate that low-cost farmers are the most risk averse. As to the impacts of the changes in AgriStability, the benefits to the farmers with low costs decline the most with the introduction of RML under GF2, while participant contributions are the highest because of their high reference margins. The adjustment of RML under CAP leads to greater benefits for farmers that have low costs, while those with medium or high costs are mostly not affected by this change. The removal of RML further increases the benefits to the low-cost farmers while some medium-cost farmers' benefits increase as well. The choice of late participation offers farmers some flexibility in enrolment, but high-cost farmers would be better off if they participate in AgriStability regularly in terms of expected gross margins.

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CHAPTER 4

DEMAND ANALYSIS FOR WEATHER INDEX-BASED INSURANCE: THEORY AND SURVEY

4.1 Introduction

There are many ways to stabilize income: Agricultural insurance, diversification and reliance on off-farm incomes are three of the useful tools that farmers can use to mitigate the volatility of revenue. Agricultural insurance products can be classified into two broad categories: traditional indemnity-based insurance that has a long history, and indexed-based insurance that has been promoted in recent years. The differences between indemnity-based insurance and indexed-based insurance are discussed in Chapter 1. In short, compared to indemnity-based insurance, indexed-based insurance can be more cost-effective because of the following reasons: no requirements for monitoring individual farms' behavior; the simple calculation of payouts based on some objective measure; and the mitigation of adverse selection and moral hazard, because no individual's actions can influence outcomes. However, basis risk might be greater with index-based insurance than with standard crop yield insurance, for example.

It is also worth noting that the uptake rates of both types of insurance are low when an actuarially fair premium is charged. Hence, in many countries, governments heavily subsidize insurance programs to encourage farmers' participation for social and political goals, or on the basis of economic arguments related to market failures and externalities (Hazell and Varangis 2020). In the U.S., the government pays 38% to 100% of premiums for crop insurance products; farmers pay about 38% of insurance premiums on average (Shields 2010; Zulauf 2016). In Canada, most crop insurance products are delivered under the AgriInsurance program; federal and provincial governments cover about 60% of total AgriInsurance premiums (Agriculture and Agri-food Canada 2017).

Most literature regarding the demand analysis for insurance assumes that producers are risk averse and maximize the expected utility (EU) of wealth. However, many observed producers' behaviours, such as the low uptake rates of some insurance products (e.g., AgriStability), are contradictory to the conclusions regarding demand for insurance derived from EU theory. More and more researchers have concluded that the EU maximization framework overestimates the demand for insurance. Babcock (2015) states that, if EU theory is correct, almost all farmers should buy the highest coverage level provided by insurers, even with actuarially fair premiums. But, in reality, about 88% of the insured acres are covered at a level less than the highest available, even when insurance premiums are subsidized. Clearly, some important factors that influence producers' insurance decision are not incorporated in EU theory, which attributes peoples' decisions to profits or wealth. For example, basis risk is one reason why indexed-based insurance is not as popular as one might expect because, for most crops, payments (indemnities) calculated on the basis of indexes are quite different from the individual losses that producers actually experience. The EU maximization framework tends to underestimate the negative impacts of basis risk on producers' insurance decisions. In recent years, an alternative theory, known as prospect theory (PT), has been gradually applied to explain crop insurance participation, coverage levels, and willingness to pay for such insurance. The key argument based on PT is that farmers treat insurance products as a stand-alone investment, instead of as a risk management tool.

This chapter applies the third generation of PT (PT3) theory to investigate the feasibility of weather-indexed insurance (WII) from the demand side. Specifically, the primary objective is to determine the conceptual feasibility of using a WII product to hedge against non-catastrophic, but quality-impacting weather conditions to complement existing crop yield insurance because there is no need to replace existing yield insurance with a new insurance product because farmers and governments are satisfied with current yield insurance's design and delivery. In this study, we use blueberry as an example to discuss the above feasibility. A blueberry grower may experience no reduction in yield, but the quality of the crop (and the price received) might be reduced dramatically by rainfall occurring at an inopportune time. In section 4.2, the literature regarding the PT framework and some applications of PT3 in the agricultural insurance field are reviewed. In section 4.3, blueberry farmers' demand for WII is discussed under the PT3 framework. Next, the results of a survey conducted among blueberry growers in British Columbia are used to analyze whether WII could be a risk management tool from the producers' point of view and to echo some points derived from the theoretical discussion for WII demand analysis. Then, in the last section, we summarize the findings.

4.2 Literature Review

Kahneman and Tversky (1979) introduced the original PT (OPT) approach to model the observed asymmetric human choices that violate EU. However, OPT is limited to analyze prospects (also called "acts") with only two non-zero outcomes with known probabilities and can violate stochastic dominance sometimes. Subsequently, Tversky and Kahneman (1992) modified and generalized their original model to cumulative PT (CPT) to accommodate uncertainty and acts with a larger number of outcomes. Four key elements of CPT are: reference dependence, loss aversion, diminishing sensitivity, and decision weights. For example, people valuate an act *f* that has n possible outcomes, using the following equation:

$$V(f) = \sum_{i=1}^{n} \pi_i v(f_i) \tag{4.1}$$

Similar to the definition of expected utility, $V(f)$ is the prospect value people place on the act *f*; $v(f_i)$ is the value function of the act *f* in the state *i*; π_i is the decision weight of the state *i*, $w(p_i)$, which is transformed based on the probability that state *i* occurs, p_i. The decision weights can be used to describe how people place a greater weight on the frequency of outcomes with small probabilities, while underweighting the frequency of outcomes with high probabilities. One key assumption separating CPT from OPT is rank dependence, which changes the definition of decision weights. Under OPT, the weights are monotonic transformations from the probabilities. With CPT, all possible outcomes of the act *f* should be ordered from the minimum to the maximum; π_i is determined by both the probability p_i and the position of i^{th} outcome in the distribution of outcomes.

Suppose for act *f* that there are n states and the ordered outcomes in terms of money are: $f_1 \leq f_2 \leq \ldots \leq f_k \leq 0 \leq f_{k+1} \leq \ldots \leq f_n$. Then equation (4.1) is modified as:

$$\mathrm{V}(f) = \sum_{i=1}^{k} \pi_i^- v(f_i) + \sum_{k+1}^{n} \pi_i^+ v(f_i) \tag{4.2}$$

where the decision weights are defined as follows:

$$\begin{cases} \pi_1^- = w^-(p_1) \\ \pi_i^- = w^-(p_1 + \cdots + p_i) - w^-(p_1 + \cdots + p_{i-1}) \quad 2 \leq i \leq k \\ \pi_i^+ = w^+(p_i + \cdots + p_n) - w^+(p_{i+1} + \cdots + p_n) \quad k+1 \leq i \leq n-1 \\ \pi_1^+ = w^+(p_n) \end{cases} \tag{4.3}$$

where and $w^-(p)$ and $w^+(p)$ are some functions of objective probabilities. If the same form of *w(p)* is applied to gains and losses, *w(p)* becomes (Schmidt, Starmer and Sugden 2008):

$$w(p) = \frac{p^{\beta}}{(p^{\beta} + (1-p)^{\beta})^{1/\beta}} \tag{4.4}$$

where β is positive. If β=1, decision weights are equal to objective probabilities. When β decreases to around 0.4, a typical inverse-S pattern of weights is generated, which places greater weight on small-probability events. Figure 4.1 provides a plot showing a typical weighting function as proposed by Tversky and Kahneman (1992).

The function $v(f_i)$ represents the value of the act *f* compared to the pre-determined reference point when the state *i* is realized and has the property of diminishing sensitivity. Further, to reflect the asymmetry of peoples' perception over gains and losses, the slope of $v(f_i)$ is steeper when f_i is negative compared to that when f_i is positive for a particular value (see Figure 4.2). Equation (4.5) shows a typical value function of CPT proposed by Tversky and Kahneman (1992).

$$v(f_i) = \begin{matrix} -\lambda(|f_i|)^{\alpha} & if\ f_i < 0 \\ (f_i)^{\alpha} & if\ f_i \geq 0 \end{matrix} \qquad (4.5)$$

where λ represents the loss aversion. A value greater than 1 reflects that people are more sensitive to a loss than to a gain of equal amount, and the typical range for the parameter's value is [1, 2.5]. The parameter α affects the value function's curvature and usually falls into the range [0.5, 1] (Schmidt et al. 2008). The utility function in EU is actually a special case of $v(f_i)$ where the initial wealth is zero, the reference point has zero value, and $v(f_i)$ is symmetric around the zero point.

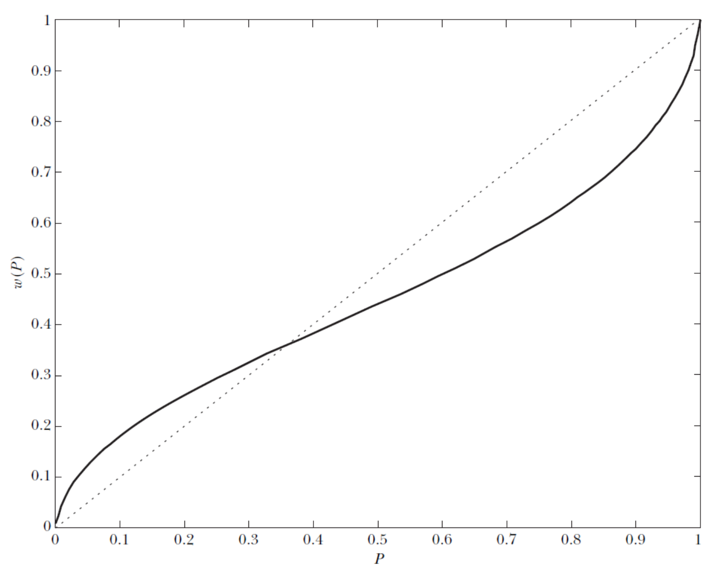

Figure 4.1 Decision weighting function (Source: Barberis 2013, p.177)

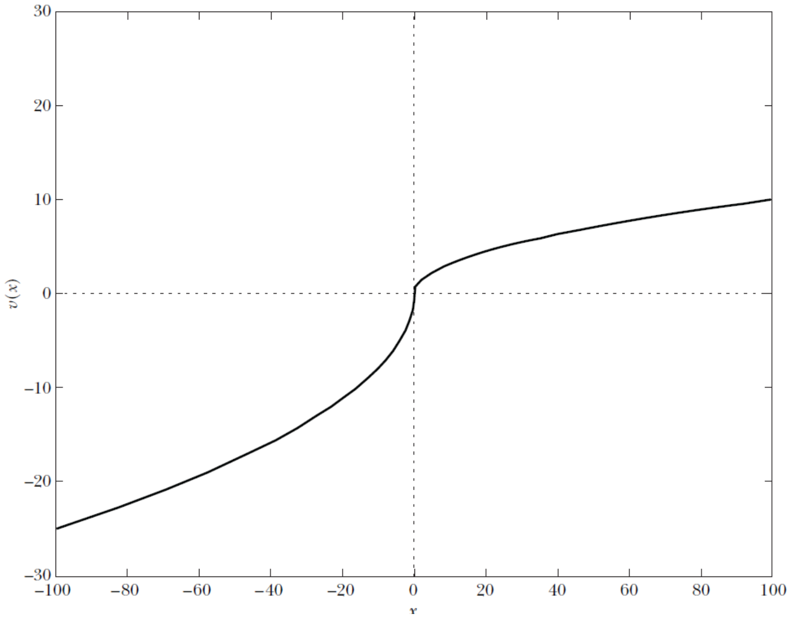

Figure 4.2 A typical PT value function (Source: Barberis 2013, p.176)

Both the original PT and CPT assume that the reference point for evaluating acts has a certain value across different states. But in real life the outcome of the reference point might change with states. For instance, when a farmer considers an insurance product, the reference point is no insurance and the gain or loss of buying insurance is not certain. When the revealed state is good and there is no indemnity payoff, the farmer considers the insurance premium as a loss. On the contrary, if the revealed state is bad and the indemnity payoff is more than the premium, buying insurance leads to a gain for the farmer. To incorporate the above feature into the model, Schmidt, Starmer and Sugden (2008) propose the third-generation prospect theory (PT3). Under PT3, the following equation is used to evaluate an act *f* compared with the reference act *h* across all n possible states:

$$V(f, h) = \sum_{i=1}^{n} \pi_i v(f_i, h_i) \quad (4.6)$$

The key difference between the equations (4.1) and (4.6) is that $v(f_i, h_i)$ reflects the relative value of the act f's result to the act h's result in the same state i. If the outcome of act h in terms of money is constant across states, equation (4.6) is nested within equation (4.1). To find the cumulative decision weights, we first compare the direct outcomes from the acts f and h in terms of money under each state i. Suppose the result is $f_1\text{-}h_1 \leq f_2\text{-}h_2 \leq \ldots \leq f_k\text{-}h_k < 0 \leq f_{k+1}\text{-}h_{k+1} \leq \ldots \leq f_n\text{-}h_n$. It is a weak gain when $f_i\text{-}h_i \geq 0$ and it is a strict loss when $f_i\text{-}h_i < 0$. Then equation (4.3) can be applied to define the cumulative decision weights.

PT3 has been applied by a number of researchers to analyze the demand for agricultural insurance. Feng, Du and Hennessy (2020) state that the findings from a mail survey targeting U.S. crop farmers provides confirmation of PT3: the willingness to pay (WTP) to buy crop insurance is much lower than the actuarially fair premium, with the difference between WTP and the premium increasing with coverage levels. WTP is the money that a farmer is willing to give to leave the reference point, which is described as no insurance and no premium related gain and loss. First, WTP is negatively affected by loss aversion. Second, when the coverage level goes up, both the premium and the probability of receiving an indemnity payoff increase. However, the marginal effect of the premium increase is decreasing because people underweight states with high probabilities. Hence, the ratio of WTP over fair premium becomes even smaller.

Lampe and Würtenberger (2020) apply PT3 to analyze the demand for rainfall index insurance. A four-state framework, which is developed from Clarke's model (2016), is applied to show the impacts of basis risk on farmers' decisions about index insurance. They argue that providing education regarding insurance to farmers helps to promote the adoption of index insurance. They use two reference points to discuss farmers' index insurance decisions: (i) no insurance coverage, and (ii) full traditional insurance coverage whose indemnity equals the premium. The former reference point is used by farmers who do not recognize the hedging benefit that insurance provides; they consider insurance as a stand-alone investment. These farmers' index insurance demand is not affected by basis risk but decreases with loss aversion. Farmers who fully recognize the hedge function that insurance provides use the latter reference point. Their demand for index insurance is negatively affected by basis risk but increases with loss aversion.

4.3 Weather-indexed Insurance: Demand Analysis

In this section, the goal is to better understand blueberry farmers' demand for WII from a theoretical perspective within the PT framework. Although the literature applying PT for insurance demand analysis considers insurance as a stand-alone investment (e.g., Feng, Du and Hennessy 2020; Lampe and Würtenberger 2020), the demand for insurance may also be affected by the level and the volatility of a farmer's total revenue. Hence, we propose a hybrid expression that assumes a farmer seeks to maximize the total utility function (see equation 4.7) to capture the rational and intuitive parts of a farmer's decision-making process. The original hybrid model is proposed by Barberis, Huang and Santos (2001) and applied by Baele et al. (2019).

The objective is:

$$\text{Maximize EU}(R_T) + \frac{\overline{R_B}}{\overline{R_T}}V(f) \tag{4.7}$$

where EU(R_T) represents a farmer's expected utility over their total revenue R_T, in the form of $\overline{R_T} - \frac{1}{2}\varphi\sigma^2$; $\overline{R_T}$ and σ^2 are the mean and variance of the distribution of R_T, and φ is the constant absolute risk aversion coefficient (CARA). $\frac{\overline{R_B}}{\overline{R_T}}$ is a scaling term used to adjust the relative weight of the EU part and the prospect valuation part; $\overline{R_B}$ is the expected revenue from berry production and $\overline{R_T}$ is the expected total revenue. $V(f)$ represents a farmer's prospect valuation over an insurance product, which will be defined later.

The objective function (4.7) demonstrates that the more a farmer's revenue comes from blueberries, the larger the benefits of purchasing insurance since the level of income volatility will decrease and the contribution of an insurance's prospect value to the total utility increases when the prospect value is positive. If an insurance helps to drop the level of income volatility significantly, a farmer might purchase insurance even when the prospect value of the insurance is negative. On the other hand, if a farmer has a diverse portfolio, especially when most of their revenue comes from a source with low volatility, like salary, the benefits of an insurance become more insignificant. A farmer will consider insurance only when it has positive prospect value and the contribution of insurance to their total utility is much smaller – the farmer might decide not to buy insurance even with a small change in their total revenue. Therefore, the importance of the revenue from blueberries relative to total revenue, and the volatility of total revenue, have large influence on the attractiveness of insurance.

In this study, a WII product is considered. To account for the impacts of basis risk of WII, we define four states; this is a revision of the frameworks proposed by Clarke (2016) and Lampe and Würtenberger (2020) (see Table 4.1). The probability of a loss L is $1–p$ and $p= p_1+ p_2$, where p_1 represents the probability that a farmer gets a payment while no loss occurs, and p_2 represents the probability of no loss and no payment. When a loss L occurs, there is a probability q that the payment I from the WII product is not less than the actual loss. The probability of overpayment is $p_1 + q$ and the probability of underpayment is $1 – p_1 – p_2 – q$. We assume $p_1 + q$ is equal to $1 – p_1 – p_2 – q$ and use p_b to represent the probability of basis risk. For a well-designed WII product, p_b should be small and p_2 should be large.

Farmers tend to divide the gains and losses from buying WII into two parts: (1) use no insurance as a reference point to calculate the gains and losses from payment that is not greater than the loss; (2) use an insurance with I=L under any circumstance (a perfect insurance) as a reference point to calculate the gains and losses caused by basis risk. For example, when the WII's payment I is less than the actual loss L, farmers consider the difference between I and the premium P as a gain compared to no insurance but treat the difference between L and I as a loss compared to a perfect insurance.

Table 4.1: Four-state framework (probabilities and outcomes)

States	No Loss		Loss	
	Payment (1)	No Payment (2)	Payment≥Loss (3)	Payment<Loss (4)
Probabilities	p_1	p_2	q	$1- p_1- p_2-q$
Revenue from blueberry, with WII	$R_B + I – P$	$R_B – P$	$R_B + I – L – P$	$R_B + I – L – P$
Gain/Loss, with WII	Gain: I – P = (0 – P) + (I – 0)	Loss: P	Gain: I – P = (L – P) + (I – L)	Gain: I – P Loss: L– I

Note: The payment I from WII is assumed to be greater than the premium P.

Recall equation (4.1): $V(f) = \sum_{i=1}^{n} \pi_i v(f_i)$, with $v(f_i)$ defined as follows using equation (4.5) and Table 4.1, and assuming I > P:

$$v(f_i)=\begin{cases} -\lambda P^{\alpha} & \text{state(2)} \\ (I-P)^{\alpha}-\lambda(L-I)^{\alpha} & \text{state(4)} \\ (I-P)^{\alpha} & \text{state (1) and (3)} \end{cases} \tag{4.8}$$

where λ >1 and α<1. The probability weighting function π_i is defined as:

$$\begin{cases} \pi_1 = w(p_2) \\ \pi_2 = w(1-p_1-q) - w(p_2) = w(1-p_b) - w(p_2) \\ \pi_3 = w(p_1+q) = w(p_b) \end{cases} \tag{4.9}$$

where $w(p) = \frac{p^{\beta}}{\left(p^{\beta}+(1-p)^{\beta}\right)^{1/\beta}}$ when $(I-P)^{\alpha}-\lambda(L-I)^{\alpha} \geq -\lambda P^{\alpha}$. Or

$$\begin{cases} \pi_1 = w(1-p_1-p_2-q) = w(1-p_b-p_2) \\ \pi_2 = w(1-p_1-q) - w(1-p_1-p_2-q) = w(1-p_b) - w(1-p_b-p_2) \\ \pi_3 = w(p_1+q) = w(p_b) \end{cases} \tag{4.10}$$

when $(I-P)^{\alpha}-\lambda(L-I)^{\alpha} < -\lambda P^{\alpha}$.

A farmer will buy WII if *V*(*f*) is positive; the condition can be written as (4.11) and modified as (4.12) when $(I\text{-}P)^{\alpha}\text{-}\lambda(L\text{-}I)^{\alpha} \geq -\lambda P^{\alpha}$:

$$-\lambda P^{\alpha}\pi_1 + \pi_2[(I\text{-}P)^{\alpha}\text{-}\lambda(L\text{-}I)^{\alpha}]+\pi_3(I\text{-}P)^{\alpha} \geq 0 \tag{4.11}$$

$$(\pi_3+\pi_2)(I\text{-}P)^{\alpha} \geq \lambda P^{\alpha}\pi_1 + \lambda(L\text{-}I)^{\alpha}\pi_2 \tag{4.12}$$

Clearly, an increase in λ, the loss aversion coefficient, leads to a decrease in the demand for WII.

As to the impacts of the probability of basis risk p_b on demand, we start with a simple case. Suppose β=1 for π_i, for i=1, 2, 3. Equation (4.12) is simplified as equation (4.13), thereby demonstrating that an increase in p_b has negative impacts on the demand for WII.

$$(1-p_2)(I\text{-}P)^{\alpha} \geq \lambda P^{\alpha}p_2 + \lambda(L\text{-}I)^{\alpha}p_b \tag{4.13}$$

Now suppose β<1 for π_i, for i=1, 2, 3. Equation (4.12) can now be written as (4.14):

$$[w(p_b)+w(1-p_b)-w(p_2)](I\text{-}P)^{\alpha} \geq \lambda P^{\alpha}w(p_2) + \lambda(L\text{-}I)^{\alpha}[w(1-p_b)-w(p_2)] \tag{4.14}$$

Because p_b is a small number, $w(p_b) > p_b$ and $w(1-p_b) < 1-p_b$ as discussed in the literature review (see Figure 4.1). When p_b becomes larger, the magnitude of the decrease in $w(p_b)$ is much larger than the increase in $w(1-p_b)$. Hence, the ratio of the left-hand-side value over the right-hand-side value drops with the increase in p_b, which means p_b negatively impacts the demand for WII.

4.4 Analysis of a Survey of Blueberry Growers

British Columbia is one of the largest producers of blueberries in the world, with the majority of production found in the Fraser Valley (hereafter lower mainland) and much less so on Vancouver Island. This section provides a brief analysis of a survey targeting blueberry growers in British Columbia, focusing on whether weather-indexed insurance (WII) is a good potential risk management tool for blueberry farmers and whether some findings from the survey are consistent with those from theoretical discussions in the previous section.

4.4.1 Summary of survey implementation

A survey instrument was developed over a period of several months. The survey was designed to provide information regarding risk management strategies and growers' views regarding the feasibility and potential uptake of WII in British Columbia.[3] The survey instrument was constructed using Monkey Survey and blueberry growers were invited to participate in the survey via an invitation placed in a Newsletter that goes out to growers via the BC Blueberry Growers Association. Two rounds of surveys were carried out and the questionnaires are in the appendices at the end of the dissertation.

The first round of the online survey was sent out in a Newsletter to BC blueberry growers during March 2020. After several weeks, growers were sent a follow-up email reminding them about the survey and its importance, and again providing a link to the survey.[4] Twenty-one blueberry growers responded to the survey, but only seventeen answered questions about their risk perceptions, the risk management strategies they employed, and the impacts of adverse weather conditions on their blueberry yields and quality. Nine farmers further specified the likelihood that they would purchase a WII product when facing different levels of yields and their WTP for WII under three scenarios with different possible payments and probabilities.

As a result of a low perceived response rate, and because the original survey went out as the Covid-19 pandemic struck and growers were preparing for the upcoming growing season, the team decided to send out a second wave of the survey in Fall, 2020. To encourage participation, the online survey was revised and greatly simplified so as to focus solely on growers' views

[3] The survey (and subsequent revisions) went through the University of Victoria's ethical review process.
[4] In addition, a leading agrologist from the University of the Fraser Valley, Tom Baumann, made personal calls to key leading growers to encourage them to tell colleagues about the survey and its potential impact for the provision of alternative forms of insurance.

regarding the potential uptake of WII. An additional incentive was also included to encourage participation in the survey.[5] Then, in the Fall 2020 Newsletter sent to BC blueberry growers on November 6, 2020, readers were provided more information about weather-indexed insurance, and the purpose, importance and the potential benefits from participation in the survey, along with a link to the survey itself. A follow-up email was sent to growers a week later.

Because only one person responded to the second survey, we were invited to join the BC Blueberries Virtual Field Day and AGM held on December 9–10, 2020. We set up an exhibitor booth and monitored it for visitors. A number of growers visited the booth, and this eventually led to four more responses over the next couple of weeks; these responses could not be directly attributed to the Newsletter, follow-up email or field day. Overall, five growers responded to the second survey, but two of them only answered the background questions.

The following reasons may lead to the low response rate: (1) The researcher for the BC Blueberry Council indicated that growers are an independent breed, with a common background, who are especially reluctant to provide any information about their operations, even anonymously, particularly if they think such information might be provided to governments. (2) WII is different from traditional yield insurance. Growers have no experience with such an insurance product and might not quite grasp the explanation provided in the survey instruments (see Appendices). Perhaps, the explanation provided in the survey was too time consuming, thereby causing potential respondents to be less willing to complete the survey. Alternatively, growers may feel content with current insurance and have no motivation to participate a survey that they assume relates to a similar or related product. (3) Perhaps the best explanation relates to the fact that the surveys were

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[5] The first survey enabled respondents to place their names in a draw for a $100 Amazon gift certificate; the second survey provided each respondent who wished a $10 Tim Horton's gift certificate.

conducted during the Covid-19 pandemic, which prevented face-to-face surveying (as originally intended).

4.4.2 Attitudes toward weather risks and risk management strategies

Weather risks and the methods that growers use to reduce risks are presented based on the data from seventeen farmers who completed the first survey (see above). Attitudes towards WII and growers' WTP for WII are presented using the information from both surveys, based on nine responses from the first survey and three from the second.

Four types of weather risks were specified in the survey: (1) Too much rainfall just prior to or during harvest; (2) extreme (or sudden onset) of high temperatures; (3) cool weather that delays harvest; and (4) a late-Spring frost or an early frost in the Fall. Adverse weather risks are a frequent phenomenon, with all respondents having encountered some weather risks in the past ten years. The top two weather events that had the greatest effect on blueberry yields and/or quality were identified to be too much rainfall just prior to or during harvest and extreme (or sudden onset) of high temperatures. Thirteen growers stated that yields were affected by some weather risks in the last three years and that yield losses were primarily in the range of 20 to 40 percent. Twelve growers said that, in the last three years, quality was affected by some weather event, usually with 20%-40% or 40%-60% of blueberries downgraded in quality. Clearly, weather conditions have direct and important impacts on blueberry yields and quality. A well-designed WII product might thus be attractive to farmers.

The survey identified seven possible risk management strategies: (1) Grow diverse crops and/or have livestock; (2) produce berries in different places; (3) carry little debt, rely on own savings and/or rely on AgriInvest; (4) rely on AgriStability; (5) purchase crop insurance; (6) employ forward contracts with blueberry processors; and (7) rely on off-farm income.

The growers who responded to the survey can be allocated into two groups: one group regularly applies at least two risk-management strategies, while the second group rarely uses any of the strategies or uses at most one. The most common strategy for addressing risk is 'reliance on off-farm income'; twelve growers rely on off-farm income to reduce risk 'sometimes' or 'quite often'. The next two common strategies are: 'diversity' and 'carrying little debt'. For each of these risk management strategies, nine out of seventeen respondents indicated that they employed the strategy. The least used strategy is 'forward contracting', with fourteen growers indicating they never or rarely used it. There are no suitable futures contracts for blueberry farmers to purchase and the cost to obtain customized forward contracts in financial markets is high for small farmers. Many blueberry farmers may rely on contracts with processors, but these are not futures or forward contracts. The survey results are consistent with the argument that a holistic approach is required to research farmers' decisions regarding risk management strategies (OECD 2011). When analyzing farmers' insurance decisions, a portfolio approach that covers two or more common strategies is better than treating insurance as a stand-alone investment, which is consistent with the settings of the hybrid model discussed in section 4.2.

4.4.3 Likeliness to buy and willingness to pay

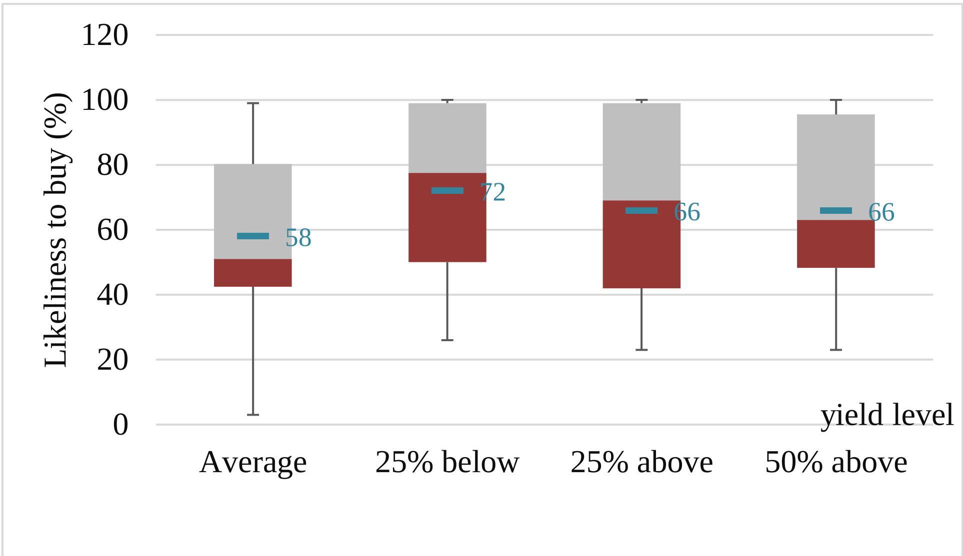
In contrast to conventional crop yield insurance, weather-indexed insurance can be used to hedge the loss caused by downgraded quality. About six weeks prior to harvest, the yield can be reasonably estimated but the quality of blueberries still depends on unrevealed weather outcomes. Then the farmer might be willing to pay extra fees to increase risk coverage at this point; that is, they may be willing to pay for increased insurance protection after considering new information that is not available before the harvest season begins. The survey designs four scenarios related to the final yield that the grower expects to realize: (i) an average yield is expected, (ii) yield is likely to be 25% below average, (ii) the expected yield is 25% above average, and (iv) the average yield is expected to be 50% above average. These scenarios are used to investigate how likely a grower might purchase a weather-indexed insurance product. Because there are only three valid responses available on the second survey, we compare the nine responses from the first survey with the twelve responses from both surveys to reflect the difference.

Overall, half of the growers indicate that their likelihood of purchasing WII exceeds 50% under each scenario (see Figure 4.3). Two thirds of growers stated that the likelihood of buying a WII product is lowest when the yield is expected to be near average. Accordingly, the average likelihood of buying rainfall-indexed insurance is lowest when yields are expected to be about the average of past years. Once the expected yield deviates from the average, regardless of whether it is higher or lower than the average yield, half of the farmers are more likely to buy WII. The likelihood of purchasing WII is the highest when the yield is expected to be lower. Figures 4.3(a) and 4.3(b) also show that participants in the second survey are much more likely to buy WII than those from the first one, which shifts the mean and median under each scenario.[6]

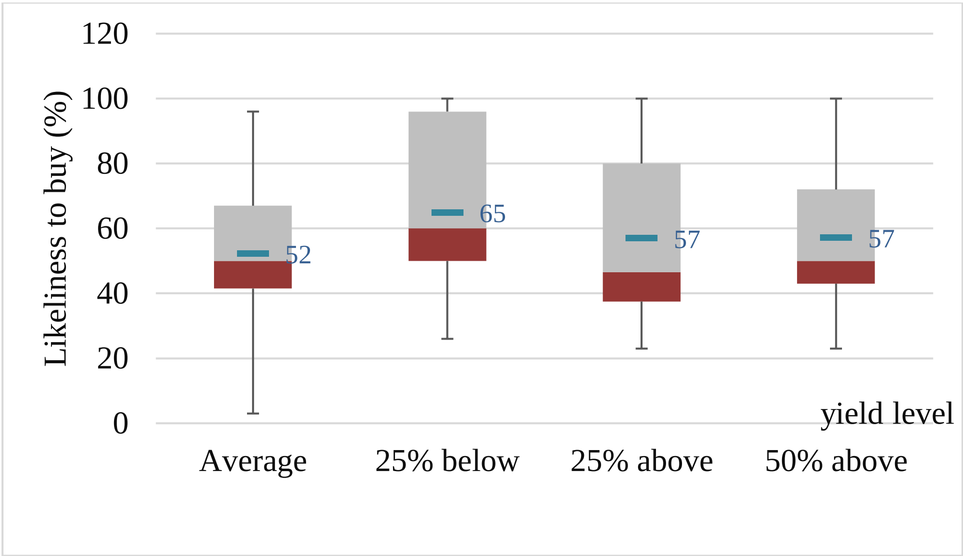
Even if farmers choose to buy WII, their WTP for a WII product is only a fraction of the actuarially fair premium (see Figure 4.4). We discuss the results from both surveys first (Figure 4.4(a)). For example, one question asks “Now suppose an excess rainfall insurance product would provide a payout of $1,000 per acre on average one year in four (scenario one). What is the MOST you would be willing to pay per acre as a premium for this insurance?” The average WTP is $34, which is 13.6% of the fair premium. The ratio of WTP over the fair premium does increase with the expected payout amount. When the payout and the related probability become $1,800 per acre

[6] It is not clear why those participating in the second survey were more likely to buy indexed insurance than those in the first survey. Low numbers prevented us from making any meaningful statistical comparisons.

on average one year in six (scenario two), the average WTP is $42, which is 14% of the fair premium. The percentage further increases to 16% when the payout and the probability become $2,500 per acre on average one year in five (scenario three).



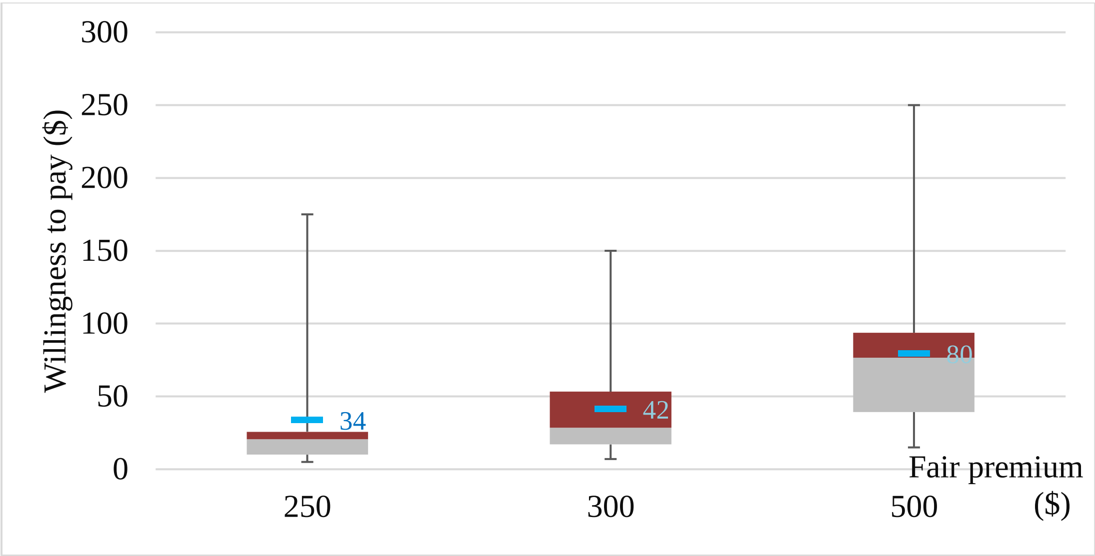
(a)



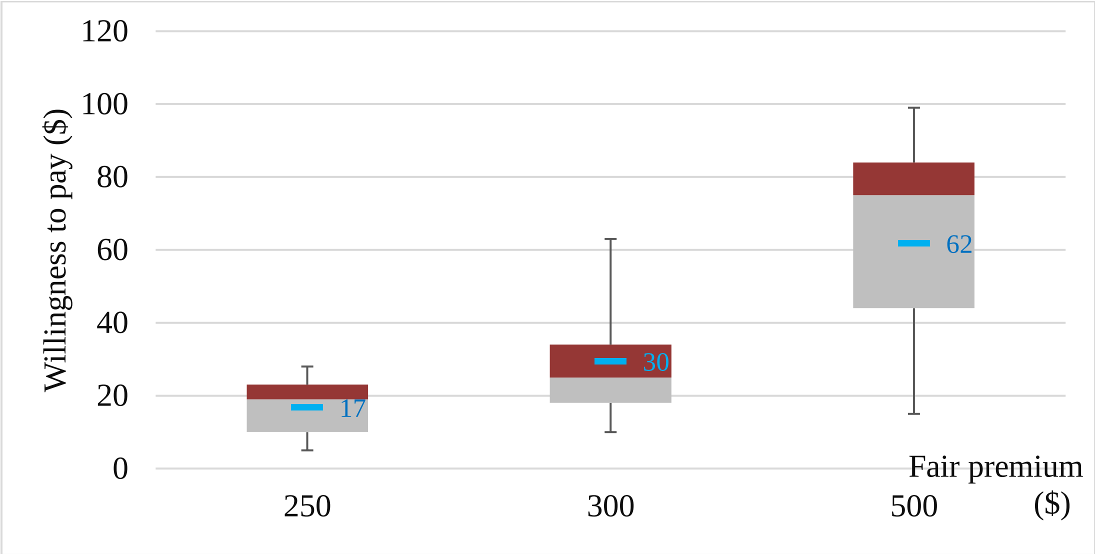
(b)

Figure 4.3 Farmers' likeliness to buy WII with different yield levels:

(a) both surveys, (b) first survey only
Note: The graph is a box plot. For each scenario, the top vertical line represents the top 25% values of likeliness to buy; the line between the grey and dark red areas represents the median, and the short blue line shows the average likeliness to buy.



(a)



(b)

Figure 4.4 Farmers' WTP for a WII product: Panel (a) both surveys; (b) first survey
Note: The graph is a box plot. For each scenario, the top vertical line represents the top 25%

values of WTP; the line between the grey and dark red areas represents the median and the short blue line shows the average WTP.

Further, most growers are more sensitive to the value of single payout than to the related probability. Compared to the first scenario, the expected payout under the second scenario increases to $300 from $250; six out of twelve growers' WTP increases by more than 20% (40% to 900%). Still compared to the first scenario, the expected payout under the third scenario doubles to $500 from $250, while nine growers' WTP increases by 132% to 1880%. The results indicate that the amount of payout has a large influence on producers' WTP for weather-indexed insurance. The reason might be that when a potential loss gets larger compared to a farmer's income, the farmer is more willing to hedge the risk. From Figures 4.4(a) and 4.4(b), we see that the WTP of the participants from the second survey are much higher in general. The maximum WTP increases from $28 to $175 under the first scenario and from $99 to $250 under the third scenario. Accordingly, the mean and median WTPs increase sharply after including the data from the second survey. The results are consistent with the findings in section 4.2 that the increase in volatility has positive impacts on the demand for WII.

It is worth noting that the second round of surveys were carried out after the virtual conference held by the BC Blueberry Council (BCBC), and the conference provided a series of workshops in blueberry research, like production and marketing, which may have made growers more open to new risk management tools. The higher levels of likeliness to buy and willingness to pay indicate that education, even if it is not directly related to WII, could promote the acceptance of WII products.

4.5 Conclusion

This chapter discusses the feasibility of WII from the demand side using PT3 theory and the results from a survey results targeting BC blueberry growers. In Chapters 2 and 3, farmers were assumed to purchase insurance and then maximize their expected utility. However, when we analyze the demand for insurance, the expected utility maximization framework largely overestimates demand because EU overlooks some key factors that influence people's insurance purchase decisions. These factors include loss aversion, distorted subjective weightings compared to objective probabilities, and basis risk. In this study, the hybrid model combing the EU and PT components reveals that the volatility of total revenue, and the proportion of a grower's total revenue coming from blueberries, are important for a farmer's decision to participate in indexed insurance. At the same time, the loss aversion coefficient and basis risk of WII products have negative impacts on farmers' demand for WII.

The results of a survey conducted among blueberry growers in British Columbia show that, when farmers consider risk management strategies, a portfolio approach is adopted and the volatility in revenue can positively impact farmers' demand for insurance. The findings support the hybrid model setting. However, it would appear that BC blueberry growers are not interested in a WII product, namely, a rainfall-indexed insurance product that protects against a pre-harvest decline in berry quality that could reduce revenues by half. The low response rate is one indication of this. The other is the expression of willingness to pay for such insurance by those who did complete the survey—average WTP appears to be well below the actuarially-sound premium plus the A&O costs that a private insurer would require as compensation. The loss aversion under the PT framework can be one of the reasons for the low level of WTP. Another reason may be that the majority of growers protect themselves against adverse declines in berry quality through off-farm income, including any off-farm income by those engaged in blueberry production plus the off-farm income earned by family members not engaged in actual agricultural activities. One more reason may be that growers expect to pay a subsidized premium as is common with crop insurance programs both in Canada and the United States.

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Chapter 5
Discussion on Key Elements of Weather Index-based Insurance

5.1 Introduction

Blueberries are sensitive to weather conditions during growth. Heat units and precipitation, as well as the timing of heat and precipitation, affect crop yields and quality. As noted in Chapter 4, blueberry growers identified three adverse weather events that affected incomes: (i) too much rainfall just prior to or during harvest, (ii) extreme (or sudden onset) of high temperatures, and (iii) early frost. Respondents to the survey of growers further explained how weather conditions impact fruit quality. First, lack of growing-season rainfall is not a concern because many farms use irrigation, but too much rainfall can cause fruit rot and/or fruit softening and splitting.

When it comes to temperatures, high temperatures themselves are not the problem. Rather, it is the rate at which temperatures change at the field level that is problematic. When temperatures increase too rapidly, plants cannot acclimatize quickly enough to the changed temperatures, because it takes time for cellular processes to produce antioxidant compounds to protect fruits against damage from rising temperatures. Fruits can get sunburn, soften and shrivel because heat and/or high UV come on too quickly.

Early frost, on the other hand, can damage blooms thereby reducing yields, and can have a negative impact on quality. Early frosts happen about once every four years, but mainly impact late-season cultivars, although these varieties comprise less than 20% of total planted acreage. Further, a certain amount of growing season heat (measured by growing degree days, say) is required for berries to ripen. Late season cultivars will then need more time to ripen, and the berries that are to be picked last may not be ripe by the time frosts begin.

In this chapter, we use secondary data to investigate the feasibility of designing a WII product for blueberry growers to hedge against quality-impacting weather conditions. To do that, after identifying the key weather factors that likely affect blueberry quality, we must investigate the possibility of constructing an index potentially used to develop a WII product representing blueberry quality, and quantify the impacts of weather conditions on quality. Once an index has been determined, we discuss further how to model the key weather factors and whether it is feasible to construct a contract using modelled data. In section 5.2, a multivariate regression model constructed to represent the relationship between weather events and blueberry quality is presented and estimated. Section 5.3 is about modelling temperature and precipitation. Section 5.4 provides preliminary discussion about pricing a rainfall index insurance. The last section concludes with some observations.

5.2 Weather and Product Quality

Combining the discussion in the introduction and the responses from a survey targeting blueberry growers in BC, the following four hypotheses regarding the relationship between key weather factors and blueberry quality will be tested using secondary data: (1) early frost has negative impacts on blueberry quality; (2) too much rainfall during the stages of fruit development, ripening and harvesting negatively impacts berry quality; (3) higher temperatures (heat units) have a positive impact on berry quality, but (4) sudden changes in temperature have a negative impact on quality.

To test these hypotheses, a multivariate regression model of the relationship between weather events and crop quality needs to be developed and applied. In this study, partial least squares structural equation modeling (PLS-SEM) is used because it has the following advantages over other estimation techniques, such as ordinary least squares regression and principal component regression: (1) it has the ability to create and model latent variables (LVs) that cannot be measured directly; (2) it capably handles multicollinearity among the independent variables; (3) it can work with small sample sizes; and (4) it is considered a suitable technique when the goal is prediction or theoretical development for exploratory models (Garson 2016). In this section, we first discuss the setting of the PLS-SEM model. Then data are introduced and the estimation results are discussed.

5.2.1 Theoretical PLS-SEM model

A PLS-SEM model consists of two components: the inner (structural) model and the outer (measurement) model. The former shows how LVs relate to each other based on substantive theory; the latter presents the relationship between the LVs and their corresponding observed indicator variables. In this study, five LVs are included in the model according to the four hypotheses defined before. The LV *frost* represents the occurrence of early frost; *range* is used to track the frequency of sudden changes in temperature during the fruit development, ripening and harvesting seasons; and *rainfall* and *temperature* are used to represent cumulative rainfall and maximum temperatures, respectively. All four weather LVs impact *quality* (which is also a latent variable). It is important to note that *rainfall* affects *temperature*, so that it has an indirect effect on *quality* via *temperature*. The rectangular box in Figure 5.1 frames the inner (structural) model and the figure is generated using SmartPLS3 (Ringle, Wende and Becker 2015),

Because all LVs (blue circles in Figure 5.1) cannot be observed directly, we use observable indicator variables (yellow rectangles in Figure 5.1) to construct LVs. For each LV, one outer (measurement) model is set up to display the relationship between the LV and its indicator variables (see the red triangles in Figure 5.1). Since the causal arrows go from the LVs to their indicators, the indicator variables are representative of the LVs. See Table 5.1 for a further description of the variables in Figure 5.1.

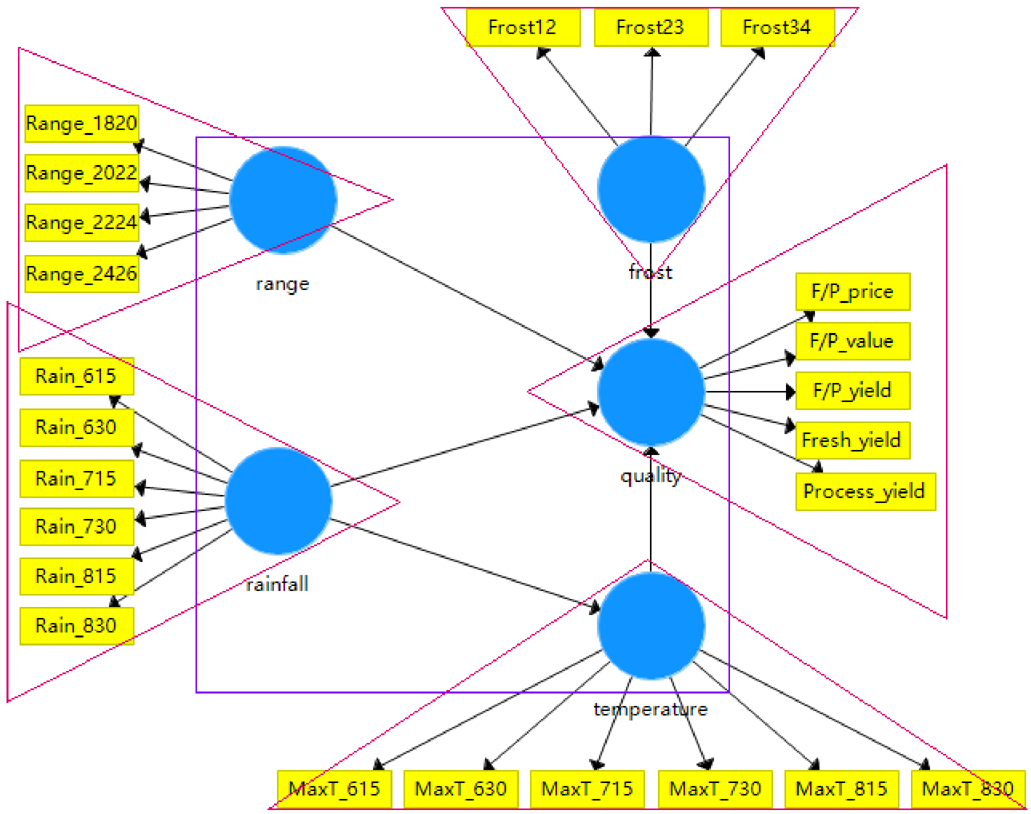


Figure 5.1 Theoretical path model

To represent blueberry quality, multiple measurements are to be considered. Farm gate values are affected by multiple factors uncorrelated to quality, such as market regulation. Meanwhile, no appropriate CPI index is available for adjusting the historical blueberry prices. Hence, the unit price of blueberries is not included as an indicator of quality. Nonetheless, the unit prices, dollar values and yields of fresh blueberries over processed blueberries are good indicators since the volatility in these ratios reflects the changes in quality quite well, with no adjustment required for these ratios.

Table 5.1: Definitions of representative indicator variables

Variable	Definition
F/P_price	(unit price of fresh blueberries)/(unit price of processed blueberries)
F/P_value	(fresh blueberry price×yield)/(processed blueberry price×yield)
F/P_yield	(fresh blueberry yields)/(processed blueberry yields)
Fresh_yield	fresh blueberry detrended yields
Process_yield	processed blueberry detrended yields
Frost12	Days between April 1 and May 15 that minimum temperature falls between –2 and –1 ^oC
Frost23	Days between April 1 and May 15 that minimum temperature falls between –3 and –2 ^oC
Range_1820	Days between May 16 and August 15 that daily temperature falls between 18 and 20 ^oC
Range_2022	Days between May 16 and August 15 that daily temperature falls between 20 and 22 ^oC
Rain_*x*15	Cumulative rainfall during 30 days before the 15th of month x, $x \in$ {June, July, August}
Rain_*x*30	Cumulative rainfall during 30 days before the end of month x, $x \in$ {June, July, August}
MaxT_*x*15	Sum of maximum temperatures during 30 days before the 15th of month x
MaxT_*x*30	Sum of maximum temperatures during 30 days before end of month x

The number of observations pertaining to indicators for weather LVs is limited, because blueberry prices and yields are available only on an annual basis. Accordingly, it is better to aggregate or bin the daily weather data to limit the number of indicator variables for the LVs. For the indicator variables for *frost* and *range*, once early frost and rapid changes in temperature occur, damages are done to blueberries. Hence, the binned weather data are used, recording whether and how many times these situations happen for particular time periods during each year. For *rainfall*, the total precipitation in a predefined period is recorded. Similar to precipitation, for *temperature* the cumulative value is important; the sum of maximum temperatures during a prespecified time period is calculated. Because different types of blueberries have different ripening and harvesting phases, each indicator variable for *rainfall* and *temperature* covers 30 days so that different products can be offered to growers for different blueberries. Table 5.1 provides the definitions of some representative indicator variables.

5.2.2 Data and results from the PLS-SEM analyses

To estimate the PLS-SEM model shown in Figure 5.1, the following data are used: (i) Annual blueberry production and yields available from Statistics Canada (2008) at the provincial level for the period 1958 to 1994. After 1994, data for fresh and processed blueberries are no longer reported separately. (ii) Historical daily minimum and maximum temperatures, and daily total precipitation, are from the Abbotsford A weather station for the period 1958 to 1994; the weather data are from Climate, Environment & Climate Change Canada (CECCC, 2011). Other weather stations do not have complete data for the required time period. (iii) Binned and cumulative weather data are calculated from the raw data.

The estimated inner model is reported in Figure 5.2. The coefficients along each of the paths, as indicated by the directional arrows, represent the direct effects of one latent variable on another LV. The corresponding p-values, obtained by repeating the bootstrap process 10,000 times, are included in parentheses. Consistent with our hypotheses, early frost and sudden changes in temperature have negative impacts on quality, although the impacts of early frost are not statistically significant. The reason is that early frost mainly damages blooms, which further reduces yields, but has no direct impact on quality. Also consistent with the hypothesis, higher temperatures benefit fruit quality.

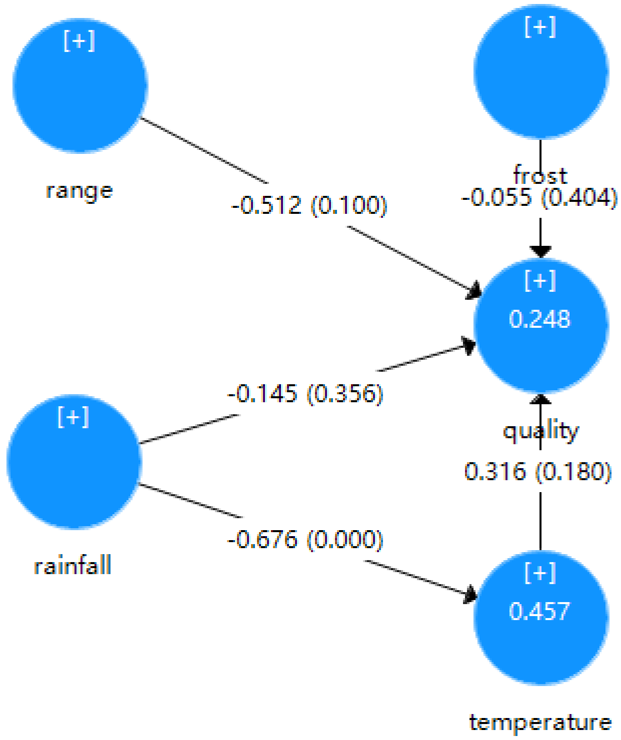


Figure 5.2 Estimated PLS-SEM inner model

Rainfall has a large indirect negative impact on quality through the *temperature* variable (–0.214 = –0.676×0.316), while having an insignificant direct impact on *quality*. Excessive rainfall leads to lower maximum temperatures, which reduce water evaporation and further causes fruit rot, softening and splitting. Based on these results, we simplify the model by removing *frost* and the direct path from *rainfall* to *quality*. The estimated revised model is provided in Figure 5.3. However, since we only have 37 observations, the magnitudes of the estimated path coefficients are not reliable. Table 5.2 reports the sample means of the path coefficients from bootstraps. The path coefficients from *range* and *temperature* to *quality* decrease in magnitude, while the magnitude of the path coefficient from *rainfall* to *temperature* increases compared to the estimated values from the original sample.

Overall, the estimation applying the PLS-SEM method demonstrates that an index using a group of variables related to yields and the monetary values of blueberries sold in the fresh and processed markets could be used to represent blueberry quality, and the relationship between key weather factors and fruit quality can be quantified. But due to the lack of more recent data for constructing the quality index, we cannot further test whether the estimated results are applicable for recent years.

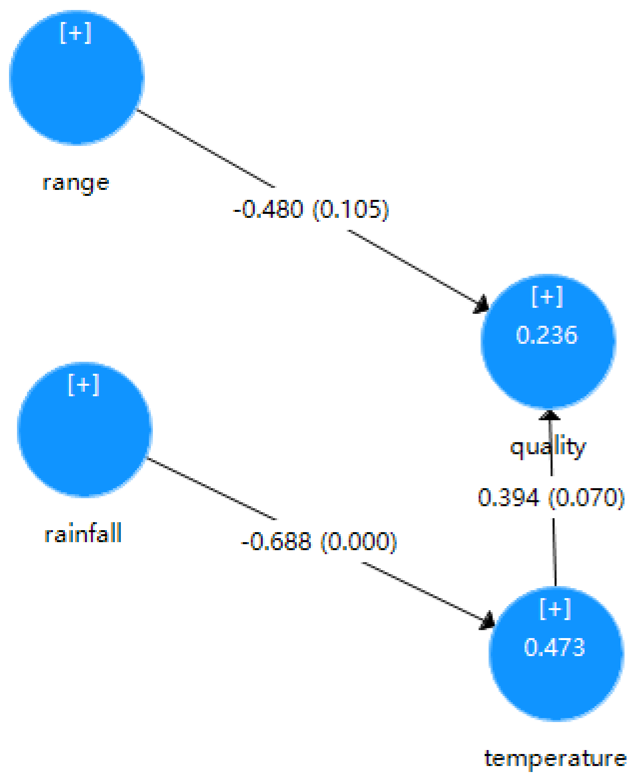


Figure 5.3 Revised PLS-SEM inner model

Table 5.2: Bootstrap results for path coefficients

	Original Sample	Sample Mean	Standard Deviation	t-statistics	p-values
Rainfall → Temperature	-0.688	-0.730	0.170	4.055	0.000
Range → Quality	-0.480	-0.379	0.382	1.256	0.105
Temperature → Quality	0.394	0.337	0.267	1.475	0.070

5.3 Modelling Temperature and Precipitation

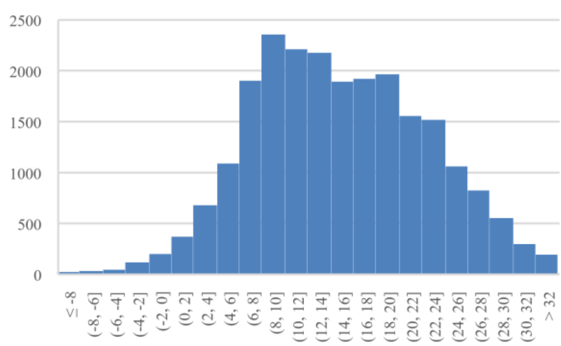
The estimated PLS-SEM model shows the relationship between key weather factors and fruit quality. However, to design a weather-indexed insurance contract, the weather variables must be modelled in a way that enables us reasonably to calculate premia. Three weather variables to be forecasted are daily minimum temperatures, daily maximum temperatures, and precipitation. Temperature data must be modelled on a daily basis so that daily temperature changes can be calculated. As to precipitation modelling, it can be for daily data or cumulative data over a pre-specified time period because only the latter is required in the PLS-SEM model. Daily rainfall provides more flexibility but the inaccuracy may accumulate over time.

To deal with the missing values in the historical data, the approach proposed by Alexandridis and Zapranis (2013) is applied. If one day's value is missing, the following the steps are employed to fill in the data: (1) calculate the average value of that particular day across years; (2) calculate the average of the preceding seven days and the following seven days; and (3) use the average value from the previous two steps.

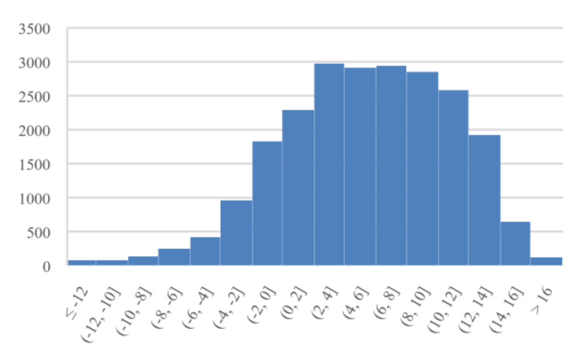
The histograms of three daily weather variables for years 1957 to 2019 are provided in Figure 5.4. Clearly, the distribution of rainfall is quite different from the histograms of temperatures because the mode of rainfall is zero and the distribution has a long right tail. Hence, the modelling approaches for rainfall and temperatures are different and will be discussed separately below.

5.3.1 Modelling temperatures

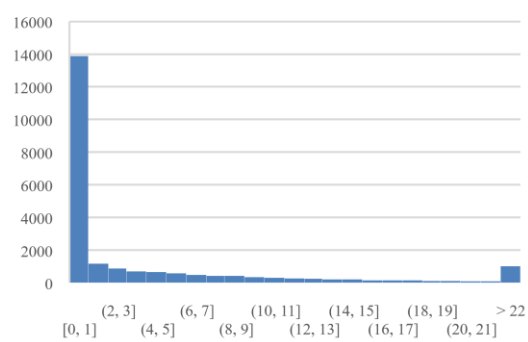
The goal of this subsection is to construct a model to capture the dynamic characteristics of the daily maximum and minimum temperatures. As Figure 5.5 shows, seasonality and autocorrelation are two key features of daily temperatures. Many stochastic models have been discussed in the literature. For example, Benth and Benth (2007) proposed an Ornstein–Uhlenbeck process with seasonality. They decompose the average daily temperature into three parts: (i) one term represents trend and seasonality; (ii) another describes the mean-reverting feature; (iii) a final one accounts for daily volatility. Then different parts need to be estimated separately, which involves multiple steps and different approaches to identify and estimate parameters. In recent years, with the development of time-series modelling, seasonal autoregressive, integrated moving-average (SARIMA) modelling has become one major method applied in meteorological applications for its ability to model and forecast climate variables.



(a) daily maximum temperature



(b) daily minimum temperature



(c) daily precipitation

Figure 5.4 Histograms of daily temperature and rainfall (1957–2019)

A SARIMA model is usually written as ARIMA(p, d, q)×(P, D, Q)$_m$, where m is for the time span of repeating seasonal pattern (e.g., 365 for daily data). The lowercase p, d, q are for the non-seasonal features: p is the AR lag order, d is the order of differencing and q is the MA order. Similarly, the uppercase P, D and Q are for the corresponding seasonal features.

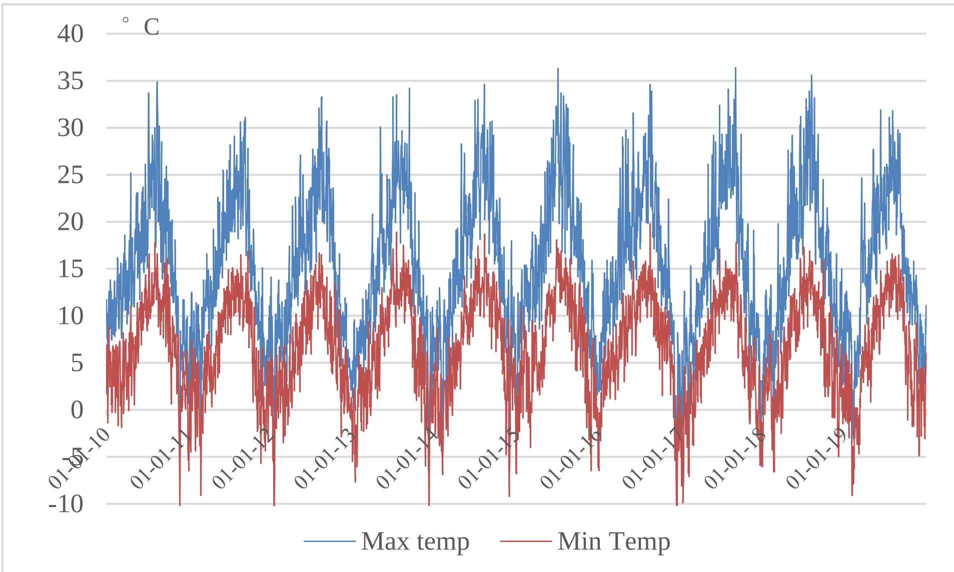


Figure 5.5 Observed daily maximum and minimum temperatures (2010-2019)

In this study, to estimate the SARIMA model, historical daily minimum and maximum temperatures from the Abbotsford A weather station from January 1957 to April 2020 are used (CECCC 2011). The package *auto.arima* in R is applied to select the best combination of six order numbers defined above using the corrected Akaike Information Criterion (Anon n.d.). The estimated models for daily maximum and minimum temperatures are ARIMA(4, 0, 2)×(0, 1, 0)$_{365}$ and ARIMA(5, 0, 1)×(0, 1, 0)$_{365}$, respectively. The estimated models indicate that the temperature process is not seasonally stationary but is stationary after first difference, which is defined as the difference between the observed value of one particular day and that of the same day from one year ago ($Temp_t - Temp_{t-365}$ at period t). For the non-seasonal part, the process is stationary while the temperature in period t is autocorrelated with the temperature up to four to five days ago plus one or two lagged error terms.

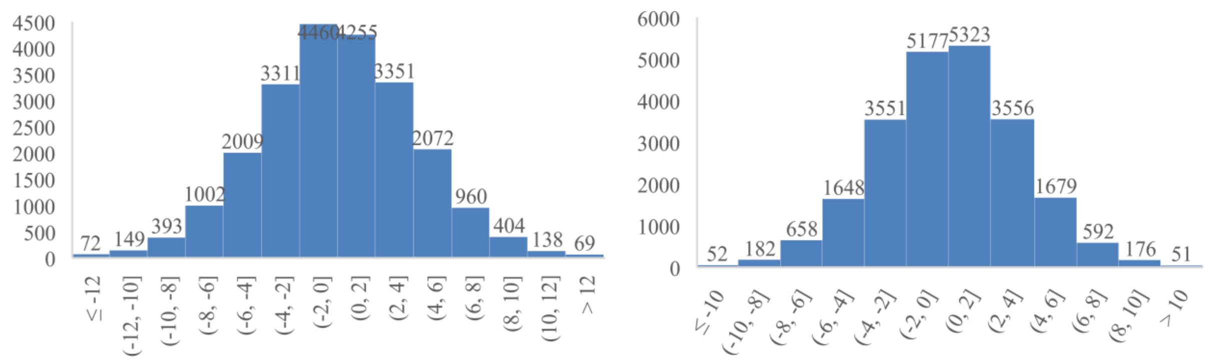
Table 5.3 compares the statistics for the observed and fitted values of indicator variables related to temperature. The mean of the fitted cumulative maximum temperature for each period is quite close to its corresponding true value, while the standard deviation is smaller. For most periods, the magnitude of skewness drops, which means the distributions of the accumulated fitted values are usually more symmetric compared to those from the true values. For most periods, the magnitude of excess kurtosis is larger, indicating the distributions of the accumulated fitted values are usually flatter with more extreme values compared to the distributions using the true values. Accordingly, for three out of four indicator variables related to daily temperature range, the averages calculated using the fitted values increase sharply.

Table 5.3: Statistics for Temperature Indicator Variables

Indicator variables[a]	Observed Values				Fitted Values			
	Mean	Standard Deviation	Skewness	Excess Kurtosis	Mean	Standard Deviation	Skewness	Excess Kurtosis
Range_1820	6.85	4.18	0.44	-0.67	6.34	3.06	0.12	-1.00
Range_2022	2.68	2.93	1.91	4.23	3.66	2.33	0.75	1.27
Range_2224	0.68	1.23	1.87	2.74	1.42	1.42	0.95	0.19
Range_2426	0.08	0.33	4.46	21.16	0.45	1.02	3.30	14.07
MaxT_615	583.7	53.2	0.4	-0.4	583.5	39.2	0.0	-0.8
MaxT_630	621.7	52.0	0.3	-0.3	621.6	40.8	0.1	-0.4
MaxT_715	665.0	54.0	0.5	-0.1	665.6	42.7	0.4	0.3
MaxT_730	717.8	54.7	0.2	-0.2	717.6	42.2	0.1	-0.4
MaxT_815	748.3	50.5	0.0	-0.6	747.5	40.8	0.1	-0.2
MaxT_830	725.4	54.8	-0.4	-0.2	724.9	43.1	-0.5	0.4

[a] See Table 5.1 for a description of the variables.

Figure 5.6 further shows the distributions of the prediction errors (fitted values − observed values) for daily maximum and minimum temperatures. Since half of the fitted minimum temperatures are lower than the corresponding true values and half of the fitted maximum temperatures are higher than the corresponding true values, the probabilities for obtaining larger daily temperature ranges increase.



(a) daily maximum temperature *(b) daily minimum temperature*

Figure 5.6 Histograms of forecast errors of daily temperature

5.3.2 Modelling precipitation

Compared to a monthly model, a daily model is more flexible since it provides more information and can be used to construct different indexes as needed. But it is harder to model daily precipitation than it is to model daily temperatures, because daily rainfall is discrete but its occurrence is more irregular and uneven than that of temperature. SARIMA and other continuous time series models are inappropriate in this situation. It is common to model daily precipitation in two steps (Alexandridis and Zapranis 2013). The first step is about the conditional probability of the occurrence of rainfall on a given day. A two-state Markov chain process can be implemented. Then the second step is to model the amount of precipitation on a given rainy day. In this subsection, the two-step approach is first applied to model daily rainfall and calculate the cumulative rainfall for the indicator variables used in the PLS-SEM model. After that, the cumulative rainfall will be directly modelled and simulated. The modelling results will then be compared and discussed.

As explained earlier, the first step in modeling daily rainfall is to estimate a Markov chain, which consists of two parts – the states and order of the chain. For precipitation, there are only rainy and dry states. Suppose the random variable R_t represents the state associated with day t so that

$$R_t = \begin{cases} 1 & \text{if day t has precipitaion (wet)} \\ 0 & \text{if day t has no precipitation (dry)} \end{cases} \tag{5.1}$$

The number of days needed to obtain the transition probability matrix is called the order. For a two-state, first-order Markov chain, the conditional transition matrix is a 2×2 matrix given by (5.2); for a two-state, second-order Markov chain, the dimension of the conditional transition matrix is 2×8 and each probability will be conditional on the states of the previous two days.

$$\begin{bmatrix} p_{00} = \Pr\,[R_t = 0|R_{t-1} = 0] & p_{01} = \Pr\,[R_t = 0|R_{t-1} = 1] \\ p_{10} = \Pr\,[R_t = 1|R_{t-1} = 0] & p_{11} = \Pr\,[R_t = 1|R_{t-1} = 1] \end{bmatrix} \tag{5.2}$$

To estimate the probabilities for each day for (5.2), we use historical data. For example, for day t,

$$\hat{p}_{00} = \frac{C_{00}}{C_{00}+C_{01}}, \tag{5.3}$$

where C_{00} is the number of dry days (day t) following dry days (day t–1) and C_{01} is the number of wet days (day t) following dry days (day t–1) (Alexandridis and Zapranis 2013).

After estimating the transition matrix, the magnitude of precipitation for rainy days will be modelled by fitting the data to a gamma, beta, exponential or some other distribution. The gamma distribution is a common one because it has the same features as the distribution of precipitation: no negative values, right skewed and asymmetric. The probability density function of a gamma distribution is:

$$f(x) = \frac{(x/\beta)^{\alpha-1} e^{(-x/\beta)}}{\beta\Gamma(\alpha)} \quad x, \alpha, \beta > 0, \tag{5.4}$$

where α and β are the parameters that can be estimated using the method of moments and $\Gamma(\alpha)$ is a gamma function for α. Similar to the transition probabilities, α and β are estimated for each day. With the estimated Markov chain models and the estimated gamma distributions, the daily rainfall data can be simulated. We estimate both first- and second-order Markov chains and use them to simulate daily rainfall and the cumulative rainfall, respectively.

Table 5.4: Statistics for Cumulative Rainfall from Observed and Simulated Data

		Rain_615	Rain_630	Rain_715	Rain_730	Rain_815	Rain_830
Observed	Mean	81.76	65.59	56.00	42.86	28.84	44.92
	Standard Deviation	43.70	38.16	43.51	31.28	26.37	42.40
	Skewness	0.75	1.80	1.35	1.30	1.15	1.30
	Kurtosis	3.49	8.98	5.23	5.44	3.99	3.94
1st order Markov	Mean	34.46	30.16	27.76	21.86	16.29	19.19
	Standard Deviation	23.54	24.18	29.31	20.55	18.78	20.89
	Skewness	1.40	2.86	2.84	1.90	3.87	2.94
	Kurtosis	6.59	15.42	13.31	7.31	23.51	15.29
2nd Order Markov	Mean	36.67	30.41	22.28	15.80	14.73	22.10
	Standard Deviation	26.50	25.96	20.04	12.57	14.69	20.39
	Skewness	1.05	2.16	3.51	1.11	1.81	2.23
	Kurtosis	3.96	9.95	20.21	3.73	6.90	9.00
Cumulative	Mean	83.83	58.50	59.29	47.10	29.78	40.06
	Standard Deviation	44.46	34.49	37.65	31.06	27.00	37.80
	Skewness	0.98	1.00	1.29	1.71	2.24	0.70
	Kurtosis	4.20	4.26	4.91	6.19	8.24	2.87

Each 30-day cumulative rainfall series can be directly modeled using a gamma distribution, since cumulative precipitation is a continuous variable. Similar to the second step for daily rainfall, α and β are estimated for each prespecified period. Table 5.4 reports the statistics for the observed and simulated cumulative rainfall for years 1957 to 2019. It shows that the cumulative rainfall series from the simulated daily data, including the first- and second-order Markov chains, have much smaller means and standard deviations than the observed values, which indicates the two-step stochastic approach does not provide reasonably accurate estimates for the needed rainfall indicator variables. On the other hand, the statistics of the directly simulated cumulative rainfall are similar to those of the observed historical data. Hence, in this case, applying gamma distributions to model and simulate each cumulative rainfall variable can provide reasonable estimates for calculating the premium of an insurance product.

5.4 Pricing a rainfall index insurance

A simplified pricing framework for rainfall-indexed insurance is presented in this section. It is worth noting that the rainfall index does not measure the actual quality changes of blueberries and the calculation of premium is related to the distribution of precipitation. To be used to hedge against quality risk, the product is only suitable if blueberry quality correlates well with excess rainfall. The PLS-SEM estimation results in section 5.2 demonstrate that rainfall has negative impacts on quality, but the time frame is restricted and the weather data are from one station. Due to the lack of data, no analysis regarding basis risk will be covered in this chapter.

Suppose we intend to provide blueberry farmers a WII product with insurance against quality risk caused by an increase in precipitation. Farmers are assumed to be risk averse and loss averse while insurers are risk neutral and loss neutral. The insurance payment is calculated based on an index value over a period $[\tau_1, \tau_2]$. Hence, to assess the premium, we define a rainfall index, model the dynamics of cumulative rainfall, and implement Monte Carlo simulation to price the insurance contract. First, the cumulative rainfall index for $[\tau_1, \tau_2]$ is defined as:

$$\mathrm{CR\_}\tau_2 = \sum_{t=\tau_1}^{\tau_2} RF(t), \tag{5.5}$$

which is simply the sum of rainfall. As explained in section 5.3, each cumulative rainfall variable is directly modelled by a gamma distribution; $\mathrm{CR\_}\tau_2$ can be represented by cumulative rainfall variables such as *Rain_615*, et cetera. Then the payment is constructed as:

$$\text{PM\_}\tau_2 = k \times \max(\text{CR\_}\tau_2 - c\text{\_}\tau_2, 0), \tag{5.6}$$

where k is the scale parameter connecting the index value and money value of payment (Taib and Benth 2012). Without loss of generality, k is set at 1, meaning one dollar will be paid out for each mm precipitation over the threshold. And c_τ_2 is the threshold, measuring the critical rainfall level, which is equal to the sum of one gamma distribution's mean and its corresponding standard deviation; it is different for each cumulative rainfall variable. Then the fair price of a contract will be (Alexandridis and Zapranis 2013):

$$P(t, \tau_1, \tau_2) = \mathrm{E}[PM\_\tau_2 | \mathbf{F_t}], \tag{5.7}$$

where $\mathbf{F}_t$ represents the available information for pricing up to time $t < \tau_1 < \tau_2$, which is the gamma distribution for $[\tau_1, \tau_2]$. For simplicity, only a pure premium is considered in this study, not a gross premium that includes loading to cover other expenses. After everything is defined, the Monte Carlo simulation is applied to estimate the expected value in equation (5.7). To be specific, for the period $[\tau_1, \tau_2]$, 10,000 scenarios of CR_τ_2 are simulated with PM_τ_2 calculated for each scenario. Then the average of PM_τ_2 provides one estimate of $P(t, \tau_1, \tau_2)$. The above method is repeated 100 times and the average is used as the expected fair price.

Two rainfall insurance products are used as examples to demonstrate the pricing results: one is for the period June 16 to July 15 and the other is for the period July 1 to July 30. Table 5.5 reports the results from three simulations and the average of 100 simulations for each product. The number of payments is usually in the range (1400, 1500) for both products and the fair prices for them are around \$5.6 and \$4.0, respectively. Figure 5.7 shows the histogram of the payouts from one 10,000-scenario simulation for the period June 16 to July 15. Clearly, many are small payouts with values less than the premium, but the distribution has a long tail, representing large payments.

Table 5.5 Simulation results for fair prices of two insurance products

Period	CR_τ_2	c_τ_2	Simulation order	$P(t, \tau_1, \tau_2)$	Number of payments (out of 10,000)
June 16 - July 15	Rain_715	99	1	5.31	1485
			2	5.80	1502
			3	5.37	1414
	Average of 100 times			5.59	1436
July 1 - July 30	Rain_730	74	1	3.81	1432
			2	3.93	1471
			3	3.82	1423
	Average of 100 times			3.98	1460

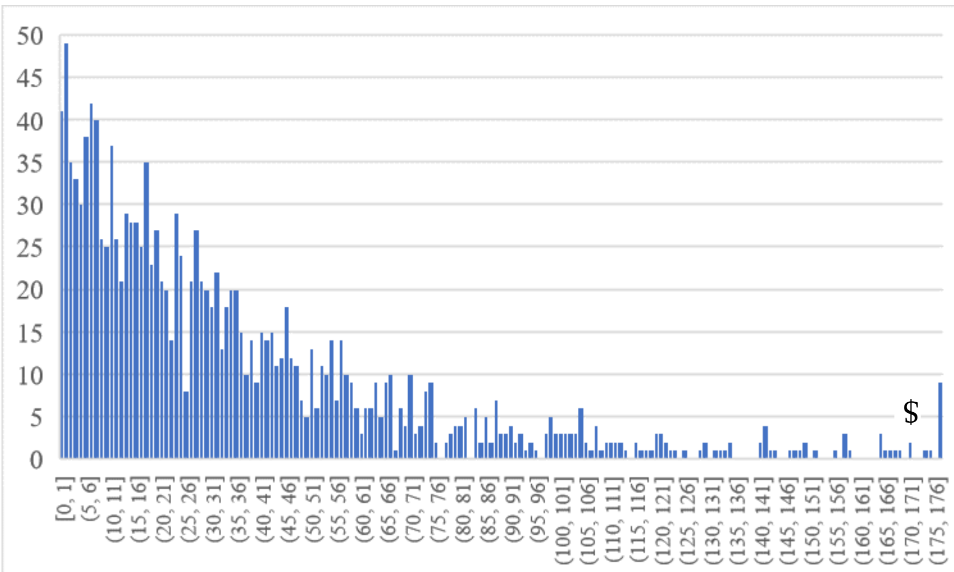


Figure 5.7 Histogram of payments from one 10,000-senario simulation

5.5 Conclusion

This chapter focuses on some key elements of a WII product for mitigating the negative impacts caused by dramatically reduced blueberry quality from the supply side. The first objective is to construct an index representing blueberry quality, to identify the key weather factors affecting blueberry quality and to quantify the impacts of weather conditions on quality. A PLS-SEM model is set up to solve the above problems. The estimated results show that it is possible to construct an quality index using a set of variables related to yields and the monetary values of blueberries sold in the fresh and processed markets, and the relationship between fruit quality and key weather factors, such as cumulative maximum temperature and cumulative excess rainfall, can be quantified. But more data are required to further verify the relationships between the latent variables and those between the latent variables and their corresponding indicator variables.

The second goal is to model temperature and rainfall to investigate the feasibility of calculating premia of a WII contract using modelled data. A time-series model, SARIMA, is applied to model daily temperature. Rainfall is modelled via a Markov stochastic process and a gamma distribution. Overall, the results show that it is possible to use estimated or simulated data for calculating premia. Finally, we demonstrated how to use a simplified pricing process for a rainfall index insurance product.

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CHAPTER 6
DISCUSSION AND CONCLUSION

This dissertation presents two studies regarding agriculture business risk management. Each study is self-contained, but both address questions related to insurance, particularly farmers' perception of insurance, and the impacts of insurance on farmers' financial status and production behaviour to answer the questions raised in Chapter 1.

In brief, we assume a farmer plans to maximize her expected utility so that their risk attitudes can be explicitly expressed. The positive mathematical programming (PMP) models whose objective function is the maximization of farmers' expected utility can be applied to calibrate farmers' risk aversion coefficients and then be used to simulate the changes in farmers' production decision and their responses to government programs. The calibration and simulation results show that farmers who are more risk-averse tend to lower their production costs and decrease their gross margin volatility. Hence, these farmers pay higher fees but benefit the least from joining risk management programs that are insurance targeting production gross margin in essence. If an insurance imposes restrictions on the amount of payments to the level that lower-cost farmers' expected utility decrease by buying the insurance, these farmers will drop out of the program, which may lead to market failure. While traditional yield insurance provides reasonable protection against yield losses caused by adverse weather conditions, it does not cover the quality risk that some fruit farmers face very well. In theory, weather indexed insurance (WII) can complement the current agricultural business risk management programs due to its flexibility to participate, the straightforward calculation of premium and payment and easy administration. However, basis risk of WII, the low acceptance rate of WII and small amounts of willingness to pay have negative impacts on the practical feasibility of WII. The rest of this chapter summarizes the key points with more details and discusses potential future work.

Governments support the incomes of farmers partly to protect them from income volatility. To avoid the distortions on farmers' production decisions, recently the EU and other countries implemented or moved toward whole farm insurance (WFI) where total farm income, not returns to individual crops, is insured (Turvey 2012; van Kooten 2021, Chapter 9). Even so, there remain concerns that the whole farm approach may distort crop production decisions due to both an insurance effect, which provides an effective lower bound on income, and a wealth effect, which reduces the farmer's aversion to risk (Finger and Lehmann 2012; Hennessy 1998).

Positive mathematical programming (PMP) models of farmers' cropping decisions have been applied to study the effect of agricultural business risk management (BRM) policies on farmers' exposure to risk, their decisions on land use, and their incomes. Before being used to examine agricultural producer responses to policy changes under the expected utility framework, the models must first be calibrated to obtain the values of the risk aversion coefficient and the cost function parameters. Hence, we first compare three calibration approaches for disentangling the risk parameter from the parameters of the cost function: one assumes a logarithmic utility function while the others employ an exponential utility function. Historical crop insurance data for southern Alberta, Canada, are used to assess the calibration performance of the three approaches, and sensitivity analysis is employed to test whether the changes in the optimal land allocation caused by the changes in the values of the parameters are practically reasonable. Only one of the three approaches, *FSSIM-ME-CARA*, is of practical use for policy analysis because it can recover the 'true' values of the parameters and the results of sensitivity analysis are reasonable.

FSSIM-ME-CARA first uses risk attitudes and volatility to explain observed land allocation as much as possible and then the calibrated cost functions to bridge the remaining gap between observed and modeled outcomes. The intention is to separate risk attitudes and cost functions to better model farmers' behavior. While there may be no way to strictly separate risk from the cost functions, it is still better than assigning all unobservable components to costs.

To investigate the impacts on production incentives of changes in Canada's AgriStability program, which essentially constitutes a form of whole farm insurance, we calibrate farm management models using the *FSSIM-ME-CARA* approach for three different Alberta regions. To further reflect the effects of the program changes on farmers who have different cost structures, we consider low-, medium- and high-cost farmers with similar land allocation choices for each region. Results indicate that farmers' observed attitudes towards risk vary with cost structure. After joining the program, all farmers alter their land allocations to some extent. The introduction of a reference margin limit (RML) in the AgriStability program under Growing Forward 2 (2013-2018), which was retained in the replacement legislation until 2020, has the most negative impact on farmers with the lowest costs. As a corollary, therefore, the removal of RML significantly increases the benefits to low-cost farmers. Further, the choice of late participation offers farmers some flexibility in enrolment, but high-cost farmers would be better off in terms of expected gross margins if they participate in AgriStability every year.

The main findings regarding the calibration and application of the PMP models in this dissertation are under one restricted assumption. The *FSSIM-ME-CARA* approach still assumes no substitutionary or complementary effects among crops and calibrates a strictly diagonal quadratic cost matrix due to the lack of the prior information about the range of the off-diagonal elements. More research can be done on how to incorporate more information into the process to address the calibration of cost functions and risk aversion within a PMP framework, while also finding a better way to measure farmers' risk attitudes. These steps are necessary to improve economists' abilities to analyze agricultural business risk management and related public policy.

Traditional insurance products provide financial support to farmers from different aspects. For example, the AgriStability program targets situations where farmers face large drop in gross margin, while crop insurance focuses on yield reduction. However, for fruit farmers, the products' quality can be greatly affected by the weather conditions during the stage of fruit development and ripening, which may lead to quality downgrade and a significant loss in revenue with little impacts on yields. Hence, the second study investigates the conceptual feasibility of using weather-indexed insurance (WII) to hedge against non-catastrophic, but quality-impacting weather conditions to complement existing traditional insurance.

When discussing the impacts of insurance on production incentives and farmers' financial outcomes in the first study, farmers are assumed to have purchased insurance and then maximize their expected utility with insurance coverage. However, when it comes to the demand analysis for insurance, the literature increasingly argues that the expected utility maximization framework largely overestimates demand. As an alternative, prospect theory has been proposed; it considers insurance as a stand-alone investment and focuses on evaluating insurance's gains and losses compared to a reference point, not the level of total revenue. But the level and the volatility of a farmer's total revenue also influence farmers' decisions to participate in an insurance program. Hence, in this dissertation, a farmer is assumed to maximize their total utility, which consist of expected utility over their total revenue and their prospect valuation over WII to reflect both the rational and intuitive parts of their decision-making process. The model demonstrates that an increase in the volatility of total revenue and the revenue proportion from blueberries increases the possibility of farmers' participation in WII. On the other hand, the increase in the value loss aversion coefficient and WII's basis risk leads to less demand for WII.

To design a WII product for blueberry growers to hedge against quality risk, a quality index must be constructed and the relationship between key weather conditions, such as cumulative maximum temperature and cumulative excess rainfall, and the quality index should be quantified. The results from a partial least squares structural equation modeling (PLS-SEM) show that the above goals are achievable. Further, rainfall and temperature can be modelled via a time-series model and statistical distributions, respectively, to provide reasonable estimates for calculating insurance premia. Future work may further explore the feasibility of a WII product for quality risk, especially the product's basis risk at the farm level, which has large negative impacts on a farmer's willingness to participate in WII.

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Appendix A The questions of the first round of survey

Survey of Potential Weather Index Insurance for Addressing Quality Shortfall in Blueberry Production

Welcome to My Survey

Thank you for participating in our survey. Your feedback is important.

1. Approximately how many acres of blueberries do you have in each of the following age categories?

0 to 2 years old

3 to 5 years old

6 to 8 years old

8+ years old (mature plants)

2. On your farm, what is the approximate average spacing between plants?

4 feet	3 feet	2.5 feet	2 feet	Don't know
○	○	○	○	○

3. For mature plantings of the following cultivars, what are your average yields? (Please indicate unit of measurement e.g. lbs/ac)

Duke

Bluecrop

Elliott

Draper

Other blueberries (please specify)

4. What proportion of your total farmland is planted to blueberries?

0% 50% 100%

5. What percentage of your berries is used on farm or directly sold off the farm (eg. farm stand, U-Pick)?

Less than 20%	21% - 40%	41% - 60%	61% - 80%	81% - 100%
○	○	○	○	○

6. If you sold to a processor, identify up to **three** products that might account for the greatest portion of your blueberry sales in the processed market.

	Products
First	
Second	
Third	

Other (please specify)

7. Compared to other producers with similar farm size, I feel

	Much lower	Somewhat lower	Average	Somewhat higher	Much higher
The amount I am willing to pay for crop insurance is					
My weather risk is					
My debt is					
My production cost is					
My average yield per acre is					
My willingness to take risks is					

8. What is your attitude towards:

	Very negative	Somewhat negative	Neutral/Don't know	Somewhat positive	Very positive
Conventional crop yield insurance					
Weather index insurance					
Flood Insurance (related to spring run-off)					
Insurance unrelated to agriculture (e.g., home or life insurance)					

9. How important are the following weather risks to your blueberry **yields**?

	Not important	Somewhat important	Of average importance	More important than average	Very important
Too much rainfall just prior to/during harvest					
Extreme (or sudden onset) of high temperatures					
Cool weather that delays harvest					
A late-Spring frost or early frost in the Fall					

Other (please specify)

10. How important are the following weather risks to the **quality** of your blueberries?

	Not important	Somewhat important	Of average importance	More important than average	Very important
Too much rainfall just prior to/during harvest					
Extreme (or sudden onset) of high temperatures					
Cool weather that delays harvest					
A late-Spring frost or early frost in Fall					

Other (please specify)

11. Please specify the **one** weather event that affected **yield** the most in your locality in the past ten years.

- Too much rainfall just prior to/ during harvest
- Extreme (or sudden onset) of high temperatures
- Cool weather that delays harvest
- A late-Spring frost or early frost in the Fall
- No significant event
- Other (please specify)

12. How long ago did the above weather event happen?

Less than 1 year ago	1 - 3 years ago	3 - 5 years ago	5 - 7 years ago	7 - 10 years ago
○	○	○	○	○

13. To what extent was your blueberry **yield** affected during that weather event?

Less than 20% loss	20 - 40% loss	41 - 60% loss	61 - 80% loss	More than 80% loss
○	○	○	○	○

14. Please specify the **one** weather event that affected **quality** the most in your locality in the past ten years.

- ○ Too much rainfall just prior to/during harvest
- ○ Extreme (or sudden onset) of high temperatures
- ○ Cool weather that delays harvest
- ○ A late-Spring frost or early frost in the Fall
- ○ No significant event
- ○ Other (please specify)

15. How long ago did the above weather event happen?

Less than 1 year ago	1 - 3 years ago	3 - 5 years ago	5 - 7 years ago	7 - 10 years ago
○	○	○	○	○

16. To what extent was the **quality** of your blueberry harvest affected by this weather event?

Less than 20% downgraded	20 - 40% downgraded	41 - 60% downgraded	61 - 80% downgraded	More than 80% downgraded
○	○	○	○	○

17. To what extent do you use the following methods to reduce farm risk?

	Never	Rarely	Sometimes	Often	Very Often
Grow diverse crops and/or have livestock					
Produce berries in different places					
Carry little debt, have savings and/or rely on AgriInvest					
AgriStability					
Crop insurance					
Forward contracts					
Rely on off-farm income					

18. Compared to other farmers, how would you rate your knowledge regarding weather index insurance (e.g., insurance to protect against too much rainfall before harvest)?

Below average	Average	Above average

19. Basis risk: *Payment may not be realized or automatic due to poor correlation between yield/quality and the weather index. In essence, there is a small chance that weather-indexed insurance leads to a payout even though one is not warranted, or that no payout is provided even though one is warranted.*

If you were to purchase weather-index insurance, you would receive a payment shortly following the outcome of the weather index. How important are the following factors in your purchase decision?

	Not important	Slightly unimportant	Of average importance	More important than average	Very important
Out of pocket cost of the insurance					
Difference between payment and actual loss					
Recommendation of insurance agent or bank manager					
Decision or recommendation of neighbours or friends					
Payments received in past years from insurance and other programs					

20. Did you make an insurance claim in 2019?

- I did not purchase insurance to cover the 2019 crop.
- No
- Yes

If yes, what was the claim amount?

21. Did you buy insurance in 2019 for any crops grown in 2020?

- No
- Yes

If yes, please specify the crops:

22. Did you make any changes in your 2020 crop insurance compared to 2019?

- No
- Yes

If yes, please indicate the changes you made or plan to make (e.g., increased or decreased coverage level, changed crops).

23. Do you plan to buy insurance in 2020 for crops grown in 2021?

- Yes
- No

If yes, please specify the crops.

24. To what extent did your farm operation participate in any of the following farm programs in the past five years?

	Never	Once	Twice	Three times	More than three times
AgriInvest					
AgriStability					
AgriInsurance (Crop yield insurance)					

25. Would you consider purchasing the **excess rainfall** insurance to cover the potential rainfall damage to blueberry quality in the future?

- Yes
- No

If no, please specify one reason.

26. Now suppose an **excess rainfall** insurance product would provide a payout of **$1,000 per acre** on average **one year in four**. What is the MOST you would be willing to pay per acre as a premium for this insurance?

$0/ac | $150/ac | $300/ac

27. If you are willing to pay for this insurance, what percentage of the total value of your blueberry crop might you consider insuring?

0% | 50% | 100%

28. Assume an **excess rainfall** insurance product would provide a payout of **$1,800 per acre** on average **one year in six**. What is the MOST you would be willing to pay per acre as a premium for this insurance?

$0/ac | $150/ac | $300/ac

29. If you are willing to pay for this insurance, what percentage of the total value of your blueberry crop might you consider insuring?

0% | 50% | 100%

30. Assume an **excess rainfall** insurance product would provide a payout of **$2,500 per acre** on average **one year in five**. What is the MOST you would be willing to pay per acre as a premium for this insurance?

$0/ac | $250/ac | $500/ac

31. If you are willing to pay for this insurance, what percentage of the total value of your blueberry crop might you consider insuring?

0% 50% 100%

32. Suppose your blueberry yield will be **about the average you have experienced** in recent years. How likely are you to purchase a weather-indexed insurance product that protects you against a reduction in product quality that would see your revenue halved?

0 (Not at all) 0.5 1 (Highly likely)

33. Now suppose your blueberry yield will be **25% below the average of past yields**. How likely are you to purchase a weather-indexed insurance product that protects you against a reduction in product quality that would see your revenue halved?

0 (Not at all) 0.5 1 (Highly likely)

34. Now suppose your blueberry yield will **exceed the average of past yields by 25%**. How likely are you to purchase a weather-indexed insurance product that protects you against a reduction in product quality that would see your revenue halved?

0 (Not at all) 0.5 1 (Highly likely)

35. Finally, suppose your blueberry yield will **exceed the average of past yields by 50% or more.** How likely are you to purchase a weather-indexed insurance product that protects you against a reduction in product quality that would see your revenue halved?

0 (Not at all) 0.5 1 (Highly likely)

36. What is your gender?

- Male
- Female
- Prefer not to answer

37. What is your age?

- 18-25
- 26-40
- 41-55
- 56-65
- 66+

38. How many years have you been farming?

39. In which municipality or district is your farm operation located?

40. Last year, did you have regular full-time OFF-FARM employment?

- Yes
- No

41. What is the approximate percentage of household income that came from OFF-FARM employment over the last 5 years?

Less than 35%	36% - 50%	51% - 70%	71% - 85%	Above 85%

42. What is your approximate average annual household income (including spouse, over the past 5 years), before taxes for both **ON-FARM** and **OFF-FARM** employment?

Less than $40,000	$40,000 - $64,999	$65,000 - $89,999	$90,000 - $114,999	$115,000 - $139,999	More than $140,000	Prefer not to answer

43. What is the highest level of schooling that you have completed?

No formal education	High school	College	University	Post-graduate/Professional degree

Appendix B The questions of the second round of survey

SHOULD BLUEBERRY GROWERS BE OFFERED PROTECTION AGAINST EXCESSIVE RAINFALL PRIOR TO HARVEST?

SHOULD BLUEBERRY GROWERS BE OFFERED PROTECTION AGAINST EXCESSIVE RAINFALL?

Welcome to the REPA Survey.

Thank you for participating in our survey. Your feedback is important. Upon completion of the survey, you will be given an opportunity to receive a Tim Hortons gift card.

This survey is conducted by the Resource Economics and Policy Analysis (REPA) Research Unit in the Department of Economics at the University of Victoria, Canada. Funding for the research is from an Agricultural Risk Initiative grant from Agriculture and Agri-Food Canada (AAFC).

Confidentiality

The data collected will be anonymous – with no personal identifiers.

1. Consent conditions of the survey are found here.

☐ I have read and agree to the consent conditions.

2. Approximately how many acres of blueberries do you have?

3. How many years have you been growing blueberries?

4. Using the following 'slider', indicate how your blueberry yields compare to those of other growers in your district.

Well below | Average | Much higher

5. Statistics Canada indicates that fruit and berry growers in BC earn an average net operating income from agriculture of $25,000. How would you rate your farm earnings relative to the BC average?

Well below | Average | Much higher

6. Approximately how much of your total household income comes from off the farm? (If question is skipped, we will assume your answer is None.)

None	50%	90%

7. In the past five years, to what extent did you participate in any of the following farm programs? **AgriInvest**?

Never	1 year	2 years	3 years	4 years	5 years

8. **AgriStability**?

Never	1 year	2 years	3 years	4 years	5 years

9. **AgriInsurance** (crop insurance)?

Never	1 year	2 years	3 years	4 years	5 years

10. To what extent do you rely on crop diversity and/or livestock to reduce farm risk? (If question is skipped, we will assume your answer is Never.)

Never	Very much

11. Would you at any time in the future consider purchasing the **excess rainfall** insurance product describ above to protect against lost revenue due to rainfall damage?

- Yes
- No

If No, please specify why:

12. Suppose an **excess rainfall** insurance product would provide a payout of **$1,000 per acre** on average **one year in four**. What is the MOST you would be willing to pay per acre as a premium for this insurance?

$0/ac	$150/ac	$300/ac

13. Now suppose an **excess rainfall** insurance product would provide a payout of **$1,800 per acre** on average **one year in six**. What is the MOST you would be willing to pay per acre as a premium for this insurance?

$0/ac $150/ac $300/ac

14. Assume an **excess rainfall** insurance product would provide a payout of **$2,500 per acre** on average **one year in five**. What is the MOST you would be willing to pay per acre as a premium for this insurance?

$0/ac $250/ac $500/ac

15. Suppose your blueberry yield will be **about the average you have experienced** in recent years. How likely are you to purchase a weather-indexed insurance product that protects you against **a reduction in product quality that would see your revenue halved**?

Not at all Highly likely

16. Now suppose your blueberry yield will be **25% below the average of past yields**. How likely are you to purchase a weather-indexed insurance product that protects you against **a reduction in product quality that would see your revenue halved**?

Not at all Highly likely

17. Now suppose your blueberry yield will **exceed the average of past yields by 25%**. How likely are you to purchase a weather-indexed insurance product that protects you against **a reduction in product quality that would see your revenue halved**?

Not at all Highly likely

18. Finally, suppose your blueberry yield will **exceed the average of past yields by 50% or more.** How likely are you to purchase a weather-indexed insurance product that protects you against **a reduction in product quality that would see your revenue halved?**

Not at all Highly likely

19. Please indicate how large the rainfall damage would have to be before you would purchase excess rainfall insurance to cover potential rainfall damage to your blueberry crop.

$0/acre	$7,500/acre	$15,000/acre

20. Please indicate how high the chance of rainfall damage would have to be before you would purchase **excess rainfall** insurance to cover potential rainfall damage to your blueberry crop:

0%	50%	100%

21. Consider the following statement: "When deciding to purchase **excess rainfall** insurance to protect against a potential loss in revenue due to rainfall damage, I do NOT consider the availability of other risk management tools." Do you agree or disagree, and to what extent?

Totally disagree	Totally agree

22. Compared to the average annual household income in BC of $80,810, I would consider my household's income to be greater or less to the following extent:

Well below	Average	Much higher