Differentiating the Effects of Risk-Aversion and Overconfidence among Agricultural Enterprises

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ABSTRACT

Differentiating the Effects of Risk-Aversion and Overconfidence among Agricultural Enterprises

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Producers are consistently faced with risks and uncertainties when making business decisions. Yet, behavioral economics shows that some producers are often irrational due to overconfident—a misperception of risks. This study proposes a feasible way to disentangle and estimate the effects of overconfidence and risk-aversion on business outcomes. This study utilizes a theoretical characterization of production behaviors and the Ontario Farm Income Database to discern the effects of risk-aversion and overconfidence. Results show that even though risk-aversion decreases the average business outcomes, moderate level of overconfidence would overweigh rationality under certain levels of risk-aversion, giving the agents competitive advantages to survive the market. The results shed light on the distribution of these behavioral traits within the population of Ontario cow-calf operations, and their effects on sector competitiveness which would not be observed otherwise.

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Chapter 1 Introduction

1.1 Background and Motivation

Producers are consistently facing risks and uncertainties (e.g. input costs, output prices, and production risks, etc.) when they deal with business decisions. Neoclassical economics argues that a rational producer takes full set of information to maximize the expected utility of profit. Yet, behavioral economics shows that this rationality assumption is often violated. Among many studies focusing on behavioral anomalies in decision-making under risk, one stand of literature has been devoted to misperception of risks. In particular, when people take less notice of the risks they face (Alpert et al 1982) or tend to believe certain outcomes are more favorable on average than the outcomes truly are (Moore et al 2007), they are overconfident. Glaser et al (2010) proposed two major facets of overconfidence: the better-than-average effect and the miscalibration effect. The former is the overestimation of one's own abilities or performances, while the latter is often manifested by the confidence interval of one's prediction that is narrower than the true variation.

Evidence of overconfidence has been found in a wide variety of research targeting specific professional fields, including lawyers, psychologists, negotiators, traders and other fields where experience and expertise are of great importance. Overconfidence is also prevalent among management personnel, such as entrepreneurs, managers and CEOs.

However, there is not much research on overconfidence among farmers although farmers who manage their own farms heavily rely upon their experience and expertise to make forecasts. According to a survey from a US compensation data firm Payscale, farmers, ranchers and other agricultural managers are listed among the top ten professions with highest percentages of overconfident workers who see themselves as the best performers at their job (Payscale 2016). A survey conducted by the Center for Agricultural and Rural Development at Iowa State University shows the evidence that overconfidence takes the form of unrealistic optimism when related to agricultural production (Jacobs et al 2015). Although this survey does not indicate the prevalence of overconfidence in corn farmers' estimate of their best fields Nitrogen needs, Jacobs et al (2015) do observe that the yield expectation of corn farmers is slightly higher than is predicted by historical data.

Some studies have also revealed the empirical evidence of overconfidence in the agricultural sector. Based on a finding from previous studies in financial markets that overconfident investors tend to overtrade than other investors, Mattos et al (2012) proposed that a negative relationship between marketing activeness and performance would suggest that farmers are overconfident. They measured the wheat market trading volume and confirmed the existence of overconfidence which is particularly strong among underperforming Canadian wheat producers. This finding shows the important role of overconfidence in agricultural production insofar as influencing farmers' business outcomes is concerned.

In the market context, studies (Hvide 2002 ; Just and Cao 2016) have shown that in theory, overconfident yet risk-averse producers would take less notice of risks they are facing to and as a result, produce more aggressively and get closer to the production level

of their risk-neutral counterparts. When it comes to market outcomes, overconfident producer may even have better chances to succeed at the extreme cases, driving the rational yet risk-averse group out of the market. So far, these results have yet been empirically tested.

This study takes advantage of a theoretical characterization of production behaviors and the Ontario Farm Income Database (OFID) to discern the effects of risk-aversion and overconfidence on market outcome and business performance. The study takes the Ontario beef sector from 2003 to 2013 as an example. OFID data offered detailed production and financial information on the enterprise level by year.

Using a model of production behavior, the study first derived a joint measure of risk-aversion and overconfidence from the OFID production data observed in the field. Since directly differentiating overconfidence from risk-aversion is not econometrically feasible, the next step of this study is to artificially generate variation on overconfidence and derive the contingent levels of risk-aversion correspondingly out of the joint measure. This step yields a full spectrum of both behavioral measures (i.e. risk-aversion and overconfidence), as well as the historically realized business performance by farm-year (such as revenue and gross profit, etc.) related to each "risk-aversion-overconfidence" combination scenario. Based on the law of large numbers, this simulated dataset enables the authors to further derive a series of econometrically consistent measures of business outcomes (such as average profit and variation of profit) and measures of welfare (*ex ante* and *ex post* certainty equivalent) which can be linked with risk-aversion and overconfidence that are revealed from the field. In the absence of large-scale surveys or questionnaires that directly report the self-evaluated level of aversion towards risk and

overconfidence, this method is a best alternative to differentiate and estimate the separate effects of risk-aversion and overconfidence on farm business outcomes.

Regression results of these performance measures on risk-aversion and overconfidence would show that even though risk-averse may decrease the expected pay-off on average, moderate level of overconfidence would over-weigh the conservativeness due to risk-aversion, leaving the producers with competitive advantages to survive the market. Market welfare analysis and the marginal effects of participating government sponsored programs, such as Business Risk Management (BRM) programs will also be discussed.

This study proposed a feasible way to empirically disentangle the effects of overconfidence and risk-aversion on business performance. The object of research is the Ontario cow-calf sector. Canada has more than 68,500 beef farms and feedlots, with the industry contributing $33 billion annually to the Canadian economy. (Canadian Cattlemen's Association). Results using historical Ontario cow-calf sector data will shed light on the distribution of these behavioral traits within the producer population and their effects on sector competitiveness, which would not be observed otherwise.

1.2 Economic Research Problem

While literature has shown the prevalence of both risk-aversion and overconfidence toward risk in business management, only a few researchers turn their sight on the interaction of these two behavioural traits in shaping the managerial and operational strategies of farm business owners (Fulton et al 2009 ; Farmer et al 2012). No research has

been conducted to incorporate these two behavioral traits in analyzing business outcomes. The inclusion of heterogeneous risk perception of farmers in studying farms' business outcomes would enable more comprehensive understanding in farmers' divergent decision-making. Cow-calf operators' business outcomes under arbitrary degrees of overconfidence and risk-aversion will be analyzed.

This research will contribute to future studies on government Business Risk Management (BRM) programs launched by Agriculture and Agri-Food Canada (AAFC). The study of how behavioral traits influence business outcomes may provide a unique perspective of the declining participation in certain BRM programs, an issue that BRM programs administrators are concerned about.

The scope of this proposed research would be confined to Ontario cow-calf farmers whose farm income tax filing information from 2003 to 2013 are recorded in the Ontario Farm Income Database (OFID).

1.3 Purpose and Objectives

The purpose of this research is to differentiate and analyze the effects of risk-aversion and overconfidence on business outcomes among agricultural enterprises.

The specific objectives of this research are as follows:

(1) To identify the research gaps by reviewing the literatures about the role of risk-aversion and overconfidence in modeling decision-making under risk

(2) To construct a conceptual framework by including overconfidence and risk-aversion in the decision-making of competitive firms.

(3) To disentangle and estimate the effects of risk-aversion and overconfidence on Ontario cow-calf farmers' business outcomes using data from the OFID.

1.4 Chapter Titles and Outlines

The remaining of this thesis starts with Chapter Two, which provides a comprehensive literature review on the role of risk-aversion and overconfidence in modeling decision-making under risk. Chapter Three discusses the conceptual framework which incorporate both risk-aversion and overconfidence in the decision-making process of competitive firms based on the work of Sandmo (1971). Chapter Four introduces the original data sets and the process of generating ready-to-use subsets, and summarizes key variables used in the analysis. Chapter Five presents the empirical models, reports the empirical results, and performs robustness check. Chapter Six summarizes the main results and implications for future studies. Some chapters include more specialized sections that can be skimmed or skipped without out missing out on the main idea of the thesis – which can be found in the Appendix.

Chapter 2 Literature Review

2.1 Chapter Introduction

This chapter provides a comprehensive background on the role of risk attitudes and risk perceptions in modeling decision-making under risk. The first part of this chapter reviews previous studies related to risk-aversion and its application in theoretical modeling as well as empirical research of choices under risk. The second part discusses the definition and category of overconfidence, a form of risk perception, and then reviewed related empirical studies.

2.2 Risk-Aversion

When decision-makers know the probability distribution of outcomes before making decisions either through calibration *a priori* or from statistics of their experience, we call they are faced with choices under risks (Knight 1921). A traditional approach to modeling behavior under risk is the expected utility approach. Von Neumann et al (1944) suggested that the expected utility approach describe the relationship between an individual's preferences and expected utility maximization. Friedman et al (1948) further used the expected utility approach to explain economic behaviors. They pointed out that risk attitudes could be explained by the curvature of the utility functions. The concave part

of an S-shaped utility function explains an individual's aversion towards risk; the convex part explains the individual is risk-loving; the linear part shows the individual is neutral to the presence of risk. The three curvature types constitute an individual's attitude towards risk—an important concept rooted in the expected utility theory.

Most interpretation of risk attitude within the expected utility framework often use utility from lottery as an example of different risk attitudes. An individual is averse to risk if the utility of the lottery is less than the utility of the expected value of the same lottery. The lottery analogy of risk attitude implies (a) risk-aversion is equivalent to concavity of the expected utility function, and (b) the degree of risk-aversion is related to the curvature of the utility function (Varian 1992). The now widely accepted metaphor was established based on the works of Arrow (1971) and Pratt (1964) which defined a commonly used measure of risk attitude. This metric, known as the Arrow-Pratt measure of absolute risk-aversion, is defined as the second derivative of the utility function divided by the first derivative. This normalized measure of risk attitude is invariant to changes in the expected utility function, thus a better measurement of risk attitude than using the second derivative of the utility function. Since then, the Arrow-Pratt coefficient of risk-aversion has been widely applied to conceptual models of decision making under uncertainty.

An important category of such conceptual models is production decision making under uncertainty. Before the introduction of risk-aversion to classic production theory, firms are assumed to be maximizers of their expected profits. Static production models based on early production theory only support the case of risk neutrality and rule out all possible responses of production to changes in risk except for some special circumstances. This argument is an unsatisfactory representation of firms' decisions because risk-aversion

is prevalent in the marketplace. The seminal work of Sandmo (1971) provides comparative static results of production decision with the presence of price uncertainty. Under the expected utility framework which assumes that firms maximize the expected utility of their profits, Sandmo proposed a model which incorporates price risk and producers' risk attitudes into firms' decision making in a competitive market. Sandmo discussed the impact of risk-aversion on production, welfare and competition, and reached to a prominent result that risk-averse producers would hedge against output price risk by producing a smaller quantity of output than they would have when faced with a certain output price.

Sandmo's work has inspired considerable number of studies which enhanced the understanding of production decision-making under risks and uncertainty. Based on Sandmo's model, Leland (1972) proposed an analytical framework capable of examining different behavioral modes of a monopolistic firm facing stochastic output demand, and concluded that risk-aversion results in a smaller production output. Turnovsky (1973) extended Sandmo's model to deal with the case where firms can make *ex post* production adjustment and found an ambiguous effect of risk-aversion on production. Batra et al (1974) applied Sandmo's paradigm to their study of input demand for a competitive firm facing price uncertainty and found that risk-averse firms produce a smaller output than under certainty because they utilize smaller quantities of inputs.

In addition to addressing input and output demand, Sandmo's model has also been used to explore firms' decisions in adopting institutional or scientific innovations. Holthausen (1979) and Feder et al (1980) drew upon Sandmo's framework and found that a partially hedging producer increases her futures market involvement by trading more actively if the producer has a constant level of absolute risk-aversion. Working on the same

approach, Feder (1982) studied innovation adoption behaviors of agricultural enterprises and identified the positive relationship between farm size and adoption decisions for a given level of risk-aversion. A comprehensive survey by Feder et al (1985) discusses producers' adoption decisions when faced with various aspects of uncertainty. Sandmo's model is also widely used in various topics of agricultural economics. Besides agricultural firms' decisions in innovation adoption (Feder et al 1985), a wide of studies also include farmers' acreage decisions under risks (Chavas et al 1990), farmers' responses of agricultural supply to their distinct risk preference classes, effects of wealth changes on different measures of farmers' risk attitudes (Bar-Shira et al 1997), production effects of agricultural income support programs (Hennessy 1998), welfare effects of food security policies (Bellemare et al 2013) and so forth.

Sandmo's theoretical propositions are partially challenged by some scholars. Finkelshtain et al (1991) show that results from Sandmo's model under output price uncertainty may not hold without certain conditions. Their characterization of producers' behavior includes both risk attitudes and ordinal preferences for goods. Using Arrow-Pratt measure of risk-aversion as the univariate measure, as they pointed out, is insufficient to determine whether more output or less production leads to expected profit maximization of a risk-averse producer. Lee et al (2015) designed a lab experiment to test Sandmo's prediction that risk-averse producers produce less when facing price uncertainty than facing certain price. Their experiment results show that firm managers produce more under price uncertainty than facing certain price, which is contradicted to the prediction of Sandmo's theory. They also found that in the presence of price uncertainty, production level decreases as price uncertainty increases. These papers along with other evidence show

some different empirical or experimental results from the original results of Sandmo's model. Therefore, it is worthwhile to use different types of data (e.g. fields or laboratory data) and add more assumptions (e.g. the existence of other influential factors) to continue verifying Sandmo's results.

In terms of production decision-making under uncertainty, risk-aversion is not the only influential factor. For example, Chavas et al (1996) developed a method which allows for joint analysis of the effect of risk preferences and technology on producers' production decision and welfare. A recent study by Hailu et al (2017) shows that farmers' willingness to pay for genotyping service is determined by their risk attitudes, belief in genomics and social interactions. Some other behavioral characteristics can also affect production behaviors when dealing with uncertainty. The next section discusses in detail one of such behavioral traits, overconfidence.

2.3 Risk Misperception: Overconfidence

2.3.1 Overconfidence and its origin from psychology

The decision-making in farm production, like other judgments about uncertain events, includes the use of numbers and the assessment of diverse types of probability. Kahneman et al (1973) proposed that people cannot make correct decisions when there are complex numerical predictions and probability calibrations; instead people use heuristics—simple and intuitive rules focusing on a single aspect of a complex issue and meanwhile ignoring other aspects—to form their judgments when faced with uncertainty. Such heuristics under certain circumstances generate cognitive biases (Kahneman et al

1972), which are regarded as systematic patterns of cognition deviation from norm or rationality in human judgment (Haselton et al 2015). For example, as one of the three heuristics summarized by Tversky et al (1974), the anchoring and adjustment effect describes the human behaviour to shift not far away from a readily available anchoring estimate. This heuristic of having one's judgment anchored and adjusted makes a person biasedly believe in his or her well-considered estimate, and leads a cognitive bias called the overconfidence effect (Stephan 1999).

Among all types of cognitive biases, overconfidence is often regarded as one of the most pervasive phenomena (Glaser et al 2010). Plous (1993) claimed that no problem in judgment and decision-making is more prevalent and more potentially catastrophic than overconfidence. Overconfidence refers to the phenomenon that a person's subjective confidence in judgments is greater than the objective accuracy of those judgments. Numerous psychology studies have shown the existence of overconfidence. Many researchers have reported that people are overconfident when answering general-knowledge questions (Lichtenstein et al 1982 ; Fischhoff et al 1977). Tetlock (2005) claimed that experts with profound case-specific knowledge are more likely to be overconfident about their forecasts. Barber et al (2001) showed that gender difference results in different overconfidence levels between mean and women. Klayman et al (1999) found stable individual differences in overconfidence such that more confident people tend to be more overconfident. Abreu et al (2012) found that overconfidence strengthen the positive association between information availability and the frequency of trading. Differences in probabilistic thinking between people with different cultural background can also be attributed to their different levels of overconfidence. For example, Yates et al

(1989) found that subjects from mainland China were more overconfident than those from the United States or Japan.

The notion of overconfidence has also been extended to interdisciplinary fields of psychology. Several types of overconfidence have been summarized throughout previous behavioral studies in economics and finance, including overestimation of one's standing, overplacement of one's position, overprecision of one's prediction, positive illusion of one's control and so forth. Evidence of these types of overconfidence is found in an overwhelming body of research targeting specific professional fields including psychologists (Oskamp 1965), lawyers (Wagenaar et al 1986), negotiators (Neale et al 1985), constituency (Ortoleva et al 2015), entrepreneurs (Camerer et al 1999 ; Bernardo et al 2001 ; Koellinger et al 2007), managers and executives (Russo et al 1992 ; Malmendier et al 2005), traders (Kyle et al 1997 ; Glaser et al 2007), security analysts and economic forecasters (Deaves et al 2010), etc.

2.3.2 Two categories of overconfidence

Glaser et al (2010) categorized those many facets into two major manifestations of overconfidence: the better-than-average effect and the miscalibration effect. The better-than-average effect is the most intuitive and well-known facet among many types of overconfidence. Overestimation and overplacement are two major manifestation of the better-than-average effect. Overestimation is a phenomenon that a person's perceived value is higher than the true value itself. Researchers found that there is a tendency for people to be unrealistically optimistic about their forecasts on future events (Weinstein 1980), to

overestimate their ability to perform well on tasks (Lichtenstein et al 1982), to overrate their performance in self-evaluations (Taylor et al 1988), and to overestimate the precision of private information (Glaser et al 2004). Overplacement happens when people think their qualities or abilities are superior to the average level in a social context. In a perhaps most cited example of the pervasive overplacement phenomenon, Svenson (1981) found that 93% of American drivers think their driving skills are above the median level.

A mathematical description proposed by Just and Cao (2016) translates the better-than-average effect to an upward biased first moment of a probability distribution regarding one's own abilities. Similarly, Just and Cao (2016) describe the miscalibration effect as a downward biased second central moment of a probability distribution forecast for some external event.

The miscalibration effect denotes the phenomenon that people choose overly narrow confidence intervals or probability distributions when asked for a range that is supposed to contain a true value with a certain probability. To put it differently, a person is subject to miscalibration if this person is "too certain" about some event. The degree of miscalibration can be measured in several different ways. In considerable empirical and experimental studies, the measurement of overconfidence captures the idea that people underestimate the variance of signals. The fractile method is often used to measure the degree of miscalibration in interval estimates. For example, an agent may repeatedly form beliefs about the 90% confidence interval for a stock price in the coming week. The agent would display overconfidence if the actual price falls in her believed 90% confidence interval less than 9/10 of the time. In fact, the hit rates (i.e. probabilities that the true value

falls in the believed interval) in many studies using 90% confidence interval are less than 50% (Russo et al 1992) and in extreme cases, about 30% (Alpert et al 1982).

The effect of the miscalibration among stock market traders has been widely discussed especially in the field of behavioral finance. Results from numerous theoretical (Wang 1998 ; Benos 1998 ; Odean 1998 ; Gervais et al 2001) literature shows that overconfident investors trade more aggressively and more frequently. However, empirical and experimental work show diverse findings regarding the relationship between overconfidence and trading volume. Odean (1999) analyzes the trading behaviors of 10,000 individual brokers. Based on the indirect evidence that these traders reduce their returns by trading, Odean found the existence of excessive trading volume in the market. Barber et al (2001) uses gender as an instrument for overconfidence in their testing of the theoretical prediction that overconfident investors have larger trade volume. They refer to the fact that male investors trade more excessively than female investors and found that compared with females, males earn less returns because of their higher frequency of trade caused by their higher level of overconfidence. Statman et al (2006) uses market level data and concludes that the high trading volume observed among overconfident traders is associated with their previous high rate of returns. In a direct test of the relationship between miscalibration and trading volume, Glaser et al (2007) asked online stock traders to answer questionnaires designed with questions about overconfidence measures including miscalibration effect, and found that, contrary to the predictions of popular overconfidence models, the miscalibration effect and investors' trading volume are not related. Biais et al (2005) also found no relationship between trading volume and miscalibration in their experimental study. Besides trading volume, miscalibration can also affect other performance measures

of overconfident agents, including their expected utilities, returns to work and volatilities of returns. Kyle et al (1997) investigated the miscalibration effect using a duopoly model. They found that traders whose overconfidence takes the form of miscalibration might earn higher expected profits than rational traders, including themselves if they traded with rationality. On the contrary, Odean (1998) found that overconfident traders have lower expected utility than their rational opponents.

Throughout the literatures, the different facets of overconfidence, such as the better-than-average effect and the miscalibration effect, are often used interchangeably and subsumed as overconfidence. In this thesis, farmers' overconfidence is more closely related to the notion of the miscalibration effect. The business risks facing farmers, such as price risk and production risk, are random variability inherent in farmers' decision making process (Patrick 1998). The perceived variability of overconfident farmers is smaller than the actual variability, which is coincide with the definition of miscalibration.

2.4 Coexistence of Risk-aversion and Overconfidence

In this thesis, I examine the potential impacts of overconfidence and risk-aversion on farmers' business outcomes in competitive markets based on Sandmo's expected utility framework. Just and Just (2016) demonstrate that the estimation of overconfidence and risk-aversion from field data may be econometrically intractable. Empirical work shows that it is difficult to discern both risk-aversion and overconfidence from behavioral traits of individuals. In the absence of a clear way to proceed econometrically, a theoretical characterization of equilibrium behavior may be an important first step.

Chapter 3 Conceptual Framework

3.1 Chapter Introduction

The theoretical model in this thesis is constructed based on the model for competitive firms under price uncertainty proposed in the work of Sandmo (1971). A major result of Sandmo's paper is that risk-averse producers hedge against output price risk and uncertainty by producing less than they would have when faced with a certain output price. In this thesis, this claim will be tested when considering the impact of overconfidence—one manifestation of firms' risk misperception. Therefore, the theoretical framework of Sandmo's model is shown below.

3.2 Sandmo's Model for Competitive Firms under Uncertainty

In Sandmo's model, firms are assumed to maximize their expected utility of profits by choosing the level of output before knowing the output price. The profit function, $\pi(x)$, can be written as

(1) $\pi(x) = px - C(x) - B,$

where $p \in \mathbb{R}_+$ is the uncertain output price and is assumed to be a nonnegative random variable with its expected value $E(p) = \mu$. x is the output level. The cost function

of the first has two components. $C(x)$ is the variable cost which is a function of output x. B is the fixed cost. Thus, the expected profit function $E[\pi(x)]$ can be written as

(2) $$E[\pi(x)] = E[px - C(x) - B] = E(p)x - C(x) - B = \mu x - C(x) - B.$$

By substituting equation (2) into equation (1), the profit function can be expressed as a function of expected profit plus the difference between expected and true revenue such that

(3) $$\pi(x) = px - C(x) - B = E[\pi(x)] + (p - \mu)x.$$

Sandmo further assumes that the firm is averse to risk by summarizing the firm's risk attitude using a concave, continuous and twice-differentiable von Neumann-Morgenstern utility function such that

(4) $$u'(\pi) > 0, u''(\pi) < 0.$$

Therefore, the firm's expected utility of profits is

(5) $$E\{u[\pi(x)]\} = E\{u[px - C(x) - B]\},$$

And the firm's objective function can be written as

(6) $$L = \max_x E\{u[\pi(x)]\} = \max_x E\{u[px - C(x) - B]\}.$$

The first-order (FOC) and the second-order condition (SOC) are necessary and sufficient conditions for a maximum. These two conditions can be written as

(7) $$FOC = \frac{\partial L}{\partial x} = E\{u'(x)[p - C'(x)]\} = 0,$$

and

(8) $SOC = \frac{\partial^2 L}{\partial x^2} = E\{u''(x)[p - C'(x)]^2 - u'(x)C''(x)\} < 0.$

Given the foregoing, Sandmo solves the firm's optimal output level under output under price uncertainty. Since output price p is a random variable with expected value μ, subtracting $E[u'(\pi)\mu]$ from both sides of the first-order condition in equation (6) can form

(9) $E[u'(x)(p - \mu)] = E\{u'(x)[C'(x) - \mu]\}.$

Given equation (3) and $u'(\pi) > 0$ in equation (4), we can know that

(10) $\begin{cases} u'(\pi) \leq u'[E(\pi)] \text{ if } p \geq \mu \\ u'(\pi) \geq u'[E(\pi)] \text{ if } p \leq \mu \end{cases}$

which follows immediately that

(11) $\begin{cases} u'(\pi)(p - \mu) \leq u'[E(\pi)](p - \mu) \text{ if } p \geq \mu \\ u'(\pi)(p - \mu) \leq u'[E(\pi)](p - \mu) \text{ if } p \leq \mu \end{cases}.$

Therefore, for all output price level p, there must be

(12) $u'(\pi)(p - \mu) \leq u'[E(\pi)](p - \mu).$

Taking expectations on both sides of equation (12) and knowing that $u'[E(\pi)]$ is a constant, we obtain

(13) $E[u'(\pi)(p - \mu)] \leq u'[E(\pi)]E(p - \mu) = u'[E(\pi)][E(p) - \mu] = 0.$

As per equation (9), equation (13) can be written as the following equation

(14) $E[u'(x)(p - \mu)] = E\{u'(x)[C'(x) - \mu]\} = u'(x)[C'(x) - \mu] \leq 0,$

where $u'(x)$, $C'(x)$, and μ are all given numbers. Since equation (4) marginal utility is always positive, equation (14) further implies that

(15) $C'(x) \leq \mu.$

Therefore, when facing output price uncertainty, the firm chooses its optimal output level that suffices equation (15). It means the marginal cost of producing an optimal level of output is less than the marginal profit of producing the optimal output which equals the expected price of output. In other words, the firm facing output price uncertainty produces less than the optimal output when output price is certain to maximize its profit. This argument has been tested in many empirical or experimental researches which may or may not support Sandmo's theoretical results. The next section introduces how Just and Cao (2016) model overconfidence as another behavioral trait besides risk-aversion using Sandmo's framework and the theoretical findings of their extended model.

3.3 Modelling Overconfidence

This thesis uses the theoretical framework developed by Just and Cao (2016). The miscalibration dimension of overconfidence is incorporated in this model. Overconfidence is represented by a decrease in the perceived variance of the distribution facing decision-makers, which further indicates that we can use a coefficient on the random variable of interest to represent the value of overconfidence. Individual perceived price variation is such a parameter representing one's degree of overconfidence because it shows the perception deviations from the true state of knowledge. The true distribution of price is described using a two-parameter probability density function, $f(s|\mu, \sigma^2)$. $s \in \mathbb{R}$ is the outcome of random wealth; μ and σ^2 are parameters showing the true mean and variance of the distribution, in this case, prices. An overconfident producer's perceived price

distribution can be given by $f(s|\mu_g, \sigma_g^2)$ where perceived variance of price $\sigma_g^2 < \sigma^2$, and/or $\mu_g > \mu$. Therefore, overconfidence parameter can be written as $\psi = \frac{\sigma_g}{\sigma}$. This measure of overconfidence is named diminishing deviation (DD) in the original theoretical framework because it represents the degree to which the individual miscalibrate the extent of the standard deviation.

In accordance with Sandmo's model under the expected utility framework, the modeling of overconfidence assume that the objective of the firm is to maximize the expected utility of profits given the DD parameter. The firm's profit function is thus given by:

(16) $\pi(x) = px - C(x) - B$

where $p \in \mathbb{R}_+$ is the price of output; $C(x)$ is the variable cost; $x \in \mathbb{R}_+$ is the level of output, $B \in \mathbb{R}$ is the fixed cost. The firm thus maximizes

(17) $E\{u[px - C(x) - B]|\mu_g, \sigma_g^2\} = \int_0^\infty u[px - C(x) - B] f(p|\mu_g, \psi^2\sigma^2)\, dp.$

The first order condition for maximizing (17) can thus be written as

(18) $L = \frac{\partial E\{u(x)|\mu_g, \sigma_g^2\}}{\partial x} = E\{u'[px - C(x) - B][p - C'(x)]|\mu_g, \sigma_g^2\} = 0.$

The first order Taylor-series approximation of the marginal utility function around the perceived mean μ_g is:

(19) $u'[\pi(x,p)] \approx u'[\pi(x,\mu_g)] + u''[\pi(x,\mu_g)] \cdot x(p - \mu_g).$

Thus, the first order condition in (18) can be approximated as:

$$(20) \quad L = \frac{\partial E\{u(x)|\mu_g, \sigma_g^2\}}{\partial x} = E\{u'[px - C(x) - B][p - C'(x)]|\mu_g, \sigma_g^2\}$$

$$= E\left\{\left[u'\left(\pi(x, \mu_g)\right) + u''\left(\pi(x, \mu_g)\right) \cdot x(p - \mu_g)\right][p - C'(x)]\middle|\mu_g, \sigma_g^2\right\}$$

$$= u'[\pi(x, \mu_g)][\mu_g - C'(x)] + u''[\pi(x, \mu_g)]x\psi^2\sigma^2 = 0.$$

The economic intuition behind (20) can be seen by dividing (20) by the marginal utility of wealth, $u'[\pi(x, \mu_g)]$, and the variance of price, σ^2.

$$(21) \quad u'[\pi(x, \mu_g)][\mu_g - C'(x)] + u''[\pi(x, \mu_g)]x\psi^2\sigma^2$$

$$= [\mu_g - C'(x)] + \frac{u''[\pi(x,\mu_g)]}{u'[\pi(x,\mu_g)]}x\psi^2\sigma^2$$

$$= [\mu_g - C'(x)] - R_A\psi^2\sigma^2 x$$

$$= \frac{\mu_g - C'(x)}{\sigma^2} - 2R_A\psi^2 x = 0,$$

where $R_A = -\frac{u''[\pi(x,\mu_g)]}{u'[\pi(x,\mu_g)]}$ is the Arrow-Pratt coefficient of absolute risk-aversion. After rearrangements, the last line of equation (21) can be written as:

$$(22) \quad R_A\psi^2 = \frac{\mu_g - C'(x)}{2x\sigma^2}$$

If the individual were risk neutral, $R_A = 0$, and expected profit maximization implies $\mu_g = C'(x)$. If we assume the individual is risk-averse, then $R_A\psi^2 > 0$ which implies that $\mu_g > C'(x)$. Moreover, with the decrease in perceived variance represented by a decline in ψ, the term on the right-hand-side of (22) draws closer to zero, pushing the condition in (22) closer to the risk neutral result. Therefore, the firm displaying diminishing deviation will produce more than a firm with the same aversion to risk but accurately

perceiving the variance in price. The smaller ψ is, the larger x will be. This inference can be coupled with Sandmo's result to find the tension between overconfidence and risk-aversion in behavior under price risk.

3.4 Welfare for the Individual Producer

The welfare measures for overconfident producers are also provided by Just and Cao. For a producer having accurate risk perception, the *ex post* producer surplus in equilibrium is defined as $\Pi_i^* \equiv E\big(\pi_i(x_i^*, X_i^*)\big) = P(X_i + x_i^*)x_i^* - C(x_i^*) - B$, which is the true average net benefit disregarding overconfidence. Producers' welfare can be represented by certainty equivalent. The *ex post* certainty equivalent is $EU\{\pi[x^*(\psi_i)]|\sigma^2\} = U(CE^{ex\,post})$, or the true certainty equivalent of choosing the level of equilibrium level of output. The *ex ante* certainty equivalent is $EU\{\pi[x^*(\psi_i)]\big|\psi_i^2\sigma^2\} = U(CE^{ex\,ante})$. It is the level of certainty equivalent perceived by the overconfident producers before knowing the true outcomes. Therefore, the *ex ante* certainty equivalent is affected by overconfidence through both the selected production level and the misperception of the distribution. Alternatively, the *ex post* certainty equivalent is the realized certainty equivalent affected by overconfidence only through the choice of equilibrium production level. I anticipate that the overconfidence effect will enable a risk-averse frim to have larger *ex ante* certainty equivalent. I can also calculate the cut-off point of risk-aversion where the *ex post* certainty equivalent of the overconfident firm starts to be larger than those with rational perception of risk, thus, together with the increased consumer surplus, implying an increase in total welfare.

In theory, certainty equivalent is defined as

(24) $u(CE_i) = E[u(\pi_i)]$.

The use of a first order Taylor-expansion around the point Π_i^* of the left side of (24) and a second order expansion around the same point for the right side can yield

(25) $u(\Pi_i^*) + u'(\Pi_i^*)\left(CE_i^{ex\ post} - \Pi_i^*\right)$

$$\approx E\left\{u(\Pi_i^*) + u'(\Pi_i^*)[\pi_i(x_i^*, X_i^*) - \Pi_i^*] + \frac{1}{2}u''(\Pi_i^*)[\pi_i(x_i^*, X_i^*) - \Pi_i^*]^2\right\},$$

or

(26) $CE_i^{ex\ post} \approx \Pi_i^* + \frac{1}{2}u''(\Pi_i^*){x_i^*}^2\sigma^2 = \Pi_i^* - \frac{1}{2}R_{Ai}{x_i^*}^2\sigma^2$.

For a risk-averse producer, the *ex post* CE is smaller than the expected profit Π_i^* with the difference $-\frac{1}{2}R_{Ai}{x_i^*}^2\sigma^2$ determined by the absolute risk-aversion R_{Ai} (evaluated at Π_i^*), the level of the actual production (a function of risk-aversion and overconfidence level) and the real variance of price σ^2. If the producer displays overconfidence with $0 < \psi_i < 1$, the *ex post* CE is always smaller than their own *ex ante* CE

(27) $CE_i^{ex\ post} \approx \Pi_i^* - \frac{1}{2}R_{Ai}{x_i^*}^2\sigma^2 \leq \Pi_i^* - \frac{1}{2}R_{Ai}{x_i^*}^2\psi_i^2\sigma^2 \approx CE_i^{ex\ ante}$.

Chapter 4 Data

4.1 Chapter Introduction

The purpose of this chapter is threefold. This chapter first introduces the two sources of data of this study, the Ontario Farm Income Database (OFID) and Statistics Canada's feeder cattle price data, and explains why these two data sets are suitable for the thesis study. The second section of this chapter presents the process of generating three subsets from the original data sets and the characteristics of the three data sets. The last section provides definitions and summary statistics of all the important variables that are useful for empirical research.

4.2 Data Sources

4.2.1 Ontario Farm Income Database (OFID)

The financial performance of the Ontario cow-calf sector has been analyzed using the Ontario Farm Income Database (OFID). The OFID is a longitudinal database collected by Ontario Ministry of Agriculture, Food and Rural Affairs (OMAFRA) to administer the suite of Business Risk Management (BRM) programs under Canada's agricultural policy frameworks. The OFID is compiled from operational and financial information of tax-filing farm operators who reported farming income in Ontario (Uzea et al 2014). As a tax-

based data set, the OFID provides a unique opportunity to evaluate farm financial viability which is unavailable with traditional farm sector data sets (Weersink et al 2012). The OFID used in this study contains data for each year between 2003 and 2013. The OFID consists of five parts: (1) non-financial characteristics of the operator; (2) income and expense data from tax files; (3) program payment data; (4) beginning and ending inventory data of commodities; and (5) production data. Some parts of the OFID are useful to this research, including farm financial information, non-financial characteristics and production data.

The use of the OFID is important to this study for four reasons:

(1) The OFID is a farm-level data set. Farm-level data are more suitable for this study than operator-level data which may also come from large-scale censuses or tax-based data sets. In operator-level data from many census or taxation data sets, associated farm operators are often regarded as separate farm owners even though they have arm's-length relationship such as working in the same farm. Each associated operator is subject to an income classification which is lower than the total farm-level income (Weersink et al 2012). Therefore, using operator-level data in a farm-level study often overestimates the number of farms that are operating and underestimates the income of farms managed by operators with arm's-length relationship. As a farm-level data set, the OFID converts operator-level data into farm-level aggregations (Poon 2013) by linking individual farm operators with their respective operations.

(2) The data from the OFID are collected directly from farm income tax-filing Ontario farmers, including cow-calf operators who are the research objects. In some behavioral economics studies, research data are collected from lab experiments

where researchers use experiment participants' answers to questionnaires or their choices under given scenarios to mimic the responses of completely different research objects. For research convenience and cost-effectiveness, scholars often hire college students as experiment participants to simulate the behavior of professionals. This method may not be effective when questions or scenarios are profession-specific. For this reason, using data directly from the research objects makes the sample more representative.

(3) The OFID is based on the objective information of farmers. It does not contain farmers' subjective self-evaluation on their behavioral traits. A major highlight of this study is obtaining farmers' behavioral traits information without asking them to answer questions in questionnaires or experiments. The financial, non-financial and production data from the OFID are sufficient to derive farmers' behavioral traits using the theoretical model of this thesis.

(4) The OFID has adequate sample size. Surveys or questionnaires that contain detailed questions on farmers' behavioral traits, financial and non-financial characteristics are often too costly to be conducted in a large scale. The size of the OFID is much larger than the size of ordinary surveys. 10,836 farms have ever been classified as cow-calf operations or feedlots during the sample period.

Farms were selected based on the sectors and subsectors they belong to. In the OFID, the beef sector has two subsectors: cow-calf operations and feedlots (which are named "beef cattle" and "cattle feeder" respectively in the OFID). The cow-calf operation is a subsector where calves are born and raised up to the weaning age. A relatively small proportion of cattle from the cow-calf subsector are retained on-farm as replacements or

sold directly to slaughters, while the majority of cow-calf operations' products—feeder cattle—are sold to feedlot operations where cattle are fed until reaching the optimum weight for being sold to a processing plant (Canadian Cattleman's Association 2017). In this thesis study, only cattle farms from the cow-calf subsector are selected for two reasons.

(1) The first reason for studying the cow-calf subsector only is that there are significant differences between the cow-calf and the feedlot subsector in terms of their positions on the beef value chain and the value and distribution of key financial indicators. As is shown in the flowchart of Ontario beef production in Figure 4.1, farmers in the cow-calf and feedlot subsector are located on different positions on the beef value chain. Cow-calf operators and feedlot operators use different production plans to make production-related forecasts. They also face different kinds and levels of risk. To avoid estimation biases, the scope of research objectives is confined to farms from the cow-calf subsector in Ontario.

Table 4.1 compares the summary statistics of key financial indicators between 1,167 cow-calf operations and 129 feedlots from a balanced panel subset of the OFID. All beef farmers in this subset were consistently categorized as cow-calf or feedlot operators in each year from 2003 to 2013. Summary statistics in Table 4.1 indicate that farms in the cow-calf subsector earn much less total operating revenue and incur much less total operating expense than farms in the subsector of feedlot in general. This reflects the fact that the average quantity of cattle in feedlot operations is much more than the number of cows and calves in cow-calf operations. The reason behind this phenomenon is the different production levels to achieve economies of scale in the cow-calf and the feedlot subsector.

Figure 4.1 Flowchart of Beef Production in Ontario

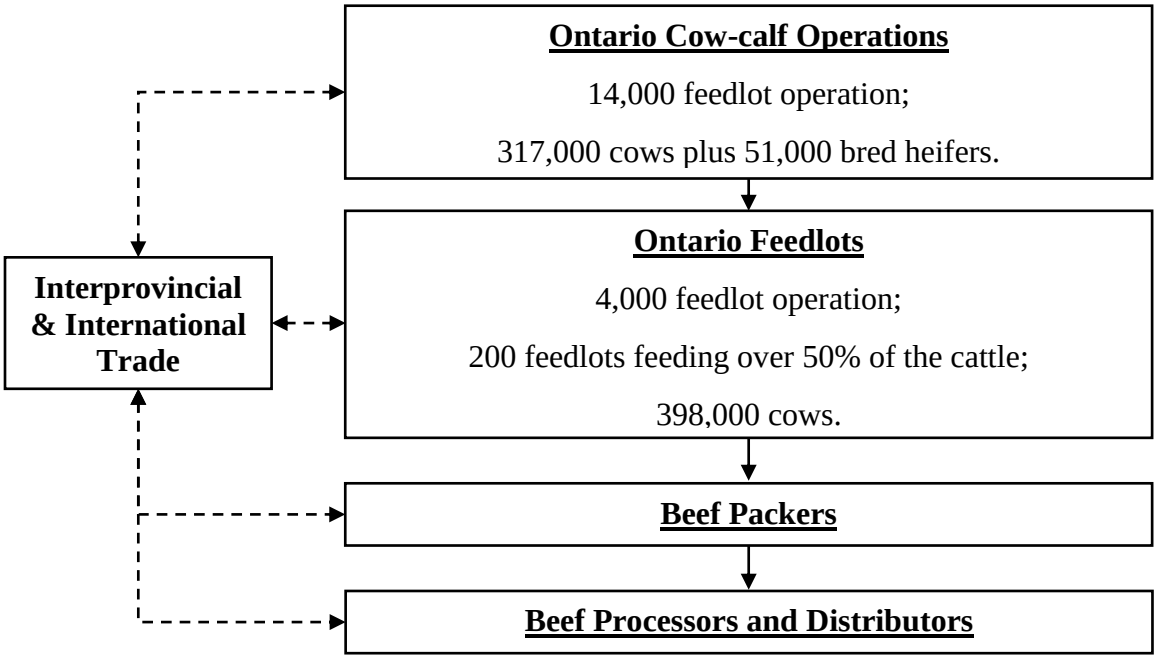


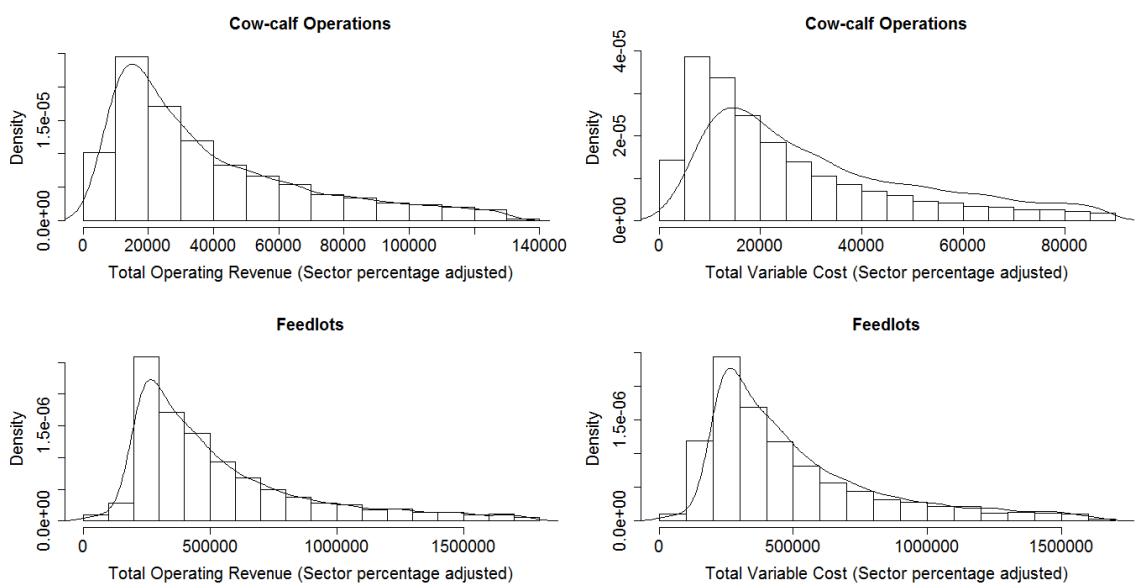
Table 4.1 Summary Statistics of Key Financial Indicators of the Cow-calf and the Feedlot Subsector

	Total Operating Revenue		Total Variable Cost	
	Cow-Calf	Feedlot	Cow-Calf	Feedlot
Observations	12,837	1,419	12,837	1,419
Minimum	291.25	188,647.80	0	0
Q_1	16,627.83	422,546.30	10,311.03	373,799.00
Median	31,069.96	721,726.20	19,783.00	664,400.90
Q_3	62,553.56	1,512,667.00	41,653.98	1,422,010.00
Maximum	1.26×10^7	5.39×10^7	1.08×10^8	6.07×10^7
Interquartile Range	45,925.73	1,090,121.00	31,342.95	1,048,211.00
Mean	55,632.17	1,781,393.00	40,588.17	1,680,000.00
Standard Deviation	250,699.40	3,443,240.00	213,356.50	3,426,334.00

Note: All currencies are in Canadian Dollars; $\mathrm{CPI}_{2007} = 100$.

Figure 4.2 shows the distributions of selected key financial indicators of the cow-calf and the feedlot operations. To facilitate observing the distribution differences between the two subsectors, extreme values that are greater than the sum of the 75th percentile point value and 1.5 times of the interquartile range are excluded when drawing the four histograms. The magnitude difference in total operating revenue and total variable cost between the cow-calf and the feedlot subsector can be easily observed. Moreover, the distributions of these two performance measures are not identical between the two subsectors. If we study the entire beef sector and not separating feedlots from cow-calf operations, the farm-size related distributions will be multimodal.

Figure 4.2 Histograms of Total Operating Revenue and Total Variable Cost in the Cow-calf and the Feedlot Subsector



Note: Outliers that are greater than $Q_3 + \frac{3}{2}\text{IQR}$ are excluded in the four descriptive histograms. Q_3 is the 75th percentile point. IQR is the interquartile range.

(2) The second reason explains why the cow-calf subsector is a more appropriate object of study given data from the OFID. Compared with the Ontario cow-calf industry which has about 14,000 operations, there are only about 4,000 feedlot producers in Ontario (Livestock Research Innovation Corporation Board 2011). In the OFID, feedlot operations account for 11.7% of farms in the beef sector compared with the 86.5% share of the cow-calf subsector; with only 5,608 farm-year observations, the size of feedlot operations cannot fully satisfy the Law of Large Numbers requirement of the data generating process. The size of the cow-calf operations meet the requirement, thus a more appropriate object of research from the data perspective. A detailed discussion of the Law of Large Numbers requirement can be found in Chapter 4.3.

4.2.2 Price Data

The price data is obtained from Statistics Canada's main socioeconomic time series database, which is also known as CANSIM. By referring to monthly data from Farm Product Prices Survey (FPPS) and Farm Product Price Index (FPPI), CANSIM Table 002-0043 reports monthly prices of farm products, including national and provincial cattle prices in Canada. Among all the cattle prices reported, monthly Ontario feeder cattle prices are utilized in this study. Feeder cattle are weaned calves that are mature enough to be placed in a feedlot where they will gain weight prior to slaughter (Womach 2005). Therefore, feeder cattle prices best represent the price levels at which cow-calf farm operators, the object of this study, sell their steers or cows to downstream feedlots. Since

the FPPI has already taken inflation into account, there is no need for the resulting feeder cattle prices to adjust for CPI.

4.3 Data Generating Process

By merging the OFID with Ontario monthly feeder cattle prices from CANSIM 002-0043, the original data set (Dat0) is generated. Data cleaning is conducted to ensure that all entries are valid and that this original data set has no null values for important variables. This original data set is a balanced panel data containing 12,837 farm-year observations, or 1,167 individual cow-calf farms in Ontario from 2003 to 2013. Put another way, farmers in the original data set have been consistently categorized into the cow-calf subsector in all sample years. Being retrieved from this original data set, three data sets are employed for summary statistics and empirical analysis in the following research.

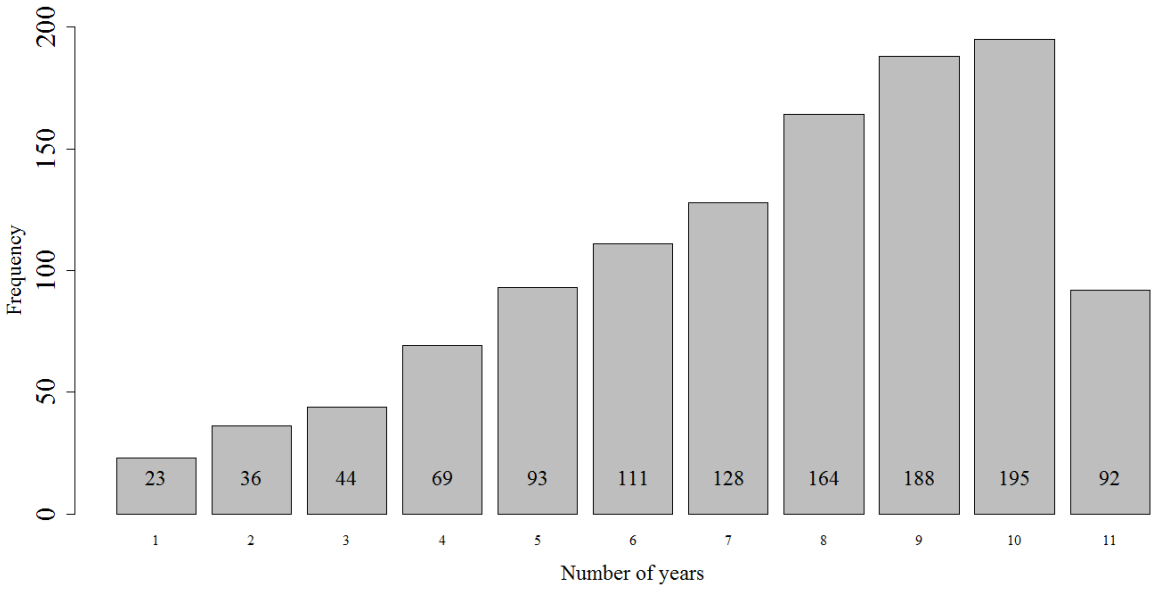
Being retrieved from the original data set, the first subset (Dat1) follows the idea of an important inference of the theoretical model. In Equation (22), $R_A\psi^2 = \frac{\mu_g - C'(x)}{2x\sigma^2}$. For firms to not withdraw from the market, the perceived price μ_g cannot be lower than the marginal cost $C'(x)$. The multiplication behavioral term $R_A\psi^2$, hence, must be greater than zero. Since $\psi^2 > 0$, the measure of risk-aversion R_A must be positive, which means that all agents are assumed to be risk-averse. Therefore, Dat1 trims off farm-year observations reporting non-risk-averse attitude towards risk.

Dat1 also excludes extreme behavioral trait values measured by $R_A\psi^2$. Some farm-year observations from the original data set are not included in Dat1 because their joint product behavioral terms, $R_A\psi^2$, are extremely large or small. In the calculation of $R_A\psi^2$,

the production quantity x in the denominator is derived from total operating revenue / feeder cattle's price. The total operating revenue reported in some farm-year observations are close to zero, making the quantity produced much higher than normal and thus resulting in the extremely large joint product behavioral term. By including only those observations that lie within the $(10^{th}, 90^{th})$ percentile range of all positive behavioral trait values, the extremely large values of $R_A\psi^2$ are excluded. Since no aggregated market inference will be made, removing the extreme values does not affect the validity of results.

Due to the removal of extreme behavioral values, 24 farms are completely removed because their multiplication behavioral term $R_A\psi^2$ reported across the 11-year period are all defined as outliers. For the same reason, some observations are omitted in the remaining 1,143 farms. This results in an unbalanced panel data set with 1 to 11 observations per farm. Figure 4.3 shows the number of records remained in each cow-calf farm (horizontal axis) and the total number of cow-calf farms with 1 to 11 years of records (vertical axis) in the unbalanced panel.

Figure 4.3 The Number of Cow-calf Operators Grouped by the Number of Records Remained in Each Cow-calf Operation



The second subset (Dat2) is developed from Dat1. In Dat1, $R_A\psi^2$ is the only variable standing for farmers' behavioral characteristics. However, it is impossible to carry out empirical analyses with proper regression functional forms if the values of risk-aversion (R_A) and overconfidence (ψ^2) are unknown. To obtain the value of R_A and ψ^2, I assume that 20 different overconfidence scenarios are assigned to each farm-year observation in Dat1. Since $\psi = 1$ means a neutral level of risk perception, it can be represented by no deviation of perceived price variation from the true variation. I define the measure of overconfidence (ψ) as 20 numbers ranging from 0.8 to 1.2, representing the moderate level of overconfidence or underconfidence of an individual. It indicates that a farmer may be at least 20% overconfident or at most 20% underconfident, in other words, his perceived price variation is 20% narrower or wider than the true price variation. To be more specific, a farmer's perceived price variation is 80% of the true price variation if the

farmer is overconfident and has $\psi = 0.8$, while the perceived price variation of an underconfident farmer with $\psi = 1.2$ is 120% of the true price variation. With these 20 overconfidence values defined, the contingent values of absolute risk-aversion (R_A) for each cow-calf farmer can be calculated by dividing the multiplication behavioral term ($R_A\psi^2$) by the squared levels of overconfidence (ψ^2). Because of this expansion in overconfidence scenarios, Dat2 has 169,920 observations, or 20 times the size of Dat1. A problem with Dat1 and Dat2 is that both data sets uptake too many individual variations. Since behavioral traits are not the most influential determinants of farmers' business outcomes, we expect the coefficients of determination (R^2) of regressions using data from Dat1 or Dat2 to be low.

A better alternative to focusing on individual farmers is to explore how a typical farm performs within a certain range of risk-aversion and overconfidence. To observe the behavioral traits and the business outcomes of different types of farmers, a third subset (Dat3) is generated by collapsing Dat2 to 400 different pairs of risk-aversion and overconfidence. To do this, the 169,920 farm-year records in Dat2 are grouped by 20 levels of overconfidence and 20 levels of risk-aversion. It should be noted that the risk-aversion levels that are used to categorize farm-year records in Dat3 are not the exact values of risk-aversion. Instead, these risk-aversion levels are represented by the upper bounds of a total number of twenty intervals where the exact risk-aversion values are located. Each interval represents a 5-percentile range of all risk-aversion values. The resulting Dat3 consists of 400 types of farmers distinguished by their levels of risk-aversion and overconfidence. Each type of farmers is a cluster of individuals with a unique pair of risk-aversion and overconfidence. Figure 4.4 shows the distribution of the 169,920 farm-year observations

on all 400 behavioral scenarios. There are 7 out of 400 pairs where no farm-year observations are located. Five such pairs are highly risk-averse and very underconfident cases on the northeastern corner of the figure, and the remaining two pairs are the least risk-averse and highly overconfidence. Over 400 farm-year observations are located on almost all other 393 pairs. The Law of Large Numbers assures that the average business performance obtained from over 400 trials on is close to the expected value.

Table 4.2 summarizes the data set generating process. Comments on data sets characteristics and a list of issues for each data set generated can be found in this table. We should notice that when converting the measure of risk-aversion from its absolute terms to percentile ranks will add some restrictions when explaining related regression results.

Figure 4.4 Number of Farm-year Observations Located on 400 Farmer Types

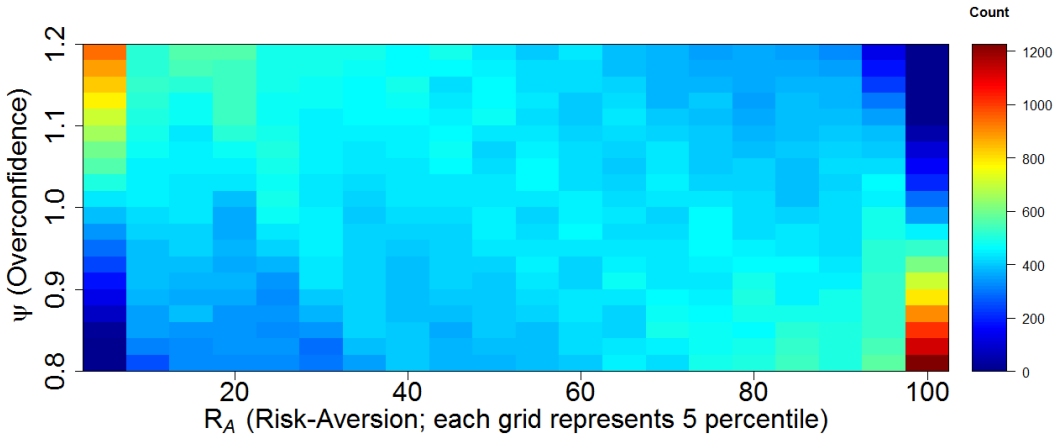


Table 4.2 Description of the Data Generating Process

Data Set	Number of Observations	Comment	Issue
Dat0	12,837	1. Original dataset; 2. Only include beef-cattle farmers from the OFID.	Include (1) farmers who are not risk-averse; (2) extreme values of the behavioral term.
Dat1	8,496	1. Trim off extreme values of the behavioral term, and farmers who are not risk-averse; 2. This dataset can be used to explore how individual farms' business outcomes are affected by their behavioral traits.	Cannot disentangle risk-aversion and overconfidence effects from the combined behavioral term.
Dat2	169,920	1. Interim data set; 2. Group all observations in Dat2 by levels of overconfidence and percentile rank of risk-aversion, yielding 400 farmer types; 3. Obtain the simulated values of risk-aversion and overconfidence.	
Dat3	400	1. Group all observations in Dat2 by levels of overconfidence and percentile rank of risk-aversion, yielding 400 farmer types; 2. Calculate the average business outcomes of each type of farmer.	1. Must obey the Law of Large Number; 2. Risk-aversion is measured in its percentile rank, not absolute values.

4.4 Key Variables

This section first defines all variables used in the data analysis. The origins of some variables are explored. The assumptions, theoretical derivation, and calculation of all derived variables are specified. The second part of this section provides a summary statistics of key variables.

4.4.1 Definitions of Variables

Some variables are directly obtained from the OFID and Statistics Canada's table, while other variables are derived from these original variables either by theoretical derivation or by assumptions. As is shown in Table 4.4, all variables can be categorized into three groups: (1) exogenous variables, (2) variables that represent farmers' behavioral traits, and (3) variables that describe farm business outcomes.

(1) Among the exogenous variables, there are four original variables which are YEAR (2003-2013), CPI (2003-2013; $\mathrm{CPI}_{2007} = 100$), and annual average/variance of monthly Ontario feeder cattle prices. The variable YEAR is used to control for time fixed effect in regression analysis. Every dollar-related performance measures from the OFID must be adjusted for inflation by applying the CPI variable. Table 4.3 reports the annual average and standard deviation of monthly feeder cattle prices per hundred weight (cwt) in Ontario from January 2003 to December 2013. The standard deviation of monthly feeder cattle prices was above ten Canadian dollars in 2013. The perceived annual average/variance of prices are derived variables. The

perceived price variance σ_g^2 is defined as $\psi^2\sigma^2$, which measures the scale of perceived price variance relative to the true price variance. The perceived average price of each farm-year observation μ_g equals the actual price in that year μ. By doing so, the original problem of maximizing the expected utility of profit with both the unknown mean and variance of perceived price is simplified into a problem with only the unknown perceived price variance. This enables us to focus better on overconfidence, which in this study manifests itself as the miscalibration effect rather than the better-than-average effect. All exogenous variables are originated from Statistics Canada's CANSIM 002-0043 with a sample size of 11.

Table 4.3 Annual Average and Standard Deviation of Ontario Monthly Feeder Cattle Prices (January 2003 to December 2013)

Year	Annual Average Monthly Feeder Cattle Prices	Annual Standard Deviation of Monthly Feeder Cattle Prices
2003	96.37	12.00
2004	76.00	6.43
2005	97.38	7.67
2006	102.17	4.21
2007	95.52	7.06
2008	90.44	7.18
2009	93.50	5.60
2010	96.90	5.95
2011	117.48	6.07
2012	129.74	3.81
2013	131.64	10.09

Note: Price unit is Canadian Dollars per hundred weight (CAD/cwt).

(2) The multiplication behavioral term $R_A\psi^2$ is the only original variable that represents farmers' behavioral traits. Its size 8,496 in the original data set. The data generating process from Dat1 to Dat3 enables the separation of risk-aversion and overconfidence from the known $R_A\psi^2$ value. Twenty overconfidence value ranging from 0.81 to 1.19 are assumed as the values of ψ. Therefore, 169,920 Arrow-Pratt absolute risk-aversion values can be derived by dividing $R_A\psi^2$ by ψ^2. The number of farm-year observations on each R_A-ψ grid is given by variable N with a size of 400. Since I use percentile range rather than absolute value to measure risk-aversion, a variable named R_A^{Upper} with a size of twenty is generated to use the upper bound of each percentile range as a proxy of risk-aversion values.

(3) The remaining variables are used to describe farm business outcomes. There are four original variables that are directly collected from the OFID. They are sector percentage, total operating revenue, cost of goods sold, and arm-length salary. Sector percentage is the proportion of cow-calf subsector in farmers' businesses. Therefore, all business outcomes must be adjusted by the sector percentage of cow-calf subsector in one's businesses. The total operating revenue can be classified into the following five classes: Class One < 10k < Class Two < 100k < Class Three < 250k < Class Four < 500k < Class Five. The average class number on R_A-ψ grid is given by variable $\overline{REVCLASS}$. The total weight of on-farm feeder cattle x is a measure of production quantity derived from total operating revenue. It can be calculated as $(OPREV/CPI \times SECTPCT)/P$. Similarly, another derived variable average cost (AC) can be calculated as $[(COGS + ALS)/CPI \times SECTPCT]/x$ where the numerator is total variable cost.

When deriving the marginal cost $C'(x)$, I suppose that the production function of cow-calf operators has constant returns to scale (CRTS). This is because the long-run average cost curve (LRAC) is "L-shaped" in most agricultural activities. The LRAC exhibits increasing returns to scale by diminishing rapidly with the increase in production scale, and then reaches to constant returns to scale as the LRAC flattens out. MacLachlan (2001) pointed out that the cow-calf operations reach to constant returns to scale at a relatively small production level and have little incentive to grow larger. That is why there are many small-scale farms in the cow-calf subsector as is portrayed in Figure 4.2. Figure 4.5 depicts the relationship between short-run average costs (SRACs) and marginal revenue (MR; or Price, P) in each year from 2003 to 2013, as well as the relationship between long-run average cost (LRAC) and marginal revenue. The "L-shape" of LRAC and SRACs is obvious across all twelve images. The marginal revenue, or the price line, overlaps the CRTS portion of both LRAC and SRACs. Figure 4.6 also supports this observation that marginal revenue overlaps the flattened part of LRAC of different income groups. Therefore, I assume the production function of cow-calf operators has constant returns to scale (CRTS), or in other words, the average cost is constant. This inference can be applied to a relationship between the average cost and the marginal cost by differentiating the average cost function as follows:

$$(28) \qquad AC'(x) = \frac{d\frac{f(x)}{x}}{dx} = \frac{f'(x)}{x} - \frac{f(x)}{x^2} = \frac{MC(x) - AC(x)}{x} = \frac{C'(x) - AC(x)}{x}.$$

Since the average cost is constant, $AC'(x) = 0$. Substitute $AC'(x) = 0$ into Equation (28) and get:

$$(29) \qquad C'(x) = AC(x).$$

Therefore, the marginal cost variable $C'(x)$ is also measured by $[(COGS + ALS)\times SECTPCT]/(x\times CPI)$.

With the production quantity x and marginal cost $C'(x)$ ready, a series of farm business outcomes can be derived as is shown in Table 4.4. With 8,496 observations, the gross profit variable (GP) reported in Dat1 is defined as $(P - MC)\times x$. The mean gross profit of all farm-year observations on each R_A - ψ grid is 400 summation values $\left(\sum_1^{N_1} GP/N_1, \sum_1^{N_2} GP/N_2, \ldots, \sum_1^{N_{400}} GP/N_{400}\right)$ reported in Dat3, where $(N_1, N_2, \ldots, N_{399}, N_{400})$ are the numbers of farm-year observations on each R_A - ψ grid. Similarly, the standard deviation of gross profit of all farm-year observations on each R_A-ψ grid, $SD(GP)$, can be calculated using the same method. The *ex ante* Certainty Equivalent ($CE^{ex\ ante}$) in Dat1 equals to $GP - \frac{(R_A\psi^2)x^2\sigma^2}{2}$. The mean *ex ante* Certainty Equivalent of all farm-year observations on each R_A-ψ grid is 400 summation values $\left(\sum_1^{N_1}\left[GP - \frac{1}{2}(R_A\psi^2)x^2\sigma^2\right]/N_1, \ldots, \sum_1^{N_{400}}\left[GP - \frac{1}{2}(R_A\psi^2)x^2\sigma^2\right]/N_{400}\right)$ in Dat3. The *ex post* Certainty Equivalent cannot be directly obtained because the overconfidence value is unknown in Dat1, but it can be derived that the mean *ex post* Certainty Equivalent of all farm-year observations on each R_A - ψ grid is a series of 400 summation values $\left(\sum_1^{N_1}\left[GP - \frac{1}{2}R_A x^2\sigma^2\right]/N_1, \ldots, \sum_1^{N_{400}}\left[GP - \frac{1}{2}R_A x^2\sigma^2\right]/N_{400}\right)$ in Dat3. The standard deviation of both *ex ante* and *ex post* Certainty Equivalent in Dat3 can be derived using the same method.

Table 4.4 Definitions of Key Variables

Original Variables	Derived Variables	Variable Definition	Calculation	Sample Size
Exogenous Variables				
$YEAR$		Year (2003-2013)		11
CPI		CPI (2007=100)		11
P		Annual average of monthly Ontario feeder cattle prices (CA$/cwt)		11
σ^2		Annual variance of monthly Ontario feeder cattle prices		11
	μ_g	Perceived annual average of monthly Ontario feeder cattle prices		11
	σ_g^2	Perceived annual variance of monthly Ontario feeder cattle prices		11
Farmer Behavioral Traits				
$R_A\psi^2$		Multiplication behavioral term	$(\mu_g - MC)/(2x\sigma^2)$	8,496
	ψ	Overconfidence (deviation of σ_g^2 from σ^2)	$(0.81, 0.83, \ldots, 1.17, 1.19)$	20
	R_A	Arrow-Pratt absolute risk-aversion	$(R_A\psi^2)/\psi^2$	169,920
	N	Number of farm-year observations on each R_A-ψ grid	$(N_1, N_2, \ldots, N_{399}, N_{400})$	400
	$R_A^{5-percentile}$	The 5-percentile range where R_A is located	$(0{\sim}5^{th},\ 5^{th}{\sim}10^{th}, \ldots,\ 95^{th}{\sim}100^{th})\ percentile$	20
	R_A^{Upper}	Upper bound of $R_A^{5-percentile}$	$(5^{th}, 10^{th}, \ldots,\ 95^{th}, 100^{th})\ percentile$	20
Farm Business Outcomes				
$SECTPCT$		Sector percentage		8,496
$OPREV$		Total Operating Revenue		8,496

	$REVCLASS$	Revenue Class		8,496
	x	Weight of on-farm feeder cattle	$(OPREV \times SECTPCT)/(P \times CPI)$	8,496
$COGS$		Cost of goods sold		8,496
ALS		Arm-length salary		8,496
	AC	Average Cost	$[(COGS + ALS) \times SECTPCT]/(x \times CPI)$	
	$C'(x)$	Marginal Cost	$^{*}MC = AC$	8,496
	GP	Gross profit	$(P - MC) \times x$	8,496
	$\overline{GP}$	Mean gross profit of all farm-year observations on each R_A-ψ grid	$\left(\sum_1^{N_1} GP/N_1, \sum_1^{N_2} GP/N_2, \ldots, \sum_1^{N_{400}} GP/N_{400}\right)$	400
	$SD(GP)$	SD gross profit of all farm-year observations on each R_A-ψ grid		400
	$CE^{ex\ ante}$	*ex ante* Certainty Equivalent	$GP - 0.5 \times (R_A \psi^2) x^2 \sigma^2$	8,496
	$\overline{CE^{ex\ ante}}$	Mean *ex ante* Certainty Equivalent of all farm-year observations on each R_A-ψ grid	$\left(\sum_1^{N_1} [GP - 0.5 \times (R_A \psi^2) x^2 \sigma^2]/N_1, \ldots, \sum_1^{N_{400}} [GP - 0.5 \times (R_A \psi^2) x^2 \sigma^2]/N_{400}\right)$	400
	$\overline{CE^{ex\ post}}$	Mean *ex post* Certainty Equivalent of all farm-year observations on each R_A-ψ grid	$\left(\sum_1^{N_1} [GP - 0.5 \times R_A x^2 \sigma^2]/N_1, \ldots, \sum_1^{N_{400}} [GP - 0.5 \times R_A x^2 \sigma^2]/N_{400}\right)$	400
	$\overline{REVCLASS}$	Average revenue class on each R_A-ψ grid		400

*Suppose that the production function has constant returns to scale (CRTS)

Figure 4.5 Long-run Average Cost (LRAC) for the 11-year Period, Short-run Average Costs (SRACs) for Each Year from 2003 to 2013, and Marginal Revenues

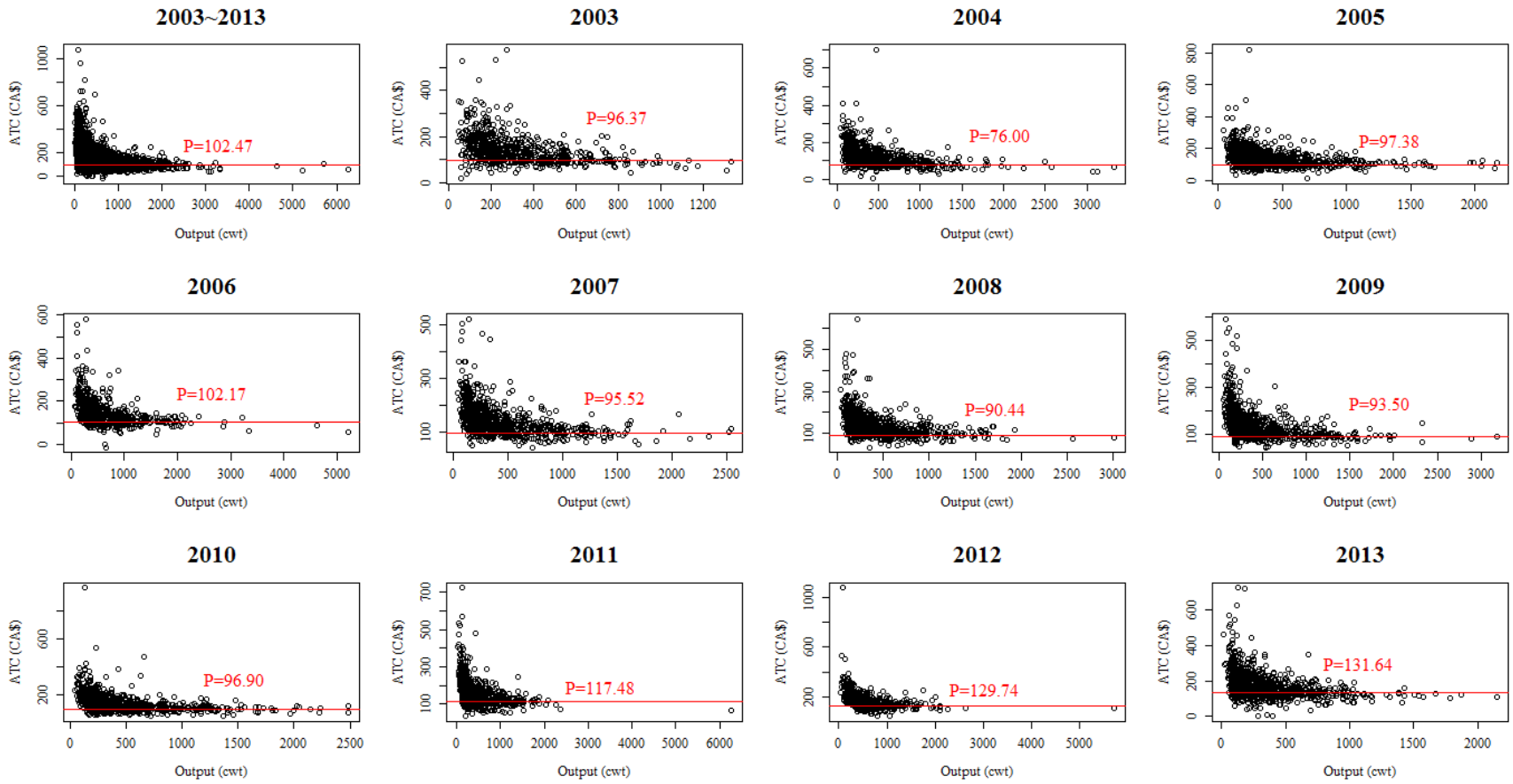
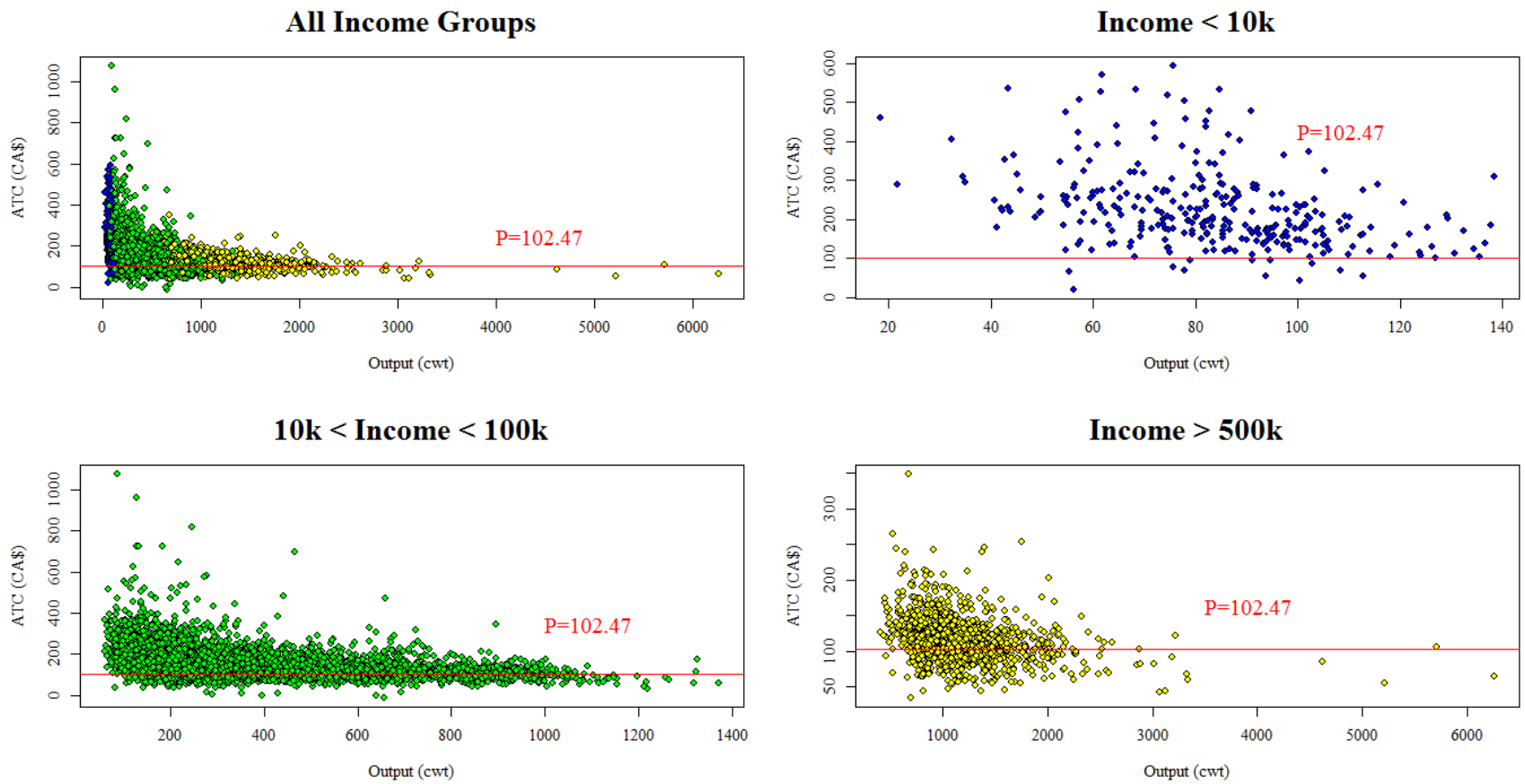


Figure 4.6 Long-run Average Cost (LRAC) across Income Groups, and Marginal Revenues



4.4.2 Summary Statistics

Table 4.5 shows the summary statistics for four key variables from Dat1. The sample size of all four variables is 8,496. The average weight of total on-farm feeder cattle weigh about 460 hundred weight or about 20.8 tons. On average the gross profit of cow-calf operators is right below $20,000 over the entire 11-year period. The average *ex ante* certainty equivalent from 2003 to 2013, by definition, is half the value of gross profit. The multiplication behavioral term $R_A\psi^2$, like the other three variables, is skewed to the right. Table 4.6 reports the summary statistics for key variables from Dat3 where 169,920 farm-year observations are categorized into 400 different groups of R_A-ψ. The average number of farm-year observations located on each R_A-ψ grid is about 430. This conformity to the Law of Large Number ensures the expected value on each R_A-ψ grid approaches to the average value. On each R_A-ψ grid, the mean and standard deviation of gross profit, mean *ex ante* and mean *ex post* certainty equivalent are calculated. The variation of mean gross profit and *ex ante* certainty equivalent are smaller than the corresponding variations without taking average, and meanwhile the central tendency of these two measures of business outcome only slightly change. The summary statistics of mean *ex post* certainty equivalent is smaller than the corresponding statistics of mean *ex ante* certainty equivalent in general, which is consistent with the theory.

Table 4.5 Summary Statistics of Key Variables in Dat1 (Sample Size = 8,496)

Variable	Variable Definition	Min	Q_1	Median	Mean	Q_3	Max	SD
$R_A\psi^2$	Multiplication behavioral term	0.0003	0.0011	0.0024	0.0034	0.0048	0.0127	0.0029
x	Weight of on-farm feeder cattle	18.4	198.1	339.8	459.2	595.2	6266.0	390.4
GP	Gross profit	52	6732	13554	19502	25457	487020	20872
$CE^{ex\ ante}$	*ex ante* Certainty Equivalent	26	3366	6777	9751	12728	243510	10436

Table 4.6 Summary Statistics of Key Variables in Dat3 (Sample Size = 400)

Variable	Variable Definition	Min	Q1	Median	Mean	Q3	Max	SD
N	Number of farm-year observations on each R_A-ψ grid	0	388	428.5	424.8	459.2	1228	0.004
R_A^{Upper}	Upper bound of $R_A^{5-percentile}$	0.0005	0.0013	0.0026	0.0041	0.0051	0.0194	0.0044
ψ	Overconfidence (deviation of σ_g^2 from σ^2)	0.810	0.905	1.000	1.000	1.095	1.190	0.115
x	Total weight of feeder cattle on farm	208.8	282.9	396.7	464.2	603.6	1133.3	218.1
$\overline{GP}$	Mean gross profit of all farm-year observations on each R_A-ψ grid	3589	9069	15380	16900	22670	35770	7728
$SD(GP)$	SD gross profit of all farm-year observations on each R_A-ψ grid	1124	1992	2468	3043	3442	37462	2420
$\overline{CE^{ex\ ante}}$	Mean *ex ante* Certainty Equivalent of all farm-year observations on each R_A-ψ grid	1794	4535	7690	8451	11336	17886	3864
$\overline{CE^{ex\ post}}$	Mean *ex post* Certainty Equivalent of all farm-year observations on each R_A-ψ grid	1664	4675	7227	7930	10493	20622	4038

4.5 Chapter Summary

The purpose of this chapter is to introduce key variables that will be used in empirical analysis. This chapter first introduces the two sources of data, the Ontario Farm Income Database (OFID) and Statistics Canada's feeder cattle price data, and explains why these two data sources are suitable for the thesis study. The second part of this chapter proposes the process of generating three data sets from the original data set and describes the characteristics of the three data sets. The third section provides definitions and summary statistics of all the key variables that are used in empirical research.

Chapter 5 Empirical Model and Results

5.1 Chapter Introduction

The purpose of this chapter is to develop empirical models which will be used to disentangle the effect of risk-aversion and overconfidence on business outcomes. The empirical estimates of the models controlling for year fixed effects and size effects are presented. The first section introduces seven functional forms which specify the relationship between farms' business outcome and behavioral characteristics. The second section explains (1) major forms of regression against four different measures of business outcomes, and reports (2) the empirical results of these models controlling for year fixed effects. The third section presented a robustness check by comparing models controlling for both year fixed effects and size effects with those only controlling for year fixed effects in the second section. Finally, a conclusion of this chapter is made.

5.2 Model Specification

Equation (30) to (36) are seven basic functional forms are developed to differentiate the effects of risk-aversion and overconfidence on farms' business outcomes when year fixed effect is controlled. It is important to control for the year fixed effects because they capture the influence of aggregate trends over time that is not attributed to explanatory variables. One of such trends in this case is the prices of feeder cattle. The major outbreak

of Bovine Spongiform Encephalopathy (BSE) stating from the second half of 2003 caused a plunge in feeder cattle prices and an increase in price volatility until the beef industry's recovery in 2005. Starting from 2011, average feeder cattle price rose steadily over years. The monthly price changes in Figure A.1 and the monthly percentage price changes in Figure A.2 both indicate the necessity to control for year fixed effect.

Equation (30) and (31) model business outcomes as a function of the multiplication of two behavioral variables: overconfidence and risk-aversion while the year fixed effect is controlled.

$$Performance_t = \beta_0 + \beta_1 (R_A \psi^2)_t + \beta_2 Y_t + \varepsilon_t \tag{30}$$

$$\ln(Performance_t) = \beta_0 + \beta_1 (R_A \psi^2)_t + \beta_2 Y_t + \varepsilon_t \tag{31}$$

Equation (30) and its logarithm functional form in Equation (31) are designed for data collected from Dat1 or Dat2. The dependent variables, $Performance_t$ or $\ln(Performance_t)$, represent business outcomes of a farm at time t. Y_t denote year fixed effect. $(R_A \psi^2)_t$ is the only behavioral trait variable of Dat1. It stands for the behavioral trait value of a farm at time t. I would expect to see the coefficient for the multiplication behavioral trait value $(R_A \psi^2)_t$ to be negative for two reasons. First, a redo of Sandmo's model in Chapter 3 confirms the negative relationship between the degree of risk-aversion and production level. Second, the measure of overconfidence ψ^2 must be positive and does not affect the sign of coefficient of the multiplication behavioral trait.

As I have discussed in the data set generating process in Chapter 4, using data from Dat1 would include too much individual variation. We can explore more interesting results using data from Dat3 where all farm-year observations are categorized into 400 groups by

their level of risk-aversion under 20 different overconfidence scenarios. Equation (32) to (36) model the mean (or standard deviation) of business outcomes as a function of various combinations of overconfidence and risk-aversion.

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} \times \psi_{it}^2 + \varepsilon_{it} \tag{32}$$

$$\ln\left(\overline{Performance}_{it}\right) = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} \times \psi_{it}^2 + \varepsilon_{it} \tag{33}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} + \beta_2\psi_{it}^2 + \varepsilon_{it} \tag{34}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} \times \psi_{it}^2 + \beta_2\left(R_A^{Upper}\right)_{it} + \beta_3\psi_{it}^2 + \varepsilon_{it} \tag{35}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} + \beta_2\psi_{it}^2 + \beta_3\psi_{it} + \varepsilon_{it} \tag{36}$$

The dependent variables, $\overline{Performance}_{it}$ or $\ln\left(\overline{Performance}_{it}\right)$, represent the central tendency or dispersion of business outcomes of farms categorized as the ith behavioral type at time t. ψ_{it}^2 or ψ_{it} are the values of the preset i^{th} scenarios of overconfidence at time t. $\left(R_A^{Upper}\right)_{it}$ is the risk-aversion value of farms categorized as the ith behavioral type at time t.

Equation (32) and (33) look like Equation (30) and (31) respectively. The difference between these two pairs is that instead of using the multiplication behavioral trait variable, Equation (32) and (33) use the value of overconfidence and risk-aversion separately. If this method is fine, I expect that in Equation (32) and (33) there is no change in the sign of β_1 and little or no change in the magnitude of β_1.

The purpose of Equation (34) and (35) is to explore how overconfidence and risk-aversion separately affect business outcomes. I would expect $\beta_1 < 0$, $\beta_2 < 0$ in Equation

(34), and $\beta_1 < 0$, $\beta_2 < 0$, $\beta_3 < 0$ in Equation (35) leading from the theoretical derivation in the conceptual framework.

The poly-nominal functional form displayed in Equation (36) captures the influencing trend. It aims to find out whether being moderately overconfident yields competitive advantages under certain level of risk-aversion, and if so, I would expect $\beta_2 < 0$ and $\beta_3 > 0$. I would expect that β_1 is still negative based on what is known from the conceptual framework.

Four different measures of farms' business outcomes are used as dependent variables. These four groups of outcome measures are:

(1) Gross Profit (GP) from Dat1 and Dat2; Mean Gross Profit ($\overline{GP}$) from Dat3, and their logarithms, $\ln(GP)$ and $\ln(\overline{GP})$;

(2) Standard Deviation of Gross Profit $SD(GP)$ from Dat3 and its logarithm, $\ln[SD(GP)]$;

(3) *ex ante* Certainty Equivalent ($CE^{ex\ ante}$) from Dat1 and Dat2, Mean *ex ante* Certainty Equivalent ($\overline{CE^{ex\ ante}}$) from Dat3, and their logarithms, $\ln(CE^{ex\ ante})$ and $\ln\left(\overline{CE^{ex\ ante}}\right)$;

(4) Mean *ex post* Certainty Equivalent ($\overline{CE^{ex\ post}}$) from Dat3 and its logarithm, $\ln\left(\overline{CE^{ex\ post}}\right)$.

Gross profit and *ex ante* certainty equivalent can be directly obtained from Dat1 and its extended version Dat2. Dat3 grouped all farm-year observations in Dat2 by farmers' degrees of risk-aversion and overconfidence. Therefore, mean gross profit, mean *ex ante* certainty equivalent and mean *ex post* certainty equivalent show the average business

outcomes for each behavioral trait match. Similarly, standard deviation of gross profit shows the variation of business outcomes for each type of farmer. The four groups of business outcome measures are discussed in the following regression analysis.

5.3 Results of Regressions

Table 5.1 shows nine forms of regression against gross profit, mean gross profit and their logarithms given different combinations of behavioral terms. Both dependent variables in Regression (1) and (2) are farm's gross profit in thousands of Canadian Dollars. The only independent variable in these two regressions is the multiplication behavioral term $R_A\psi^2$. The major difference between Regression (1) and (2) is that Regression (1) uses data from dat1 while Regression (2) uses data from dat2. Since the size of Dat2 is exactly 400 times the size of dat1, the standard deviations of the independent variables of Regression (1) are exactly $\sqrt[4]{400} \approx 4.47$ times the standard deviations of the same independent variables of Regression (2). The values of adjusted R-squared in both regression are below 4%, which are as low as expected because behavioral traits are not the most influential determinants of individual farmers' business outcomes. The logarithm-form regression using data from Dat1 is reported in Regression (7). Estimates for $R_A\psi^2$ are statistically significant in Regression (1), (2) and (7). The signs of these estimates are negative, which are consistent with the hypothesized signs in the theoretical model.

The rest of regression forms use data from Dat3. It should be noted that the values of R_A in any regression forms using Dat3 data are the upper bound each 5-percentile range where those values are located. Therefore, $R_A\psi^2$ are recalculated as multiplying the preset

level of overconfidence by the corresponding upper bound risk-aversion value. Since the business outcome variables in Dat3 show the average performance of each farmer type, the dependent variable in these regression forms should be the mean gross profits across different types of farmers. To eliminate the influence of different time periods, year fixed effects in regression forms using data from Dat3 are removed. This has been done by conducting the following steps. First, I used all farm-year observations in each of the 400 farm types to do 400 regressions of gross profit on 10 year-dummies (the default year is 2007, the year CPI is set equal to 100). Then I replaced the mean gross profit of each farm type by the intercept value of the 400 regressions. These mean gross profits after controlling year fixed effects are used as the dependent variable of Regression (3) to (6) and Regression (8) to (9).

A result of the averaging effect of Dat3 is that individual variation is greatly reduced, and over 50% of the mean gross profit variation is predictable from the independent variable(s) across all regression forms. Using the recalculated multiplication behavioral term $R_A\psi^2$, Regression (3) shows a statistically significant estimate and a correct sign for the coefficient of $R_A\psi^2$. This estimate is very close to the two coefficients of $R_A\psi^2$ reported in Regression (1) and (2), indicating that the marginal effect of $R_A\psi^2$ on gross profit is robust after its recalculation with separate values of R_A and ψ^2. Similar results can be observed in Regression (8) and (9) where the logarithm-form of mean gross profit is used as a dependent variable.

Regression (4) regresses the mean gross profit on risk-aversion and overconfidence. The estimates for both behavioral variables are significant and their signs are consistent with both the theoretical model and previous literatures. An increase in risk-aversion by

the value of its standard deviation (0.0044) results in a decrease of over 6.2 thousand CAD (-1410.12×0.0044) in the mean gross profit of a certain type of farmer. Holing risk-aversion constant, an increase in the degree of overconfidence by one level (-0.02) results in an increase of the mean gross profit by 0.246 to 0.354 thousand CAD depending on the starting value of overconfidence. A detailed calculation scheme of the effect of one incremental overconfidence level on mean gross profit is listed in **Table A.5**. This further implies that the mean gross profit of the most overconfident farmer type is 5.7 thousand CAD $\left(-7.50\times(0.81^2-1.19^2)\right)$ higher than that of the least confident farmer type if holding risk-aversion constant. Therefore, as ψ^2 decreases, a typical farm becomes more overconfident and has larger mean gross profit.

Similar results can be obtained from Regression (5) where the interaction term of risk-aversion and overconfidence is included. Using the concept of marginal effect at the means (MEMs), we can know the marginal effects of both behavioral terms when their interaction term is involved in the regression. The MEMs allows the estimation of the marginal effects evaluated at the mean values of the covariates. Given $\text{mean}(R_A) = 0.0041$ and $\text{mean}(\psi^2) = 1$, we can obtain the following results:

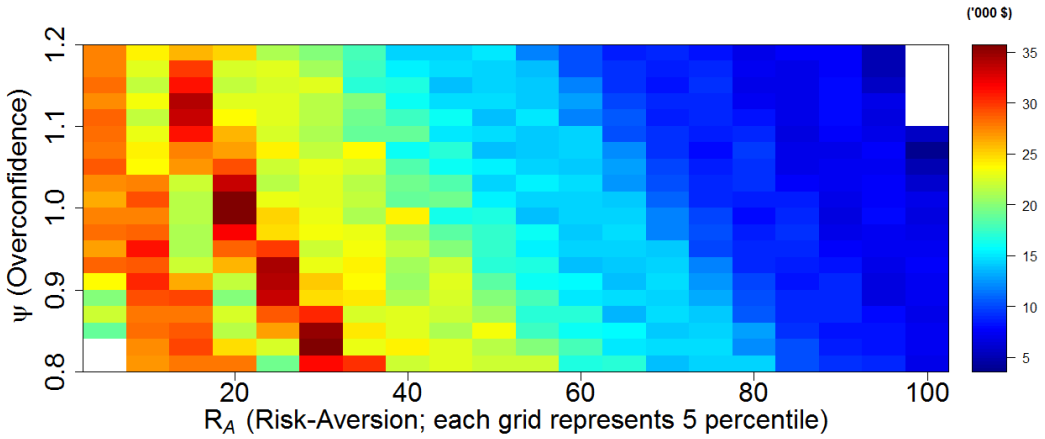
(1) Holding ψ^2 at its mean, The MEM of R_A on the mean gross profit is -1447.03 ($-857.47\times1-589.56$). Overconfidence increases the magnitude of the marginal effect of risk-aversion on mean gross profit by 36.91 $\left(-1447.03-(-1410.12)\right)$. This is equivalent to 0.16 thousand CAD (-36.91×0.0044) less mean gross profit when risk-aversion increases by one standard deviation.

(2) Holding R_A at its mean, The MEM of ψ^2 on the mean gross profit is -7.82 ($-857.47\times0.0041-4.30$) . Risk-aversion increases the magnitude of the

marginal effect of overconfidence on mean gross profit by 0.32 $\left(-7.82-(-7.5)\right)$. This is equivalent to 0.011 to 0.015 thousand CAD more mean gross profit when overconfidence increases by one level (See Table A.6 for a detailed calculation scheme).

Regression (6) tells an interesting, though not significant, effect of overconfidence on mean gross profit. The inclusion of ψ and its quadratic term ψ^2 indicates that only a moderate level of overconfidence can increase mean gross profit. When a farmer is so overconfident that his or her perceived price variance is 32.4% $\left(= -\frac{7.19}{-11.09\times 2}\right)$ of the true price variance, the marginal effect of overconfidence on mean gross profit is zero. At this point, this farmer reaches the mean gross profit-maximizing level of overconfidence. This finding is consistent with what is shown in Figure 5.1, a graph depicting mean gross profit across 400 behavioral types of farmers: if controlling for the level of risk-aversion, moderate level of overconfidence increases mean gross profit, but too much of it will finally decrease mean gross profit.

Figure 5.1 Mean Gross Profit across 400 Behavioral Types of Farmers



The semi-log regression presented in Column (9) of Table 5.1 shows the semi-elasticities of mean gross profit with respect to risk-aversion and overconfidence. A semi-elasticity is the percentage change in the dependent variable in terms of a non-percentage-wise change of an independent variable (Wooldridge 2015). Assume ψ^2 decreases by 0.04, or in other words, the overconfidence value ψ decreases by 0.2. If R_A decreases by 0.04, the same amount of the change in ψ^2, then the mean gross profit increases by 404% with respect to the decrease of R_A by 0.04; the mean gross profit increases by 2.08% with respect to the decrease of ψ^2 by 0.04. This finding is consistent with Figure A.3, which indicates that risk-aversion dominates overconfidence in the power of affecting mean gross profit.

In addition to the effects of risk-aversion and overconfidence on average business outcomes, the effect of risk-aversion and overconfidence on business outcome variations is another research interest. Table 5.2 shows some examples using standard deviation of gross profit and its logarithm-form as dependent variables. Year fixed effects are also controlled following the same procedures mentioned in the treatment of Table 5.1. All six regression in Table 5.2 show that an increase in risk-aversion results in a decrease in gross profit variation. These effects are all statistically significant across all six regressions. Regression (2), (3) and (6) show that an increase in the degree of overconfidence increases gross profit variation. This is consistent with the volatility findings in previous literature.

Specifically, the use of MEMs in explaining Regression (3) reaches to the following results:

(1) Holding ψ^2 at its mean, The MEM of R_A on the standard deviation of gross profit is -136.68 $(595.68 \times 1 - 732.36)$. Overconfidence decreases the magnitude of the

marginal effect of risk-aversion on standard deviation of gross profit by 25.64 $\left(-136.68-(-162.32)\right)$. This is equivalent to a 0.11 thousand CAD (-25.64×0.0044) decrease in the standard deviation of gross profit when risk-aversion increases by one its standard deviation.

(2) Holding R_A at its mean, The MEM of ψ^2 on the standard deviation of gross profit is -1.70 $(595.68\times 0.0041-4.14)$. Risk-aversion decreases the magnitude of the marginal effect of overconfidence on the standard deviation gross profit by 0.21 $\left(-1.70-(-1.91)\right)$. This is equivalent to a decrease of 0.007 to 0.010 thousand CAD in the standard deviation of gross profit when overconfidence increases by one level (See Table A.7 for a detailed calculation scheme).

Although the effect is not significant, I found that a typical farm with a moderate level of underconfidence may have an opportunity to minimize its gross profit variation in Regression (4). When a farmer is not so confident and his or her perceived price variance is 1.37 times $\left(=-\frac{-14.30}{5.22\times 2}\right)$ of the true price variance, the marginal effect of underconfidence on standard deviation of gross profit is zero. At this point, this farmer reaches the level of underconfidence that minimizes the standard deviation of gross profit.

Table 5.3 shows nine forms of regression against *ex ante* certainty equivalent, mean *ex ante* certainty equivalent their logarithms given different combinations of behavioral terms. Since $CE^{ex\ ante}=Gross\ Profit-\frac{1}{2}(R_A\psi^2)x^2\sigma^2$ and $R_A>0$, *ex ante* certainty equivalent must be less than gross profit, which explains why the coefficients in Regression (1) and (2) of Table 5.3 are smaller in magnitude than the corresponding coefficients in Regression (1) and (2) of Table 5.1. Since all coefficient signs of Table 5.3 are identical

with the coefficient signs in Table 5.1, the implications of the coefficient estimates are similar.

Table 5.4 presents five regressions against mean *ex post* certainty equivalent. Regression (4) shows that moderate level of confidence can bring competitive advantages. A detailed calculation using Regression (3) shows that at any R_A^{Upper} above 0.0081 $\left(R_A > \frac{9.80}{1204.23}\right)$, or in other words, if a cow-calf operator is among the 15% most risk-averse producers, being overconfident yields greater *ex post* certainty equivalent than being neutrally or less-overconfident. However, if a cow-calf operation does not belong to the 15% most risk-averse producers, it has greater *ex post* certainty equivalent when being neutrally or less-overconfident. Therefore, together with the increased surplus due to overproduction, overconfidence can improve the total welfare conditional to the degree of risk-aversion of the producer.

Table 5.1 Gross Profit/Mean Gross Profit Regressed on $R_A\psi^2$ (Year Fixed Effect Adjusted)

Variables	Gross Profit	Gross Profit	Mean Gross Profit	Mean Gross Profit	Mean Gross Profit	Mean Gross Profit	ln(Gross Profit)	ln(Mean Gross Profit)	ln(Mean Gross Profit)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$R_A\psi^2$	-1382.84***	-1383.84***					-47.33***		
	(76.01)	(16.99)					(3.89)		
$R_A^{Upper}\times\psi^2$			-1463.90***		-857.47**			-105.82***	
			(63.10)		(305.18)			(3.28)	
R_A^{Upper}				-1410.12***	-589.56*	-1410.43***			-100.91***
				(62.50)	(298.54)	(62.60)			(3.35)
ψ^2				-7.50***	-4.30**	-11.09			-0.52***
				(1.11)	(1.59)	(21.58)			(0.06)
ψ						7.19			
						(43.20)			
Constant	24.21***	24.21***	22.67***	30.08***	26.97***	26.52	9.57***	10.04***	10.54***
	(0.34)	(0.08)	(0.36)	(1.20)	(1.62)	(21.39)	(0.02)	(0.02)	(0.06)
N	8,496	169,920	400	400	400	400	8,496	400	400
df	8,494	169,918	391	390	389	389	8,494	391	390
Year dummies	Y	Y	–	–	–	–	Y	–	–
Multiple R^2	0.038	0.038	0.579	0.579	0.587	0.579	0.017	0.727	0.709
Adjusted R^2	0.037	0.038	0.578	0.577	0.584	0.575	0.017	0.726	0.707

Note:
(a) $\mathrm{CPI}_{2007} = 100$;
(b) In (1) to (6), dependent variables are in thousands of CAD; in (7) to (9), dependent variables are in CAD;
(c) R_A^{Upper} is the upper bound of the percentile rank;
(d) In (3) to (6), (8) and (9), year fixed effect is eliminated;
(e) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table 5.2 Standard Deviation (SD) of Gross Profit Regressed on $R_A\psi^2$ (Year Fixed Effect Adjusted)

Variables	SD Gross Profit	SD Gross Profit	SD Gross Profit	SD Gross Profit	ln(SD Gross Profit)	ln(SD Gross Profit)
	(1)	(2)	(3)	(4)	(5)	(6)
$R_A^{Upper}\times\psi^2$	-147.79***		595.68***		-44.62***	
	(29.53)		(137.78)		(4.75)	
R_A^{Upper}		-162.32***	-732.36***	-161.69***		-49.69***
		(28.60)	(134.78)	(28.63)		(4.49)
ψ^2		-1.91***	-4.14***	5.22		-0.33***
		(0.51)	(0.72)	(9.87)		(0.08)
ψ				-14.30		
				(19.75)		
Constant	3.63***	5.62***	7.78***	12.69	8.08***	8.44***
	(0.17)	(0.55)	(0.73)	(9.78)	(0.03)	(0.09)
N	400	400	400	400	400	400
df	391	390	389	389	391	390
Multiple R^2	0.060	0.100	0.572	0.102	0.184	0.256
Adjusted R^2	0.058	0.096	0.569	0.095	0.182	0.252

Note:
(a) $\mathrm{CPI}_{2007} = 100$;
(b) In (1) to (4), dependent variables are in thousands of CAD; in (5) and (6), dependent variables are in CAD;
(c) R_A is the upper bound of the percentile rank;
(d) Year fixed effect is eliminated;
(e) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table 5.3 *ex ante* Certainty Equivalent ($CE^{ex\ ante}$)/Mean *ex ante* Certainty Equivalent ($\overline{CE^{ex\ ante}}$) Regressed on $R_A\psi^2$ (Year Fixed Effect Adjusted)

Variables	$CE^{ex\ ante}$	$CE^{ex\ ante}$	$\overline{CE^{ex\ ante}}$	$\overline{CE^{ex\ ante}}$	$\overline{CE^{ex\ ante}}$	$\overline{CE^{ex\ ante}}$	$\ln(CE^{ex\ ante})$	$\ln(\overline{CE^{ex\ ante}})$	$\ln(\overline{CE^{ex\ ante}})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$R_A\psi^2$	-691.42***	-691.42***					-47.33**		
	(38.01)	(8.50)					(3.89)		
$R_A^{Upper}\times\psi^2$			-731.95***		-428.74**			-105.82***	
			(31.55)		(152.59)			(3.28)	
R_A^{Upper}				-705.06***	-294.78*	-705.22***			-100.91***
				(31.25)	(149.27)	(31.30)			(3.35)
ψ^2				-3.75***	-2.15**	-5.55			-0.52***
				(0.56)	(0.79)	(10.79)			(0.06)
ψ						3.60			
						(21.60)			
Constant	12.11***	12.11***	11.34***	15.04***	13.48***	13.26	8.88***	9.34***	9.85***
	(0.17)	(0.04)	(0.18)	(0.60)	(0.81)	(10.70)	(0.02)	(0.02)	(0.06)
N	8,496	169,920	400	400	400	400	8,496	400	400
df	8,494	169,918	391	390	389	389	8,494	391	390
Year dummies	Y	Y	–	–	–	–	Y	–	
Multiple R^2	0.038	0.038	0.579	0.579	0.587	0.579	0.017	0.727	0.709
Adjusted R^2	0.037	0.038	0.578	0.577	0.584	0.575	0.017	0.726	0.707

Note:
(a) $CE^{ex\ ante} = Gross\ Profit - \frac{1}{2}(R_A\psi^2)x^2\sigma^2$;
(b) $\mathrm{CPI}_{2007} = 100$;
(c) In (1) to (6), dependent variables are in thousands of CAD; in (7) to (9), dependent variables are in CAD;

(d) In (1), (2) and (7), R_A is the exact value; in (3) to (6), (8) and (9), R_A is the upper bound of the percentile rank;
(e) In (3) to (6), (8) and (9), year fixed effect is eliminated;
(f) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table 5.4 Mean *ex post* Certainty Equivalent ($\overline{CE^{ex\,post}}$) Regressed on $R_A\psi^2$ (Year Fixed Effect Adjusted)

Variables	$\overline{CE^{ex\,post}}$	$\overline{CE^{ex\,post}}$	$\overline{CE^{ex\,post}}$	$\overline{CE^{ex\,post}}$	$\ln(\overline{CE^{ex\,post}})$	$\ln(\overline{CE^{ex\,post}})$
	(1)	(2)	(3)	(4)	(5)	(6)
$R_A^{Upper}\times\psi^2$	-638.66***		-1204.23***		-95.24***	
	(39.24)		(154.55)		(4.60)	
R_A^{Upper}		-651.49***	500.89**	-655.84***		-100.32***
		(33.69)	(151.19)	(32.96)		(3.56)
ψ^2		5.30***	9.80***	-43.86***		0.66***
		(0.60)	(0.80)	(11.36)		(0.06)
ψ				98.55***		
				(22.75)		
Constant	10.45***	5.15***	0.78	-43.58***	9.22***	8.58***
	(0.22)	(0.64)	(0.82)	(11.26)	(0.03)	(0.07)
N	400	400	400	400	400	400
df	391	390	389	389	391	391
Multiple R^2	0.404	0.551	0.612	0.572	0.523	0.709
Adjusted R^2	0.402	0.549	0.609	0.569	0.522	0.707

Note:
(a) $CE^{ex\,post} = Gross\ Profit - \frac{1}{2}R_A^{Upper}x^2\sigma^2$;
(b) $\mathrm{CPI}_{2007} = 100$;
(c) In (1) to (4), dependent variables are in thousands of CAD; in (5), dependent variables are in CAD;
(d) R_A is the upper bound of the percentile rank;
(e) Year fixed effect are eliminated;
(f) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

5.4 Robustness Check

In the previous section, the year fixed effect is controlled when modelling business outcomes as a function of behavioral trait variables. I want to check the robustness by controlling farm size because in summary statistics I have observed that business outcomes are closely related to farm size. Due to the limitation of data, farm size cannot be directly obtained. Therefore, I use the class of total operating revenue as a proxy of farm size. The total operating class is reported in variable $REVCLASS$ in Dat1 and Dat2. The corresponding average revenue class number on each R_A-ψ^2 grid is reported in variable $\overline{REVCLASS}$. The logic behind it is that larger cow-calf farms have greater sales which constitutes most of total operating revenues. After considering both the year fixed effect and size effect, the regression functional forms can be written as follows:

$$Performance_t = \beta_0 + \beta_1(R_A\psi^2)_t + \beta_2 Y_t + \beta_3 REVCLASS_t + \varepsilon_t \tag{37}$$

$$\ln(Performance_t) = \beta_0 + \beta_1(R_A\psi^2)_t + \beta_2 Y_t + \beta_3 REVCLASS_t \tag{38}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} \times \psi_{it}^2 + \beta_2 \overline{REVCLASS}_i + \varepsilon_{it} \tag{39}$$

$$\ln\left(\overline{Performance}_{it}\right) = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} \times \psi_{it}^2 + \beta_2 \overline{REVCLASS}_i + \varepsilon_{it} \tag{40}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} + \beta_2 \psi_{it}^2 + \beta_3 \overline{REVCLASS}_i + \varepsilon_{it} \tag{41}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} \times \psi_{it}^2 + \beta_2\left(R_A^{Upper}\right)_{it} + \beta_3 \psi_{it}^2 + \beta_4 \overline{REVCLASS}_i + \varepsilon_{it} \tag{42}$$

$$\overline{Performance}_{it} = \beta_0 + \beta_1\left(R_A^{Upper}\right)_{it} + \beta_2 \psi_{it}^2 + \beta_3 \psi_{it} + \beta_4 \overline{REVCLASS}_i + \varepsilon_{it} \tag{43}$$

$REVCLASS_t$ in Equation (37) and (38) represents the revenue class a farm belongs to at time t. In Equation (39) to (43), $\overline{REVCLASS_i}$ is the average revenue class number on the ith R_A-ψ^2 grid.

In Appendix A, Table A.1 to Table A.4 shows the regression results of when Table 5.1 to Table 5.4 control for the effect of revenue class. In Table A.1 and Table A.3, all coefficients' signs do not change except the sign for the multiplication behavioral term $R_A\psi^2$ in Regression (7) of both tables. Regression (7), however, is a regression only for reference and does not provides any insights. Regression (5) and (6) suffer various losses of significance for some estimates, but the signs remain unchanged. If letting alone Regression (7), we can say that the regressions against (mean) gross profit and mean *ex ante* certainty equivalent do not have serious robustness issue. The results in Table A.2 shows most regressions are not robust except Regression (3). Therefore, the regression results about the effects of behavioral variables on the variation of business outcomes in previous section may not hold due to the robustness issue. Table A.4 shows that the series of regression against (mean) *ex post* certainty equivalent are robust because all signs remain unchanged and all coefficients are statistically significant.

Chapter 6 Summary and Discussion

6.1 Summary and Policy Implications

This thesis disentangles and estimates the effects of risk-aversion and overconfidence on the business outcomes for a sample of Ontario cow-calf operations. The thesis begins with an exploration of the research gap by reviewing literatures related to risk-aversion and risk perception in the form of overconfidence with a specific focus on decision-making under risks. Sandmo's model under the expected utility framework, along with the theoretical model developed by Just and Cao, provide a feasible way to quantify one's behavioral trait which is composed of risk-aversion and overconfidence. To elicit the separate effects of risk-aversion and overconfidence, 20 levels of overconfidence are preset and the degree of risk-aversion for each farm-year observation in each of the 20 overconfidence scenarios is calculated.

The product of risk-aversion and overconfidence negatively affect the mean gross profit of farms. This relationship suggests that the inclusion of overconfidence as a part of one's behavioral trait does not challenge an important result of Sandmo's: when faced with price uncertainty, the more risk-averse producers would hedge against price risk by producing less. This extension of Sandmo's result not only considers farmers' behavioral traits more comprehensively, but also reaffirms an important implication of Sandmo's finding, that the existence of price uncertainty leads to the needs for farm insurance

programs such as the Business Risk Management (BRM) programs accessible to Canadian farmers.

Further empirical findings show that disaggregating farms' behavioral traits into risk-aversion and overconfidence contributes to the better understanding of the separate effects of these two behavioral characteristics on farms' business outcomes. Both risk-aversion and overconfidence affect cow-calf farmers' business outcomes, yet differently. Between the two behavioral traits, Risk-aversion plays a major role in influencing business outcomes. A more risk-averse type of cow-calf farms tends to have lower average gross profit and less gross profit variation. In comparison, overconfidence slightly offsets the influence of risk-aversion on the two business outcomes of cow-calf operations. An interesting finding shows that a moderate level of overconfidence might make producers better off. A type of cow-calf operation may reach its maximal gross profit if this type of farm is about 3 times as confident as a neutrally confident competitor. On the other hand, a type of underconfident farmers whose perceived variance of output price is about 1.4 times greater than the true output price variance may reach its the minimal level of gross profit variation. Being overconfident, under certain circumstance, can improve the producer surplus and even the total welfare. For the 15% most risk-averse cow-calf operators, being overconfident yields greater *ex post* certainty equivalent than being neutrally confident or underconfident. It means that for these most risk-averse farm types, overconfidence decreases the true welfare of farmers after they know the true price outcomes. For the 85% not so risk-averse types of cow-calf farmers, however, overconfidence increases the *ex ante* certainty equivalent and decreases the *ex post* certainty equivalent.

These findings have implications for both policy makers who design farm insurance programs and farm operator. From the perspective of program designers, it is important for them to know that some cow-calf farmers can even optimize their business outcomes at certain levels of overconfidence. Conditional to the relative degree of risk-aversion, being overconfident can improve the welfare of some cow-calf operators. It indicates that, whether intentionally or not, compulsory farm insurance programs may be counterproductive if such programs offset participants' overconfidence. Given the pervasive overconfidence among farmers, insurance programs that allow farmers' voluntary enrolment and exit may avoid negatively affecting farms' business outcomes. From the perspective of cow-calf farmers, it is worth noting that, despite some potential benefits of being overconfident, too much overconfidence hurts farms' business outcomes. Cow-calf farmers should control their overconfidence levels by getting exposed to more accurate market information which helps them make as correct production-related predictions as possible.

6.2 Limitation

In the theoretical framework, overconfidence is strictly defined as one's overly narrow prediction. Another dimension of overconfidence, as known as the better-than-average effect, cannot be derived using this theoretical model. Therefore, this thesis's finding about the effect of overconfidence is confined to the miscalibration dimension of overconfidence. If overconfidence exhibits in the form of the better-than-average effect among the research objects, the explaining power of this model will be influenced. The

measure of overconfidence is limited in a range of 0.8 to 1.2 to ensure moderate level of confidence. In future studies, the range of overconfidence will be expanded to see how results will change under extremely overconfident or underconfident scenarios.

Another limitation of this study is that farmers cannot easily observe their relative rankings of overconfidence and risk-aversion. Without a clear knowledge of the behavioral type he or she belongs to, a farmer will not know whether being more confident or less confident leads to best business performances. Therefore, this thesis's conclusion may need further evidence from surveys or questionnaires containing farmers' self-evaluated overconfidence and risk-aversion.

In the robustness check, all sets of regressions remain consistent signs and approximate magnitude of their coefficients, except the set of regressions on the standard deviation of gross profit. This may be due to the revenue class variable used to control for the income fixed effect. Although revenue class is the best variable available in the OFID, it is not good enough due to the quality of the data. The original classification of revenue class has many overlapping observations in some groups. As a trade-off, the revenue classification used in this thesis is correct by rough. This might be one influence of the inconsistent sign and magnitude for the regressions on the standard deviation of gross profit.

The scope of this research is determined by the OFID which contains tax-filing information of farmers who ever participated in Business Risk Management programs. This raises the concern that the confined scope might affect the generality of findings. Future research may use wider range of data to avoid the generality issue.

6.3 Contributions to Future Research

As far as I know, this thesis is the first of its kind to estimate the effect of overconfidence on business outcomes without using data from surveys or questionnaires. The measure of overconfidence is derived using variables from the OFID that are required by theoretical framework of this thesis. It indicates that apart from survey data, other types of data may be useful in overconfidence-related studies. Researchers can derive an objective measure of overconfidence using appropriate data instead of obtaining subjective self-evaluations on overconfidence levels from survey respondents.

This thesis sheds light on how farmers' risk attitudes and risk perceptions affect their business outcomes, which may be a concern of administrators of farm business risk management programs. In Canada, the participation rates for some farm income support programs have been declined in these years. Appendix B reviews typical farm income support programs under different agricultural policy frameworks and declining program participation under the current Growing Forward 2 framework. This thesis's findings on the positive income effect of overconfidence may provide another perspective of exploring the declining participation in farm business risk management programs to future studies.

Appendix A

Table A.1 Gross Profit/Mean Gross Profit Regressed on $R_A\psi^2$ (Year Fixed Effect and Size Effect Adjusted)

Variables	Gross Profit	Gross Profit	Mean Gross Profit	Mean Gross Profit	Mean Gross Profit	Mean Gross Profit	ln(Gross Profit)	ln(Mean Gross Profit)	ln(Mean Gross Profit)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$R_A\psi^2$	-111.48	-111.48***					13.49***		
	(0.08)	(0.00)					(0.00)		
$R_A^{Upper}\times\psi^2$			-555.79***		-510.05*			-62.84***	
			(0.00)		(0.02)			(0.00)	
R_A^{Upper}				-526.05***	-46.93	-526.37***			-58.028***
				(0.00)	(0.83)	(0.00)			(0.00)
ψ^2				-2.21***	-0.36	-5.90			-0.26***
				(0.00)	(0.76)	(0.71)			(0.00)
ψ						7.39			
						(0.81)			
$REVCLASS$	32.89***	32.89***					1.57***		
	(0.00)	(0.00)					(0.00)		
$\overline{REVCLASS}$			34.55***	34.80**	34.45***	34.80***		1.64***	1.69***
			(0.00)	(0.01)	(0.00)	(0.00)		(0.00)	(0.00)
$Constant$	-47.61***	-47.61***	-51.92***	-50.30***	-51.33***	-53.95***	6.14***	6.51***	6.64***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)

N	8,496	169,920	400	400	400	400	8,496	400	400
df	8,493	169,917	390	389	388	388	8,493	390	389
Year dummies	Y	Y	-	-	-	-	Y	-	-
Multiple R^2	0.372	0.372	0.783	0.780	0.783	0.780	0.315	0.836	0.822
Adjusted R^2	0.372	0.372	0.782	0.778	0.781	0.778	0.315	0.836	0.821

Note:
(a) The values inside the parentheses are the p-values for the T-tests;
(b) $\mathrm{CPI}_{2007} = 100$;
(c) In (1) to (6), dependent variables are in thousands of CAD; in (7) to (9), dependent variables are as in CAD;
(d) R_A^{Upper} is the upper bound of the percentile rank;
(e) In (3) to (6), (8) and (9), year fixed effect is eliminated;
(f) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table A.2 Standard Deviation (SD) of Gross Profit Regressed on $R_A\psi^2$ (Year Fixed Effect and Size Effect Adjusted)

Variables	SD Gross Profit	SD Gross Profit	SD Gross Profit	SD Gross Profit	ln(SD Gross Profit)	ln(SD Gross Profit)
	(1)	(2)	(3)	(4)	(5)	(6)
$R_A^{Upper}\times\psi^2$	222.38***		730.17***		32.82***	
	(0.00)		(0.00)		(0.00)	
R_A^{Upper}		163.58***	-522.31***	164.20***		17.83***
		(0.00)	(0.00)	(0.00)		(0.00)
ψ^2		-0.04	-2.61***	7.14		0.07
		(0.93)	(0.00)	(0.39)		(0.23)
ψ				-14.23		
				(0.39)		
$\overline{REVCLASS}$	14.08***	12.83***	13.33***	12.83***	2.95***	2.66***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Constant$	-26.78***	-24.01*	-22.53***	-16.98*	1.72***	2.30***
	(0.00)	(0.00)	(0.00)	(0.05)	(0.00)	(0.00)
N	400	400	400	400	400	400
df	390	389	388	388	390	389
Multiple R^2	0.405	0.379	0.441	0.380	0.690	0.657
Adjusted R^2	0.402	0.374	0.435	0.374	0.688	0.654

Note:
(a) The values inside the parentheses are the p-values for the T-tests;
(b) $\mathrm{CPI}_{2007} = 100$;
(c) In (1) to (4), dependent variables are in thousands of CAD; in (5) and (6), dependent variables are in CAD;
(d) R_A^{Upper} is the upper bound of the percentile rank;
(e) Year fixed effect is eliminated;
(f) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table A.3 *ex ante* Certainty Equivalent ($CE^{ex\ ante}$)/Mean *ex ante* Certainty Equivalent ($\overline{CE^{ex\ ante}}$) Regressed on $R_A\psi^2$ (Year Fixed Effect and Size Effect Adjusted)

Variables	$CE^{ex\ ante}$	$CE^{ex\ ante}$	$\overline{CE^{ex\ ante}}$	$\overline{CE^{ex\ ante}}$	$\overline{CE^{ex\ ante}}$	$\overline{CE^{ex\ ante}}$	$\ln(CE^{ex\ ante})$	$\ln(\overline{CE^{ex\ ante}})$	$\ln(\overline{CE^{ex\ ante}})$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$R_A\psi^2$	-55.74	-55.74					13.49***		
	(0.08)	(0.00)					(0.00)		
$R_A^{Upper}\times\psi^2$			-277.89***		-255.02*			-62.84***	
			(0.00)		(0.02)			(0.00)	
R_A^{Upper}				-263.02***	-23.46	-263.19***			-58.02***
				(0.00)	(0.83)	(0.00)			(0.00)
ψ^2				-1.11**	-0.18	-2.95			-0.26***
				(0.01)	(0.761)	(0.71)			(0.00)
ψ						3.69			
						(0.81)			
$\overline{REVCLASS}$	16.45***	16.45***	17.28***	17.40***	17.22***	17.40***	1.57***	1.64***	1.69***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Constant$	-23.81***	-23.81***	-25.96***	-25.15***	-25.66***	-26.98	5.44***	5.81***	5.950***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	8,496	169,920	400	400	400	400	8,496	400	400
df	8,493	169,917	390	388	388	388	8,493	390	389
Year dummies	Y	Y	-	-	-	-	Y	-	-
Multiple R^2	0.372	0.372	0.783	0.780	0.783	0.834	0.315	0.836	0.822

Adjusted R^2	0.372	0.372	0.782	0.778	0.781	0.832	0.315	0.836	0.821

Note:

(a) $CE^{ex\ ante} = Gross\ Profit - \frac{1}{2}(R_A^{Upper} \times \psi^2)x^2\sigma^2$; $\overline{CE^{ex\ ante}} = \overline{Gross\ Profit - \frac{1}{2}\left(R_A^{Upper} \times \psi^2\right)x^2\sigma^2}$;

(b) The values inside the parentheses are the p-values for the T-tests;

(c) $\mathrm{CPI}_{2007} = 100$;

(d) In (1) to (6), dependent variables are in thousands of CAD; in (7) to (9), dependent variables are as per CAD;

(e) R_A^{Upper} is the upper bound of the percentile rank;

(f) In (3) to (6), (8) and (9), year fixed effect are eliminated;

(g) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table A.4 Mean *ex post* Certainty Equivalent ($\overline{CE^{ex\ post}}$) Regressed on $R_A\psi^2$ (Year Fixed Effect and Size Effect Adjusted)

Variables	$\overline{CE^{ex\ post}}$	$\overline{CE^{ex\ post}}$	$\overline{CE^{ex\ post}}$	$\overline{CE^{ex\ post}}$	$\ln(\overline{CE^{ex\ post}})$	$\ln(\overline{CE^{ex\ post}})$
	(1)	(2)	(3)	(4)	(5)	(6)
$R_A^{Upper}\times\psi^2$	-290.61***		-1037.74***		-60.22***	
	(0.00)		(0.00)		(0.00)	
R_A^{Upper}		-213.91***	760.91***	-218.22***		-57.33***
		(0.00)	(0.00)	(0.00)		(0.00)
ψ^2		7.92***	11.69***	-41.29***		0.91***
		(0.49)	(0.00)	(0.00)		(0.00)
ψ				98.65***		
				(0.00)		
$\overline{REVCLASS}$	13.24***	17.23***	16.51***	17.23***	1.33***	1.69***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
$Constant$	-18.14***	-34.63***	-36.74***	-83.42***	6.34***	4.67***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
N	400	400	400	400	400	400
df	390	389	388	388	390	389
Multiple R^2	0.513	0.732	0.777	0.753	0.587	0.810
Adjusted R^2	0.511	0.730	0.774	0.750	0.585	0.809

Note:

(a) $\overline{CE^{ex\ post}} = \overline{Gross\ Profit - \frac{1}{2}R_A^{Upper}x^2\sigma^2}$;

(b) The values inside the parentheses are the p-values for the T-tests;

(c) $\mathrm{CPI}_{2007} = 100$;

(d) In (1) to (4), dependent variables are in thousands of CAD; in (5) and (6), dependent variables are as per CAD;

(e) R_A^{Upper} is the upper bound of the percentile rank;

(f) Year fixed effect are eliminated;

(g) Significance codes: *** p = 0; ** p = 0.001; * p = 0.01.

Table A.5 Calculation Scheme of the Effect of One Incremental Overconfidence Level on Mean Gross Profit Using Regression (4) of Table 5.1

ψ_1	ψ_2	$\psi_2^2 - \psi_1^2$	$Coef_\psi \times (\psi_2^2 - \psi_1^2)$
0.83	0.81	-0.0328	0.246
0.85	0.83	-0.0336	0.252
0.87	0.85	-0.0344	0.258
0.89	0.87	-0.0352	0.264
0.91	0.89	-0.0360	0.270
0.93	0.91	-0.0368	0.276
0.95	0.93	-0.0376	0.282
0.97	0.95	-0.0384	0.288
0.99	0.97	-0.0392	0.294
1.01	0.99	-0.0400	0.300
1.03	1.01	-0.0408	0.306
1.05	1.03	-0.0416	0.312
1.07	1.05	-0.0424	0.318
1.09	1.07	-0.0432	0.324
1.11	1.09	-0.0440	0.330
1.13	1.11	-0.0448	0.336
1.15	1.13	-0.0456	0.342
1.17	1.15	-0.0464	0.348
1.19	1.17	-0.0472	0.354

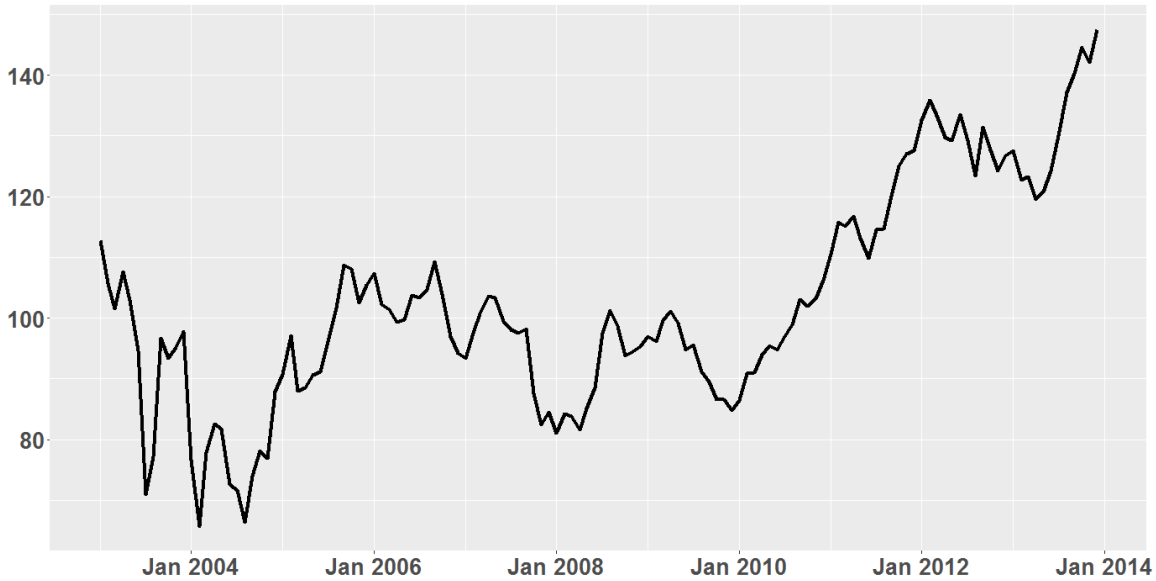
Table A.6 Calculation Scheme of the Marginal Effect at Means (MEMs) of One Incremental Overconfidence Level on Mean Gross Profit Using Regression (5) of Table 5.1

ψ_1	ψ_2	$\psi_2^2 - \psi_1^2$	$Coef_\psi \times (\psi_2^2 - \psi_1^2)$	$Coef_\psi^{MEM} \times (\psi_2^2 - \psi_1^2)$	$\left(Coef_\psi^{MEM} - Coef_\psi\right) \times (\psi_2^2 - \psi_1^2)$
0.83	0.81	-0.0328	0.246	0.256	0.010
0.85	0.83	-0.0336	0.252	0.263	0.011
0.87	0.85	-0.0344	0.258	0.269	0.011
0.89	0.87	-0.0352	0.264	0.275	0.011
0.91	0.89	-0.0360	0.270	0.282	0.012
0.93	0.91	-0.0368	0.276	0.288	0.012
0.95	0.93	-0.0376	0.282	0.294	0.012
0.97	0.95	-0.0384	0.288	0.300	0.012
0.99	0.97	-0.0392	0.294	0.307	0.013
1.01	0.99	-0.0400	0.300	0.313	0.013
1.03	1.01	-0.0408	0.306	0.319	0.013
1.05	1.03	-0.0416	0.312	0.325	0.013
1.07	1.05	-0.0424	0.318	0.332	0.014
1.09	1.07	-0.0432	0.324	0.338	0.014
1.11	1.09	-0.0440	0.330	0.344	0.014
1.13	1.11	-0.0448	0.336	0.350	0.014
1.15	1.13	-0.0456	0.342	0.357	0.015
1.17	1.15	-0.0464	0.348	0.363	0.015
1.19	1.17	-0.0472	0.354	0.369	0.015

Table A.7 Calculation Scheme of the Marginal Effect at Means (MEMs) of One Incremental Overconfidence Level on the Standard Deviation of Gross Profit Using Regression (3) of Table 5.2

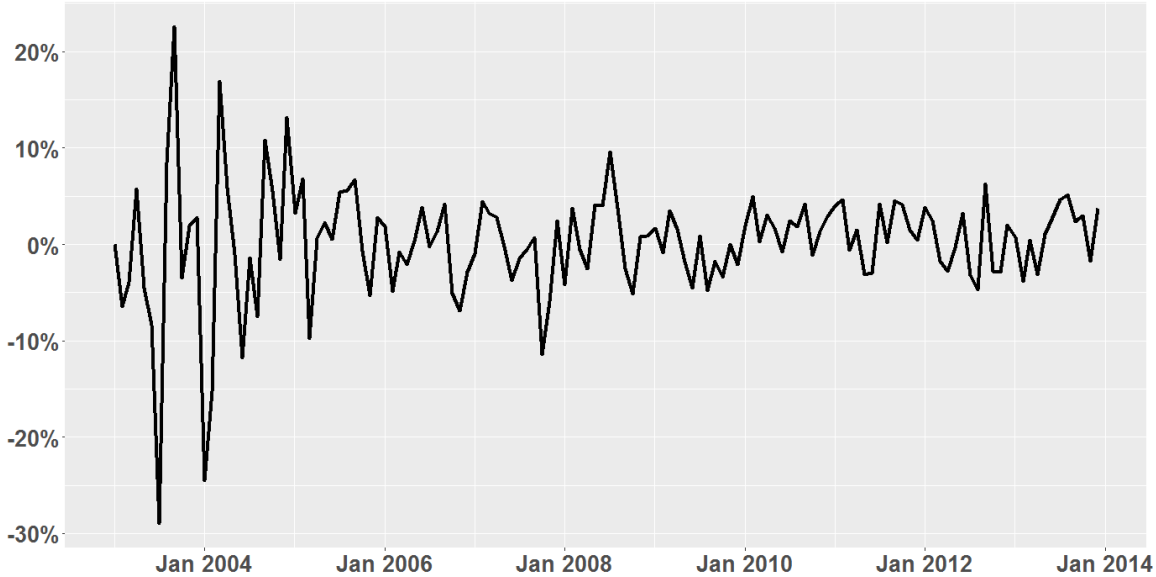
ψ_1	ψ_2	$\psi_2^2 - \psi_1^2$	$Coef_\psi \times (\psi_2^2 - \psi_1^2)$	$Coef_\psi^{MEM} \times (\psi_2^2 - \psi_1^2)$	$\left(Coef_\psi^{MEM} - Coef_\psi\right) \times (\psi_2^2 - \psi_1^2)$
0.83	0.81	-0.0328	0.063	0.056	-0.007
0.85	0.83	-0.0336	0.064	0.057	-0.007
0.87	0.85	-0.0344	0.066	0.058	-0.007
0.89	0.87	-0.0352	0.067	0.060	-0.007
0.91	0.89	-0.0360	0.069	0.061	-0.008
0.93	0.91	-0.0368	0.070	0.062	-0.008
0.95	0.93	-0.0376	0.072	0.064	-0.008
0.97	0.95	-0.0384	0.073	0.065	-0.008
0.99	0.97	-0.0392	0.075	0.067	-0.008
1.01	0.99	-0.0400	0.076	0.068	-0.008
1.03	1.01	-0.0408	0.078	0.069	-0.009
1.05	1.03	-0.0416	0.079	0.071	-0.009
1.07	1.05	-0.0424	0.081	0.072	-0.009
1.09	1.07	-0.0432	0.083	0.073	-0.009
1.11	1.09	-0.0440	0.084	0.075	-0.009
1.13	1.11	-0.0448	0.086	0.076	-0.010
1.15	1.13	-0.0456	0.087	0.077	-0.010
1.17	1.15	-0.0464	0.089	0.079	-0.010
1.19	1.17	-0.0472	0.090	0.080	-0.010

Figure A.1 Monthly Feeder Cattle Prices (CAD/hundred weight) in Ontario (January 2003 to December 2013)



Source: Statistics Canada. Table 002-0043

Figure A.2 Percentage Change in Monthly Feeder Cattle Prices (CAD/hundred weight) in Ontario (February 2003 to December 2013)



Source: Statistics Canada. Table 002-0043

Figure A.3 Mesh Plot of the Mean Gross Profit across 400 Behavioral Types of Farmers

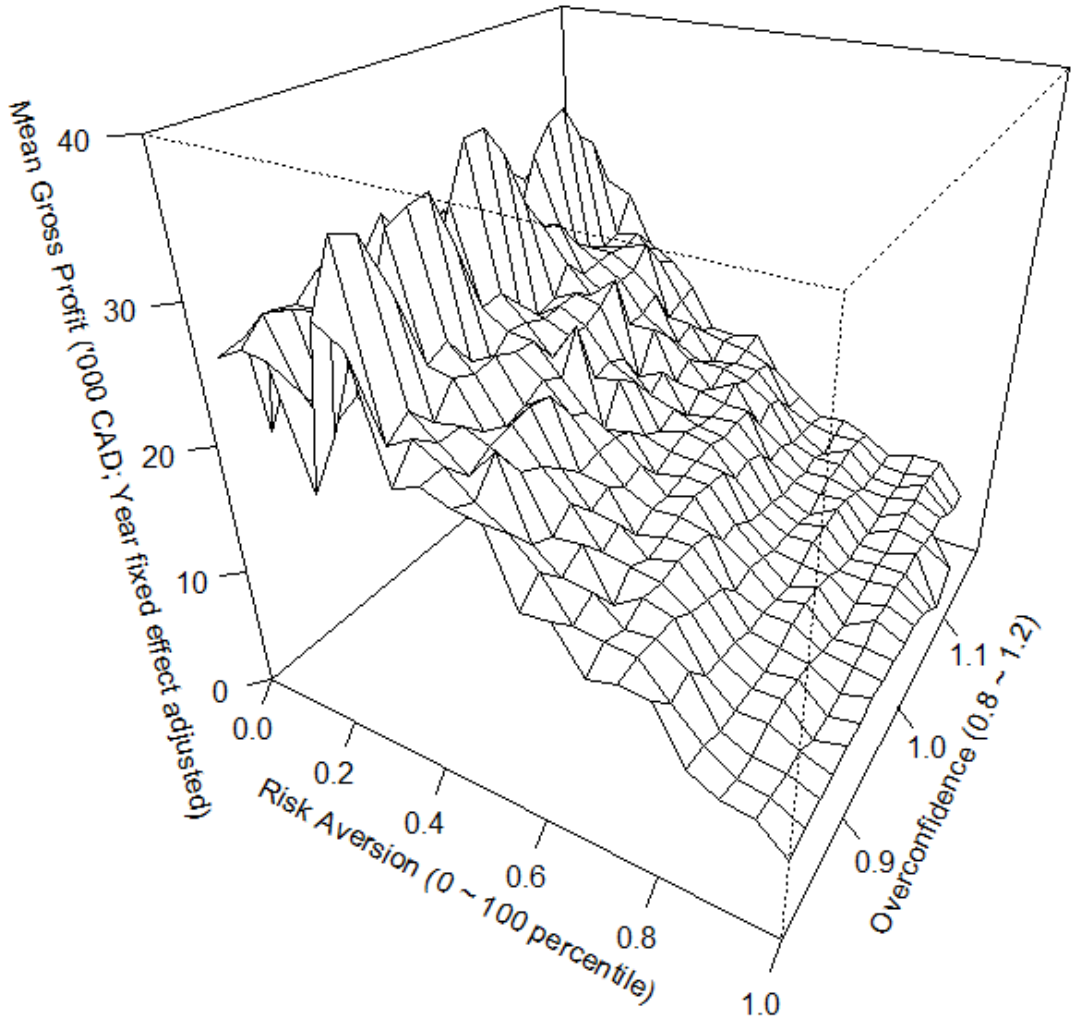


Figure A.4 Mesh Plot of the Standard Deviation of Gross Profit across 400 Behavioral Types of Farmers

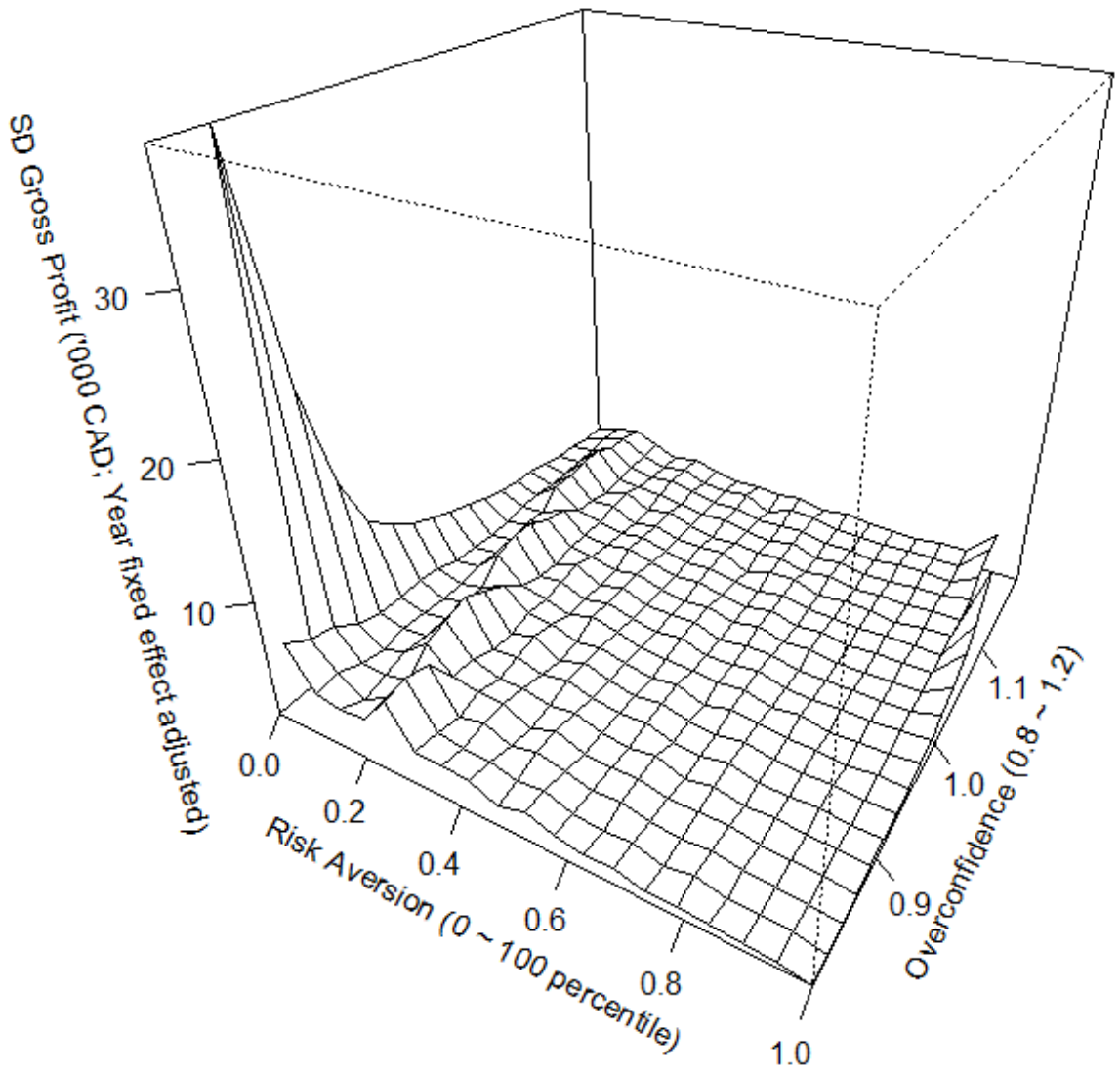


Figure A.5 Mesh Plot of the Mean of *ex ante* Certainty Equivalent across 400 Behavioral Types of Farmers

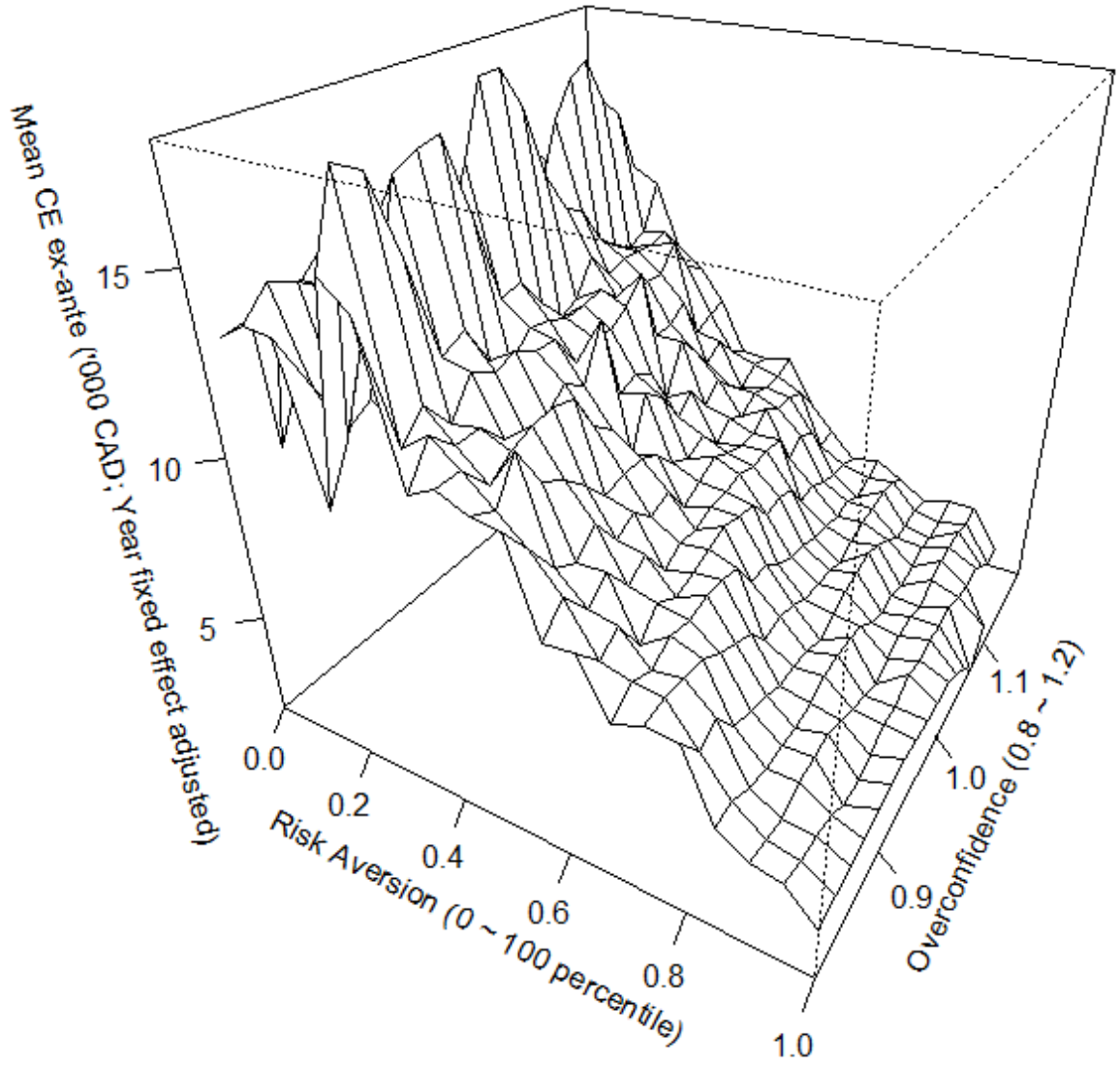
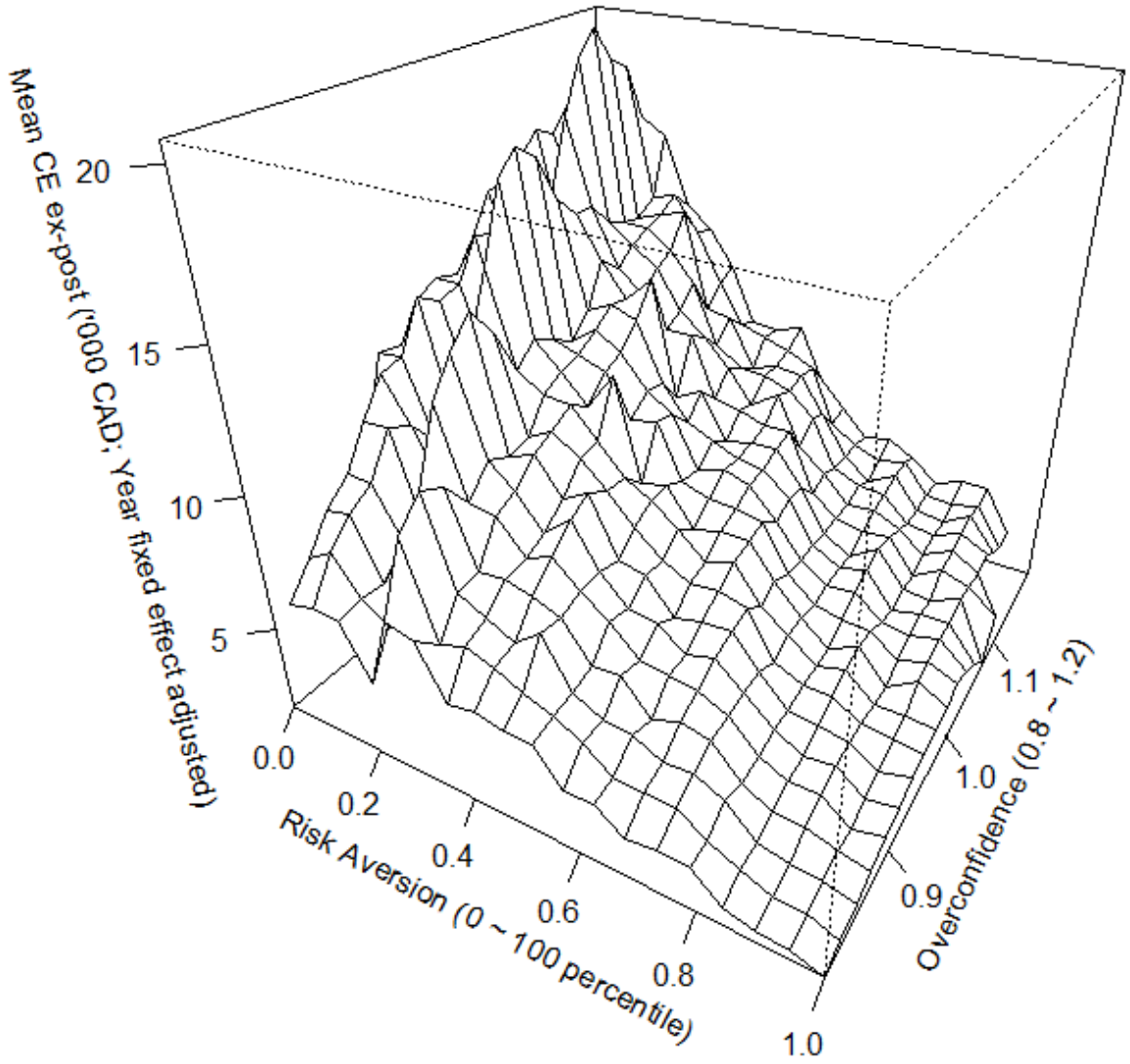


Figure A.6 Mesh Plot of the Mean of *ex post* Certainty Equivalent across 400 Behavioral Types of Farmers



Appendix B

B.1 Canadian Agricultural Policy Frameworks and Business Risk Management (BRM) Programs

The Farm Income Protection Act (1991) marked a turning point of the Canadian agricultural policy framework from price stabilization to income support. In addition to meet the compliance requirements of the GATT/WTO, this transition was also intended to provide more effective income support to Canadian farmers, as the price stabilization programs only provided limited support to farmers during the world grain prices decline in the late 1980s (Schmitz et al 2010). Since then, some margin stabilization programs were established, such as the Gross Revenue Insurance Program (GRIP) and the Net Income Stabilization Account (NISA) in 1991, and the Agricultural Income Disaster Assistance program (AIDA) in 1998.

Since the beginning of the 21st century, a major concern of Canadian agricultural sectors is their competitiveness and innovation ability. To address this concern, the federal and provincial governments set up the Agricultural Policy Framework (APF) in 2003. In the field of farm risk management under the APF, the Canadian Agricultural Income Stabilization (CAIS) replaced the three safety net programs established in the 1990s. After the expiration of the APF, the federal and provincial governments introduced the Growing Forward Policy Framework (GF1) in 2008, to reinforce the long-term competitiveness and sustainable development of the agricultural sectors. Its subsequent framework, the

Growing Forward 2 (GF2), is a five-year program from 2013 to 2018 focusing on innovation, competitiveness and market development. As successors of the CAIS under the GF1 and the current GF2 framework, a suite of farm business risk management (BRM) tools, such as AgriInvest, AgriStability, AgriInsurance, AgriRecovery and Ad hoc measures, compose the major farm income stabilization programs under the GF2 framework.

B.2 AgriStability

As one of the five major farm income stabilization tools under the GF2, AgriStability aims at providing Canadian agricultural producers with an ongoing whole farm risk-management tool that provides protection against both small and large drops in income. In Ontario, AgriStability is funded under the GF2 framework with the federal government coving 60% of the program payments and administrative expenses. The Government of Ontario covers the remaining 40%. Agricorp, a provincial crown corporation, is responsible for administering AgriStability in Ontario. From 2003 to 2009, the federal and provincial governments on average have funded $777 million and $646 million to the AgriStability respectively (Rude et al 2013).

The layering of AgriStability is determined by the margin loss as a proportion of the reference margin, while the reference margin is calculated as an Olympic average of previous years' profit margins. As is shown if Figure B.1, AgriStability is composed of three layers under the GF1 framework and two layers under the GF2 framework. Under the GF1, AgriStability pays 80% of the margin loss between 0 and 70% of the reference

margin and 60% of the negative margin loss. Under the GF2, these two coverage ratios both change to 70%. Under the GF1, for the margin loss between 70% and 85% of the reference margin, AgriStability covers 70% of the margin loss. This compensation is canceled under the GF2. Figure 2 approximately described the coverages of events with different frequencies of occurrence and coverages of different sources of risk, for the five farm risk management tools under the GF1 framework. Compared with the other major farm business risk management tools, AgriStability is a more versatile program because its coverage ranges from frequent small events to rare large events, and from nature risks to market risks (Antón et al 2011).

Despite the huge AgriStability payments from the federal and provincial governments and the versatile nature of AgriStability, farm participation levels for AgriStability and its predecessor CAIS have been decreasing since 2004, the year CAIS was established. Poon (2013) found that, in Ontario, there was a significant decline in AgriStability participation from 73.4% in 2004 to 56.5% in 2009. A larger share of farms that exit the AgriStability are field crop operations, with the exiting rate rising from 35% in 2004 to 54% in 2010.

Poon (2013) analyzed reasons for the declining participation in AgriStability. He found that field crop operations are more resilient to risks. The crop price increase during that sample period (2003-2011) also explains the reduced participation rate. Other reasons that explain the declining participation levels are the rigid payment schemes of AgriStability which are not tailored to actual conditions of individual farms, and the delay in AgriStability compensation which fails to coordinate production plans of participating farms (Antón et al 2011).

The declining farm participation levels for AgriStability poses problems for the program funders and administrators. First, with fewer and fewer participating farms, it is difficult for the governments to realize the objective of AgriStability and to achieve the vision of the agricultural policy framework. Second, as will be discussed later in the Economic Problem section, program administrators such as Agricorp face a hike of the average administrative expenses due to the reduction in the number of participating farms. The increased average administrative expenses directly affect the efficiency appraisal of the administrators.

Figure B.1 Layering and Cost Sharing of AgriStability under Growing Forward 1 and Growing Forward 2

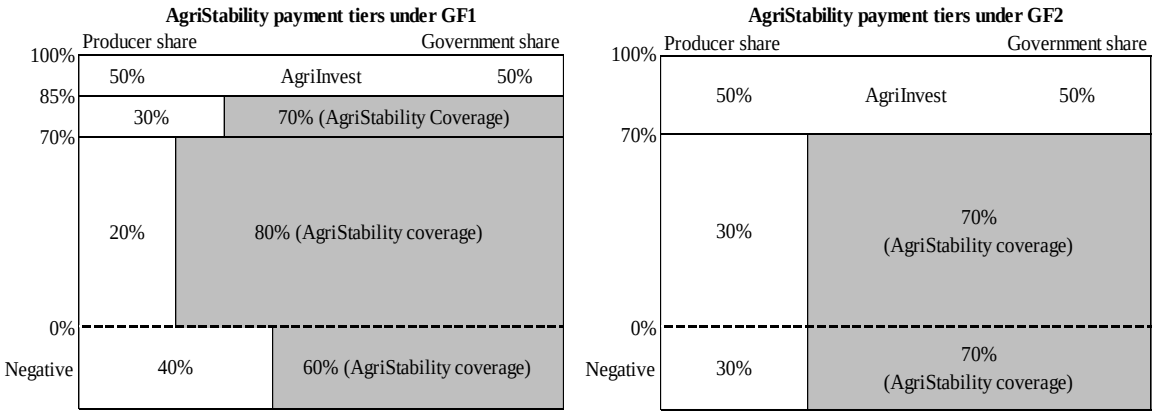
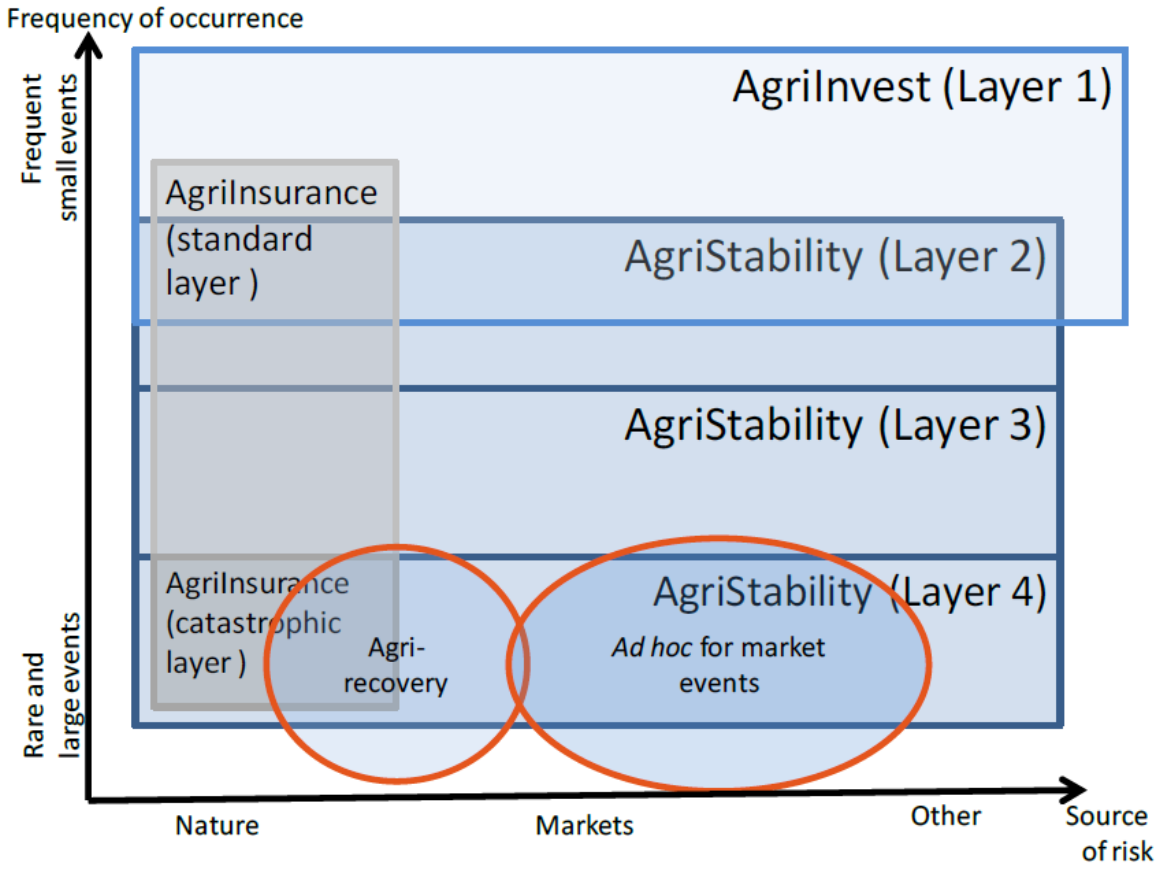


Figure B.2 Canadian Risk Management Programs under Growing Forward 1: Frequency and Type of Events Covered



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