

Formation and Adaptation of Reference Prices

by Manitoban Grain Farmers:

An Experimental Study

By

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of

Master of Science

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Abstract

This thesis examines formation and adaptation of reference prices by Manitoban farmers. Research shows that preferences are reference-dependent and that marketing decisions are affected by reference prices. Results obtained in this research suggest that Manitoban farmers' reference prices for grain are formed primarily by a weighted average price and by the highest price indicated in the experiment. Reference prices were found to adapt in the same direction as market prices, where adaptation to increasing prices was found to be larger than adaptation to decreasing prices. When deciding to sell grain, farmers were more likely to sell when they expected prices to decrease over the next month and when their reference price adjusted downwards towards the current price.

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Index

	Page
Abstract	ii
Acknowledgements	iii
Table of Contents	iv
List of Tables	viii
List of Figures	ix
Chapter 1: Introduction	1
Chapter 2: Theory	5
2.1 Introduction	5
2.2 Expected Utility Theory	6
2.2.1 Assumptions and Axioms	8
2.3 Violations to Expected Utility Theory	9
2.3.1 Continuity	10
2.3.2 Completeness	13
2.3.3 Transitivity	13
2.3.4 Independence	14
2.3.5 Utility	17
2.4 Prospect Theory	20
2.4.1 The Value Function	22
2.4.1.1 Loss Aversion	26
2.4.2 The Decision Weighting Function	27
2.4.3 The Fourfold Pattern	29
2.5 Reference Points	30
2.5.1 Preference Reversal	32

2.5.2 Disposition Effect	35
2.5.3 Equity Premium Puzzle	36
2.5.4 Adaptation	37
Chapter 3: Reference Prices in the Literature	40
3.1 Introduction	40
3.2 Reference Price Formation	40
3.3 Reference Price Adaptation	44
3.4 Multiple Reference Prices	48
3.5 Reference Prices and Regret	51
3.6 Reference Prices in Marketing Decisions of Farmers	54
Chapter 4: Methodology	58
4.1 Introduction	58
4.2 Subjects and Experiment Procedure	58
4.3 Experimental Hypotheses	62
4.3.1 Reference Prices.....	62
4.3.2 Reference Price Adaptation	65
4.3.3 Expectations	67
4.4 Analysis	68
4.4.1 Predictive Success of a Reference Price	68
4.4.2 Regression Analysis of the Reference Price	70
4.4.3 Regression Analysis of Incremental Adaptation of the Reference Price	72
4.4.4 Regression Analysis of Total Adaptation of the Reference Price	73

4.4.5 Regression Analysis of Decisions to Sell Grain	74
4.5 Model Estimation	75
4.5.1 Advantages of Panel Data	76
4.5.2 Disadvantages of Panel Data	78
4.6 Panel Data Procedure	79
4.6.1 Selecting Random Effects or Fixed Effects	81
4.6.2 The Fixed Effects Method	84
Chapter 5: Results...	85
5.1 Introduction	85
5.1.1 Descriptive Statistics of the Data	85
5.2 Selecting the Optimal Reference Price	88
5.2.1 Descriptive Statistics	88
5.2.2 Predictive Success of Reference Prices	89
5.3 Model 1: Formation of Reference Prices	92
5.3.1 Descriptive Statistics	92
5.3.2 Regression Results	95
5.4 Model 2: Incremental Adaptation of Reference Prices	98
5.4.1 Descriptive Statistics	98
5.4.2 Regression Results	101
5.5 Model 3: Total Adaptation of Reference Prices	104
5.5.1 Descriptive Statistics	104
5.5.2 Regression Results	107
5.6 Model 4: Decisions to Sell Grain	110
5.6.1 Descriptive Statistics	110

5.6.2 Regression Results	111
5.7 Categorical Subsamples	114
5.7.1 Subsamples for Reference Price Formation	114
5.7.2 Subsamples for Incremental Adaptation of the Reference Price ..	115
5.7.3 Subsamples for Total Adaptation of the Reference Price	116
5.7.4 Subsamples for Selling Decisions	117
Chapter 6: Conclusions.....	119
6.1 Introduction	119
6.2 Conclusions	119
6.3 Implications for Farmers and Other Stakeholders	122
6.4 Limitations	123
6.5 Recommendations for Future Research	124
References	125
Appendices	129
1: Questionnaire	129
2: Measure of Risk Attitudes	135
3: Price Sequences	136
4: Histograms	139
5: Subsample Models	144

List of Tables	Page
Table 1: Descriptive Statistics for the Survey	87
Table 2: Number of Observations for Each Sequence	88
Table 3: Monthly and Annual Wheat Sold (Percent of Total Crop).....	89
Table 4: Descriptive Statistics for the Predictive Success Model: Reference Prices	90
Table 5: Descriptive Statistics for Formation of Reference Prices	94
Table 6: Estimated Panel Regression Model: Formation of Reference Prices	96
Table 7: Descriptive Statistics for Incremental Reference Price Adaptation	100
Table 8: Estimated Panel Regression Model: Incremental Reference Price Adaptation	103
Table 9: Descriptive Statistics for Reference Price Adaptation	105
Table 10: Estimated Panel Regression Model: Total Reference Price Adaptation	109
Table 11: Descriptive Statistics for Selling Decisions	111
Table 12: Estimated Panel Regression Model: Selling Decisions	113
Table 13: Estimated Panel Regression Model by Subsamples: Formation of Reference Prices- Selected Coefficients	115
Table 14: Estimated Panel Regression Model by Subsamples: Incremental Adaptation of Reference Prices – Selected Coefficients	116
Table 15: Estimated Panel Regression Model by Subsamples: Total Adaptation of Reference Prices – Selected Coefficients	117
Table 16: Estimated Panel Regression Model by Subsamples: Selling Decisions – Selected Coefficients	118

List of Figures	Page
Figure 1: The Certainty Effect	10
Figure 2: The Certainty Effect (2)	11
Figure 3: The Isolation Effect	12
Figure 4: The Common Ration Effect	15
Figure 5: The Common Ration Effect (2)	16
Figure 6: The Common Consequence Effect	17
Figure 7: The Value Function	23
Figure 8: Risky Outcomes	25
Figure 9: The Decision Weighting Function	28
Figure 10: The Fourfold Pattern of Risk Attitudes	30
Figure 11: Preference Reversal	33
Figure 12: Adaptation	39
Figure 13: Risk Preferences	61
Figure 14: Fixed Effect or Random Effect	83
Figure 15: Average Monthly Satisfy and Goal Prices	95
Figure 16: Satisfy and Goal Prices for Increasing Price Sequences-	
Monthly Averages Across Farmers	106
Figure 17: Satisfy and Goal Prices for Decreasing Price Sequences-	
Monthly Averages Across Farmers	106

Chapter 1 – Introduction

Decisions under uncertainty have traditionally been examined under the expected utility framework, where all decisions are rational and lead to utility maximization. However, recent empirical evidence has shown that decisions are often guided by the presentation of the opportunity, rather than by the probable outcome. For example, individuals may behave in a risk adverse manner for one opportunity and a risk seeking manner for another opportunity, despite both holding the same range of outcomes presented in two different ways (Kahneman & Tversky, 1979). Behaviors such as these are perceived as irrational by expected utility theory and do not lead to utility maximization.

Prospect theory has grown rapidly in popularity over the past two decades to model decision making under risk and uncertainty as an alternative to expected utility theory. Developed from empirical observations, the model is unique because it derives value from a reference point, as opposed to an absolute value of wealth. This model assumes that each economic opportunity is evaluated separately rather than as a collective whole. Value received from each economic transaction is derived from the interaction of a value function and a probability weighting function. The origin of the value function is the reference point and distinguishes a transaction as a gain or loss. Reference points are values maintained in the mind for a good which represent indifference between purchasing and selling a good. It is the point where an individual is indifferent between taking an opportunity or letting it pass. In this framework, reference points have a significant impact on decision making under uncertainty.

The reference point will affect how decisions under uncertainty are framed. Selling a good at any price will create income. However, if the current market price is above the reference point, selling the good feels like a gain and if current market price is below the reference point, selling the good feels like a loss. According to prospect theory, risk attitudes will change as the transaction is perceived as a gain or a loss. Further, the difference between the reference point and selling price will cause more emotional pain for losses than pleasure for gains. Given the vast effects of reference points, it is critical to understand how reference points form and adapt.

The objective of this research is to understand how Manitoban farmers form and adapt reference points while marketing their grain. The research will explore which market prices have the greatest influence on reference points, how price expectations affect farmer's decisions to price their grain, how reference points adapt to changes in market prices, if adaptation to gains is faster than to losses, the effects of the size of gains and losses on reference point adaptation and the effects of time in a gaining or losing position on reference point adaptation. Data for this research was obtained by a questionnaire and experiment administered to farmers across Manitoba.

There is a general lack of consensus among economists concerning how reference points are formed and adapted to by decision makers (Baucells et al., 2011). Developing a dynamic choice model incorporating reference points requires compatible theories of choice under uncertainty and reference point adaptation. Different theories may cause different reference points to be calculated (Baucells et al., 2011). Risk preferences which are not quantifiable and unique among individuals create further challenges.

Studies have explored the formation and adaptation of reference points in an investment context (Baucells et al., 2011; Lee et al., 2009), but not in a marketing context. Reference points have been applied to decision making analysis in marketing (McNew & Musser, 2002; Meulenberg & Pennings, 2002; Fryza, 2011) using economic theory to select the reference point as opposed to experimental evidence. Exploring the formation and adaptation of reference points in agricultural marketing will help fill this gap in empirical research.

Once a model of reference point formation and adaptation is complete, agricultural producers and agricultural industry employees can benefit from a greater understanding of the decision making processes in grain marketing. More generally, this model of reference points may also be applied to other economic models.

This thesis is structured in the following manner. Chapter 2 presents theory used for decision making under risk and uncertainty. An overview of expected utility theory and the violations found in empirical research concerning decision making under uncertainty is presented. Prospect theory and reference points are then discussed in detail. Chapter 3 provides a review of empirical literature on reference prices. It examines how reference prices are formed, how they adapt, how they create regret and value and how they affect marketing decisions. Chapter 4 presents research methods that were used to collect the data and the hypotheses that were tested. Chapter 5 presents the procedures with which the models are estimated. Chapter 6 presents analysis of the economic models. Chapter 7 presents conclusions of the research. Appendix 1 presents the questionnaire used for data collection, appendix 2 presents the measure of risk attitudes, appendix 3 presents the price sequences used in the experiment, appendix 4

presents histograms of data collected during the survey and experiment and appendix 5
presents the results of each model for subsamples.

CHAPTER 2 – THEORY

2.1 Introduction

This chapter will first compare the categorical differences between normative theories and positive theories. It will then explain expected utility theory, a widely accepted normative theory of decision making under uncertainty. Descriptions of violations found in experimental and market data of expected utility theory will be presented to demonstrate where the model does not accurately describe decision making under uncertainty. Prospect theory, a positive theory introducing reference points and framing is then presented as an alternative model to expected utility theory. And finally, a detailed description is given of why reference points exist, the effects they can have on risk preferences, how they are formed, and how they adapt over time.

Economic theories can be categorized as either normative or positive. Positive analysis attempts to explain and predict economic behavior in the marketplace whereas normative analysis describes what ought to be. Various models of each have been developed in order to explain how individuals make choices and to help predict choices in the future.

Positive analysis uses cause-and-effect relationships to explain phenomena, testing observations found in the market place and in laboratory experiments. Those observations are used to describe behavior, whether or not the behavior can be explained by existing theories. Quantitative analysis is used to measure economic effects within descriptive models. Data for analysis is usually collected from experiments or

questionnaires since isolation of uncertain prospects is difficult from observed market behavior.

Normative analysis is used to determine how individuals are expected to behave given that their goal is to achieve profit-maximizing allocations of resources. Most normative economic theories are grounded in the assumption that preferences should be utility maximizing and consistent; they do not attempt to determine what preferences should be. Axioms are used to describe normative models and are based on how individuals ought to behave in order to maximize welfare.

2.2 Expected Utility Theory

Von Neumann and Morgenstern (1947) developed Expected Utility (EU) theory and defined axioms to model what individuals ought to prefer when faced with choices under uncertainty. The concept of expected utility itself was first proposed by Bernoulli in 1738. Preferences in EU theory are determined by a combination of not only the value of the payouts and probability of the payouts occurring, but also by the utility received from the expected payouts.

Each uncertain choice will have one or more possible outcomes with a probability less than one of occurring. Outcomes x_i occur with probability p_i and are denoted as $\{x; p\} = [(x_1, x_2, \dots, x_n); (p_1, p_2, \dots, p_n)]$. For simplicity, (x, p) will be used in the presence of null outcomes such as $(x, p; 0, 1-p)$; you receive $\$x$ if a fair coin is flipped and lands on heads with probability p , you receive nothing otherwise. Certainty will be denoted as (x) ; you will receive $\$x$ for certain. The uncertain choice, $\{x; p\}$, has an expected value denoted as $E[x] = \sum p_i x_i$. A set of probabilities, p_i , which contain all possible outcomes

will sum to unity, $\sum p_i=1$; there is a 50% chance the flipped coin will land as heads and a 50% chance it will land on tails; therefore, there is a 100% chance that the coin will land either heads or tails.

Each unit of goods purchased or consumed creates a feeling of well-being or pleasure called utility. The utility received from a good, x , is denoted as $u(x)$. The utility we expect to receive from an uncertain outcome is the summation of the utility of receiving each individual outcome multiplied by the probability of that outcome occurring. Assume our mom has packed us a lunch. We are uncertain whether she included an apple or an orange, but there is an equal chance of finding either fruit. Assume we know that an apple would bring us 10 units of enjoyment, or utility, and an orange would bring us 12 units of utility. The expected utility from our lunch is 11 utils ($0.5*10 + 0.5*12$). We can symbolize this in the functional form as $E[U(x)] = \sum p_i U(x_i)$. Individuals seek to maximize expected utility based on total wealth, and are assumed to express their preferences by selecting the outcome which would lead to maximum total utility. These choices between uncertain outcomes exhibit preferences. Strict preferences, where A is always (never) preferred to B is denoted as $A > B$ ($A < B$). Weak preferences, where A is either preferred (not preferred) or indifferent to B is denoted by $A \geq B$ ($A \leq B$). Indifference between choices is denoted by $A \sim B$. Preferences are assumed to be consistent and rational.

Utility functions are used to describe preferences in an ordinal manner. An individual will prefer x over y if and only if she receives greater utility from x than from y , $u(x) > u(y)$. A utility function is continuous if all four axioms described above hold true. Utility functions are assumed to begin at the origin and can be concave due to

diminishing marginal utility and risk aversion. Risk aversion, when certain outcomes are always preferred to risky outcomes of the same expected value, is assumed to decrease the utility of uncertain outcomes. A utility function is concave if $f(tx + (1-t)y) \geq tf(x) + (1-t)f(y)$ for all x and y and such that $0 < t < 1$. Individuals are assumed to exhibit preferences yielding the maximum total utility within their budget constraints.

2.2.1 Assumptions and Axioms

EU theory is based on assumptions and axioms implying rational behavior. A few assumptions, as described by Varian (1992), are used when analyzing choices under uncertainty, or lotteries. A lottery where outcome x has a probability p of occurring and outcome y has a probability $(1-p)$ of occurring will be denoted as $(x, p; y, 1-p)$. The first assumption states that receiving x with probability one is the same as receiving x for certain; $1x + (1-1)y \sim x$. Second, ordering of preferences is irrelevant; $px + (1-p)y \sim (1-p)y + px$. Third, perceptions concerning the lottery are only affected by the final probability of receiving each outcome; $q(px + (1-p)y) + (1-q)y \sim (qp)x + (1-qp)y$ where $0 \leq q \leq 1$ and which represents a multi-stage lottery compared to a single-stage lottery with the same expected outcomes. These assumptions follow from the standard economic model that choices are ‘rational’.

Von Newmann and Morgenstern (1947) defined a set of axioms which are necessary and sufficient in order to represent choices under uncertainty while maximizing expected utility. The four axioms are as follows: completeness, transitivity, continuity and independence. Considering uncertain choices A , B and C and their probabilities of occurrence p_i , completeness requires that preferences exist over all uncertain choices, i.e.

$A \geq B$, $B \geq A$, or $A \sim B$. Transitivity implies that uncertain choices are ranked consistently. If $A \geq B$ and $B \geq C$ then $A \geq C$. The third axiom, continuity, states that some combination of the best and worst uncertain choices will be preferred to an intermediate choice, and the intermediate choice will be preferred to some other combination of the best and worst uncertain choices. For $A \geq B \geq C$, there exists p_1 and $p_2 \in (0,1)$ such that $p_1A + (1-p_1)C \geq B$ and $B \geq p_2A + (1-p_2)C$. Finally, the independence axiom states that if one uncertain choice is preferred to another, then a mixture of both preferences or the addition of other uncertain choices should not alter this preference. For any A , B , and C , and $p \in (0,1)$, $A \geq B$ iff $pA + (1-p)C \geq pB + (1-p)C$.

By these axioms, it can be proved that $A \geq B$, iff $\sum p_i^a u(x_i^a) \geq \sum p_i^b u(x_i^b)$ (Fox, 2009). This equation states that the expected utility of A is greater than or equal to the expected utility of B if A is preferred or indifferent to B . In order to use a uni-dimensional scale, it is necessary that the axioms of completeness and transitivity hold, which allow preferences to be (weakly) ordered. Establishment of a continuous trade-off between probability and outcomes stems from the continuity axiom. Weighting utilities of outcomes by their respective probabilities is possible due to the independence axiom.

2.3 Violations to Expected Utility Theory

Expected utility theory has become the mainstream normative theory for decision making under uncertainty. However, there are many anomalies which cannot be explained by EU theory. The anomalies described in this section decrease the descriptive validity of EU theory and have spurred many studies which question EU theories axioms,

assumptions and framework. Each of the four axioms of expected utility theory has been found to be violated in experimental studies.

2.3.1 Continuity

The certainty effect violates continuity in EU theory. Kahneman and Tversky's (1979) argue that preferences are discontinuous in a neighborhood of certainty. Gains (losses) with certainty are disproportionately more (less) desirable than gains (losses) with high probabilities. The first problem, shown in Figure 1, contains a choice between \$3,000 for certain and $\{(\$4000); (0.8)\}$. The second problem contains a choice between -\$3,000 for certain and $\{(-\$4000); (0.8)\}$. In the diagram, squares are decision nodes where the subject must decide to follow the path of option a) or option b) and circles are chance nodes where the outcomes will be determined randomly based on their respective probabilities. The preferred option, a) or b), as found in experimental studies, can be seen in bold.

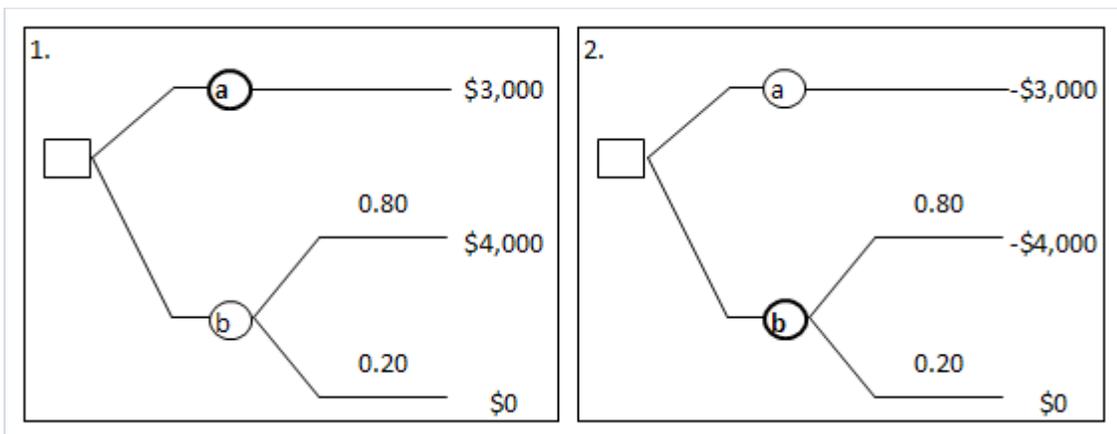


Figure 1: The Certainty Effect

Continuity states that subjects should prefer either b) in both options, being risk seeking, or a) in both options, being risk adverse. Switching between a) and b) across problems violates continuity and hence EU theory, and was commonly observed in experiments. Comparison of the choice problems displays an overweighting of certainty because most respondents chose a) in the first problem and b) in the second problem (Kahneman & Tversky, 1979). The choices reflected in these problems may simply be due to favoring of certainty for gains and fear of certainty for losses.

The certainty effect is also found in the following choice problem where the uncertain option is clearly dominant (Figure 2). Subjects often select a) because the 1% probability of receiving nothing outweighs the 10% probability of \$5 million (Quiggin, 1993). These behaviors suggest that the utility function is discontinuous in the area of certainty. Significant non-linearity has been found empirically near the boundaries, 0 and 1, of the probability weighting function (Wu & Gonzalez, 1996).

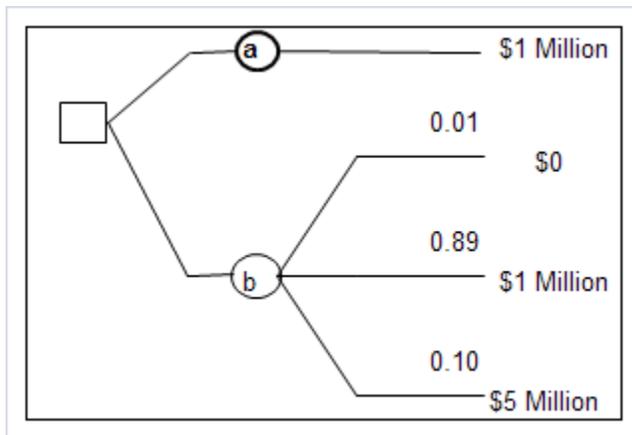


Figure 2: The Certainty Effect (2)

Continuity is also violated in experimental studies due to the isolation effect; compound lotteries are perceived differently than simple lotteries, despite identical expected values. Kahneman and Tversky (1979) developed two problems to demonstrate this violation (Figure 3). The first problem proposes a choice between $\{(\$4000); (0.2)\}$ and $\{(\$3000); (0.25)\}$. The second problem contains two stages; the first stage has a 75% chance of the game ending and a 25% chance of moving on to the second stage which contains a choice between $\{(\$4000); (0.8)\}$ and $\$3000$ for certain.

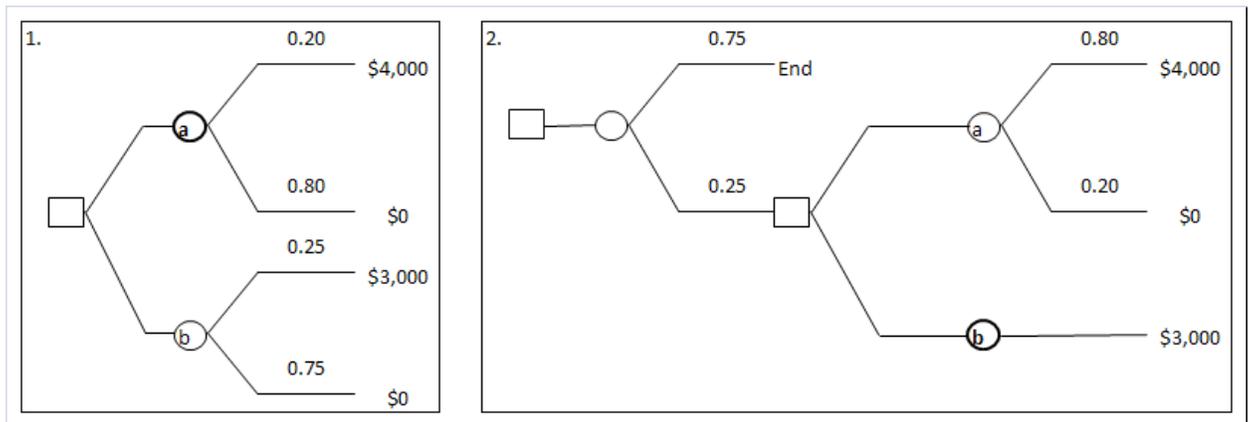


Figure 3: The Isolation Effect

The final probabilities of winning each cash prize in the second problem are $0.25 \cdot 0.8 = 0.2$ probability of winning \$4,000 and a $0.25 \cdot 1 = 0.25$ probability of winning \$3,000. These are the same probabilities of winning each prize in the first problem. Based on the continuity assumption, EU theory predicts that individuals should select either a) for each problem or b) for each problem. This is not the case; a majority of respondents chose a) in the first problem while a majority chose b) in the second problem. Kahneman and Tversky (1979) argue that in the second problem, the common

components in the first stage are ignored and the second stage decision is made independently, leading to preference reversal¹.

2.3.2 Completeness

Completeness, $A \geq B$, $B \geq A$, or $A \sim B$, has been shown to be violated by identifying discrepancies in stated preferences (Lichtenstein & Slovic, 1971). Preference reversals were elicited when two gambles were offered, one containing a modest gain with a high probability and one containing a large gain with a low probability and a small loss with a higher probability. They predicted and found that the respondents would violate EU theory by selecting to play the option with a high probability of a gain but in turn would place a higher bid to play the bet with a larger gain. This shows preference reversal, where participants prefer one option yet offer a higher bid for the other option.

2.3.3 Transitivity

Transitivity, if $A \geq B$ and $B \geq C$ then $A \geq C$, was also shown to be violated by Slovic and Lichtenstein (1983). They found that probability was the primary determinant for decisions under uncertainty, unless the difference in probability was sufficiently small, then the amount available to be won became the primary determinant. The switch from choices based on probability to amount can lead to preference reversal and violation of transitivity. A survey with the following five gambles was conducted,

¹ Preference reversal occurs when preferences are changed due to changes in the frame of the question.

A: (\$5.00, 7/24) B: (\$4.75, 8/24) C: (\$4.50, 9/24)
D: (\$4.25, 10/24) E: (\$4.00, 11/24)

Most respondents chose $A > B$, $B > C$, $C > D$, and $D > E$. These decisions were believed to be due to a greater focus by the subjects on the increase in amount available to be won as opposed to the slight decrease in probability. Given these results, the transitivity axiom was violated when respondents revealed preferences for $E > A$; most likely due to the larger change in probabilities.

2.3.4 Independence

The independence axiom has received much scrutiny concerning descriptive ability. Violations of the independence axiom due to preference reversals are observed in the common ratio effect and the common consequence effect. These inconsistent choices violate the independence axiom because, according to EU theory, fractions of problems and identical changes to each problem within a set should not affect preferences.

The common ratio effect, or the Allais paradox, was first presented by Allais (1953) and is a prime example of inconsistent choices concerning the independence axiom of EU theory. The following example was presented by Kahneman and Tversky (1979) and contains two parts (Figure 4).

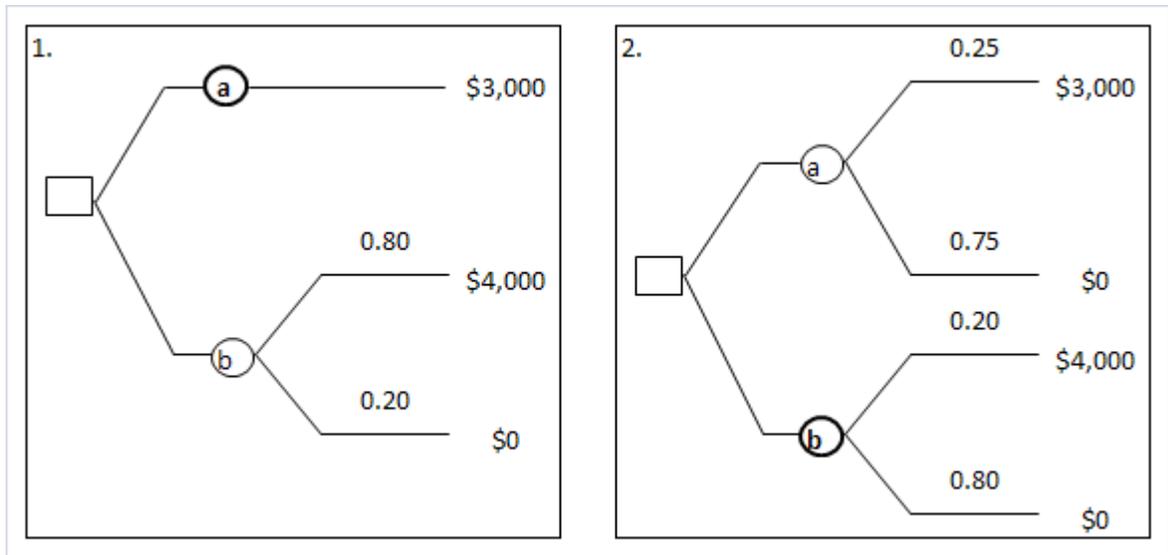


Figure 4: The Common Ratio Effect

The majority of subjects chose a) of part one and b) of part two (Figure 4). These results are inconsistent because the ratio of the probabilities is the same, i.e. the probability of winning \$3,000 in part one is four times the probability of winning \$3,000 in part two ($1=4 \times 0.25$) and the same proportion to the probabilities of winning \$4,000 in each part ($0.8=4 \times 0.2$). Therefore, EU theory predicts that individuals should select either a) for both options or b) for both options. Despite the apparent violation of EU theory, it can be argued that this example does not prove an inconsistency because, once again, individuals may simply prefer certainty (Quiggin, 1993).

In order to determine if the paradox is due to preferences for certainty or a true anomaly, Kahneman and Tversky (1979) developed another example and presented an alternative choice problem that does not contain certain prospects. The two-part problem is as follows (figure 5).

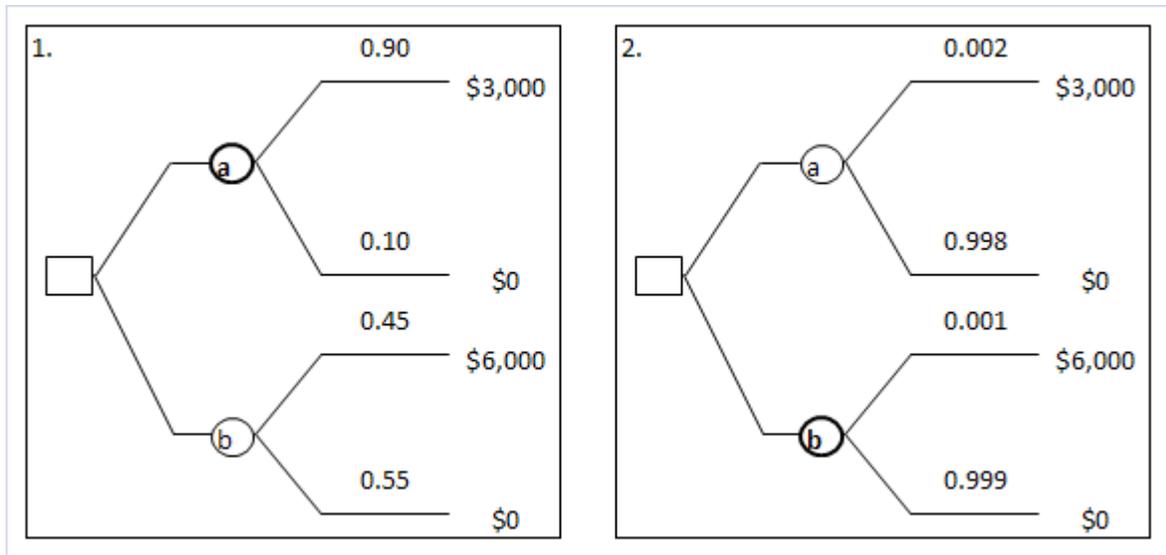


Figure 5: The Common Ratio Effect (2)

Both scenarios have the same ratio of the probabilities; 0.9/0.002 of winning \$3,000 is the same as 0.45/0.001 of winning \$6,000 (figure 5). A majority of the subjects choose a) for the first option and b) for the second option. These choices reflect preferences for larger probabilities where the chances of winning are probable and preferences for large payouts when the probability of winning is small. Findings from these two studies are evidence of violation of the independence axiom.

Another example of the Allais problem, as designed by Quiggin (1993), is known as the common consequence effect, and demonstrates inconsistent choices related to the independence axiom. In figure 6, most subjects chose a) in problem one and b) in problem two. Problem two is simply a variation of problem one, where an 89% chance of \$1m has been changed to an 89% chance of \$0². Since the same change has occurred to both options of problem two, EU theory states that respondents should have selected a)

² Note that a certain gain of \$1 million in problem one can also be thought of as an 11% chance of winning \$1 million combined with an 89% chance of winning \$1 million.

for both choices or b) for both choices. Overweighting of the 0.01 probability of receiving nothing causes option b) of the first problem to be unappealing, leading to selection of option a) despite dominance of option b). These results provide further evidence that the independence axiom of EU theory is not an accurate representation of behavior in cases of uncertainty.

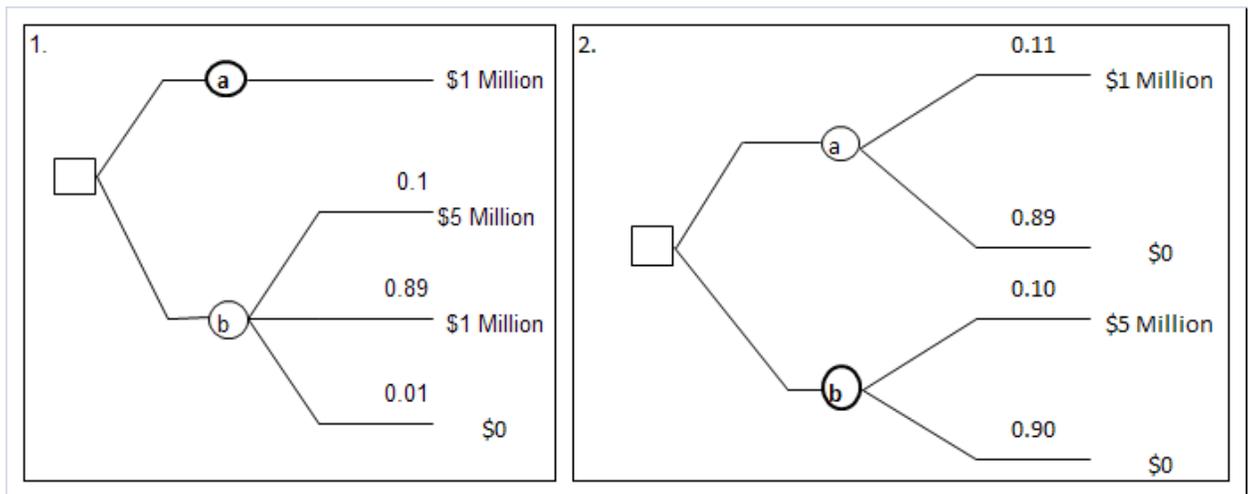


Figure 6: The Common Consequence Effect

2.3.5 Utility

Expected utility theory is built upon the framework of utility theory and indifference curves. Utility curves are ordinal, require consistency of preferences, and cannot cross or intersect at any point. They are also reversible; if an individual is indifferent about moving from point A to B, then they should be indifferent about moving from point B to A (Knetsch, 1992). If these requirements are not met under uncertainty, EU theory is lacking as a descriptive model under uncertainty.

Empirical studies have also identified other violations to the rationality assumption adopted by expected utility theory. For example, Knetsch and Sinden (1984) demonstrated the endowment effect by offering choices between lottery tickets and \$2 cash. The endowment effect creates higher valuation of goods which are owned than those which are not owned due to the painful experience of losing a good. Each subject was endowed with a ticket or cash and was given the opportunity to trade. If the endowment effect did not exist, the percentage of people paying \$2 (giving up their \$2 to receive a ticket) was expected to be approximately the same as those refusing \$2 (choosing to keep their ticket). This did not occur. Original allocations appeared to be valued higher, which was reflected in most participants' decision to retain their original allocation. Sellers' willingness to accept (WTA) payment for selling a good they owned was found to be approximately double the buyers' willingness to pay (WTP) for purchasing a good they did not own.

Other experiments were undertaken by Kahneman, Knetsch, and Thaler (1991) to quantify and determine causes of the endowment effect. Half of the individuals in their experiment were given mugs and the other half received nothing. They were asked to identify their WTP and WTA, from which supply and demand curves were elicited, market clearing prices were calculated and trades were made. Of the 22 mugs distributed per group, half were anticipated to trade, but only 1 out of 5 mugs were traded. The median WTA for each mug was \$5.25 and the median WTP for each mug was \$2.25-\$2.75, hence WTP was about half the WTA. The authors were curious whether the lack of trading was due to a reluctance to buy or a reluctance to sell. A second study added a third group of subjects, choosers, whom were not given an initial allocation and were ask

to select a price at which they would be indifferent between receiving the mug or the money. Choosers submitted bids which were similar to buyers, rather than similar to sellers. These findings suggest that low trade volume is mostly due to sellers' reluctance to lose the mugs they were endowed.

Using similar techniques as just described, Knetsch³ (Kahneman et al., 1991) found irreversibility in indifference curves. He experimented with ball point pens and cash endowments to identify indifference curves through a series of accept or reject offers. Those endowed with pens valued pens more than cash, and those endowed with cash valued cash more than pens; leading to intersecting indifference curves.

The instant endowment effect was found to be due to the pain from losing a good by Loewenstein and Kahneman⁴ (Kahneman et al., 1991). Pens and redeemable tokens were given to students initially. They were then asked to rank the attractiveness of a group of six possible gifts (including the pens). Finally, they chose between two of the six ranked gifts, either pens or two chocolate bars. Of those endowed with pens, 56% choose pens. Of those endowed with tokens, only 24% choose pens. The attractiveness rating of pens was not higher in the pen endowed group; therefore aversion to loss was concluded to be the determining factor.

Given the violations of expected utility theory's axioms and assumptions, alternative theories were developed. One of the most promising non-expected utility theories is Prospect Theory, which will be discussed in the next section.

³ Knetsch, Jack L., "Derived Indifference Curves," working paper, Simon Fraser University, 1990.

⁴ Loewenstein, George, and Daniel Kahneman, "Explaining the Endowment Effect," working paper, Department of Social and Decision Sciences, Carnegie Mellon University, 1991.

2.4 Prospect Theory

Prospect Theory is a descriptive model of decision making under uncertainty. Prospects are opportunities with uncertain outcomes. Kahneman and Tversky (1979) first proposed the theory in their article 'Prospect Theory: An Analysis of Decision Under Risk', which quickly gained popularity (Goldstein, 2011). Kahneman and Tversky (1979) tried to develop a model that could address the violations to EU theory found in empirical studies. Therefore, they wanted to incorporate the notions that each prospect is evaluated from a unique reference point where gains promote risk adverse behavior, losses promote risk seeking behavior, deviation from the reference point causes diminishing sensitivity and losses are felt more acutely than gains. The model was developed from the viewpoint of an individual on their own gains or losses and addresses the empirical evidence which invalidated many aspects of EU theory. Prospect theory mimics physiological behavior observed in physical changes, such as how it is easier to differentiate between a change from 3° to 6° than a change between 13° and 16°. It also applies to economic gains or losses, such as how a change in losses from \$100 to \$200 is more painful than a change in loss from \$1100 to \$1200. When determining the value of prospects, individuals will first *judge* what the value of the prospect is, and then *decide* if they would like to accept the prospect presented (Monroe, 1990). Similarly, the new model decouples the evaluation of uncertain prospects into two parts, editing and evaluation.

The first step of the editing phase is coding. Outcomes are perceived as gains or losses relative to a reference point⁵. The reference point is a value at which an individual feels indifferent between accepting or rejecting the prospect. This point is commonly assumed to be the status quo. Next, common components may be combined in order to evaluate the distinctive components. For example, you are given a bag with one white marble, one blue marble and 8 black marbles. If you pick the white or blue marble you win \$100, otherwise you win nothing. Prospects such as these, (100, .10; 100, .10), may be perceived as (100, .20). Segregation of prospects into riskless and risky components will help decipher between sure gains or sure losses and the remaining risk. A prospect (100, .75; 150, .25) can be perceived as a sure \$100 gain and a risky prospect (50, .25). Another prospect (-50, .66; -75, .34) can be perceived as a combination of a sure loss of \$50 and a risky prospect of (-25, .34). Once these editing phases are complete for each prospect, the following phases will be applied to the newly created set of prospects. Cancellation of shared components occurs when two prospects have similar outcomes and unique outcomes. Given a choice between the following two prospects (100, .50; 200, .20) and (100, .50; 300, .10), individuals may focus only on each prospect's unique outcomes (200, .20) and (300, .10). Prospects can also be simplified, where a prospect of (51, .26) is edited into (50, .25). Detection of dominance is also common where prospects are discarded because it is clearly inferior to one or more other prospects. For example, (100, .50) would be discarded when chosen between it and the prospect

⁵ Prospects are not evaluated in terms of wealth, as is assumed in EU theory. (Kahneman & Tversky, 1979)

(150, .75). The order of editing phases is dependent upon each individual and may create different final perceived prospects. Once the editing phase is complete, evaluation of the edited prospects will begin.

Formally, prospects will be evaluated based on the value function, $v(\text{outcome})$, and the decision weighting function, $\pi(\text{probability})$. Prospect Theory assumes that a risky outcome will be preferred over another risky outcome if it has a higher value $V(X) = \sum \pi(p_i)v(x_i)$ where x is a possible outcome and p_i is the probability of this outcome. The interaction between the value function and decision weighting function will lead to preferences for prospects. The prospect with the highest value, the perceived value of the outcomes multiplied by their respective weighted probability, will be preferred to all other prospects.

2.4.1 The Value Function

Kahneman and Tversky (1979) presented three primary characteristics of the value function based on their empirical observations; the function is defined as a deviation of the stated price from a reference point and is expressed in terms of gains and losses from a reference point, concavity for gains and convexity for losses, and a steeper function for losses than gains. The origin of the value function is the reference point, which is the point of indifference between accepting and rejecting the prospect. The S-shaped value function, as presented in Figure 7, is steeper near the reference point and becomes increasingly linear for larger gains and losses.

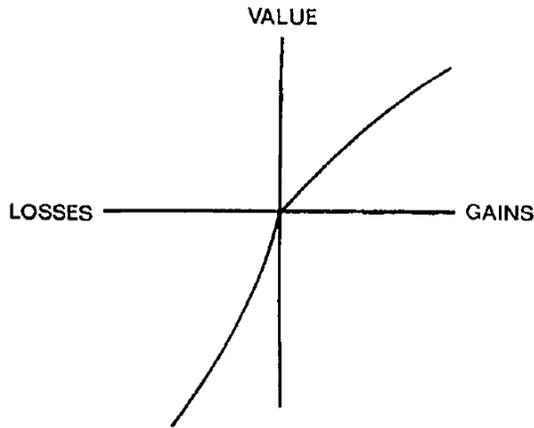


Figure 7: The Value Function

(Kahneman & Tversky, 1979)

The value function in prospect theory is unique due to its derivation from changes in wealth or welfare rather than final states. The reference point, often assumed to be the status quo, adapts to prices and expectations that change over time (Kahneman & Tversky, 1979). Reference points will differ across goods and individuals depending on past experiences and adaptation levels. For example, sell grain for \$7 may appear as a gain if you expected to sell the same grain for \$6 while selling the grain for \$7 may appear as a loss if you expected to sell the same grain for \$8. Evaluating a prospect compared to a reference point does not change the value of the prospect, but changes the perception of gains and losses and risk preferences depending on deviations from the stated price in relation to the reference point. A detailed account of reference points will be presented in section 2.4.

The shape of the value function is assumed to be concave in the gain domain (outcome above the reference point), representing risk adverse behavior, and convex in the loss domain (outcome below the reference point), representing risk seeking behavior.

When given an option between a sure gain (\$450) and an uncertain prospect with a slightly higher expected value (\$1000; 0.5), most individuals will choose the sure gain (Kahneman & Tversky, 1979). Risk adverse behaviors reflect a strong desire to avoid receiving nothing when something could have been received. When given an option between a sure loss (\$-450) and an uncertain prospect with a slightly lower expected value (\$-1000; 0.5), most individuals will choose the uncertain prospect. Risk seeking behaviors reflect a strong desire to retain the potential to avoid a loss, even if that means accepting the risk of losing an even larger amount. These behaviors create the S-shaped value function.⁶

Application of the value function can be seen in the following example of behavior under risky choices. Risk aversion is found for gains and risk seeking is found for losses in Figure 8.

⁶ Kahneman and Tversky also note that special circumstances such as prospects which hold the opportunity to move an individual up into or down out of the status quo social class are able to sharply increase or decrease the value function in order to avoid life altering losses or allow for the possibility of life altering gains. These opportunities can create areas of the value function, which are far from the reference point, that are risk averse for losses and risk seeking for gains.

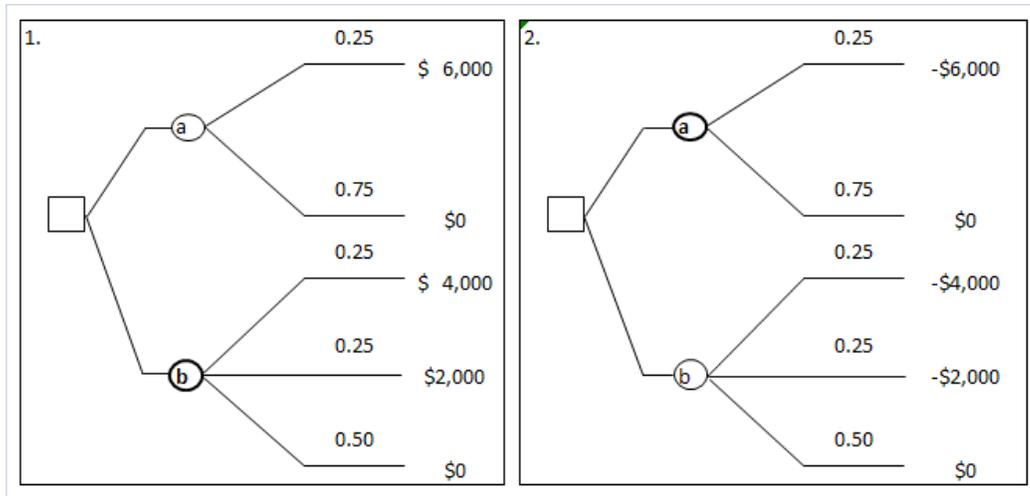


Figure 8: Risky Outcomes

For the first choice problem, a majority of respondents chose option b), maximizing the probability of receiving a gain while forfeiting the opportunity for even higher gains which suggests risk adverse behavior. For the second choice problem, a majority of respondents chose option a), minimizing the probability of receiving a loss while assuming the risk of an even larger loss which suggests risk seeking behavior. Applying these results to the value and weighting function, the following inequalities can be computed $\pi(0.25)v(6000) < \pi(0.25)[v(4000) + v(2000)]$ and $\pi(0.25)v(-6000) > \pi(0.25)[v(-4000) + v(-2000)]$. Canceling out the weighting function on each side of both equations, the following inequalities remain: $v(6,000) < [v(4,000) + v(2,000)]$ and $v(-6,000) > [v(-4,000) + v(-2,000)]$. These findings are consistent with a concave value function for gains and a convex value function for losses (Kahneman & Tversky, 1979).

A common parameterization of the value function was first presented by Tversky and Kahneman (1992) as deviations from the reference point, to reflect concave and convex curves for gains and losses respectively, and a steeper slope for losses. They used

a power function as follows, $v(x) = x^\alpha$ for $x \geq 0$ and $v(x) = -\lambda(-x)^\beta$ for $x \leq 0$, where $\alpha, \beta > 0$ measure the curvature of the value function for gains and losses respectively and λ is the coefficient of loss aversion. Their estimated values of these coefficients were $\alpha = 0.88$, $\beta = 0.88$ and $\lambda = 2.25$.

2.4.1.1 Loss Aversion

The idea of loss aversion comes from observations that symmetric prospects such as a 50% chance of gaining \$10 and a 50% chance of losing \$10, $(x, 0.50; -x, 0.50)$, are commonly found to be unappealing. Losses are felt more acutely than gains, creating greater emotional impact for losses than for gains of similar value. Loss aversion creates an asymmetry of the value function. The curve below the reference price (loss) was found to be approximately twice as steep as the curve above the reference price (gain), leading to a coefficient of loss aversion of approximately 2 (Kahneman & Tversky, 1991). Loss aversion also creates greater impact when comparing losses as opposed to comparing gains. 'In general, a given difference between two options will have greater impact if it is viewed as a difference between two disadvantages than if it is viewed as a difference between two advantages' (Kahneman et al., 1991).

Several definitions of loss aversion have been presented. Kahneman and Tversky (1979) first proposed a definition that negative values of losses are larger than that of the corresponding gain, $-v(-x) > v(x)$ for all $x > 0$, from which they proposed a coefficient of loss aversion by a mean or median value of $-v(-x)/v(x)$ over a finite range of x .

Kahneman and Tversky (1991) presented another definition stating that given value functions with exponents, loss aversion must be the ratio of value of losing a dollar to

gaining a dollar, $-v(-\$1) > v(\$1)$, leading to a coefficient of $-v(-\$1)/v(\$1)$. Tversky and Wakker (1995) later defined that loss aversion occurs when the slope of the value function with respect to losses is greater than the slope of the value function for corresponding gains, $v'(-x) > v'(x)$, and thus defined the coefficient of loss aversion as the mean or median value of $v'(-x)/v'(x)$. All three definitions will lead to the same coefficient if the value function is linear over the range evaluated.

2.4.2 The Decision Weighting Function

The decision weighting function is similar to but not synonymous to probability. Decision weights ($\pi(p)$) are inferred from selections between prospects to form an increasing function of probability (p), with $\pi(0) = 0$ and $\pi(1) = 1$. Decision weights typically create an inverse S-shaped function, as shown in Figure 9, where $\pi(p) > p$ for small probabilities and $\pi(p) < p$, for large probabilities. Decision weights are not the same as probabilities and do not necessarily obey the probability axioms. In fact, subcertainty is common for decision weights, where the collective underweighting of all probabilities sum to less than unity, $\pi(p) + \pi(1-p) < 1$, where $0 < p < 1$. The underweighting of most probabilities has a greater net effect than the overweighting of very small probabilities. Due to the overweighting of small probabilities and underweighting of other probabilities, the subcertainty effect will be greater when probabilities are larger.

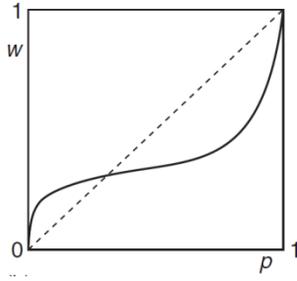


Figure 9: The Decision Weighting Function

(Fox, 2009)

Due to subcertainty, preferences have been found to be less sensitive to changes in probability than previously believed. The exception is at the natural boundaries of 0 and 1, which are exponentially more sensitive, thus creating boundary areas of the function that are not well behaved. Changes in sensitivity of the outermost areas may reflect the categorical distinction from certain to nearly certain and impossible to nearly impossible. The editing phases of simplification or detection of dominance may account for rounding of near boundary probabilities to impossibility and certainty.

The slope of the weighting function reflects the sensitivity of perceptions with respect to changes in probability. The center of the curve is nearly linear, creating less than proportional effects on the decision weight when changes in probabilities occur. This effect is called subproportionality.

A decision weighting function was first estimated parametrically by Tversky and Kahneman (1992) using a single-parameter functional form, $\pi(p) = p^\gamma / (p^\gamma + (1-p)^\gamma)^{1/\gamma}$ which is inverse S-shaped for $\gamma < 1$ (Figure 8), S-shaped for $\gamma > 1$, and linear for $\gamma = 1$. Therefore, the parameter γ controls the curvature of the function. Other functional forms have been developed, and some incorporate another parameter to account for the

elevation of the function. Another popular form of the function is $\pi(p) = \delta p^\gamma / (\delta p^\gamma + (1-p)^\gamma)$ where $\gamma > 0$ measures the degree of curvature of the weighting function and $\delta > 0$ measures the elevation (Lattimore et al., 1992).

2.4.3 The Fourfold Pattern

Attitudes towards risk are essentially an interaction between the value function and the weighting function. Risk adverse behavior is predicted to occur whenever $\pi(p) < v(xp)/v(x)$ ⁷ where (x, p) is a gamble, (px) is the gamble's expected value and $x > 0$ (Fox, 2009). The weighting function is underweighted, making the risky alternative less appealing. Risk seeking behavior is predicted to occur whenever $\pi(p) > v(xp)/v(x)$ ⁸, and $x > 0$ (Fox, 2009). The weighting function is over weighted, making the risky alternative more appealing.

Interactions of these functions can explain observed behavior known as the fourfold pattern of risk attitudes: risk seeking for gains and risk aversion for losses of low probabilities, and risk aversion for gains and risk seeking for losses of high probability (Tversky & Wakker, 1995). This pattern can be seen in Figure 10. A risky prospect offers choices between potential gains of \$100 or -\$100, with either a 5% or 95% probability of occurring, and a certain option of either \$5, -\$5, \$95, or -\$95. The values in the boxes represent options most often selected by subjects.

⁷ Note that $\pi(p) < v(xp)/v(x)$ implies $\pi(p) \times v(x) < v(xp)$.

⁸ Note that $\pi(p) > v(xp)/v(x)$ implies $\pi(p) \times v(x) > v(xp)$.

	Gain	Loss
Low Probability	(100, 0.05) (5) (Risk Seeking)	(-100, 0.05) (-5) (Risk Aversion)
High Probability	(100, 0.95) (95) (Risk Aversion)	(-100, 0.95) (-95) (Risk Seeking)

Figure 10: The Fourfold Pattern of Risk Attitudes

For gains with high probability, underweighting of the probability and risk aversion decrease the subjective benefits of the gain and leads to preference for certainty. This behavior is observed when a plaintiff prefers to settle a lawsuit. For losses with high probability, underweighting of the probability and risk seeking behavior decrease the subjective costs of the loss and leads to preference for the risky alternative. This behavior is observed when a defendant does not wish to settle a lawsuit. For gains with low probability, overweighting of the probability increases the subjective benefits of the gain and outweighs risk aversion, leading to preferences for the risky alternative. This behavior is observed with the purchase of lottery tickets. For losses with low probability, overweighting of the probability increases the subjective costs of the loss and outweighs risk seeking behavior, leading to preferences for certainty. This behavior is observed with the purchase of insurance.

2.5 Reference Points

It has become a widely accepted view in the fields of behavioral economics, behavioral finance, and marketing that reference points have a significant effect on behavior (Baucells et al., 2011). Deriving value from changes in wealth, relative to a reference point, gained popularity after Kahneman and Tversky's (1979) article

presenting Prospect Theory. Reference points are frames of reference which create the feeling of gains or losses when compared to prospects and are critical determinants of risky behavior (Baucells et al., 2011). This section will examine how reference points affect decisions under uncertainty, why they are important, and theory of how they are formed and adapt.

Mathematical representations of preferences with respect to reference points can be denoted with a subscript r after an inequality, \leq_r or \geq_r . The reference structure is used to exhibit preferences with respect to a reference point. X is weakly preferred to Y from the reference point r can be expressed mathematically as $X \geq_r Y$. Similar notations are used for strict preferences and indifference.

The value of the reference point in relation to the prospect's outcome can affect the evaluation process based on whether the prospect or the outcome is larger and the distance between both values. A reference point above the market price will create a feeling of loss, which is felt more acutely than that of similar sized gains when the reference point is below the market price (Kahneman & Tversky, 1979). Purchasing a good for \$10 when the expected price was \$12 will feel like a deal, whereas purchasing the good for \$14 will seem like it was overcharged. The \$2 'loss' will be felt more acutely than the \$2 'gain'. The distance between the reference point and the outcome will determine the slope of the value function and will therefore affect diminishing marginal sensitivity to changes. From a reference point of zero, receiving a fine of \$200 feels much worse than a fine of \$100, whereas a fine of \$1500 does not feel much worse than a fine of \$1400. A greater distance from the reference point to the prospects

outcome will decrease sensitivity to changes. Changes such as these, which are created by different reference points, can alter risk preferences.

Sensitivity near reference points has also been found for probabilities. Reference points for probabilities are assumed to be at the endpoints $p = 0$ and $p = 1$, certainty and impossibility (Fox & Poldrack, 2009). Increased sensitivity has been found for changes in probabilities at the endpoints, and decreased sensitivity for mid-range probabilities. The slope of the weighted probability curve is highest nearer to the natural boundaries and decreases as the weighted probability moves away from the natural boundaries as can be seen in Figure 8 (p. 22). This behavior is similar to that of the value function with steeper slopes near the origin, suggesting zero and one are reference points for probabilities.

2.5.1 Preference Reversal

The notion that reference points affect small scale decisions under uncertainty is shown in figure 11. There are three similar scenarios, one containing two positive prospects, one with two negative prospects, and one with two negative prospects which are offered after a positive payment of \$100 (Wakker, 2010). A majority of respondents chose certainty, a), in part 1 while the expected value of b) is $\$100 \cdot .50 = \50 . Due to risk aversion, as predicted by both EU theory and Prospect Theory, a risky expected value of \$50 creates less value than \$50 for certain, leading to preferences for option a). In part 2, a majority of respondents chose uncertainty. Utility theory cannot explain this behavior because it states that a risky expected value of $-\$50$ will create more disutility than $-\$50$ for certain, predicting preferences for certainty. Conversely, this choice is consistent

with Prospect Theory because it predicts preferences for uncertainty due to loss aversion; option a) and b) both have an expected loss of \$50, but option b) holds the possibility to lose nothing. Therefore, option b) holds more value than option a). A majority of respondents chose uncertainty in part 3, despite final outcomes which are identical to those of option a)⁹. Segregation of mental accounts, as defined in the editing phase of Prospect Theory, predicts individuals will evaluate part 3 before the initial gain of \$100 is integrated. This behavior leads to selection of the uncertain outcome, option b), as observed in part 2. If the initial gain in part 3 is integrated before evaluation, subjects are expected to be risk averse as they were in part 1.

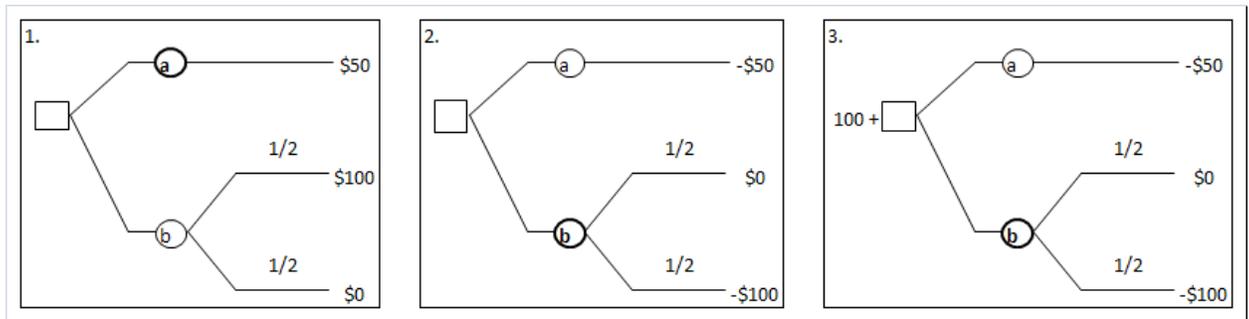


Figure 11: Preference Reversal

Reversal of preferences from part 1 to part 3 is due to a change in the reference point. Part 1 is presented from the reference point 0, and the final outcomes are reached through gains. Part 3 is presented from the reference point \$100, and the final outcomes are reached through losses. The change in reference creates a feeling of loss rather than a feeling of gain, altering risk preferences. Similar results have been presented by Tversky and Kahneman (1981) and Sullivan and Kida (1995).

⁹ a) $100 - 50 = 50$, b) $100 - 0 = 100$, and $100 - 100 = 0$

Kahneman and Tversky (1979) demonstrate preference reversals for prospects under moderate-scale uncertainty due to reference points. They developed two choice problems with identical outcomes, each with one risky option and one certain option, but changed the frame by presenting the problem from different reference points. The first problem is framed from a low reference point (\$1,000) and the second problem is framed from a high reference point (\$2,000), as shown below.

Problem 1: In addition to whatever you own, you have been given \$1,000. You are now asked to choose between

A: (1,000, 0.5) and B: (500).

Problem 2: In addition to whatever you own, you have been given \$2,000. You are now asked to choose between

C: (-1,000, 0.5) and D: (-500).

In problem 1, 84% of subjects chose the certain gain, option B, while in problem 2, 69% chose the uncertain prospect, option C. These results are consistent with prospect theory, where risk aversion is preferred for gains and risk seeking is preferred for losses. However, note that options A and C are the same when the initial endowment is considered in the calculation, i.e. (\$2,000, 0.5; \$1,000, 0.5). Similarly, options B and D are the same when the initial endowment is considered, i.e. a sure gain of \$1,500. Kahneman and Tversky emphasize that under EU theory, the choice between a 50% chance of \$2,000 and a 50% chance of \$1,000 (option A and C) or \$1,500 for certain

(option B and D), should not be dependent on the original starting point of \$1,000 or \$2,000. Individuals whose decisions are influenced by the frame (chose A and D or B and C) have committed a heuristic bias, and those who are not influenced by the frame (chose A and C or B and D) follow the normative rule (Poulton, 1994). Kahneman and Tversky (1979) concluded that ‘the carriers of value or utility are changes of wealth, rather than final asset positions’ (p. 273).

These examples show that reference points play a crucial role in decision making, how they can change decisions under uncertainty, and demonstrates where EU theory does not converge with experimental data.

2.5.2 Disposition Effect

Prospect theory has been supported in many experimental studies, but must also be observed in market data in order to be widely accepted as an accurate representation of market behavior. The disposition effect is a widely observed phenomenon where reference points, as defined by prospect theory, affect economic decisions. The disposition effect occurs when investors sell winners too early and retain losers for too long (Shefrin et al., 1985).

The following example, by Shefrin, Statman and Constantinides (1985), demonstrates the disposition effect. A stock was purchased for \$50. One month later it is selling for \$40 and can either be sold or held for one additional period. There is a 50% chance the stock price will increase by \$10 and a 50% chance the stock price will decrease by \$10 over the next period. Prospect theory predicts that the decision to sell or hold the stock will be framed in the following manner: option a) Sell the stock and accept

the \$10 loss on the transaction, option b) Hold the stock and accept a 50% chance of losing \$20 or 'breaking even'.

This problem is now framed as a loss. Prospect Theory predicts that the stock will be held, option b), due to risk seeking behavior. Had the stock originally increased in price rather than decreased, the problem would be framed as a gain. Prospect Theory would have predicted sale of the stock due to risk adverse behavior. This example demonstrates investors' disinclination to realize a loss (selling losing stock) and eagerness to realize gains (selling a winning stock). Shefrin, Statman and Constantinides (1985) observed patterns in financial markets which are consistent with the disposition effect commonly observed in experiments. The disposition effect is a product of reference points creating risk adverse behaviors for gains and risk seeking behaviors for losses.

2.5.3 Equity Premium Puzzle

Another widely observed phenomenon is the equity premium puzzle, which refers to larger premiums for stocks over bonds than justifiable according to the risk-return trade-off theory (Forbes, 2009). Reference points and their respective feelings of gains or losses create the equity premium puzzle. Relative risk and return are common guidelines to optimize financial investments. Equity investments earn a premium over bonds to compensate for the increased risk in equity (Berk et al., 2007). William Forbes (2009) disputes this assessment due to the relative riskiness of bonds. Using over 100 years of international equity data collected by Dimson, Marsh and Staunton (2000), Forbes calculated equity return premiums over treasury bills in the United Kingdom to be

6.1% and found higher premiums in other countries. With an average return of 12% for equity, the premium for unsystematic risk is as high as for systematic risk. This premium is unjustified, due to relative risk. 'The standard deviation of real equity returns is just over three times that of the mean return and the standard deviation of treasury bill prices is more than six times its mean return, so it appears that in the very long term bonds may be more risky than equity.' (Forbes, 2009; p. 269)

Evidence of preference reversals, the disposition effect and the equity premium puzzle all show how reference points affect decision making under uncertainty and risk. Although these examples assume a fixed reference point, they are not static and can change over time (Helson, 1964). Prospect Theory can be applied to choices under uncertainty using the unique characteristic that reference points are not stationary and change over time.

2.5.4 Adaptation

Expectations of prospects are continuously adapting to our environment's new and old stimuli and how they are perceived relative to a reference point. Reference levels do not adapt immediately to new stimuli because past values and trends remain applicable. The environment in which we live is dynamic and ever changing, causing adaptation to be a continuous process where full adaptation is rare.

Adaptations in other choices under uncertainty most likely arise from physiological and biological levels. Our bodies are quick to respond if our core temperature deviates slightly from its normal value of 98.6 degrees, or if the pH content of our blood strays from 7.4. Socially, periods of peace indicate a state of equilibrium;

conversely, danger and unrest are commonly products of imbalance (Helson, 1964). As environments continuously change, adaptation leads to dynamic equilibriums.

A changing equilibrium is desirable in many circumstances; it allows us to become better adapted to new environments, creates variety and novelty, and encourages us to reach our potential. An individual with nothing will work towards saving \$1,000, will work towards \$10,000 when they have \$1,000, and \$1,000,000 when they have \$500,000 (Helson, 1964). This behavior is not striving for equilibrium, but for new pleasure and possibilities. Helson (1964) emphasizes that the reference point is the point from which behavior is measured, predicted and understood, not what behavior is attempting to achieve.

A lack of adaptation can change our preferences for future prospects, as seen in figure 12. Suppose an individual has recently lost \$2000. Later, she is presented with an opportunity which offers \$1000 or a 50% chance of \$2000, as seen in the first picture. If she has adapted to her losses, the new opportunity will not change, as seen in the second picture. If she has not adapted, the new opportunity will be combined with the previous loss, as seen in the third picture. The level of adaptation, or a shift in the reference point, has affected the perceived opportunity and will change risk preferences. Risk aversion is predominantly observed in problems 1 and 2 as option a) is typically chosen, and risk seeking is predominantly observed in problem 3 as option b) is typically chosen. Preferences for risk are observed where preferences for certainty would have existed if adaptation had occurred.

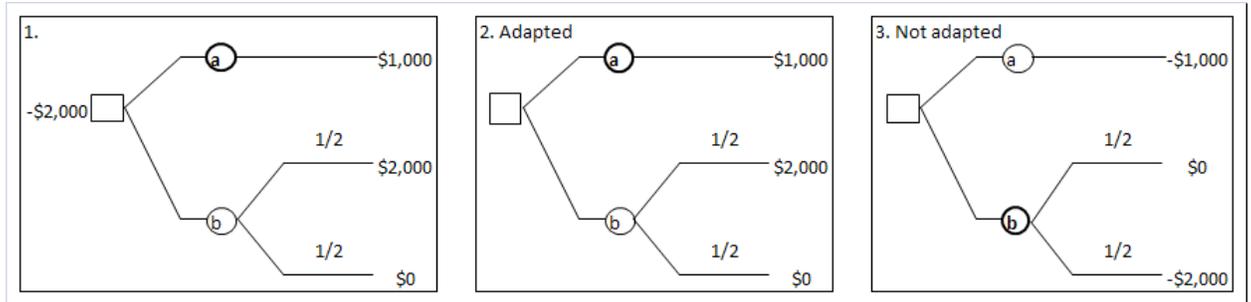


Figure 12: Adaptation

Several studies have found evidence that reference points are formed and updated by numerous factors. Reference levels may be determined by a combination of the original purchase price (Arkes et al., 2008), the status quo, social norms and aspirations (Kahneman & Tversky, 1979), the historical peak (Zwick & Rapoport, 2005), purchase price, current price, intermediate prices (Baucells et al., 2011) and non-action (had they not been involved at all) (Lin et al., 2006). Prices at which investors made a decision, bought or sold, may also carry more influence than other prices (Baucells et al., 2011). These studies will be further discussed in the next chapter.

CHAPTER 3 - REFERENCE PRICES IN THE LITERATURE

3.1 Introduction

Reference points were originally assumed to be the status quo by Kahneman and Tversky's (1979). Subsequent empirical research to verify this hypothesis has been generally supportive. When conducting experiments with reference points in financial decisions, prices of goods and services are often used. Purchase prices are often assumed to be the status quo, and have been found to carry significant weight in many studies. As time progresses and prices change, reference points have been found to adapt to these changes. Kahneman and Tversky (1979) also hypothesized that future expectations will affect reference points. From now on the discussion will focus on financial decisions and hence the term reference price¹⁰ will be used instead of reference point. Experiments investigating reference price formation, reference price adaptation, the effects of multiple reference prices, reference prices and regret, and reference prices in marketing decisions are discussed in this chapter.

3.2 Reference Price Formation

Determining how reference prices are formed is a critical aspect of decision making analysis under prospect theory. Only when the reference price has been determined can computation of the value and weighting function be performed. Several studies have explored how reference prices are formed, mainly using controlled

¹⁰ Reference prices are a subset of reference points in a financial context.

experiments, and have found that the purchase price of an asset is commonly used as a reference price.

Baucells et al. (2011) sought to understand how reference prices are formed over time. They presented 55 subjects with graphs of stock prices in three to ten time periods and instructed them to imagine that they had purchased the stock in the first time period and that the price had evolved in the pattern shown. Subjects were then asked to indicate at which selling price they would be neither happy nor unhappy about the sale, indicating their reference price, for each price sequence. This process was repeated 60 times for each subject for various price sequences which varied by several factors: the purchase price, the current price, the highest price, the lowest price, the average price, a weighted average with higher weights given to more recent prices and intermediate prices. The authors calculated which of these price factors contributed most towards the reference price.

Analysis was conducted separately between sequences when only one price factor varied, as well as when all price factors varied together. Both methods of analysis found the same results, i.e. the first and last prices held the greatest influence in determining the reference price. Baucells et al. (2011) suggest this is a reflection of the salience created for prices at which investors acted. Intermediate prices each held similar influences on the reference price, but held less weight overall than the first and last prices. The effect of the highest price in the sequence on the reference price was found to be small and statistically insignificant, contrary to many expectations. Identifying the effects of peak prices was also found to be difficult by Langer et al. (2005) when subjects evaluated

numerical sequences. Predetermining the price sequences allowed the authors to attribute changes in the reference price to isolated price movements.

Gneezy sought to identify reference prices by analyzing risk behaviors in a dynamic experiment and exploring the influence of prior gains and losses on the decision to hold or sell a risky asset (Zwick & Rapoport, 2005). The experiment began with a starting price of 3, 5, or 7, on a scale of 0 to 10. Each period had a 60% chance of a 1-unit increase and a 40% chance of a 1-unit decrease in price, after which each subject would decide whether to continue (hold) or sell the asset. The experiment continued until the price reached either 0 or 10. The subjects' goal was to receive the highest price possible.

This experiment found a reluctance to sell the asset below the purchase price (starting price) and below the highest price to date. Subjects were more likely to sell the asset at or above the purchase price than at the highest price, suggesting the initial purchase price as a proxy for the reference price. By design of the experiment, support for the purchase price as the reference price will be found whenever the highest price is the reference price (if subjects sell at the highest price, they are also selling above the purchase price.) Due to this, area theory developed by Selton (1991) was used to eliminate the biased support for the purchase price; the accuracy of each hypothesis was tested based on random points of sale (10% probability of selling at each time period) and was subtracted from the accuracy of each hypothesis. The random points of sale indicate the frequency at which the subject was expected to sell if the reference price did not affect the decision. The result indicates the frequency of sell decisions which can be attributed to the reference price. After elimination of all biases in the experimental

design, the highest price to date yielded the greatest predictive success as the reference price.

The effect of reference prices on the valuation of non-market goods has also been explored. Huber et al. (2008) used iterative choices to analyze trade-off rates of environmental quality and the cost of living, identifying reference prices for non-market goods. A hypothetical option to move to one of two regions was presented. Region one has a \$100 increase in annual cost of living where 40% of lakes and rivers have good water quality. Region two has a \$300 increase in annual cost of living where 60% of lakes and rivers have good water quality. Some participants were given the national water standard, others were not. Subjects were asked to indicate which region they preferred, or if they had no preference. If they chose region one, the price of region one would increase by half of the difference in price between region one and region two, for up to four iterations. If they chose region two, the percentage of water quality of region two would decrease by 5 percentage points, for up to four iterations. If they reported no preference, the iterations would end. The iterations, or sequential approach, allows for estimation of how much money individuals would be willing to pay for a one percent increase in regional water quality.

Respondents who were told the national environmental standard were more likely to reject a region with water quality below the national average than those who were not given the standard. This finding is consistent with loss aversion and supports the hypothesis that the status quo is the reference point. The trade-off ratio for the first iteration, here a cost of \$10 for a 1% increase in environmental quality, was found to have a significant effect on the final valuation of good water quality. This finding is

known as the starting reference effect and is also consistent with prospect theory; cost-to-benefit ratio's above the first ratio appear expensive and unappealing (a loss) and cost-to-benefit ratio's below the first ratio appear cheap and appealing (a gain.)

The experiments discussed above are examples of studies exploring reference prices and which generally find support for the hypothesis that the status quo (purchase price or national standard) is a strong reference price. Other factors determining reference prices might change according to experimental design. For example, variations concerning the effects of the highest price on the reference price between Baucells et al. (2011) and Gneezy (Zwick & Rapoport, 2005) may be due to study design. When viewing a price sequence after it occurred, subjects may know that earning the highest price possible is rarely achievable. Before subjects closed their positions, they reflected a desire to achieve a higher return than that of those they previously declined. Overall, the first price and the highest price appear to hold the greatest weight in determining the reference price.

3.3 Reference Price Adaptation

Reference prices are not necessarily static. Once they have formed, they can change over time. Studies have explored if and how reference prices change over time by adapting to new information and an evolving environment. Helson (1964) originally specified adaptation level to be the average of all prices. This theory implies that each new piece of information is just as important as the last and that each has an equal effect on change in reference price. Further research has shown that extreme stimuli have smaller effects than predicted by Helson (Sarris, 1967) and that more recent prices hold

greater influence than older prices (Parducci, 1968). Therefore, a stimulus that is very far from the reference price and is not expected to occur again will have a smaller effect on adaptation than new stimuli that is expected to become the norm. Chen and Rao (2002) suggest that reference price adaptation occurs immediately but incompletely (the reference price is not replaced by the most recent price) and Arkes et al. (2008) have shown that reference prices adapt faster to gains than to losses.

Arkes et al. (2008) developed a study to observe adaptation levels of reference prices subsequent to gains and losses. They first presented half of the subjects with the following scenario: 'You purchased a stock for \$30, and the price increased \$6 after one period. What change in price would make you just as happy in the next period as you felt after the change in price in the last period?' The other half were told the price decreased \$6, and were asked what price change would make them feel just as sad. Further variations of this scenario include selling the stock after the first price increase (decrease) and purchasing it again (no further price change), as well as purchasing two stocks (one whose price increased and one whose price decreased) and questioning what price change would make them just as happy (sad) for the stock which increased (decreased). In order to determine if subjects are risk averse for gains and risk seeking for losses, and if they have asymmetric adaptation for prior losses and gains, they are posed two questions: 'Which prospect is more attractive, a \$40 gain with probability 0.8, or a \$30 gain for certain? Which prospect is more attractive, a \$40 loss with probability 0.8, or a \$30 loss for certain?' In order to control for expectations, they presented subjects with the following information: the price at time period zero is \$50, the price at time period one can increase by \$6 or decrease by \$6 with equal probability, and the price at time period

two can increase further by \$4 or decrease further by \$4 with equal probability. Prior to time period one, subjects were asked what price would make them indifferent between continuing the gamble and selling the gamble. Finally, the last question was designed to determine if monetary incentives affect reference price adaptation or asymmetric adaptation. Subjects were told the price of the stock they purchased and the increase or decrease which materialized over the first week. They were then asked to state their minimum selling price, given even chances of a price increase and a price decrease over week two. If a randomly drawn price (between the upcoming week's high and low price) was higher than the indicated minimum selling price, subjects would receive that random price; if it was lower, subjects would receive the upcoming week's price.

Arkes et al. (2008) found that upward adaptations for reference prices occurred after gains, downward adaptations occurred after losses, and that the magnitude of adaptation was significantly larger after gains than after losses of equivalent size. These effects occurred both when monetary incentives for participation were present and when they were not present. Similar adaptation patterns were found for individual stocks and for stocks within a portfolio. The asymmetry of adaptation for gains and losses is believed to be due to mental accounting and hedonic maximization¹¹. Faster adaptation was observed if the subject sold the stock and repurchased it again, than if the stock was owned for the duration of the price movements. They hypothesized that the faster adaptation observed was due to the closing and reopening of a mental account. Updating and segregating gains allows new gains or losses to be assessed independently, not integrated with prior gains or losses. Updating and segregating by each investor will lead

¹¹ Hedonic maximization: choices leading to maximum net pleasures or happiness.

to unique adaptation, and thus affect risky behavior while choosing to hold or sell investments.

Even though empirical evidence largely suggests that individuals are reluctant to sell losing investments, they eventually do sell if losses persist. Lee et al. (2009) sought to determine how and at what point this psychologically painful decision is made. Each subject was told that they had recently invested a given amount into stock X. Information on stock performance was provided after each period (usually that the price decreased), and they were asked four questions: ‘In the next period, what is the price of stock X that would make you feel satisfied?’; ‘In the next period, if the stock price increases, what is the price you would sell at?’; ‘How do you think the price of stock X will change in the next period?’; and ‘Do you want to hold or sell stock X now?’ By assuming that the prospect theory value function is constant, the authors assumed that adaptations in the price at which they would be satisfied and the price at which they would sell are reflections of adaptation for the reference price. For example, a one dollar increase in the satisfy price or a one dollar increase in the selling price reflect a one dollar increase in the reference price.

Lee et al. (2009) found that the tendency to exit a losing position occurs more often when the investment has negative expectations, as the total loss becomes larger and as time in the losing position becomes longer. The effects of negative expectations were observed to be greater when investors had not fully adapted to their losses. Investors who have relatively maintained their high reference price after a loss are more likely to sell an investment when their expectations are negative because there is a smaller chance it will return to their reference price (avoiding the feeling of a loss). Therefore, an individual

who has not yet adapted to losses is more likely to sell the investment. Results were also consistent with the assumption that the initial purchase price is a good proxy for the reference price, particularly soon after the investment is purchased. A strong attribute of this study is the generalizability of the findings due to a wide range of loss sizes and intermediate price dynamics across the study's ten periods.

3.4 Multiple Reference Prices

Reference prices have significant effects on decisions under uncertainty, but have so far been assumed to be one single value at any given point. The analysis has assumed that all prior information is amalgamated into one reference price. Some studies have investigated the notion that decisions under uncertainty can also be assessed when two or more reference prices were used. Sullivan and Kida (1995) studied decision makers' risk seeking and risk aversion behavior under a reference system where there are two reference prices' and also considered the effects of prior gains and losses on risk preferences. In the first experiment, investment options were presented to the subjects (corporate managers), with one risky alternative and one certain alternative. They were also told that their division earned 8% return on their investments last year and has a target performance level of 12% for this year. There were a total of eight investment options, with a range of percentage returns from below both references, between references, or above both references. They also conducted a second experiment, with the same group of subjects, containing one-stage gambles and two-stage gambles, for gains and losses. Each one-stage gamble contained a risky alternative and a certain alternative and the two-stage gamble contained a prior gain or loss, and a risky alternative and a

certain alternative. Each one-stage gamble had a respective two-stage gamble with identical end results.

Expected behaviors for risky prospects were observed when both reference points were above or below outcomes for the prospect, i.e. risk aversion for gains and risk seeking for losses. Risky prospects between the two reference points led to a combination of risk seeking and risk adverse behaviors with subjects tending towards risk aversion unless there was a high probability of a loss. In the second experiment, significant differences were found between the one-stage and two-stage gambles. The authors observed that subjects exhibited more risk seeking behavior after a prior gain than after a prior loss, commonly known as the house money effect. The break even effect, where risk seeking is commonly found after losses, was observed when risky prospects held the potential to eliminate prior losses. Shifts between risk seeking and risk avoiding were observed. Their finding also suggested that prior gains or losses were integrated in their decisions. The effects of multiple reference points and prior gains or losses must be taken into consideration when analyzing and predicting risky behavior across a variety of prospects.

Fox et al. (2004) also investigated the notion of risk adverse behavior for gains and risk seeking behavior for losses, but included an examination of the effects on framing when prospects are compared to close friends' outcomes. Subjects were presented with a hypothetical stock which they had previously invested in. This stock had earned either a gain or a loss of 50% in the previous period. Subjects were given the opportunity to either sell the stock now or hold it for another period, which has a 50% chance of doubling the current price or becoming worthless. Returns from stocks

obtained by close friends were then presented, with either much better profits, better profits, equal outcomes, worse losses, or much worse losses, and were asked if they would prefer to hold their stock for another period or sell it now. Afterwards, they were questioned as to whether they defined their results as a loss, a gain or neither, as well as ranking the confidence in their choice and their feelings of inequity from comparing their results to those of friends.

When comparing to one's own past results, risk adverse behavior was observed when the previous investment was successful and risk seeking behavior was observed when the previous investment was unsuccessful. When subjects were able to compare their results to others, risk preferences were altered. Risk seeking (holding the stock for another period) was predominant when the subjects' returns were higher than their friends' while risk aversion (selling the shares) was predominant when their returns were lower than their friends'. When outcomes were positive, subjects sought risk most when their outcomes were similar to other participants. The authors suggest that these findings may have materialized because the losses were viewed as threats and gains were viewed as opportunities. Own losses and others' relative gains may create a feeling of self-failure, encouraging risk aversion. Own gains and others' similar results may augment the subjective probability of future success in the stock, encouraging risk seeking.

Wilson et al. (2008) set out to determine how individuals perceive gains and losses of others and how individuals feel that others perceive their gains or losses. Subjects were asked to rate how they feel (self), how a known person feels (self to family), how an unknown person feels (self to stranger), how a known person feels about the subject (family to self), and how an unknown person feels about the subject

(unknown to self) concerning gains (100 or 10) or losses (-100 or -10) in three different contexts: financial (dollars), environmental (acres of habitat from a local nature preserve), or social (jobs from a nearby factory). In line with previous studies, they found evidence of loss aversion for financial gains and losses of others, but not for similar situations framed within a social or environmental context. Subjects also perceived that strangers would considerably underestimate the subjects own losses, under any context. These findings highlight areas where errors may be made when evaluating gains and losses; a policy maker may evaluate a loss of 100 jobs as the economic value of those jobs, whereas those affected will feel as if approximately 200 jobs were lost, due to a coefficient of loss aversion of approximately 2. This study is significant because the results suggest that individuals such as risk managers who rely on their own attitudes or beliefs may not make accurate predictions of how their choices affect others.

3.5 Reference Prices and Regret

Reference prices may not only affect our economic view of prospects, but also our feelings of regret after the outcomes of our decisions materialize. Lin et al. (2006) suggest that individuals' decisions might also be affected by comparisons between "what is" and "what might have been." For example, between outcomes that were obtained and possible outcomes that could have been obtained if different choices had been made.

Lin et al. (2006) seek to determine how real investors are affected by regrets when multiple reference prices are available. They evaluate how reference prices create regret when their chosen prospect performed unfavorably compared to other prospects, yet can create delight when the same prospect performed better than others. Investors were

presented with a list of stocks and asked which stock they had most recently purchased, the percentage they expected to earn from that stock at time of purchase (expected profits), and which two other stocks they considered purchasing but did not (forgone options). Subjects were then presented with the real profits of the chosen and forgone stocks, alongside the expected profits, and were asked if they feel sorry for having chosen the stock and if they feel regretful for having chosen the stock (ranging from strongly disagree, -3, to strongly agree, 3).

Using regression analysis, the status quo, or inaction, was found to be the reference price which held the most weight, in particular for those who lost money from their choices. This implies that investors felt greater regret based on how much they lost compared to not investing, as opposed to how much they lost compared to hypothetical returns had they chosen another investment. The next greatest influences on regret stem from the differences in return compared to their expectations and the best-performing alternative. The regret from these reference prices was even stronger than from the absolute value of the gain or loss.

The effect of experienced regret on reference price selection in post-choice valuation is also analyzed by Tsiros (1998). Subjects were told that they are managers of a hypothetical company and had recently decided to remain with their current distributor (rather than choosing other potential distributors) and that the company expects constant sales in the next period. The chosen company would either perform positively (+5%) or negatively (-5%), and in comparison to the two forgone alternatives either performed favorably (greater returns than the other companies), unfavorably (lower returns than the

other companies) or mixed (greater returns than one forgone company and lower returns than the other forgone company).

When the chosen company performed better than expected (5%), subjects used the second best performing alternative as a reference price from which regret was influenced. When the chosen company performed worse than expected (-5%), the worst performing alternative was used as a reference price. It was found that the level of satisfaction was affected by the performance of the chosen company, while the forgone alternative affected the level of regret experienced. The forgone alternative chosen as a reference price, as implied by subjects' regret, was that which yielded returns closest to the returns the investor received. The implied reference prices lead to neutralizing regret, rather than maximizing or minimizing regret. These findings held for both positive and negative cases. Thus, when both forgone alternatives were less (more) than the selected alternative, the best-performing (worst-performing) alternative was selected. If both forgone alternatives held the same difference from the chosen alternative, an average would be used, neutralizing regret once again. Such behavior is believed to be in response to a desire to compare oneself with a "similar other." The authors reflect that selection of the outcome most similar to the subjects own selection may have been the easiest selection and may not necessarily reflect their true behavior.

A second study by Tsiros (1998), conducted to determine the effect of experienced regret on reference price selection in post-choice valuation, used real monetary gains and losses to heighten the level of motivation and involvement of subjects. Subjects received points for positive performance in gambles of varying risk and were deducted points for negative performance. Each point was used as an entry into

a draw for \$100, and negative points were a debt owed that needed to be worked off at a later date (the subjects were told their debt was absolved as they left).

They found that the potential reference price with the highest return was used when the subjects' chosen alternative yielded positive returns and the potential reference price with the lowest return was used when the subjects' chosen alternative yielded negative returns. Increased personal responsibility caused subjects to be more strategic when choosing reference prices. When subjects' outcomes were positive, they strategically preferred reference prices which would make them improve in the future. When their outcomes were negative, they strategically preferred reference prices which would make themselves feel better. These findings suggest that individuals will be more deliberate with their selection of reference prices in post-choice valuation when increased personal responsibility and the value of consequences increase. The availability of alternative reference prices, which marketers have some ability to strategically position, can influence post-choice valuation.

3.6 Reference Prices in Marketing Decisions of Farmers

McNew and Musser (2002) examine farmers forward pricing decisions in order to determine if the primary goal is to manage price risk or to enhance prices. If farmers believe that forward prices are unbiased and are using the forward markets purely to reduce risk, then a high proportion of the crop is expected to be forward hedged and the proportion hedged is expected to remain relatively constant over time. If enhanced prices are the primary goal, varying levels of forward pricing are expected throughout the marketing season and across years. The authors assume the previous year's high price is

the current years' price expectation and that farmers are expected to hedge less if the current price is below last years' price (in the risk seeking portion of the value curve) and to hedge more if the current price is above last years' price (in the risk adverse portion of the value curve.) This assumption is based on predictions by Prospect Theory where last year's price is the reference price. Marketing data for pre-harvest (January to November) pricing of corn was used from six marketing clubs to test the hypotheses.

Farmers were not found to have a consistent marketing strategy, but were found to hedge more when prices were relatively low. Due to these findings, McNew and Musser (2002) assume that farmers used current price trends as their price expectations; low prices or negative price movements encourage forward pricing and high prices or positive price movements discourage forward pricing. Residual variations in the data also suggest that farmers use additional information in their hedging decisions which is not included in the model. The authors state that additional measurements of marketing strategies would be beneficial in understanding farmers' marketing behavior.

Meulenbergh and Pennings (2002) identified variables which will distinguish farmers who initiate futures contracts for risk management purposes in the Dutch hog industry from those who do not. Variables which were found to contribute towards futures contract usage were frequency of trading in the market, farmer's market orientation, level of understanding the futures market, perceived performance of futures markets and the ratio of futures price level in relation to the farmer's psychological reference price.

Meulenbergh and Pennings (2002) hypothesise that the futures price will become more attractive as it increasingly exceeds the reference price (as stated by the managers)

and that the futures price will become less attractive as it decreases relative to the reference price. Reference prices were positively correlated to the cost of raising hogs and were found to have a statistically significant effect on the decision to initiate futures contracts. Heterogeneity in the reference price across farmers was found; particular futures market price levels do not carry the same attractiveness across farmers.

Reference prices have also been used in a model designed to identify relevant variables in marketing decisions of Canadian grain farmers (Fryza, 2011). Explanatory variables included are past marketing performance, price signals and price trends. Variables incorporated the notion of reference prices in decision making theory. The price received this year less the pool price (the price received by all farmers from the annual collective sale of wheat) was used to evaluate marketing performance, positive (negative) values are found to increase (decrease) use of the contract. A price spread, the futures price on the day the contract was entered less the expected pool price on the day the contract was entered indicates if the contract entered was expected to earn higher or lower returns than could have been expected from the pool; positive (negative) values are found to increase (decrease) use of the contract. A price trend, the difference between the futures price on the date the contract was entered and the average futures price from the 10 days before the contract was entered indicates if the futures price had been increasing or decreasing and by what magnitude; positive (negative) values are found to increase (decrease) use of the contract.

Given these results, a useful extension of Fryza's (2011) study would be to estimate reference prices in agricultural commodity markets. Studies such as Fryza's

(2011) can be augmented by an estimate of reference price formation and adaptation by Canadian grain farmers.

CHAPTER 4 – METHODOLOGY

4.1 Introduction

In this thesis a dynamic experiment is developed to test how Manitoban grain farmers' reference prices are formed and updated. The main focus is to determine which prices are the primary contributors to a farmers' reference price and how the reference price adapts to new price changes. Prospect theory states that individuals are generally expected to be risk averse in the gain domain and risk seeking in the loss domain, as well that losses weigh heavier than gains. Based on this theory, it is predicted that farmers will be reluctant to market their grain when the price is below their reference selling price and will be eager to sell when the price is above their reference selling price, as well that the level of adaptation for gains will be faster than for losses. The effect of reference prices on decisions to sell grain will also be explored. Details of the experiment and hypotheses are discussed in the next sections.

4.2 Subjects and Experiment Procedure

Decision making under risk was investigated in a sample of 75 Manitoban grain farmers. These farmers were identified through Manitoba Agricultural Food and Rural Initiatives, business development specialists contacted farmers and those who agreed to participate were later contacted by the researchers. The participants were responsible for marketing the grain produced on their farm. They may or may not be advised on marketing decisions by an external party, but they make the final decision of when to price their grain.

The farmers took part in the experiment during July and August of 2012. The experiment was administered with pen and paper and took approximately 25 minutes to complete, ranging from 15 minutes to 45 minutes. Most experiments were completed in individual farmers' homes. One group of six completed the experiment in the local MAFRI office and one group of fifteen completed the experiment at their weekly marketing meeting. Before the experiment began, each farmer was asked background information such as age, farm size, and risk preferences. They were not able to discuss the experiment amongst themselves and completed each sequence without interruption. To encourage participation in the experiment, farmers received an equal opportunity in a draw for a cash prize of \$400. Each farmer received one ticket with a number between 00 and 99. The winning number was determined by the final two numbers of the lotto 649 extra on September 1st, 2012. The questionnaire which was presented to the farmers can be found under appendix 1.

Grain farmers were presented with the problem of marketing their wheat over ten months and were encouraged to behave as they would on their own farms. The scenario presented began on September 1st 2012, where farmers were asked how much wheat they expect to have available for sale on the cash market this crop season, excluding any sold in forward, futures, or options contracts, and were given the current market price. A short series of questions were presented. The first two questions address farmers' goals for marketing their wheat. The first is to measure the price at which they would be satisfied: 'In the next period, what is the price of wheat which would make you feel satisfied if you were to sell the rest of your wheat'. The second is to estimate a selling price: 'In the next period, if the price of wheat increases, what is the price you would sell

the remainder of your wheat at?’ Expected price changes are estimated by the third question; ‘How do you think the price of wheat will change over the next month?’ Questions are adapted from Lee et al. (2009). The fourth question determines farmers desire to hold onto or sell their wheat: ‘Do you want to hold or sell wheat now and what amount.’ On the next page (they were instructed not to flip back through the pages) they were told that one month has passed and were given the new market price, a graph of the price history, beginning in September, and the same short series of questions. This process continued until June 1st 2013, over which there were ten opportunities for sale, four questions in each period, for a total of 40 questions.

Each farmer was presented with the questions above twice. For all farmers, there were six predetermined price sequences available, three of which were generally increasing and three of which were generally decreasing. The price sequences are based on hard red spring wheat price trends over the past ten years. Price movements reflect historical volatility in the wheat market, but are not a replication of price movements for any particular year. The mean and standard deviation of monthly price changes were calculated for each month over the past ten years, and were used to generate monthly price changes. The price ranges of the sequences remain within the range of market price for the past four years, since the financial crisis. The six price sequences can be seen in appendix 3. The two price sequences were presented to the farmers in a random order. Between each price sequence, farmers were given a few minutes to refocus their attention in order to minimize the effects of memories from the first price sequence on the second price sequence. If the first price sequence had decreasing prices, it is undesirable for that feeling of a loss to affect the next price sequence. Before each experiment, farmers were

encouraged to think of the price sequences as an ‘average’ year and not of the high prices during the experiment.

A small experiment to assess risk preferences of farmers was used as a distraction between sequences. They were presented with a hypothetical opportunity to choose between a gamble offering the chance to win either \$100 or \$0 with equal probability or a fixed amount for certain (Gonzalez & Wu, 1999). The farmers were presented with a table and were asked to indicate their preference for either a sure gain or the gamble (100, 0.5), with the values of the sure gain being \$100, \$80, \$60, \$40, \$20, or \$0 (figure 13).

Money (no gamble)	Prefer Sure Thing	Prefer Gamble
100		
80		
60		
40		
20		
0		

Figure 13: Risk Preferences

The shift of preferences from certainty (sure gain) to the gamble indicates a range for the certainty equivalent, such as between \$40 and \$60. The certainty equivalent is the dollar value at which they feel indifferent between selecting the gamble and certainty.

The farmers were then presented with a similar table in four dollar increments spanning from the lowest value where certainty is preferred to the highest value where the gamble is preferred in the first table. A third and final table presented one dollar increments, selected in the same manner as the previous table. Examples of these tables can be seen in appendix 2. The midpoint of the shift in preferences in the third table will indicate the

certainty equivalent of the gamble, which is used as a measure of risk preferences. A larger value for the certainty equivalent represents increasing risk seeking behaviour and a lower value represents increasing risk adverse behaviour. On farm risk attitudes have been found to be significantly related to farmers global risk attitudes (Pennings & Garcia, 2001). Risk preferences found in this experiment will be used as a proxy for on farm risk preference in the reference price experiment.

At the end of the process, a prize of \$400 was provided to one farmer. Each farmer was able to select a number between 00 and 99. They were presented tickets for their numbers and were instructed that the winning ticket would contain the same two numbers as the final two numbers of the lotto 649 extra on September 1st, 2012. Overall, the farmers were enthusiastic to complete the survey and eager to view the results.

4.3 Experimental Hypotheses

4.3.1 Reference Prices

Using the information generated from the experiment, marketing decisions are analyzed forming estimates of how reference prices form and adapt. Reference price formation is analyzed using two methods. First, applicability of reference prices is analyzed using the framework of prospect theory and area theory. Second, multiple regression analysis is used to explore reference price formation and adaptation and the effects of reference prices on decisions to sell grain.

In the first part of the analysis, area theory is used to determine which reference price is the optimal proxy as adopted by producers. Following prospect theory, decisions to sell wheat, suggesting risk adverse behavior, should occur most often when the market

price is above the reference price. Decisions to hold wheat, suggesting risk seeking behavior, should occur most often when the market price is below the reference price. A greater frequency of sell decisions above the reference price relative to the frequency of sell decisions that can be expected if the reference price does not affect their decisions will provide greater support for the hypothesis.

The reference price is often assumed to be the status quo or the first price in the sequence (Baucells et al. 2011). The market price at harvest is the first opportunity farmers have to sell their wheat on the cash market. If the original price given on September 1st is the reference price, farmers are expected to market their grain above this price if possible.

Hypothesis 1: The farmer will sell wheat more often above the market price on September 1st (first price in the sequence) than below the market price on September 1st.

The reference price has also been found to be the historical peak by Gneezy (Zwick & Rapoport, 2005). Farmers may establish a reference price which is the highest price to date within the season.

Hypothesis 2: The farmer will sell wheat more often at the highest market price in the sequence than below the highest market price in the sequence.

If a farmer sells his wheat at the highest market price to date, they have also sold at or above the first price. Therefore, any decisions consistent with hypothesis 2 will also

be consistent with hypothesis 1. The opposite is not true. Marketing decisions in accordance with hypothesis 1 and 2 do not definitively imply behavior under prospect theory, as adaptation to the price sequence will occur over each time period.

Farmer's may also use their break-even price as their reference price. This is the price at which accounting profits and losses would be determined. Farmers were asked to indicate their break-even price of wheat in the survey. If the break-even price is the farmer's reference price, they will not market their wheat below this price.

Hypothesis 3: The farmer will sell wheat more often above the break-even price than below the break-even price.

The predictive success of hypothesis 1 through 3 will be compared and used to determine which price (the purchase price, the highest price, or the break-even price) is best suited as a proxy for the reference price. These three variables are compared as they can all be determined through market data and in farm financial data. The predictive success is the frequency of sell decisions above the reference price relative to the frequency of sell decisions that can be expected if the reference price does not affect their decisions.

The satisfy price and goal prices may be good proxies for reference prices, and will be elicited in the survey and tested in the same manner. The satisfy price is the price of wheat which would make the farmers feel satisfied selling the rest of their wheat in the next period. The goal price is the price at which the farmer would sell the remainder of their wheat in the next period given an increase in price in the next period. If the satisfy

price is a proxy for the reference price, farmers are expected to sell their wheat when the market price is above their satisfy price and to hold onto their wheat when the market price is below their satisfy price.

Hypothesis 4: The farmer will sell wheat more often above the satisfy price than below the satisfy price.

If the farmer's goal is a proxy for the reference price, as identified by the farmer in the survey, they are expected to sell their wheat when the market price is above their goal price and to hold onto their wheat when the market price is below their goal price.

Hypothesis 5: The farmer will sell wheat more often above the goal price than below the goal price.

The predictive success of hypothesis 4 and 5 will be compared and used to determine which price (the satisfy price or the goal price) is best suited as a proxy for the reference price. These two variables are compared as they cannot be observed in market data or in farm financial statements.

4.3.2 Reference Price Adaptation

Adaptation theory states that reference prices adapt upwards as gains accrue and that reference prices adapt downwards as losses accrue. Reference prices have also been shown to adapt faster to gains than to losses since loss aversion is expected to prevent

subjects from coming to terms with their losses, creating deviations in adaptation levels for gains and losses (Arkes et al., 2008).

Hypothesis 6.1: Each period with an increasing price (decreasing price) will lead to an upward (downward) adaptation of the reference price.

Hypothesis 6.2: Adaptation to increasing prices will be faster than adaptation to decreasing prices.

Similarly, reference prices are expected to adapt upwards as total gains (current price > first price) accrue and to adapt downwards as total losses (first price > current price) accrue. Adaptation to gains over the duration of the series is also expected to occur faster than adaptation for losses.

Hypothesis 7.1: A larger size of total price increases or price decreases will lead to larger adaptations of the reference price.

Hypothesis 7.2: Adaptation to total price increases will be faster than adaptation to total price decreases.

Reference prices have been shown to adapt over time (Lee et al., 2008). As time passes, subjects are expected to come to terms with previously occurring gains and losses, therefore adapting their reference price. Adaptation to gains over time is also expected to occur faster than adaptation to losses over time as loss aversion prevents subjects from coming to term with their losses.

Hypothesis 8.1: A longer time in a price increasing (decreasing) position will lead to a reference price which has larger upward (downward) adaptations.

Hypothesis 8.2: Time in a price increasing position will have a greater effect on adaptation than time in a price decreasing position.

4.3.3 Expectations

Standard finance theory predicts that individuals will sell an investment if the expected increase in price is not sufficient to compensate for the risk of holding the investment, and that an investment will be held if the expected increase in price is sufficient to compensate for the investment risk. The following hypotheses adapted from Lee et al. (2008) will be tested.

Hypothesis 9.1: Increased quantities of wheat are expected to be sold in the current period if future prices are expected to decrease than if future prices are expected to increase.

Hypothesis 9.2: Increased quantities of wheat are expected to be sold in the current period as the reference price decreases relative to the current price.

Subjects may expect prices to rise after a series of downward price movements because they expect prices to re-gain some of their losses (Andreassen, 1988). This negative recency, also known as the gambler's fallacy, may play into farmers' expectations during this survey. Subjects may also expect the opposite outcomes, where

prices rise after previous price increases and for prices to fall after previous price decreases (Ayton & Fisher, 2004). This positive recency, also known as the hot-hand fallacy, may also play into farmers' expectations during this survey. Negative and positive recency will have opposing yet simultaneous effects on expectations, which are expected to affect the probability of selling and the amount chosen to be sold at each time period.

4.4 Analysis

4.4.1 Predictive Success of a Reference Price

Hypothesis one through five are analyzed using area theory (Selton, 1991) as applied by Gneezy (Zwick & Rapoport, 2005). This theory accounts for the accuracy of each hypothesis while adjusting for the frequency that the hypothesis is expected to be correct. In order to determine the predictive success (m) of each hypothesis, the hit rate (r) is subtracted by the area rate (a).

$$m = r - a \quad (1)$$

where the hit rate is calculated as the ratio (number of days where wheat was sold above the reference price for all farmers) / (total number of days where wheat was sold for all farmers) and the area rate is calculated as the ratio (total number of days where the current price was greater than the reference price for all farmers) / (total number of days in the experiment for all farmers).

First, the percentage of observations which are consistent with each hypothesis is calculated (hit rate). If there are ten decisions by farmers to sell their wheat, and seven of those decisions are consistent with the hypothesis, then the hit rate is 70%. The hit rate is

the proportion of sell decisions which are above the reference price in the data set of all sell decisions. Next, the same process is used for all decisions points (area rate). If, on average, four out of ten decision points are consistent with the hypothesis, then the area rate will be 40%. This value is the proportion of days that subjects would be expected to make decisions consistent with the hypothesis if they did not follow a decision rule to sell above the reference price. This value is the frequency of observations that are expected to be consistent with the hypothesis if the sell decisions were determined randomly. In order to determine the predictive success of each hypothesis, the percentage of sell decisions which are consistent with a hypothesis will be subtracted by the percentage of observations that are expected to be consistent with each respective hypothesis given random decisions to sell. Therefore, the predictive success will be 30% ($0.7-0.4$).

The values of the hit rate (r) and the area rate (a) can range from 0 to 1, where 0 indicates that there are no data points which supported the hypothesis within the subsample and 1 indicates that all data points supported the hypothesis within the subsample. The predictive success (m) can range from -1 to 1. A predictive success of 1 can only occur when $r = 1$ and $a = 0$, indicating that farmers always follow the hypothesis despite the expectation that they would never follow the hypothesis if they made decisions randomly. A predictive success of -1 can only occur when $r = 0$ and $a = 1$, indicating that farmers never follow the hypothesis despite the expectation that they would always follow the hypothesis if they made decisions randomly. A predictive success of 0 can only occur when $r=a$, indicating that farmers follow the hypothesis exactly as often as would be expected if they made decisions randomly.

If predictive success is positive, the hypothesis is supported by subjects' behavior more often than it is expected to be supported if they make decisions randomly; the hypothesis is increasingly supported as values become more positive. If predictive success is negative, the hypothesis is supported by subjects' behavior less often than it is expected to be supported if they make decisions randomly; the hypothesis is decreasingly supported as values become more negative. This process is applied to hypothesis one through five.

4.4.2 Regression Analysis of the Reference Price

Equation (2) will be used to quantify the determinants of the reference price; adapted from Baucells et al. (2011).

$$RP_{it} = \alpha + \beta_1 FP_{it} + \beta_2 CP_{it} + \beta_3 HP_{it} + \beta_4 LP_{it} + \beta_5 WP_{it} + \beta_6 E_{it} + \beta_7 IPS_{it} + \beta_8 AI_{it} + \beta_9 AD_{it} + \sum_{j=1}^9 \theta_{ij} M_{ij} + \varepsilon_{it} \quad (2)$$

where RP is the reference price, either the satisfy price or the goal price, FP is the first price in the price sequence, CP is the current price, HP is the highest historical price in the sequence, LP is the lowest historical price in the sequence, WP is the recency-weighted average price of the sequence, E is the expectations of price increases or decreases over the next month, IPS is a dummy variable for increasing price sequences, AI is a dummy variable for sequences after a sequence with increasing prices, AD is a dummy variable for sequences after a sequence with decreasing prices, M is nine dummy

variables for each month from October to June, ε is the random disturbance (error) term, i is the subject (farmer) and t is the decision point.

A regression model explores how reference prices are determined. The dependent variable is the reference price; where the satisfy price and goal prices are used as proxies for the reference price. Explanatory variables are the first price in the price sequence, the current price, the highest historical price in the sequence, the lowest historical price in the sequence and the recency-weighted average price of the sequence. All prices are in log form. Increasing price sequences (1 if for price sequences 1, 2 or 3; 0 if for price sequences 4, 5 or 6), sequences after gains (0 if for the first sequence; 0 if for the second sequence and the first sequence was 4, 5 or 6; 1 if for the second sequence and the first sequence was 1, 2 or 3) and sequences after losses (0 if the first sequence, 0 if for the second sequence and the first sequence was 1, 2 or 3; 1 if for the second sequence and the first sequence was 4, 5 or 6) are included in the model as control variables. Two regressions are calculated using the satisfy price and the goal price as the dependent variable. The data is analyzed in panel form for each subject i at each decision point t . The price expectations are elicited in the experiment; which can range between -1 if they expect the price will surely decrease over the next month and 1 if they expect the price will surely increase over the next month. These variables are analyzed through multiple regression analysis to determine how each variable influences the reference price. Statistical significance of the estimated coefficients are assessed with t-tests.

The expectations variable (E) is calculated using an average of the expected probabilities that prices will increase, remain about the same, or decrease, as elicited in the experiment. Expectations that the price will increase is assigned a value of one,

expectations that the price will remain about the same is assigned a value of zero, and expectations that the price will decrease is assigned a value of negative one. The variable ranges from one to negative one, where one represents certainty that the price will increase and negative one represents certainty that the price will decrease.

Given previous studies by Baucells et al., (2011), Gneezy (Zwick & Rapoport, 2005) and Kahneman and Tversky (1979), the purchase price, historical peak and expectations are expected to hold the greatest influence upon the reference price. The lowest price and the recency-weighted average price are expected to hold the least influence upon the reference price.

4.4.3 Regression Analysis of Incremental Adaptation of the Reference Price

Adaptation of the reference price is analysed using the satisfy price and the goal price (Arkes et al., 2008; Lee et al., 2009).

In order to test hypotheses 6.1 and 6.2, equation (3) was developed. The following explanatory variables are regressed on the incremental adaptation of the reference price; the current reference price subtracted from the previous month's reference price.

$$IA_{it} = \alpha + \beta_1 \Delta IP(p)_{it} + \beta_2 \Delta IP(n)_{it} + \beta_3 E_{it} + \beta_4 IPS_{it} + \beta_5 AI_{it} + \beta_6 AD_{it} + \varepsilon_{it} \quad (3)$$

where IA denotes the incremental adapted reference price, $\Delta IP(p)$ is the incremental price change if the price change was positive over the previous month, $\Delta IP(n)$ is the incremental price change if the price change was negative over the previous month. E is

the expectations of price increases or decreases over the next month, IPS is a dummy variable for increasing price sequences, AI is a dummy variable for sequences following a sequence with increasing prices and AD is a dummy variable for sequences following a sequence with decreasing prices; variables are determined in the same manner as equation (2). ε is the random disturbance (error) term, i is the subject (farmer) and t is the decision point.

Hypothesis 6.1, an increasing price (decreasing price) will lead to an upward (downward) adaptation of the reference price, will be supported if $\beta_1 > 0$ and $\beta_2 < 0$.

Hypothesis 6.2, adaptation to increasing prices will be faster than adaptation to decreasing prices, will be supported if $|\beta_1| > |\beta_2|$.

4.4.4 Regression Analysis of Total Adaptation of the Reference Price

In order to test the effects of total price changes and time on the reference price, hypotheses 7.1, 7.2, 8.1 and 8.2, equation (4) will be estimated. The following explanatory variables are regressed on total adaptation of the reference price; the current reference price subtracted from the reference price in September (first decision point).

$$TA_{it} = \alpha + \beta_1 M(i)_{it} + \beta_2 M(d)_{it} + \beta_3 \Delta TP(p)_{it} + \beta_3 \Delta TP(n)_{it} + \beta_4 E_{it} + \beta_5 AI_{it} + \beta_6 AD_{it} + \varepsilon_{it} \quad (4)$$

where TA denotes the total adaptation of the reference price from September, M(i) is the month for increasing sequences (September=1, October=2, ... , June=10 if price sequence is 1, 2 or 3), M(d) is the month for decreasing sequences (September=1, October=2, ... , June=10 if price sequence is 4, 5 or 6), $\Delta TP(p)$ is the price change since

September for prices sequences 1, 2, or 3, $\Delta TP(n)$ is the price change since September for prices sequences 4, 5, or 6. E is the price expectations, AI is a dummy variable for sequences following a sequence with increasing prices, AD is a dummy variable for sequences following a sequence with decreasing prices; variables are determined in the same manner as equation (2). ε is the random disturbance (error) term, i is the subject (farmer) and t is the decision point.

Hypothesis 7.1, a larger size of total price increases or price decreases will lead to larger adaptations of the reference price, will be supported if $\beta_3 > 0$ and $\beta_4 < 0$.

Hypothesis 7.2, adaptation to total price increases will be faster than adaptation to total price decreases, will be supported if $|\beta_3| > |\beta_4|$. Hypothesis 8.1, a longer time in a price increasing (decreasing) position will lead to a reference price which has larger upward (downward) adaptations, will be supported if $\beta_1 > 0$ and $\beta_2 < 0$. Hypothesis 8.2, time in a price increasing position will have a greater effect on adaptation than time in a price decreasing position, will be supported if $|\beta_1| > |\beta_2|$.

4.4.5 Regression Analysis of Decisions to Sell Grain

In order to test the effects of price expectations and reference price adaptation on wheat sold, hypotheses 9.1 and 9.2, the follow explanatory variables are regressed on percentage of wheat sold. Two equations are analysed, once with the satisfy price as the reference price, and once with the goal price as the reference price.

$$\%S_{it} = \alpha + \beta_1 E_{it} + \beta_2 (CP_{it} - RP_{it}) + \beta_3 (E_{it})(CP_{it} - RP_{it}) + \beta_4 IPS_{it} + \beta_5 AI_{it} + \beta_6 AD_{it} + \sum_{j=1}^9 \theta_{ij} M_{ij} + \varepsilon_{it} \quad (6)$$

where %S denotes the percent sold at time t , E is the expectation, CP is the current price, RP is the reference price (satisfy price or goal price), IPS is a dummy variable for increasing price sequences, AI is a dummy variable for sequences following a sequence with increasing prices, AD is a dummy variable for sequences following a sequence with decreasing prices, ε is the random disturbance (error) term, i is the subject (farmer) and t is the decision point.

Hypothesis 9.1, increased quantities of wheat are expected to be sold in the current period if future prices are expected to decrease than if future prices are expected to increase, will be supported if $\beta_1 < 0$. Hypothesis 9.2, increased quantities of wheat are expected to be sold in the current period as the reference price decreases relative to the current price, will be supported if $\beta_2 > 0$.

4.5 Model Estimation

Econometric models are often used to estimate relationships between economic variables. Before statements can be made about the model, the proper econometric techniques must be applied in order to maximize confidence in the statements.

Pooled ordinary least squares (OLS), cross-section and time-series regressions are commonly used in econometric analysis. Generally, OLS regressions group all data points together for each subject, while cross-sectional and time series regressions account for the uniqueness of each individual and time period, respectively, in the error term.

The availability of larger and more structured data sets has allowed the study of several cross-sections across different time periods. Panel data sets follow a sample of

subjects' decisions over a given time period, creating multiple observations for each subject and is therefore able to model the uniqueness of each individual as well as each time period (Frees, 2004). Panel data encompass both individual effects and time effects, as opposed to only one of the two affect as in cross-section and time-series analysis.

Furthermore, since applied econometrics is used to search for the partial effects of observable explanatory variables. Unobservable random variables must be held constant in order to isolate the effects of the explanatory variables. Dummy variables are generally introduced to account for the effects of the omitted variables that are specific to each individual and those that are specific to each time period. Panel data is an alternative method to account for unobserved individual effects that are assumed to be additive and time-invariant and time effects that are assumed to be additive and individual-invariant (Cameron and Trivedi, 2005).

Since the current research explores decisions of different individuals during distinct time periods, panel regression techniques will be adopted to estimate the model in equations one through five.

4.5.1 Advantages of Panel Data

Panel data allows for a more complicated econometric model to be developed as well as creates a range of benefits that cannot be obtained with cross-sectional or time-series data individually (Baltagi, 2005). It allows for maximum utilization of the data by accounting for unobserved effects across individuals and over time. By pooling both types of data in this manner, panel data can improve the efficiency of the model because of the larger number of data points, which increases the degrees of freedom and reduces

the collinearity between the explanatory variables (Hsiao, 2003; Baltagi, 2005). A primary advantage of panel data is the ability to diminish, and sometimes even resolve, the affects of omitted variables that are correlated with explanatory variables (Hsiao, 2003).

As panel data is typically from real-life events, it can be affected by many factors that cannot be included within the model. These factors that cannot be included may be correlated with the independent variables and can cause parameter heterogeneity (Hsiao, 2003). If these effects are not accounted for, estimates of the parameters may be inconsistent and of little value. Including all variables that could affect the outcome is not desirable; observing the effects of the fundamental forces affecting the outcome is the primary goal. Variable-intercept models help control for unaccounted variables.

Conditional on the explanatory variables, it can be assumed that three types of variables drive the effects of all omitted variables; individual time-invariant, period individual-invariant, and individual time-varying (Hsiao, 2003). Individual time-invariant variables are the same for each individual across time but vary across each individual, period individual-invariant are variables that are the same for all individuals at each point in time but differ through time, and individual time-varying variables vary across individuals at each point in time and also vary through time. Variable-intercept models thus assume that the numerous variables unaccounted for within the model, which are individually inconsequential but collectively significant, are captured by the intercepts and assumes that they are uncorrelated with all other independent variables as a random variable would be (Hsiao, 2003). The assumption that the variables are uncorrelated becomes obsolete because the effects of the omitted variables are absorbed into the

intercept term of the regression model. This allows for heterogeneity within the panel data and the assumption that omitted variables are uncorrelated to be relaxed.

Heterogeneity can be observed as the correlations between multiple observations from an individual. Positive correlations are expected to be found between multiple observations from an individual due to unobserved individual-specific parameters with positive correlations (Frees, 2004). The inclusion of dummy variables in order to control for heterogeneity is motivated by omitted variables that bias model estimates. Solving the omitted variable problem is the primary motivation for applying panel data (Wooldridge, 2005).

Dummy variables create unique intercepts that can capture the baseline differences between individuals, controlling for individual heterogeneity. The model will essentially learn which factors are unique to each individual and create a more accurate representation of each individual. The same effect can also be obtained for each time period. Panel data thus allows the researcher to account for behavioral and time effects that cannot be controlled with pooled, cross-sectional or time-series data alone.

4.5.2 Disadvantages of Panel Data

A primary difficulty of panel data is that it is frequently observed to be affected by selection bias (Frees, 2004). The least-squares estimates of coefficients, standard-errors and t-statistics may be biased if the sample is non-random. The sampled group will be non-random if it is not a fair representation of the population, which will occur if the subjects can self-select, choose not to respond or drop out of the sample before completion. Measurement errors may occur when collecting panel data due to unclear

questions, errors in memory, distortion of responses, errors in the recording of responses and interviewer effects (Baltagi, 2005). The data may also have limited extrapolative abilities if the time-series dimension is too short.

If unobserved variables are not systematically related to the models explanatory variables they will not affect the results of the model. If unobserved variables are systematically related to the model's explanatory variables they will create heterogeneity bias. Additional information is required in order to consistently estimate the parameters of the model.

Accounting for heterogeneity bias and selectivity bias is necessary in order to retain confidence in the model's results.

4.6 Panel Data Procedure

Panel data regression equations contain a double subscript, as opposed to a single subscript for time-series and cross-section; one denoting the individual and one denoting time (Baltagi, 2005). Therefore it takes into account both individual (cross-sectional) effects and time (time-series) effects and allows the intercept and slope coefficients to vary for both individuals and time. The model can focus on individual effects or time effects (one-way effects) or on individual and time factors together (two-way effect). Panel data can be analysed by a simple linear regression with n individuals and t time periods as follows.

$$Y_{it} = \alpha + \beta_{it}X_{it} + \epsilon_{it} \quad i= 1, \dots, N; t= 1, \dots, T \quad (7)$$

where Y is the dependent variable, X is the independent variable, ϵ is the random disturbance term, i is the individual and t indexes time. If the total number of

observations is $n \cdot T$, where there are the same number of observations for every individual and every time period, the panel is balanced (Wooldridge, 2002). The data can be organized by decision units as follows.

$$y_i = \begin{bmatrix} y_{i,1} \\ y_{i,2} \\ \vdots \\ y_{i,T} \end{bmatrix} \quad X_i = \begin{bmatrix} X_{i,1}^1 & X_{i,1}^2 & \cdots & X_{i,1}^k \\ X_{i,2}^1 & X_{i,2}^2 & \cdots & X_{i,2}^k \\ \vdots & \vdots & \ddots & \vdots \\ X_{i,T}^1 & X_{i,T}^2 & \cdots & X_{i,T}^k \end{bmatrix} \quad \beta = \begin{bmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_k \end{bmatrix} \quad \varepsilon_{i,t} = \begin{bmatrix} \varepsilon_{i,1} \\ \varepsilon_{i,2} \\ \vdots \\ \varepsilon_{i,T} \end{bmatrix}$$

A one-way error component for the disturbance is commonly used in the application of panel data, with

$$\varepsilon_{it} = \mu_i + v_{it} \quad (8)$$

where μ_i denotes the unobserved individual effect and v_{it} denotes the remainder disturbance term. The unobserved individual effect, accounting for tastes and preferences not included in the model, is included in the error term because it is often impossible to measure. These effects are constant across time and can be either uncorrelated or correlated with the explanatory variables. The remainder disturbance will vary across individuals as well as across time and is assumed to be uncorrelated with the explanatory variables and well behaved (Baltagi, 2005; Wooldridge, 2002).

A two-way error component for the disturbance is also used in the application of panel data, with

$$\varepsilon_{it} = \mu_i + \lambda_t + v_{it} \quad (9)$$

where μ_i denotes the unobserved individual effect, λ_t denotes the unobserved time effect and v_{it} denotes the remainder disturbance term. The unobserved time effect, accounting for all time-specific effects not included in the model, is also included in the error term

due to the difficulty of measurement. These effects are constant across individuals and can be either uncorrelated or correlated with the explanatory variables.

It is possible that individual effects and time effects are correlated with the explanatory variables. Fixed effect and random effect methods are used to account for these unobserved variables. The fixed-effect model allows for the error term to be correlated with the observed variables. This allows for arbitrary correlation between the observed variables and the unobserved variables and does not necessarily imply that the error term is non-random (Wooldridge, 2002). The random effects model assumes that the error term, u_i , is uncorrelated with the explanatory variables and that it is an independently identically distributed random variable with a mean of zero and a variance of sigma squared.

4.6.1 Selecting Random Effects or Fixed Effects

If the data was not generated from a random sample of the population, the error term cannot be assumed to be uncorrelated with the explanatory variables; therefore the fixed effects method should be used.

If the random sample of subjects is large relative to the population, it is typically appropriate to treat the explanatory variable (the observed effect) and the unobserved effects as randomly selected from the population (Wooldridge, 2002; Baltagi, 2005). This approach applies even in the presence of omitted variables and heterogeneity. With the assumption that error terms are random, the random effect and the fixed effect are both possible methods. The defining characteristic between choosing to apply the random effect method or the fixed effect method is the correlation between the omitted

variables and the explanatory variables. If the omitted variables are not correlated with the explanatory variables, the random effect method should be applied. If the omitted variables are correlated with the explanatory variables, the fixed effect method should be applied. If the additional assumption is incorrect, random-effect estimators will be inconsistent. The Hausman test can be used to determine which method to apply, with a null hypothesis that both models are acceptable, which will produce similar coefficients, and an alternative hypothesis that the fixed-effect model is acceptable and the random-effect model is not, which will produce different coefficients. Statistical differences of the coefficients for each variable between the fixed-effect regression and the random-effect regression suggest use of fixed effects and a lack of statistical differences of the coefficients for each variable between the fixed-effect regression and the random-effect regression suggest use of random effects. Application of the random effect method will produce higher degrees of freedom (Frees, 2004). Selection between the random effect method and the fixed effect method is summarized in figure 14.

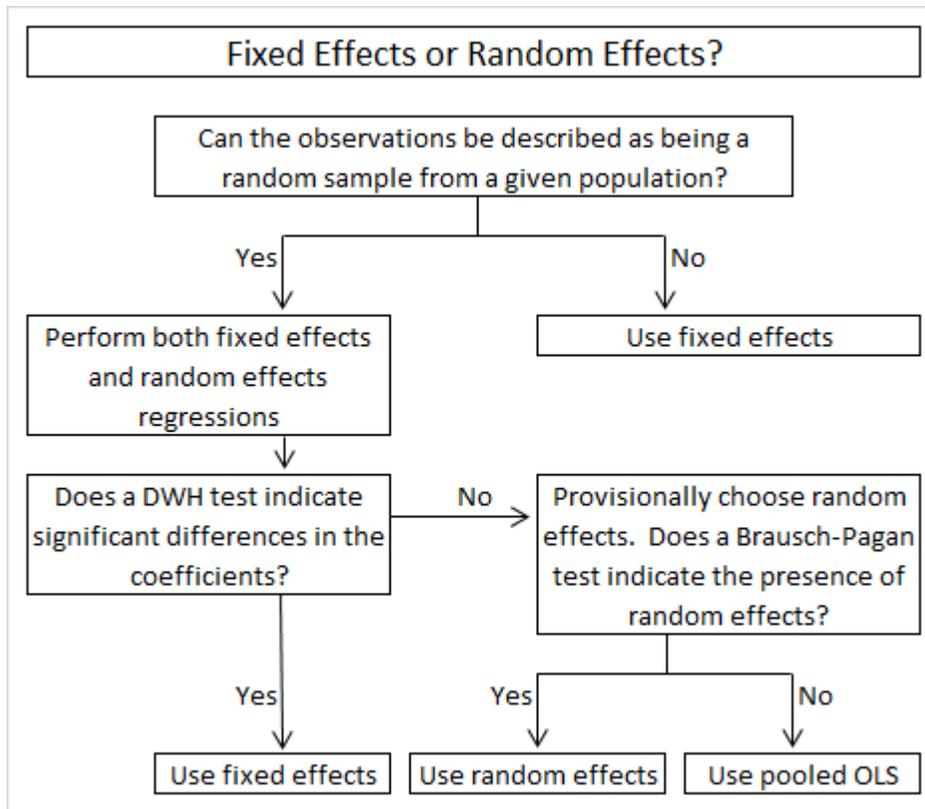


Figure 14: Fixed Effect or Random Effect

Source: Dougherty (2007)

As the data collected for this thesis represents a small portion of Manitoban farmers that was not randomly selected, the fixed effects method will be used for analysis of the panel data.

4.6.2 The Fixed Effects Method

A dummy variable is assigned for each individual, which creates a unique intercept for each individual by capturing the effects of omitted variables. The fixed effect method is applied to the estimation procedure by combining equation (7) with equation (8) as demonstrated below.

$$Y_{it} = \alpha + \beta_{it}X_{it} + \mu_i + v_{it} \quad i= 1, \dots, N; t= 1, \dots, T \quad (10)$$

The first step in using the fixed effect method in equation (10) is to calculate the average of each individual over time.

$$Y_i = \alpha + \beta_i \bar{x}_i + \bar{\mu}_i + \bar{v}_i \quad i= 1, \dots, N \quad (11)$$

The second step is to subtract equation (11) from (10) for each t. The unobserved effect is constant over time, therefore $\mu_i = \bar{\mu}_i$ and will be dropped from the equation.

$$(Y_{it} - Y_i) = \beta_{it}(X_{it} - \bar{x}_i) + (v_{it} - \bar{v}_i) \quad i= 1, \dots, N; t= 1, \dots, T \quad (12)$$

Any independent variables which are constant over time will not appear in the fixed effect model since $X_{it} - \bar{x}_i = 0$. These equations dealt with one-way individual effects.

The same application and conclusions can be drawn for time effects.

The description of application of the fixed effects method for panel data described above will be used in the estimation of regression models in this thesis.

CHAPTER 5- RESULTS

5.1 Introduction

This chapter discusses the data collected and the economic models presented in the previous chapter. Each of the four models will be discussed independently.

5.1.1 Descriptive Statistics of the Data

Data was collected between July 4th and August 17th, 2012. Farmers were contacted through Manitoba Agriculture, Food and Rural Initiatives (MAFRI) and through colleagues at the University of Manitoba. Interviews were conducted across Southern Manitoba in, but not exclusive to, the following towns: Beausejour, Dominion City, Arborg, Starbuck, Killarney, Gladstone, Souris and Melita. All experiments were conducted in person; most were conducted individually at each farmer's home and two groups completed the experiment in their home towns, one group of 15 and one group of six. One group consisted of a farmer's weekly marketing club, gathering to discuss current market conditions amongst themselves and with occasional guest speakers. The other group consisted of farmers invited to their local MAFRI office for the experiment. These groups of 15 and 6 respectively completed the experiment simultaneously but individually. Both groups were instructed not to interact during the experiment. In total, 75 farmers completed the experiment and took an average of 25 minutes, ranging from 15 to 45 minutes.

Table 1 shows descriptive statistics of the variables collected in the survey before the experiment. Farmer's average age was 47 years and ranged from 19 to 78 years.

Their education ranged from middle school to post graduate degrees, while nearly half hold at most a high school diploma and nearly half have completed a post secondary degree or diploma. Price expectations for September 2012 wheat ranges from \$5.50 to \$12.00, with an average expected price of \$8.80. Indicated farm break-even prices for wheat range from \$3.00 to \$8.50, and have an average break-even price of \$5.45. Generally, they considered themselves to have slightly above average farm sizes compared to other Manitoban farms. On average, farmer's hedged a portion of their crop 3.5 years out of the past 5 years, some farmers did not hedge any years but at least half hedged each of the 5 years (median=5). On average 25% of the crop was hedged in the past five years, ranging from 0 to 85%. Most farmers hedged a relatively small portion of their crops, since the median is 25% and the third quartile is 35%. The survey provides conflicting results for the two questions about primary marketing strategy focusing on reducing price or obtaining a high price. In both cases the median values are four, suggesting that in each question half of the subjects agree that their primary marketing strategy is to reduce risk and to obtain a high price. However, the question about certainty equivalent suggests farmers are generally willing to take risk. The median value for the certainty equivalent is \$54.5 and its first quartile is \$48, suggesting that most farmers have a certainty equivalent very close to or greater than \$50, indicating risk seeking behavior.

Table 1: Descriptive Statistics for the Survey

Variable	Statistic					
	average	minimum	1st quartile	median	3rd quartile	maximum
age	46.76	19.00	37.00	49.00	56.00	78.00
gender*	0.99	0.00	1.00	1.00	1.00	1.00
education **	2.47	1.00	2.00	3.00	3.00	4.00
september price expectation	8.81	5.50	8.12	9.00	9.50	12.00
break-even price of wheat	5.45	3.00	4.69	5.50	6.06	8.50
number of years using hedging (past 5 years)	3.52	0.00	2.00	5.00	5.00	5.00
percentage of crop hedged (annual)	0.25	0.00	0.15	0.25	0.35	0.85
I have a larger farm than most farmers in Manitoba***	2.76	1.00	2.00	3.00	3.00	5.00
compared to other farmers, I have above average skills at predicting price movements***	2.78	1.00	2.00	3.00	3.00	5.00
I prefer less risk than most farmers***	2.90	1.00	2.00	3.00	4.00	5.00
My primary marketing strategy is to reduce risk***	3.48	1.00	3.00	4.00	4.00	5.00
My primary marketing strategy is to obtain a high price***	4.12	2.00	4.00	4.00	5.00	5.00
I am willing to take higher financial risks in order to realize higher average returns***	3.58	1.00	3.00	4.00	4.00	5.00
When selling my wheat, I prefer financial certainty to financial uncertainty***	3.60	1.00	3.00	4.00	4.00	5.00
certainty equivalent of a gamble (50% chance to win \$100)	57.57	20.00	48.00	54.50	70.50	80.50

* 1=male, 0=female

** 1=middle school, 2=high school, 3=post secondary, 4=post graduate

*** 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4=agree, 5=strongly agree

5.2 Selecting the Optimal Reference Price

5.2.1 Descriptive Statistics

Each of the 75 farmers completed two hypothetical crop seasons with different price scenarios. Each scenario spanned from September until June, 10 months, for a total of 20 possible time periods. On average, 17.3 time periods were completed with a maximum of 20 observations per individual and a minimum of 4. Seventy of the farmers completed at least 12 time periods and 44 of the farmers completed at least 19 time periods. Detailed statistics can be found in table 2.

Table 2: Number of Observations for Each Sequence

Variable	Statistic					
	average	minimum	1st quartile	median	3rd quartile	maximum
number of observations						
total	8.65	2	8	10	10	10
1st sequence	8.65	2	9	10	10	10
2nd sequence	8.64	2	8	10	10	10

From the 75 farmers, 1297 data points were collected and 567 sell decisions were made. The average percentage of wheat sold per month and annually can be seen below in table 3. A larger percentage of wheat was sold in the fall months and in June. Bin space is often limited as harvest progresses and as new crop approaches. Average sales were smaller yet consistent from December through May. On average, 85% of the wheat was sold, as they were not required to dissolve their positions by June.

Table 3: Monthly and Annual Wheat Sold (Percent of Total Crop)

Month	Average Wheat Sold		
	total	1st sequence	2nd sequence
September	11%	13%	9%
October	12%	11%	12%
November	12%	10%	13%
December	6%	5%	7%
January	7%	7%	7%
February	5%	5%	6%
March	7%	8%	6%
April	6%	5%	6%
May	7%	7%	8%
June	12%	8%	15%
Total	85%	80%	90%

5.2.2 Predictive Success of Reference Prices

Table 4 presents the number of observations where the current price is greater than the reference price; data is summarized for all observations and for observations where farmers decided to sell. Of the 1297 observations, the current market price was higher than the first market price for 743 data points, the current price was the highest price for 415 data points, the current price was greater than the break-even price for 1090 data points, the current price was greater than the satisfy price for 59 data points and the goal price was greater than the market price for 28 data points. These values are used to determine the area rate of each hypothesis. Of the 567 decisions to sell wheat, the current market price was higher than the first market price for 412 data points, the current price was the highest price for 265 data points, the current price was greater than the break-even price for 524 data points, the current price was greater than the satisfy price for 37 data points and the goal price was greater than the market price for 22 data points. These

values are used to determine the hit rate of each hypothesis. These variables will be used to test hypotheses 1 through 5.

Table 4: Descriptive Statistics for the Predictive Success Model: Reference Prices

Reference Price	The number of observations where the current price is greater than or equal to the reference price		Area Theory		
	for all observations	decisions to sell	hit rate*	area rate**	predictive success***
first price	743	412	0.727	0.573	0.154
highest price	415	265	0.467	0.320	0.147
break-even price	1090	524	0.924	0.840	0.084
satisfy price	59	37	0.065	0.045	0.020
goal price	28	22	0.039	0.022	0.017

*frequency of sales where the current price is above the reference price
**frequency of observations where the current price is above the reference price
***hit rate - area rate)

Table 4 also describes the predictive success of five potential reference prices, the market price in September (hypothesis 1), the highest market price (hypothesis 2), the break-even price (hypothesis 3), the satisfy price (hypothesis 4) and the goal price (hypothesis 5). According to prospect theory, a market transaction where the current price is greater than the reference price should create the feeling of gain and promote risk adverse behavior leading to a greater frequency of sales. These hypotheses will be supported if the frequency of sales is greater above the reference price than can be expected if the decision to sell is random. In order to test these hypotheses, predictive success for each reference price will be analyzed.

Predictive success will be determined by the difference between the hit rate and the area rate. The hit rate is the percentage of decisions to sell that occurred when the current market price was equal to or greater than the reference price. The area rate is the percentage of observations where the current market price was equal to or greater than

the reference price. The predictive success is the hit rate subtracted by the area rate; determining how frequently farmers decided to sell their wheat at market prices above the reference price than can be expected if they randomly chose when to sell their grain.

Results can be found in table 4.

Of farmers' decisions to sell, 72.7% occurred when the current price was greater than or equal to the first price (hit rate). The current price was greater than or equal to the first price for 57.3% of the total data points (area rate). The predictive success is 15.4% ($0.727-0.573$); farmers were 15.4% more likely to sell their grain above the reference price than can be expected if they randomly chose when to sell. Of farmers' decisions to sell, 46.7% occurred when the current price was equal to the highest price (hit rate). The current price was greater than or equal to the first price for 32.0% of the total data points (area rate). The predictive success is 14.7% ($0.467-0.320$); farmers were 14.7% more likely to sell their grain above the reference price than can be expected if they randomly chose when to sell. The predictive success for the break-even price, satisfy price and goal price are found using the same method. The predictive success for each reference price is positive, indicating that each reference price affects farmers' decisions to sell grain.

These results are consistent with the expectation that risk aversion will lead to an increased proportion of sell decisions when the market price is above the reference price. The first three potential reference prices, the first price, highest price and break-even price, have relatively high predictive success; 15.4%, 14.7% and 8.2% respectively. Of these three, the first price has the highest predictive success as a reference price. This results leads to the conclusion that hypothesis one should be accepted and hypothesis two

and three should be rejected. The last two reference prices, the satisfy price and the goal price, have low predictive success; 1.6% and 1.5% respectively. This is due to low area rates because the satisfy price and the goal price were above the experimental price for most observations (possibly due to high market price). This result leads to the conclusion that the fourth hypothesis should be accepted and the fifth hypothesis should be rejected. As the predictive success of the satisfy price and goal price are very similar, both reference prices will be analyzed in the econometric models of this thesis.

5.3 Model 1: Formation of Reference Prices

5.3.1 Descriptive Statistics

Descriptive statistics of the components utilized in analyzing formation of the reference price can be found in table 5. The satisfy prices and goal prices vary widely between farmers. The average satisfy price is \$8.02/bu and ranges between \$5.50/bu and \$10.50/bu. The average goal price is \$8.37/bu and ranges between \$5.50/bu and \$11.50/bu. For each farmer, the satisfy price and goal price were generally above the current price and the goal price was generally above the satisfy price. The variable next month price expectations indicate that farmers, on average, expected a 29% probability that the market price would increase over the next month; the variable ranges from surely increase (1) to surely decrease (-1). The final three independent variables are control variables to account for the design of the experiment. Each farmer completed two hypothetical sequences of grain marketing, where the reference price established in the first scenario may influence the reference price in the second scenario. The final three variables are designed to account for carry-over from the first scenario to the second

scenario. Increasing price sequence is a dummy variable for price sequences which generally increase over time; 51% of the observations are part of increasing price sequences. Sequence after an increasing sequence and sequence after a decreasing sequence reflect proportions of the second sequence which were preceded by an upward price trend and a downward price trend respectively. Approximately 60% and 40% of the observations in the second sequences follow an increasing price sequence and a decreasing price sequence respectively. Further statistics can be found in table 5.

Table 5: Descriptive Statistics for Formation of Reference Prices

Variable	Statistic					
	average	minimum	1st quartile	median	3rd quartile	maximum
satisfy price (\$/bu)	8.02	5.50	7.50	8.00	8.50	10.50
goal price (\$/bu)	8.37	5.50	7.50	8.50	9.00	11.50
first price (\$/bu)	6.77	6.66	6.68	6.78	6.88	6.88
current price (\$/bu)	6.87	5.27	6.14	6.78	7.78	8.82
highest price (\$/bu)	7.34	6.66	6.68	6.86	7.93	8.82
lowest price (\$/bu)	6.40	5.27	5.96	6.78	6.88	6.88
weighted average price (\$/bu)*	6.85	5.51	6.17	6.78	7.47	8.46
expectations**	0.29	-1.00	0.00	0.20	0.60	1.00
increasing price sequence***	0.51	0.00	0.00	1.00	1.00	1.00
sequence after an increasing sequence****	0.61	0.00	0.00	1.00	1.00	1.00
sequence after a decreasing sequence*****	0.39	0.00	0.00	0.00	1.00	1.00

* $0.5*CP + 0.5*(CP \text{ at } t-1)$
** price will surely increase over the next month = 1, price will surely decrease over the next month=-1
*** increasing price sequences=1, decreasing price sequences=0
**** sequences following increasing sequences=1, otherwise=0
***** sequences following decreasing sequences=1, otherwise=0

The behavior of the satisfy price and goal price during the marketing period generally shows a downward movement (figure 15). The average satisfy price begins in September at \$7.95/bu, reaches a peak in November at \$8.25/bu, and drops to \$7.77/bu by June. The average goal price begins in September at \$8.38/bu, reaches a peak in November at \$8.53/bu, and drops to \$8.05/bu by June.

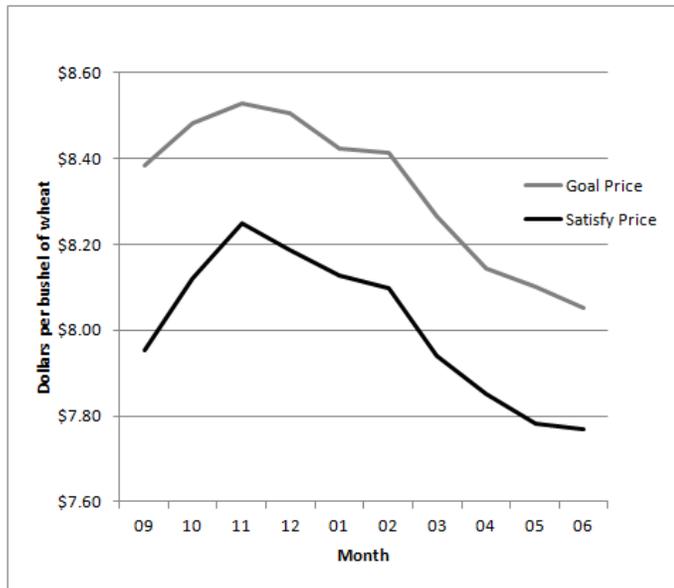


Figure 15: Average Monthly Satisfy and Goal Prices

5.3.2 Regression Results

A panel regression with individual fixed effects was used to estimate how Manitoban farmer form reference prices. Fixed effects were used due to a non-random sample from the given population. As there are a range of observations for each farmer, the data is unbalance. Table 6 presents the results of the estimated model for formation of the reference price; the satisfy price and goal price are proxies for the reference price. Dummy variables for the months of the marketing period represent time-specific effects. Robust covariance estimators were applied due to the presence of heteroskedasticity as

indicated by the Modified Wald Test. The coefficient point estimates and standard errors of all parameters can be found in the table; individual specific effects are applied but not included in the table.

Table 6: Estimated Panel Regression Model: Formation of Reference Prices

$$\ln(\text{RP}_{it}) = \alpha + \beta_1 \ln(\text{FP}_{it}) + \beta_2 \ln(\text{CP}_{it}) + \beta_3 \ln(\text{HP}_{it}) + \beta_4 \ln(\text{LP}_{it}) + \beta_5 \ln(\text{WP}_{it}) + \beta_6 \text{E}_{it} + \beta_7 \text{IPS}_{it} + \beta_8 \text{AI}_{it} + \beta_9 \text{AD}_{it} + \sum_{j=1}^9 \theta_{ij} \text{Month}_{ij} + \varepsilon_{it}$$

	ln(satisfy price)		ln(goal price)	
	coefficient	std. error	coefficient	std. error
ln(first price- FP)	-0.474	0.717	-0.211	0.692
ln(current price- CP)	0.144***	0.061	0.171***	0.062
ln(highest price- HP)	0.213*	0.114	0.231*	0.124
ln(lowest price- LP)	-0.198*	0.112	-0.203*	0.103
ln(weighted price- WP)	0.330**	0.111	0.270**	0.118
expectations (E)	0.024**	0.007	0.021**	0.009
increasing price sequence (IPS)	0.013	0.018	0.007	0.020
sequence after an increasing sequence (AI)	0.009	0.009	0.010	0.009
sequence after a decreasing sequence (AD)	-0.039**	0.016	-0.036**	0.015
October	-0.007*	0.007	-0.014*	0.008
November	-0.014**	0.013	-0.030**	0.013
December	-0.023**	0.014	-0.036**	0.015
January	-0.027***	0.015	-0.043***	0.015
February	-0.030**	0.018	-0.044**	0.017
March	-0.046***	0.019	-0.060***	0.019
April	-0.052***	0.020	-0.071***	0.020
May	-0.063***	0.023	-0.080***	0.023
June	-0.071***	0.022	-0.095***	0.023
constant	2.038	1.339	1.630	1.339
r-sq within	0.472		0.440	
between	0.251		0.219	
overall	0.317		0.291	
number of observations	1277		1287	
number of producers	75		75	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

All coefficients are distinguishable from zero in the model except for the first price in the sequence and the dummy variables for increasing price sequences and for price sequences following gains. All prices are in log form, and therefore the coefficients represent elasticities of each price variable. The current price, highest price, lowest price and weighted average price are found to have the largest effect on the reference price, where their effects were all positive except for the lowest price. The weighted price has the greatest overall effect on the reference price and the highest price has the next largest effect on the reference price. For example, if the highest price increases by 10% the satisfy price is expected to increase by 2.13% and the goal price is expected to increase by 2.31%. Likewise, if the weighted average price decreases by 10%, the satisfy price and the goal price are expected to decrease by 3.3% and 2.7% respectively. These results show a positive relationship between the market prices analyzed (except for the lowest price) and the reference prices. A possible explanation for a negative coefficient for the lowest price is that lower market prices create feelings of loss, causing farmer's to increase their reference price hoping to 'make-up' for the losses. The estimated regression model suggests that the reference price is formed by a combination of market prices.

The estimated coefficient for next month price expectations is positive, implying that a farmer's reference price will be higher if he expects the market price will increase in the next month than if he expects it will decrease over the next month. The satisfy price is expected to be 4.8% higher if the farmer expects the market price will surely increase ($E=1$) than if he expects the market price will surely decrease ($E=-1$). If the farmer expects the price to increase, there is additional incentive not to sell and would

therefore require higher prices today to become satisfied or to sell. The dummy variable for sequences after a decreasing sequence is statistically distinguishable from zero; the satisfy price is expected to be 3.9% lower after a decreasing scenario than in the first scenario. The coefficients for increasing price sequences and sequences after an increasing sequence are not statistically distinguishable from zero.

The month dummy variables are statistically distinguishable from zero compared to September for all other months. All coefficients for the month dummy variables are negative, indicating lower reference prices as the crop year progresses. Farmer's satisfy and goal prices are estimated to be 7.1% and 9.5% lower in June than in September of the previous calendar year. These results may reflect the increased attractiveness of selling all of their wheat as the year progresses; marketing the remainder of a crop in the fall months is uncommon. The reference prices may also be affected by time specific factors such as cash flow and storage, as well as carrying costs.

5.4 Model 2: Incremental Adaptation of Reference Prices

5.4.1 Descriptive Statistics

Descriptive statistics of the components utilized in analyzing incremental adaptation of the reference price can be found in table 7. The incremental reference price adaptation was calculated as the current reference price subtracted from the reference price of the previous month; adaptation ranged from a decrease of \$2 to an increase of \$1.50 and \$1.80 for the satisfy and goal price respectively. Positive incremental price changes are calculated as the current market price subtracted from the market price of the previous month, any negative values are replaced with a value of zero. Negative

incremental price changes were calculated as the absolute value of the difference between the market price of the previous month and of the current market price, any decreases in market price are replaced with a value of zero. On average, incremental price changes were 0.16 and -0.14 per month for positive and negative price movements respectively. The incremental price change variables are designed to capture asymmetric adaptation of the reference price due to incremental price changes where prices are generally increasing or generally decreasing. The statistics for the expectations variable and the round dummy variable are as previously stated.

Table 7: Descriptive Statistics for Incremental Reference Price Adaptation

Variable	Statistic					
	average	minimum	1st quartile	median	3rd quartile	maximum
incremental satisfy price adaptation*	-0.01	-2.00	0.00	0.00	0.00	1.50
incremental goal price adaptation*	-0.03	-2.00	0.00	0.00	0.00	1.80
positive inc. price change**	0.16	0.00	0.00	0.00	0.25	0.96
negative inc. price change**	0.14	0.00	0.00	0.00	0.21	0.90
expectations***	0.29	-1.00	0.00	0.20	0.60	1.00
increasing price sequence****	0.51	0.00	0.00	1.00	1.00	1.00
sequence after an increasing sequence*****	0.61	0.00	0.00	1.00	1.00	1.00
sequence after a decreasing sequence*****	0.39	0.00	0.00	0.00	1.00	1.00

* reference price - reference price at t-1
** absolute value of (current price - current price at t-1)
*** price will surely increase over the next month = 1, price will surely decrease over the next month = -1
**** increasing price sequences = 1, decreasing price sequences = 0
***** sequences following increasing sequences = 1, otherwise = 0
***** sequences following decreasing sequences = 1, otherwise = 0

5.4.2 Regression Results

Table 8 demonstrates how reference prices adapt to price changes after each period. The coefficients for incremental price changes are found to be statistically distinguishable from zero at the 1% level. A one dollar increase in the market price is expected to lead to a 49 (42.3) cent increase in the satisfy (goal) price and a one dollar decrease in the market price is expected to lead to a 24.7 (23.9) cent decrease in the satisfy (goal) price. As the market price increases, the reference price is expected to increase. As the market price decreases, the reference price is expected to decrease. Increases in the market price are expected to have a larger effect on the reference price than decreases in the market price.

The coefficient for next month price expectations is found to be statistically different from zero at the 5% level for the satisfy price and the 1% level for the goal price. A change in expectations from expecting the price to surely decrease ($E=-1$) to expecting the price will surely increase ($E=1$) is expected to increase adaptation of the satisfy price by 17.4 cents and the goal price by 19.6 cents for a given month. Farmers are expected to increase adaptation of their reference price if they expect the market price to increase than if they expect the market price to decrease. The coefficients for increasing price sequence are positive and statistically distinguishable from zero; farmers' adaptation of the reference price is expected to be greater if market prices are generally increasing than if they are generally decreasing. The coefficients for sequences after an increasing sequence and sequence after a decreasing sequence are not found to be statistically distinguishable from zero.

Hypothesis 6.1 is supported by the positive incremental price change variable, as $\beta_1 > 0$ and is supported by the negative incremental price change variable, as $\beta_2 < 0$. Hypothesis 6.2 is supported by the incremental price change variables, as $|\beta_1| > |\beta_2|$.

Table 8: Estimated Panel Regression Model: Incremental Reference Price Adaptation

$$IA_{it} = \alpha + \beta_1 \Delta IP(p)_{it} + \beta_2 |\Delta IP(n)|_{it} + \beta_3 E_{it} + \beta_4 IPS_{it} + \beta_5 AI_{it} + \beta_6 AD_{it} + \varepsilon_{it}$$

	Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error
positive incremental price change	0.490***	0.047	0.423***	0.052
negative incremental price change (absolute value)	-0.247***	0.046	-0.239***	0.054
expectations (E)	0.087**	0.033	0.098***	0.037
increasing price sequence (IPS)	0.069***	0.026	0.064**	0.030
sequence after an increasing sequence (AI)	0.013	0.021	0.017	0.025
sequence after a decreasing sequence (AD)	-0.007	0.030	-0.010	0.029
constant	-0.111***	0.023	-0.126***	0.025
R-sq within	0.241		0.187	
between	0.103		0.075	
overall	0.223		0.172	
number of observations	1277		1297	
number of producers	75		75	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

5.5 Model 3: Total Adaptation of Reference Prices

5.5.1 Descriptive Statistics

Descriptive statistics of the components utilized in analyzing total adaptation of the reference price can be found in table 9. Total satisfy and goal adaptation are calculated as the current reference price subtracted by the reference price in September. The average adaptation of the satisfy price and goal price is \$0.00 and -\$0.09 respectively. Month (increasing price sequence) is a time variable for each month of increasing price sequences where September is one, October is two, and so on; if the price sequence is decreasing, the month variable is zero. Month (decreasing price sequence) is a time variable for each month of decreasing price sequences where September is one, October is two, and so on; if the price sequence is increasing, the month variable is zero. For each observation, one month variable will have a positive value and one month variable will be zero. The month variables are designed to capture asymmetric adaptation of the reference price due to the amount of time spent in a sequence where prices are generally increasing or generally decreasing. Positive and negative total price changes are calculated as the absolute value of the difference between the current market price and the market price in September. If the price sequence is decreasing, positive total price change will be zero and if the price sequence is increasing, negative total price change will be zero. For each observation, one total price change variable will have a positive value and one total price change variable will be zero. Total price change is designed to capture asymmetric adaptation of the reference price due to total increased price changes and total decreased price changes. The average total price change was \$0.40 and \$0.30 for gains and losses respectively. Expectations (next

month), sequence after a gains and sequence after a loss are calculated in the same manner as for the previous model.

Table 9: Descriptive Statistics for Reference Price Adaptation

Variable	Statistic					
	average	minimum	1st quartile	median	3rd quartile	maximum
total satisfy price adaptation*	0.00	-2.50	0.00	0.00	0.00	2.00
total goal price adaptation*	-0.09	-3.00	-0.50	0.00	0.00	2.30
month (gains)**	2.49	0.00	0.00	1.00	5.00	10.00
month (losses)**	2.64	0.00	0.00	0.00	5.00	10.00
positive total price change***	0.40	0.00	0.00	0.00	0.96	1.94
negative total price change***	0.30	0.00	0.00	0.00	0.62	1.49
expectations****	0.29	-1.00	0.00	0.20	0.60	1.00
sequence after an increasing sequence*****	0.61	0.00	0.00	1.00	1.00	1.00
sequence after a decreasing sequence*****	0.39	0.00	0.00	0.00	1.00	1.00

* reference price - reference price in September
 ** September = 1, October = 2, ... , June = 10
 *** absolute value of (current price - price in September)
 **** price will surely increase over the next month = 1, price will surely decrease over the next month = -1
 ***** sequences following increasing sequences = 1, otherwise = 0
 ***** sequences following decreasing sequences = 1, otherwise = 0

Figures 16 and 17 provide further detail of how the satisfy and goal prices change for increasing and decreasing price sequences. For increasing price sequences, the satisfy and goal price both increase by approximately 55 cents per bushel in the first two months and then slowly decreases to a 30 cent gain per bushel by June. The average market price increased by \$1.18 per bushel in the first two months and ended with a final price increase of 82 cents. For decreasing price sequences, the satisfy price decreased by 70 cents over the ten month period and the goal price steadily decreased by 88 cents over the ten month period. The average market price decreased by 75 cents over the ten month period.

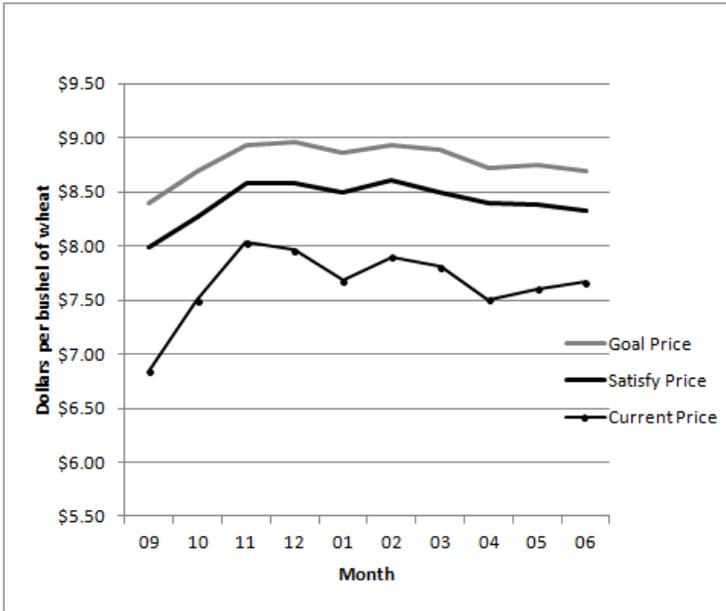


Figure 16: Satisfy and Goal Prices for Increasing Price Sequences- Monthly Averages Across Farmers

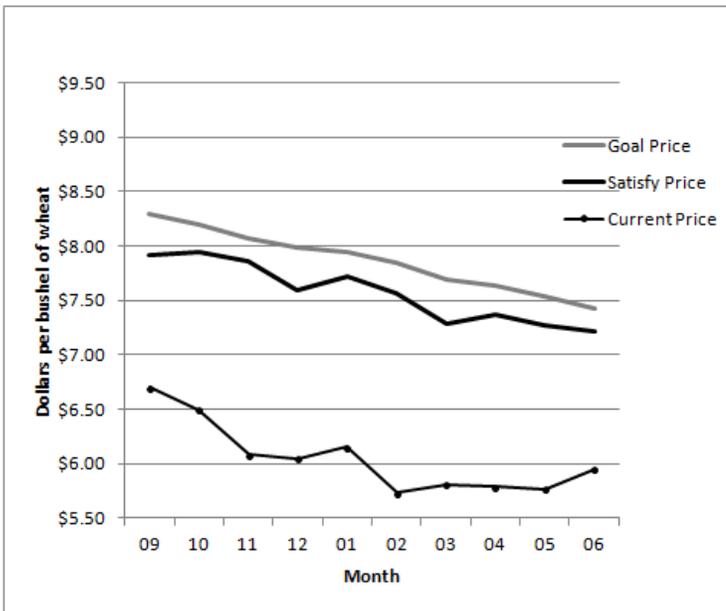


Figure 17: Satisfy and Goal Prices for Decreasing Price Sequences- Monthly Averages Across Farmers

5.5.2 Regression Results

Table 10 shows regressions for total adaptation of the satisfy price and goal prices for increasing and decreasing price sequences. The coefficients for month are negative and statistically distinguishable from zero. On average, total adaptation decreases by 1.8 (5.8) cents and 3.8 (7.3) cents for the satisfy price and goal prices respectively, in increasing (decreasing) price sequences. Adaptation appears to be stronger for the goal price and in downward sequences. As both reference prices are above the market price, a decrease in the reference price is adapting towards the market price. Coefficients for total price change are also found to be statistically distinguishable from zero. A dollar increase in the market price is expected to cause the satisfy price and goal prices to increase by 47 and 49 cents respectively. A dollar decrease in the market price is expected to cause the satisfy and goal prices to decrease by 26 and 19 cents respectively. Therefore, adaptation is stronger for positive price changes.

The coefficient for expectations is found to be positive and statistically distinguishable from zero for adaptation of the satisfy price. Expectations of price increases is expected to lead to greater positive adaptation of the satisfy price. Coefficients for expectations of goal adaptation, and for sequences after an increasing price sequence and sequences after a decreasing price sequence are not found to be statistically distinguishable from zero.

Hypothesis 7.1 is supported by the positive total price change variable, as $\beta_3 > 0$ and is supported by the negative total price change variable, as $\beta_4 < 0$. Hypothesis 7.2 is supported by the total price change variables, as $|\beta_3| > |\beta_4|$.

Hypothesis 8.1 is not supported by the month variable for increasing price sequences, as $\beta_1 < 0$, but is supported by the month variable for decreasing price sequences, as $\beta_2 < 0$. Month for increasing price sequences may not be supported due to the majority of reference prices being greater than the current price. Hypothesis 8.2 is not supported by the month variables, as $|\beta_1| < |\beta_2|$.

Table 10: Estimated Panel Regression Model: Total Reference Price Adaptation

$$TA_{it} = \alpha + \beta_1 \text{Month}(i)_{it} + \beta_2 \text{Month}(d)_{it} + \beta_3 \Delta TP(p)_{it} + \beta_4 \Delta TP(n)_{it} + \beta_5 E_{it} + \beta_6 AI_{it} + \beta_7 AD_{it} + \varepsilon_{it}$$

	Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error
month (increasing price sequence)	-0.018**	0.009	-0.038***	0.011
month (decreasing price sequence)	-0.058***	0.011	-0.073***	0.013
positive total price change ($\Delta P(p)$)	0.471***	0.047	0.492***	0.060
negative total price change ($\Delta P(n)$)	-0.255**	0.097	-0.188*	0.103
expectations (E)	0.155**	0.060	0.085	0.079
sequence after an increasing sequence (AI)	-0.008	0.073	-0.005	0.108
sequence after a decreasing sequence (AD)	0.001	0.111	0.090	0.119
constant	0.035	0.051	0.016	0.068
R-sq within	0.480		0.416	
between	0.377		0.265	
overall	0.436		0.362	
number of observations	1277		1287	
number of producers	75		75	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

5.6 Model 4: Decisions to Sell Grain

5.6.1 Descriptive Statistics

Descriptive statistics of the components utilized in analyzing farmer's decisions to sell can be found in table 11. Farmer's sold 9% of their crop on average in each month, quantity sold ranged from selling no grain to selling all of their grain. Farmer's on average expected a 29% chance that the market price would increase over the next month; their expectations ranged from expecting the price would surely decrease to expecting the price would surely increase. The next two variables represent the difference between the current market price and the reference price. The market price was, on average, \$1.14 and \$1.49 lower than the satisfy and goal prices respectively. The satisfy (goal) price was a maximum of \$4.73 (\$4.73) above the market price and a maximum of \$1.12 (\$0.62) below the market price. The next two variables are the interaction terms of next month price expectations and the difference between the current market price and the reference price. The statistics for the dummy variables are as previously stated.

Table 11: Descriptive Statistics for Selling Decisions

Variable	Statistic					
	average	minimum	1st quartile	median	3rd quartile	maximum
percentage sold per month*	0.09	0.00	0.00	0.00	0.15	1.00
expectations**	0.29	-1.00	0.00	0.20	0.60	1.00
current price - satisfy price	-1.14	-4.73	-1.67	-0.91	-0.44	1.12
current price - goal price	-1.49	-4.73	-2.12	-1.29	-0.74	0.62
expectations * (price - satisfy price)	-0.45	-4.73	-0.58	-0.08	0.00	1.86
expectations * (price - goal price)	-0.55	-4.73	-0.89	-0.17	0.00	2.15
increasing price sequence***	0.51	0.00	0.00	1.00	1.00	1.00
sequence after an increasing sequence****	0.61	0.00	0.00	1.00	1.00	1.00
sequence after a decreasing sequence*****	0.39	0.00	0.00	0.00	1.00	1.00
* quantity sold/ quantity available for sale in September						
** price will surely increase over the next month = 1, price will surely decrease over the next month = -1						
*** increasing price sequences = 1, decreasing price sequences = 0						
**** sequences following increasing sequences = 1, otherwise = 0						
***** sequences following decreasing sequences = 1, otherwise = 0						

5.6.2 Regression Results

Table 12 demonstrates factors which contribute to farmers' decisions to market their wheat. The coefficient of the expectations variable is statistically different than zero at the 10% level when the satisfy price is used as the reference price. An increase in expectations, from expecting the market price to surely decrease ($E=-1$) to surely increase ($E=1$), is expected to result in an 8.2% decrease in sales for a given month. Farmers are more likely to sell grain if they expect prices will decrease over the next month. Statistical significance is not found for the model when the goal price is used as the reference price. As the farmer's reference price adapts downwards towards the market price or the market price increases towards the reference price, the difference between the reference price and market price will become less negative (more positive if the reference price is below the market price.) As the reference price becomes more adapted, the variable (current price – reference price) increases. The coefficient of this variable is positive and statistically different than zero at the 1% level. A dollar increase in

adaptation is expected to lead to a 5.9% (5.2%) increase of sales in a given month when the satisfy (goal) price is used as the reference price. Therefore, as farmers become more adapted to the market price, they are expected to sell an increased percentage of the crop. The coefficient of the interaction terms for expectations and (current price – reference price) is not found to be statistically distinguishable from zero.

The coefficients for the variables increasing price sequence and sequence after an increasing sequence are positive and statistically distinguishable from zero. They are expected to sell more of their crop if the current price sequence is generally increasing or if the previous price sequence was generally increasing. Farmers are also found to sell less of their crop in the middle of the marketing season, from December to May, compared to September.

Hypothesis 9.1 is supported by the expectations variable, as $\beta_1 < 0$. Hypothesis 7.2 is supported by the reference price subtracted from the current price variable, as $\beta_2 > 0$.

Table 12: Estimated Panel Regression Model: Selling Decisions

$$\%S_{it} = \alpha + \beta_1 E + \beta_2 (CP_{it} - RP_{it}) + \beta_3 (E_{it})(CP_{it} - RP_{it}) + \beta_4 IPS_{it} + \beta_5 AI_{it} + \beta_6 AD_{it} + \sum_{j=1}^9 \theta_{ij} M_{ij} + \varepsilon_{it}$$

	Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error
expectations (E)	-0.041*	0.024	-0.042	0.027
current price (CP) - reference price (RP)	0.059***	0.013	0.052***	0.012
(E) * (CP - RP)	-0.019	0.015	-0.015	0.014
increasing price sequence (IPS)	0.036**	0.015	0.040**	0.017
sequence after an increasing sequence (AI)	0.024**	0.009	0.023**	0.009
sequence after a decreasing sequence (AD)	-0.018	0.016	-0.012	0.016
October	-0.005	0.015	-0.006	0.015
November	0.002	0.019	-0.002	0.020
December	-0.052***	0.013	-0.055***	0.013
January	-0.040***	0.014	-0.043***	0.015
February	-0.047***	0.016	-0.049***	0.016
March	-0.034**	0.016	-0.036**	0.017
April	-0.040**	0.016	-0.044***	0.016
May	-0.024	0.017	-0.028*	0.016
June	0.019	0.023	0.013	0.022
constant	0.157***	0.022	0.167***	0.026
R-sq within	0.122		0.121	
between	0.149		0.165	
overall	0.110		0.120	
number of observations	1277		1287	
number of producers	75		75	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

5.7 Categorical Subsamples

This section explores whether farmers exhibit different behavior across subsamples. Subsamples discussed include farmers whose break-even price is greater than \$5.50 and less than \$5.50 and who have a certainty equivalent of greater than \$50 and less than \$50 for a gamble with a 50% chance of winning \$100. Estimated panel regressions for the subsamples of these two model can be found in appendix 5, as well as for subsamples of farmers whose September price expectation is greater than \$9 and less than \$9, who have hedged their crop in each of the past five years and who have not hedged in at least one of the past five years, who are older than 50 and who are younger than 50, and those who have attended post secondary education and those who have not.

5.7.1 Subsamples for Reference Price Formation

Explanatory variables that are statistically distinguishable between subsamples of reference price formation can be seen in table 13. For farmers with a break-even price higher than \$5.50/bu, expectations are found to have a smaller positive effect on the satisfy price compared to those with a break-even price lower than \$5.50/bu. For farmers with a certainty equivalent value greater than \$50, expectations are found to have a smaller positive effect on the satisfy price, the current price is found to have a smaller positive effect on the goal price, and a sequence after a decreasing sequence is found to have a smaller negative effect on the goal price compared to those with a certainty equivalent value greater than \$50.

Table 13: Estimated Panel Regression Model by Subsamples: Formation of Reference Prices – Selected Coefficients¹²

Reference Price = Satisfy Price					
Subsamples	variable	coefficient 1		coefficient 2	stat. sig.
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	expectations	0.021	≠	0.026	1%
Certainty Equivalent (≥ 50 , < 50)	expectations	0.018	≠	0.032	1%
Reference Price = Goal Price					
Subsamples	variable	coefficient 1		coefficient 2	stat. sig.
Certainty Equivalent (≥ 50 , < 50)	current price	0.150	≠	0.194	1%
Certainty Equivalent (≥ 50 , < 50)	after decreasing	-0.042	≠	-0.051	1%

5.7.2 Subsamples for Incremental Adaptation of the Reference Price

Explanatory variables that are statistically distinguishable between subsamples of incremental reference price adaptation can be seen in table 15. For farmers with a break-even price higher than \$5.50/bu, incremental changes in prices (both positive and negative) are found to have a smaller effect on the satisfy price and the goal price compared to those with a break-even price lower than \$5.50/bu. For farmers with a certainty equivalent value greater than \$50, incremental changes in price (both positive and negative) are found to have a larger effect on the satisfy price and goal price, except for negative incremental price changes on the satisfy price, and expectations are found to have a smaller positive effect on the satisfy price, compared to those with a certainty equivalent value less than \$50.

¹² Selected coefficients: coefficients which are statistically distinguishable from zero in both subsamples.

Table 14: Estimated Panel Regression Model by Subsamples: Incremental Adaptation of Reference Prices – Selected Coefficients¹³

Subsamples	Reference Price = Satisfy Price				
	variable	coefficient 1	coefficient 2	stat. sig.	
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	inc. Δ price (+)	0.314	\neq 0.562	1%	
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	inc. Δ price (-)	-0.209	\neq -0.293	1%	
Certainty Equivalent (≥ 50 , < 50)	inc. Δ price (+)	0.464	\neq 0.374	1%	
Certainty Equivalent (≥ 50 , < 50)	inc. Δ price (-)	-0.225	\neq -0.277	1%	
Certainty Equivalent (≥ 50 , < 50)	expectations	0.081	\neq 0.089	1%	
Subsamples	Reference Price = Goal Price				
	variable	coefficient 1	coefficient 2	stat. sig.	
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	inc. Δ price (+)	0.297	\neq 0.569	1%	
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	inc. Δ price (-)	-0.195	\neq -0.293	1%	
Certainty Equivalent (≥ 50 , < 50)	inc. Δ price (+)	0.462	\neq 0.362	1%	
Certainty Equivalent (≥ 50 , < 50)	inc. Δ price (-)	-0.274	\neq -0.184	1%	

5.7.3 Subsamples for Total Adaptation of the Reference Price

Explanatory variables that are statistically distinguishable between subsamples of reference price adaptation can be seen in table 14. For farmers with a break-even price higher than \$5.50/bu, the month variable for decreasing price sequences is found to have a larger negative effect on the satisfy and goal price and total positive changes in price are found to have a smaller positive effect on the satisfy and goal price compared to those with a break-even price lower than \$5.50/bu. For farmers with a certainty equivalent value greater than \$50, the month variable for decreasing price sequences is found to have a greater negative effect on the goal price and total positive changes in price are found to have a greater positive effect on the satisfy price and goal price compared to those with a certainty equivalent value greater than \$50.

¹³ Selected coefficients: coefficients which are statistically distinguishable from zero in both subsamples.

Table 15: Estimated Panel Regression Model by Subsamples: Adaptation of Reference Prices – Selected Coefficients¹⁴

Subsamples	Reference Price = Satisfy Price				
	variable	coefficient 1	coefficient 2	stat. sig.	
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	month (-)	-0.066	≠	-0.051	1%
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	Δ price (+)	0.404	≠	0.556	1%
Certainty Equivalent (≥ 50 , < 50)	Δ price (+)	0.537	≠	0.373	1%
Subsamples	Reference Price = Goal Price				
	variable	coefficient 1	coefficient 2	stat. sig.	
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	month (-)	-0.091	≠	-0.052	1%
Break-Even Price ($\geq \$5.50$, $< \$5.50$)	Δ price (+)	0.442	≠	0.544	1%
Certainty Equivalent (≥ 50 , < 50)	month (-)	-0.089	≠	-0.051	1%
Certainty Equivalent (≥ 50 , < 50)	Δ price (+)	0.563	≠	0.374	1%

5.7.4 Subsamples for Selling Decisions

Explanatory variables that are statistically distinguishable between subsamples of selling decisions can be seen in table 16. For farmers with a break-even price higher than \$5.50/bu, the current price minus reference price variable is found to have a larger positive effect on the satisfy price and the goal price and increasing price sequences are found to have a smaller positive effect on the satisfy price compared to those with a break-even price lower than \$5.50/bu. For farmers with a certainty equivalent value greater than \$50, the current price minus reference price variable is found to have a larger positive effect on the satisfy price and goal price compared to those with a certainty equivalent value greater than \$50.

¹⁴ Selected coefficients: coefficients which are statistically distinguishable from zero in both subsamples.

Table 16: Estimated Panel Regression Model by Subsamples: Selling Decisions –
Selected Coefficients¹⁵

Reference Price = Satisfy Price					
Subsamples	variable	coefficient 1		coefficient 2	stat. sig.
Break-Even Price ($\geq \$5.50, < \5.50)	current price - reference price	0.062	≠	0.053	1%
Break-Even Price ($\geq \$5.50, < \5.50)	increasing price sequence	0.037	≠	0.041	1%
Certainty Equivalent ($\geq 50, < 50$)	current price - reference price	0.065	≠	0.056	1%
Reference Price = Goal Price					
Subsamples	variable	coefficient 1		coefficient 2	stat. sig.
Break-Even Price ($\geq \$5.50, < \5.50)	current price - reference price	0.054	≠	0.045	1%
Certainty Equivalent ($\geq 50, < 50$)	current price - reference price	0.063	≠	0.043	1%

¹⁵ Selected coefficients: coefficients which are statistically distinguishable from zero in both subsamples.

CHAPTER 6: CONCLUSIONS

6.1 Introduction

This chapter covers conclusions about reference price formation and adaptation by Manitoban farmers, and their effects on selling decisions. Implications of the research are discussed as they effect farmers and other stakeholders. This chapter will conclude with limitations of the research and recommendations for future research.

6.2 Conclusions

Data was collected by the experimenter in order to study how farmers' reference prices are formed, how they adapt over time, and how they affect decisions to sell grain. In particular, this research aimed to: isolate which market prices have the largest effect on reference price formation; to quantify how reference prices adapt to short term and long term price changes; and to explore how the relationship between the market price and the reference price effect decisions to sell grain.

Reference prices are analyzed using area theory to isolate which price is optimal as a proxy for the reference price. The first price (price in September), the highest market price to date and the break-even price are ranked against each other as their prices can all be found in market data or in a farm's financial statements. Between the three prices, the first price is found to have the highest predictive success and is suggested to be used as a proxy for the reference price if other estimates are unavailable. The satisfy price and goal price are ranked against each other as they are both subjective and account for reference price formation through a range of prices and environmental factors. Between the two

subjective prices, the satisfy price is found to have higher predictive success than the goal price and is suggested to be used as a proxy for the reference price if subjective data is available. Due to a small margin between the satisfy price and the goal price, both prices were analyzed in this research.

The first model was developed to isolate the effect market prices have on the formation of reference prices. Data was collected from 75 farmers through a marketing simulation over the 2012-2013 crop year. Panel regression models were estimated to investigate how the first price (price in September), the current price, the highest price, the lowest price and a weighted average price affect the reference price in each month. Regression results indicate that farmers' reference prices are most influenced by the weighted average price and the highest price to date, both with a positive impact. The lowest price and the current price were also found to contribute to reference price formation, though to a slightly smaller effect. The lowest price was found to have a negative relationship with the reference price; this may be due to a feeling of loss and desire to compensate for perceived losses from sales at low prices. The effect of the first price could not be isolated statistically, perhaps attributable to being identical to either the highest or the lowest price for each series. Farmers were also found to increase their reference price if they expected the market price to increase over the next month, were found to decrease their reference price if the scenario was preceded by a scenario with a decreasing price trend, and were found to decrease their reference price as the year progressed. However, the impact of these final three variables is relatively small.

The second model quantifies the effects of total price changes and time on total adaptation of the reference price. Farmers' reference prices are found to be effected by

positive total price changes to a greater extent than by negative total price changes. Thus, farmers are more likely to accept new market prices during increasing sequences than to new market prices during decreasing sequences. As each month passes, farmers are found to decrease their reference price regardless if the market price is moving upwards or downwards. Their adaptation due to time is found to have a greater negative effect for decreasing sequences than for increasing sequences. Note, the indicated reference prices are usually above the market price and a downward movement overtime indicates adaptation towards the market price for both increasing sequences and decreasing sequences. Price change is generally found to have a larger effect on reference price adaptation than the time effect, except for losses nearing the end of the market year. The expectation that the market price will increase over the next month is also found to have a positive effect on reference price adaptation.

The third model is a variation of the second model, developed to isolate the incremental effects of changing market prices on adaptation of the indicated reference prices. The effects of incremental price changes on farmers' reference price are found to be similar to those of total price change. Their reference price is found to be influenced more by positive incremental price changes than negative price changes. Once again, farmers' reference prices are found to be slightly higher when they expect the market price will increase over the next month and when the market prices are generally increasing.

The final model was developed to study farmers' decisions to sell their wheat based on the relationship between their reference price and the market price, and on their price expectations. As farmers became more confident that the market price would

increase over the next month, they began to sell less grain. As farmers adapted their reference price downwards toward the market price, they became more likely to sell their grain. When reference prices remained relatively high, farmers behaved in a more risk seeking manner by choosing to sell less of their grain. Farmers were also found to sell more grain if the current or previous price sequences followed upward trends.

6.3 Implications for Farmers and Other Stakeholders

This research will provide farmers with additional tools for marketing their grain. Learning about prospect theory will help them isolate differences between psychological gains and losses against accounting gains and losses. Understanding the implications of gains and losses on choices under uncertainty may help farmers improve their marketing decisions. The results from the reference price formation and reference price adaptation models may help farmers improve their understanding of how their own reference prices are formed, as well as how other farmers' reference prices behave. The results from the selling model present to farmers the effect reference prices can have on their grain marketing decisions, and thus their revenues, emphasizing the importance of reference prices.

The results from this research will help the government reach program goals by guiding farmers' decisions using their own reference prices. The government can position prices within programs to encourage behavior that is targeted by its programs or that is expected to be beneficial to farmers.

Market advisors may be able to improve their services to farmers using results from this research. Advisors will be able to emphasize the effects of reference prices on marketing decisions and help farmers minimize biases from reference prices.

Tools which aid in estimating farmers reference prices can help grain companies market to farmers. Strategically pricing above the farmers' estimated reference price may encourage farmers to market their grain when demand is high and strategically pricing below the farmers' estimated reference price may discourage farmers from marketing when storage is limited or when sales to processor or international markets are low.

6.4 Limitations

The number of farmers interviewed for this study is small relative to the number of grain producers in Manitoba. This is due to the nature of the research, primarily conducted through one-on-one in person interviews or small groups also conducted in person. The farmers who participated are generally more involved with MAFRI than the typical Manitoban farmer and needed to be on farm with spare time to complete the interview. Therefore, farmers in this study do not necessarily form a representative sample of all Manitoban farmers.

The decisions points indicated in the research may be affected by factors not controlled for in the study. Factors that may have weighed on farmers' decisions (although not required by the study) include prices from the CWB, futures prices, storage capacity, cash flow, seasonal trends, marketing strategies, and personal factors. A time limitations is that the marketing scenarios are only set in 2012. Another major factor that may have affected farmers' reference prices was the strong agricultural commodity price

uptrend in the market at the time of the study. Wheat prices were near record highs for most of the experiment, causing an increase in their reference price prior to the study. Therefore, the number of years in the study is not only limited to one year, but to one with atypical market prices.

6.5 Recommendations for Future Research

A useful extension of this study is to contact farmers over a longer period of time. Collecting data about farmers' reference prices over one or more crop seasons with market prices, rather than hypothetical prices, will help increase the accuracy of the results and limit biases. Numerous data collection sessions would also allow for additional questions at each time period, allowing an increase in the scope of the study. Extensions can include controlling for marketing habits, personality traits and other attributes that may affect individuals' reference prices.

Researchers will be able to apply the experimental design in other regions in Canada, as well as in international markets. Methods developed for this study can also serve as a starting point for marketing research of other industries.

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APPENDIX 1: QUESTIONNAIRE

Preliminary demographic questions:

What town is located nearest to your farm?

- _____

What is your age?

- _____

What is your gender?

- Male
- female

What was the highest level of education you completed?

- Middle school
- High school
- Post- secondary (diploma or degree)
- Post-graduate degree

What is your expectation for the price of wheat in September of 2012?

- _____

What is your break-even price of producing one bushel of wheat this year (2012/13)?

- _____

Over the past 5 years, how many years did you use any form of forward, futures, or options contracts?

- _____

Of the years you used forward, futures, or options contracts, what percentage of your crop did you hedge on average?

- _____

What do you recall to be the average market price in your area for #1CWRS wheat over the past 5 years?

- _____

What do you recall to be the highest market price in your area for #1CWRS wheat over the past 5 years?

- _____

What do you recall to be the lowest market price in your area for #1CWRS wheat over the past 5 years?

- _____

Please indicate how much you agree or disagree with the statements below on the following scale.

1=strongly disagree 2=disagree 3=neither agree or disagree

4=agree 5=strongly agree

I have a larger farm than most farmers in Manitoba.

Strongly Disagree

Strongly Agree

1

2

3

4

5

Compared to other farmers, I have above average skills at predicting price movements.

Strongly Disagree

Strongly Agree

1

2

3

4

5

I prefer less risk than most farmers.

Strongly Disagree

Strongly Agree

1

2

3

4

5

My primary marketing strategy is to reduce risk.

Strongly Disagree

Strongly Agree

1

2

3

4

5

My primary marketing strategy is to obtain a high price.

Strongly Disagree

Strongly Agree

1

2

3

4

5

I am willing to take higher financial risks in order to realize higher average returns.

Strongly Disagree

Strongly Agree

1

2

3

4

5

When selling my wheat, I prefer financial certainty to financial uncertainty

Strongly Disagree

Strongly Agree

1

2

3

4

5

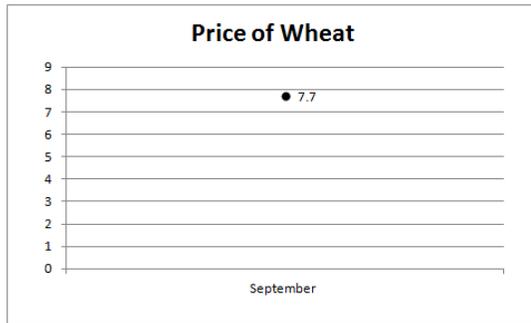
Presentation of the scenario:

It is September 1st 2012 and you would like to market the remainder of your wheat for this season. Over the next ten months, September to June, you will market your grain using strategies you would typically use on your own farm. On the 1st of every month, you will be presented with a new nearby futures price and will be asked a few short questions including how much of your wheat you would like to sell at the respective market price. In each month you can choose to sell no wheat, all of your wheat, or any quantity you like, you are not required to sell all of your wheat by the end of June. Once you have turned a page, please do not turn back to it. Once you have sold all of your wheat, please return the questionnaire to the experimenter.

If you have any questions, you are encouraged to ask them now.

September 1st

I expect to have _____ bushels of wheat to sell in the cash market this crop season.



The market price on September 1st is \$7.70 for a bushel of wheat. Please answer the following questions.

In the next period, what is the price of wheat which would make you feel satisfied if you were to sell the rest of your wheat? _____

In the next period, if the price of wheat increases, what is the price you would sell the remainder of your wheat at? _____

How do you expect the price of wheat will change over the next month? Please enter the probability of each scenario in the space provided.

I expect the price will increase _____%

I expect the price will remain about the same _____%

I expect the price will decrease _____%

Total = 100%

Do you want to hold or sell wheat now?

Hold all _____

Sell all _____

Sell some _____ How many bushels? _____

You have _____ bushels of wheat available to market in the next period.

The previous page of the questionnaire will be replicated nine times for November 1st to July 1st. Each page will represent a new time period with a new price addition to the price sequence with another choice to sell, and to state their reference prices and expectations.

APPENDIX 2: MEASURE OF RISK ATTITUDES

You are presented with the opportunity of participating in a gamble or receiving a fixed dollar amount for certain. For the gamble, a fair coin will be flipped. If the coin lands heads, you will receive \$100. If the coin lands tails, you will receive \$0. Please indicate for each dollar amount which you would prefer, either accepting the sure thing or accepting the gamble.

	Prefer	Prefer
Money (no gamble)	Sure Thing	Gamble
100		
80		
60		
40		
20		
0		

60-40	Prefer	Prefer
Money (no gamble)	Sure Thing	Gamble
60		
56		
52		
48		
44		
40		

40-20	Prefer	Prefer
Money (no gamble)	Sure Thing	Gamble
40		
36		
32		
28		
24		
20		

60-56	Prefer	Prefer	I Do
Money (no gamble)	Sure Thing	Gamble	Not Know
60			
59			
58			
57			
56			

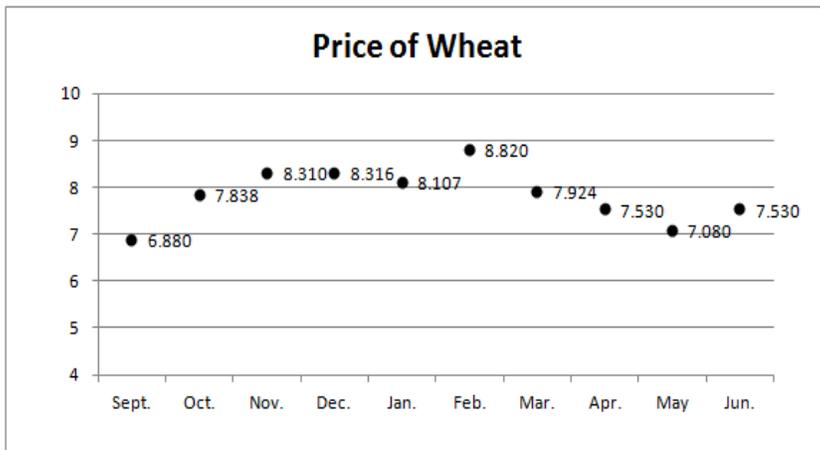
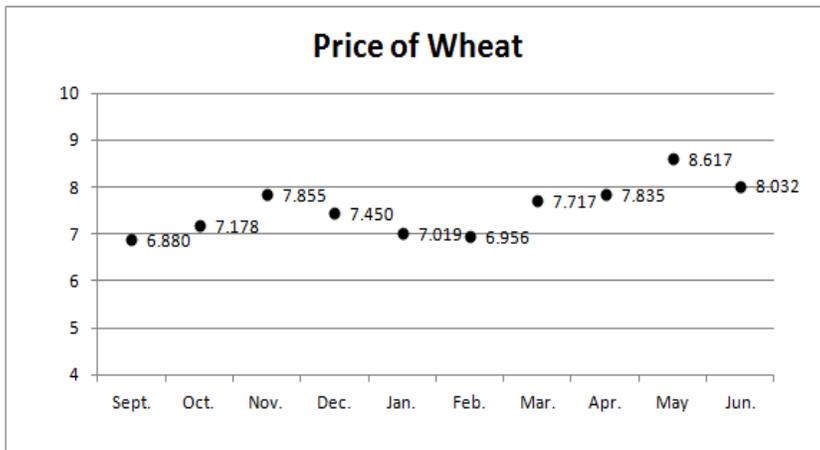
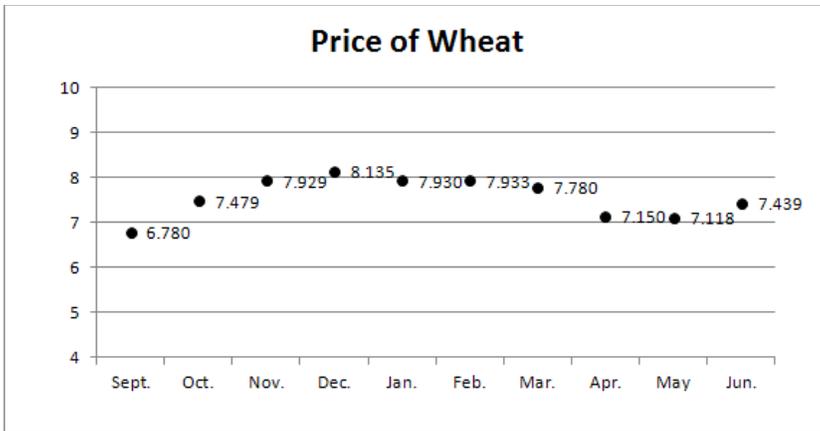
56-52	Prefer	Prefer	I Do
Money (no gamble)	Sure Thing	Gamble	Not Know
56			
55			
54			
53			
52			

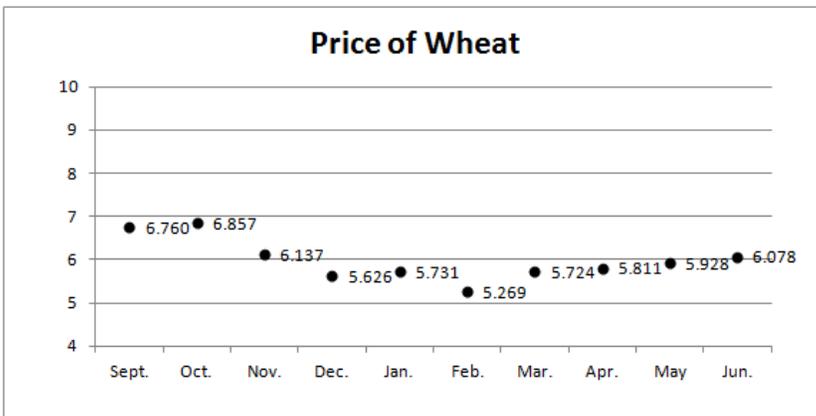
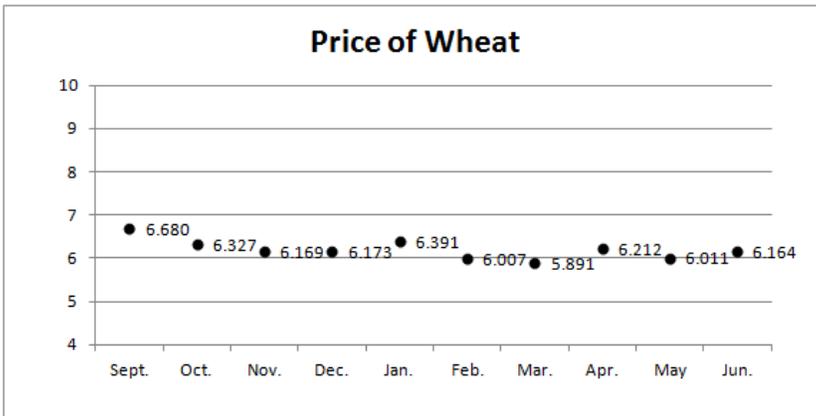
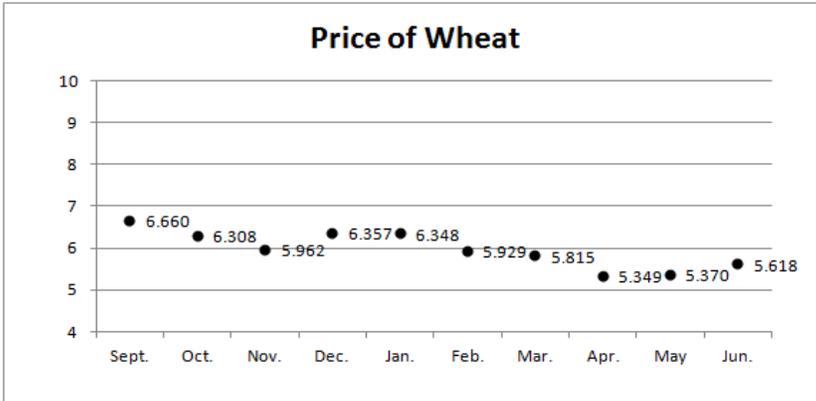
40-36	Prefer	Prefer	I Do
Money (no gamble)	Sure Thing	Gamble	Not Know
40			
39			
38			
37			
36			

36-32	Prefer	Prefer	I Do
Money (no gamble)	Sure Thing	Gamble	Not Know
36			
35			
34			
33			
32			

APPENDIX 3: PRICE SEQUENCES

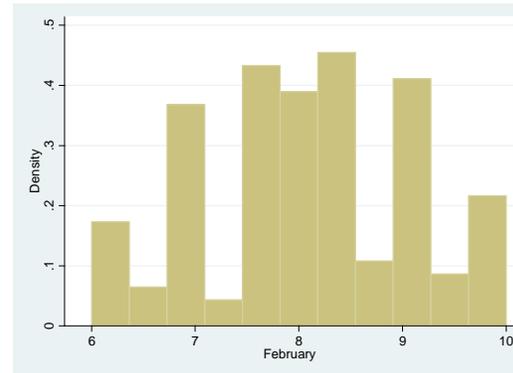
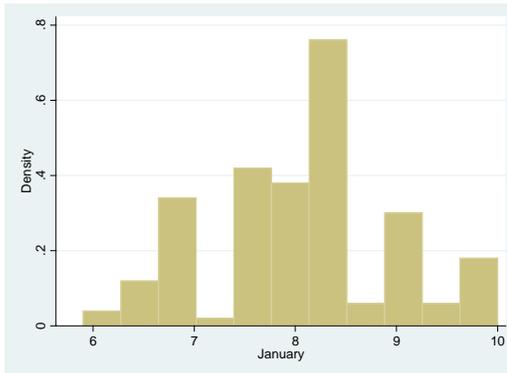
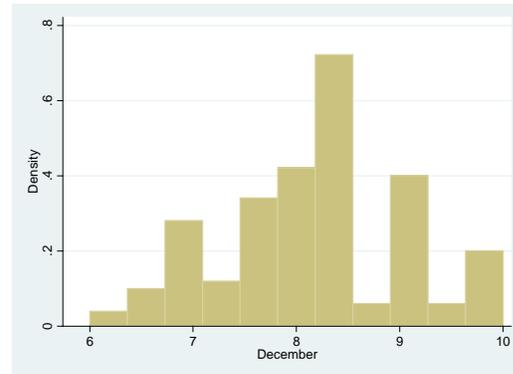
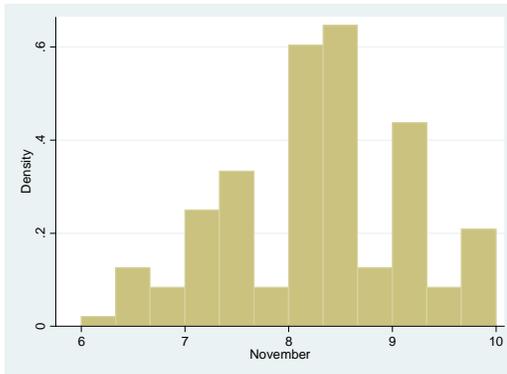
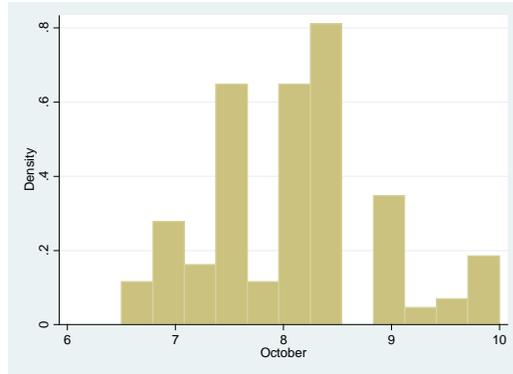
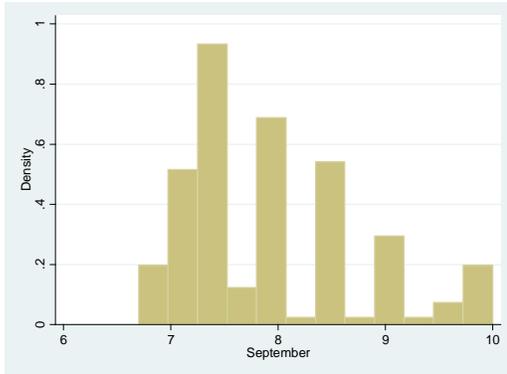
	Price Sequences					
	1	2	3	4	5	6
September	6.780	6.880	6.880	6.660	6.680	6.760
October	7.479	7.178	7.838	6.308	6.327	6.857
November	7.929	7.855	8.310	5.962	6.169	6.137
December	8.135	7.450	8.316	6.357	6.173	5.626
January	7.930	7.019	8.107	6.348	6.391	5.731
February	7.933	6.956	8.820	5.929	6.007	5.269
March	7.780	7.717	7.924	5.815	5.891	5.724
April	7.150	7.835	7.530	5.349	6.212	5.811
May	7.118	8.617	7.080	5.370	6.011	5.928
June	7.439	8.032	7.530	5.618	6.164	6.078

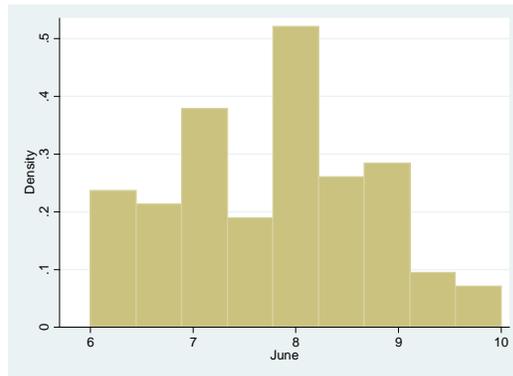
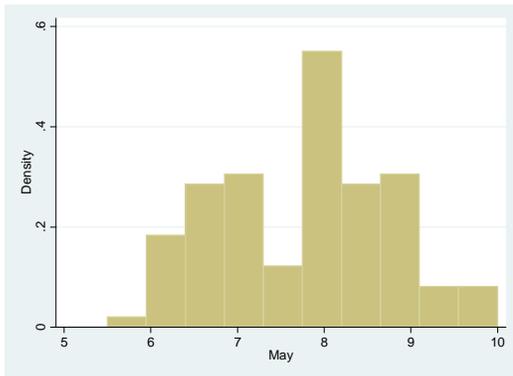
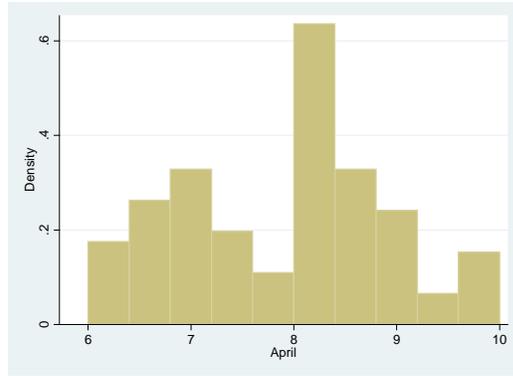
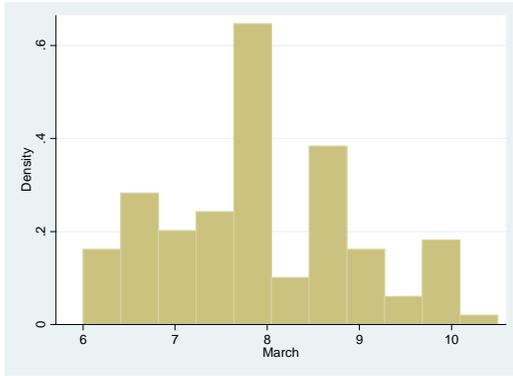




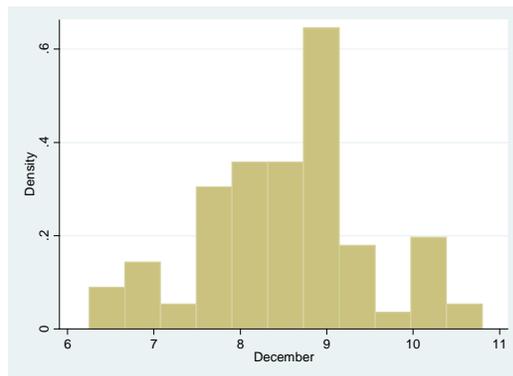
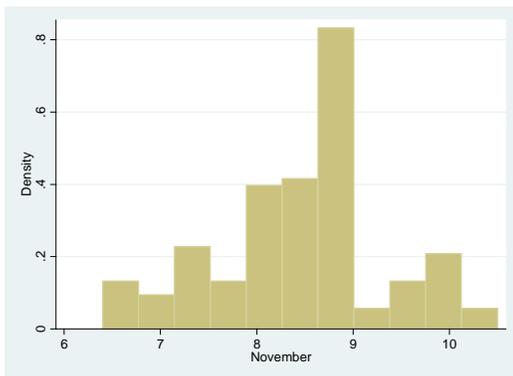
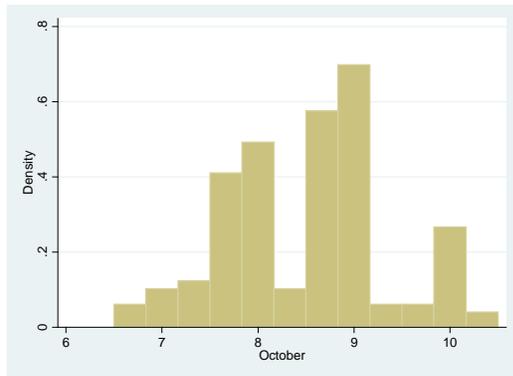
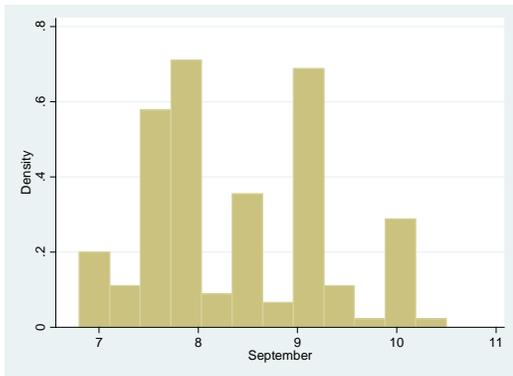
APPENDIX 4: HISTOGRAMS

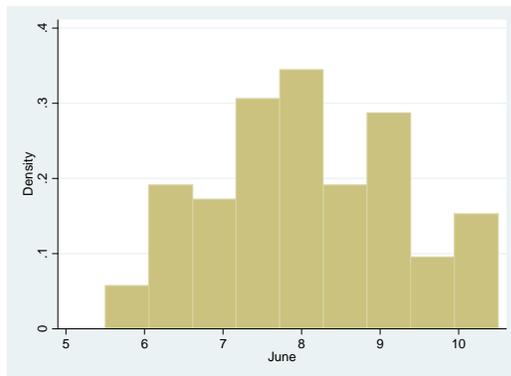
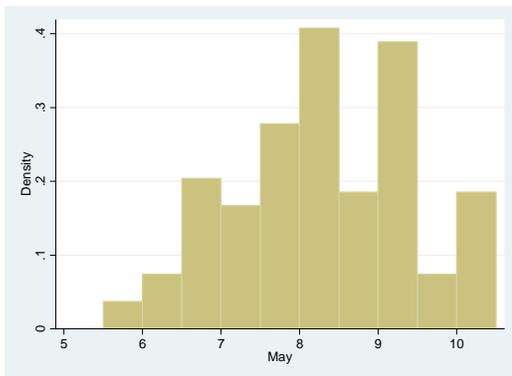
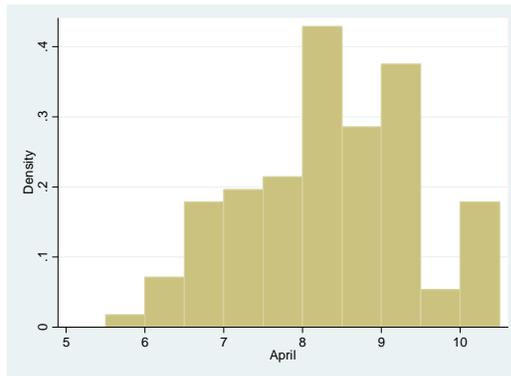
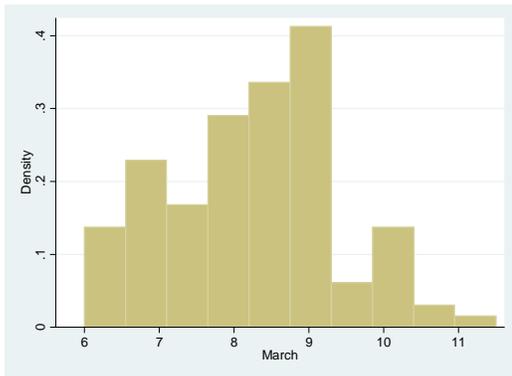
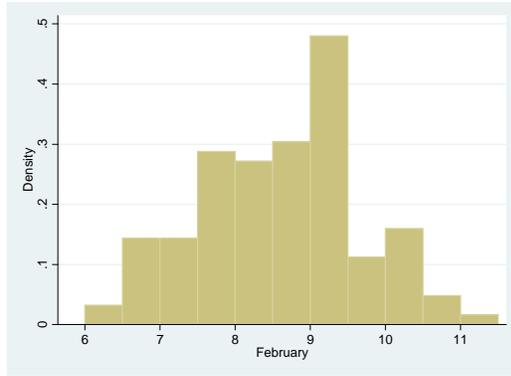
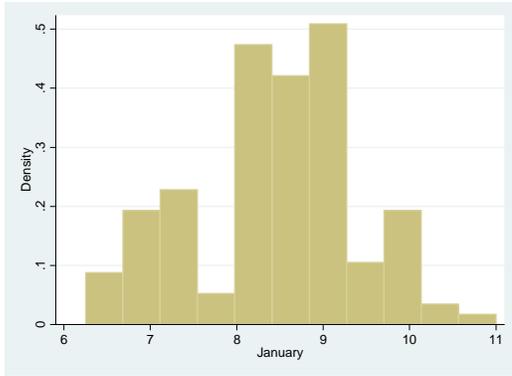
Satisfy Price



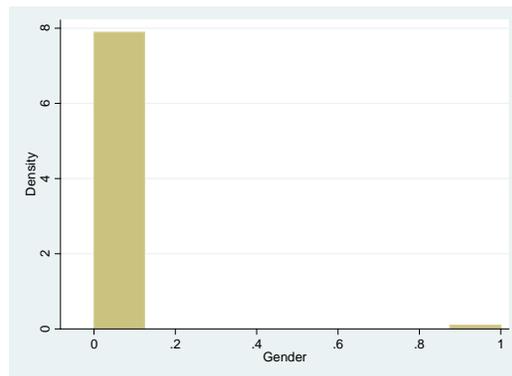
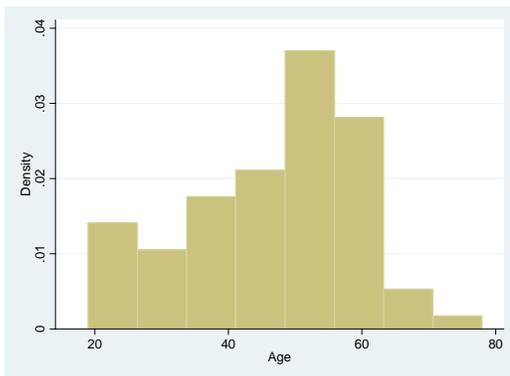


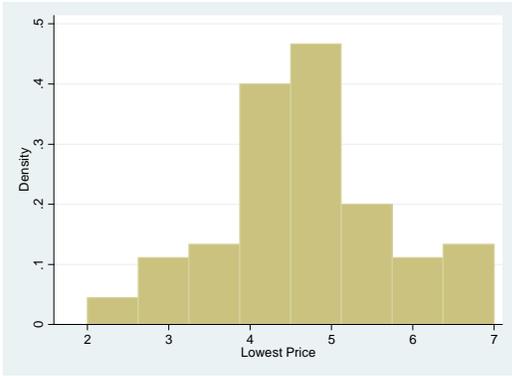
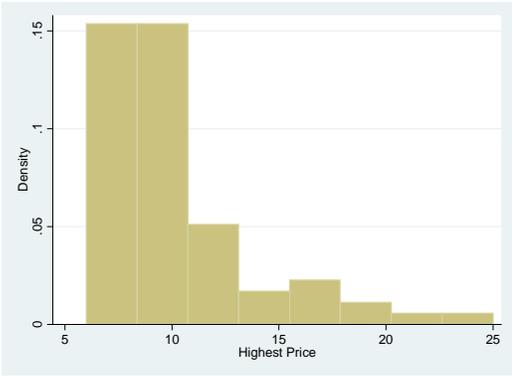
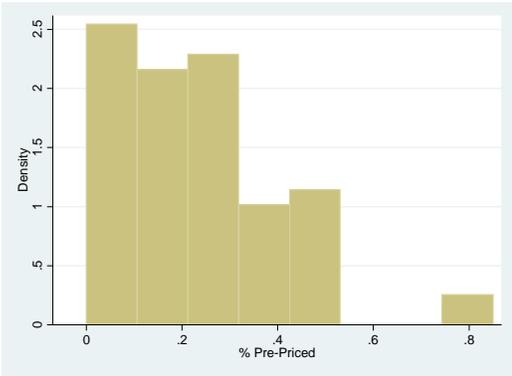
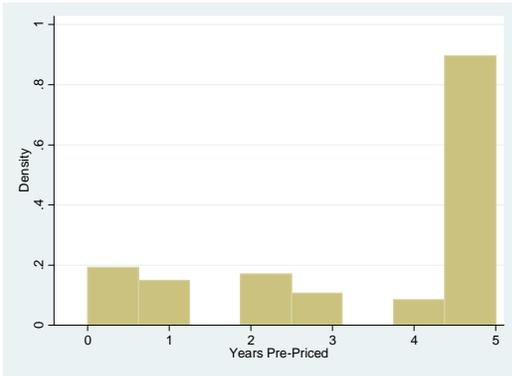
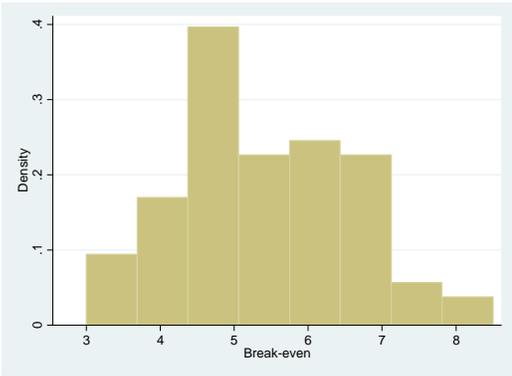
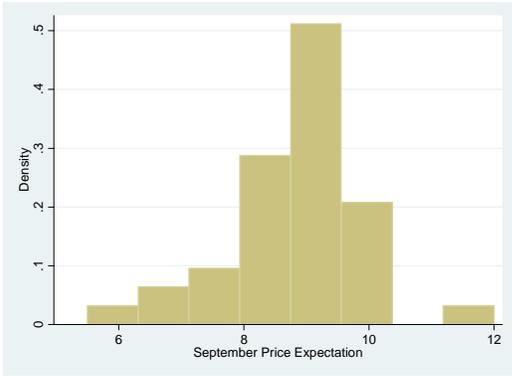
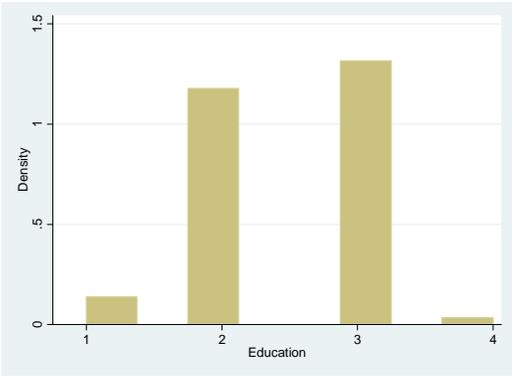
Goal Price

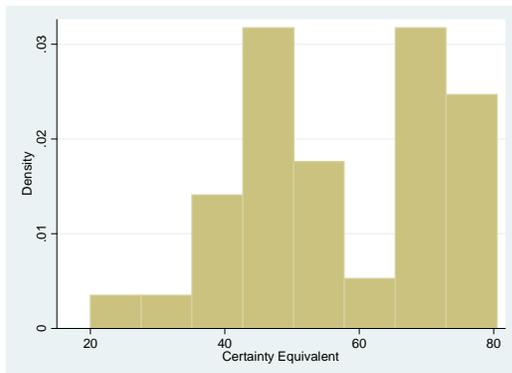
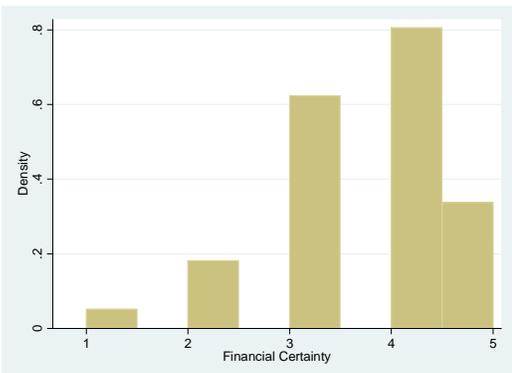
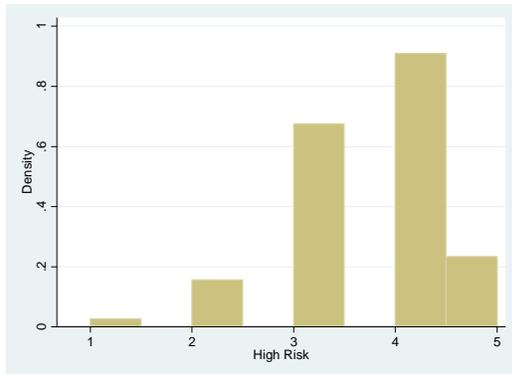
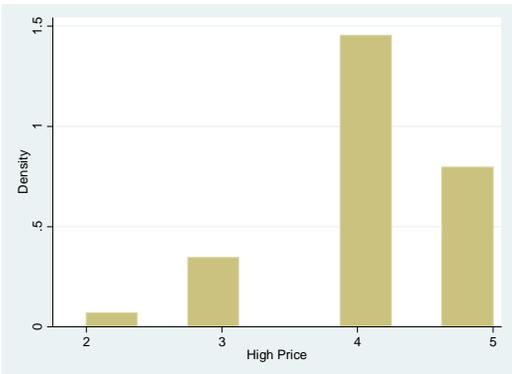
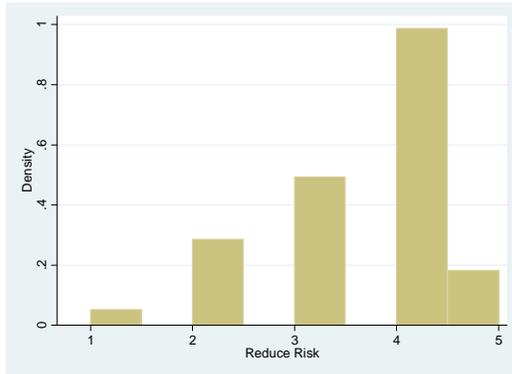
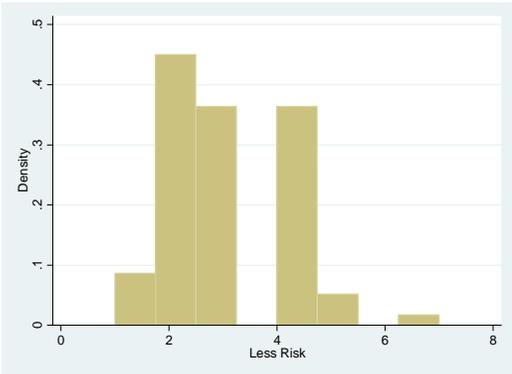
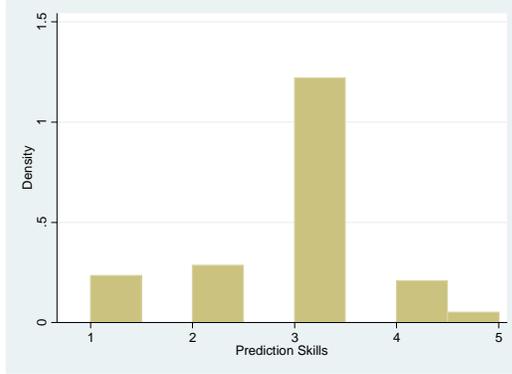
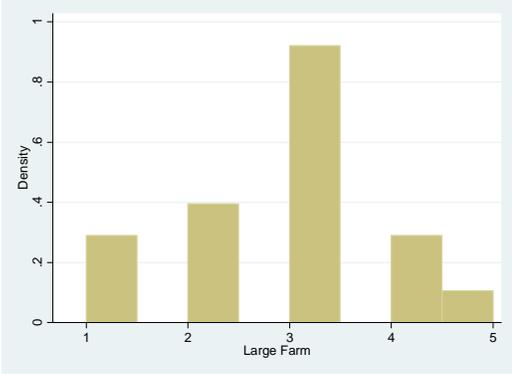




Survey Descriptors







APPENDIX 5: SUBSAMPLE MODELS

	September Price Expectations \geq \$9				September Price Expectations $<$ \$9			
	ln(Satisfy Price)		ln(Goal Price)		ln(Satisfy Price)		ln(Goal Price)	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
ln(first price- FP)	-0.911	0.952	-0.285	1.026	0.475	1.014	0.040	0.967
ln(current price- CP)	0.166**	0.075	0.212**	0.082	0.113	0.094	0.090	0.093
ln(highest price- HP)	0.246*	0.139	0.317**	0.149	0.082	0.154	0.104	0.189
ln(lowest price- LP)	-0.316**	0.119	-0.212*	0.118	-0.078	0.176	-0.213	0.153
ln(weighted price- WP)	0.243	0.159	0.109	0.166	0.525***	0.153	0.542***	0.172
expectations (E) (ϕ_s)	0.025*	0.013	0.029**	0.014	0.024***	0.008	0.017	0.013
increasing price sequence (IPS)	0.030	0.027	0.006	0.033	-0.010	0.025	0.001	0.027
sequence after an increasing sequence (AI)	0.018	0.012	0.017	0.014	0.003	0.011	0.001	0.012
sequence after a decreasing sequence (AD)	-0.053***	0.018	-0.047**	0.019	-0.003	0.021	-0.009	0.023
October	-0.018**	0.008	-0.020*	0.010	0.009	0.010	-0.005	0.013
November	-0.026*	0.014	-0.039**	0.016	0.003	0.018	-0.018	0.021
December	-0.03**	0.016	-0.041**	0.018	-0.008	0.020	-0.032	0.022
January	-0.037**	0.017	-0.047**	0.018	-0.013	0.021	-0.041*	0.022
February	-0.043**	0.020	-0.051**	0.020	-0.011	0.025	-0.037	0.026
March	-0.059**	0.022	-0.066***	0.022	-0.025	0.027	-0.053*	0.029
April	-0.071***	0.022	-0.078***	0.023	-0.022	0.029	-0.062*	0.031
May	-0.085***	0.027	-0.092***	0.028	-0.025	0.032	-0.061*	0.035
June	-0.092***	0.026	-0.102***	0.027	-0.038	0.031	-0.083**	0.035
constant	3.176*	1.835	1.873	2.039	-0.104	1.806	1.014	1.768
r-sq within	0.379		0.369		0.677		0.573	
between	0.167		0.122		0.466		0.514	
overall	0.219		0.193		0.578		0.536	
number of observations	748		748		529		539	
number of producers	43		43		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Break-Even Price \geq \$5.50				Break-Even Price $<$ \$5.50			
	ln(Satisfy Price)		ln(Goal Price)		ln(Satisfy Price)		ln(Goal Price)	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
ln(first price- FP)	-1.235	1.024	-0.647	0.868	-0.228	0.836	-0.141	0.966
ln(current price- CP)	-0.018	0.070	0.057	0.078	0.339***	0.090	0.305***	0.094
ln(highest price- HP)	0.434***	0.148	0.464***	0.153	-0.016	0.163	-0.020	0.187
ln(lowest price- LP)	-0.427***	0.146	-0.372***	0.125	0.138	0.148	0.048	0.169
ln(weighted price- WP)	0.486***	0.153	0.317*	0.170	0.089	0.157	0.178	0.172
expectations (E) (ϕ_s)	0.021*	0.012	0.017	0.013	0.026***	0.009	0.022	0.015
increasing price sequence (IPS)	0.045*	0.023	0.021	0.022	-0.015	0.030	-0.008	0.036
sequence after an increasing sequence (AI)	0.030**	0.012	0.015	0.011	-0.016	0.010	0.001	0.014
sequence after a decreasing sequence (AD)	-0.064**	0.024	-0.052**	0.023	-0.011	0.014	-0.012	0.019
October	-0.028***	0.010	-0.034***	0.011	0.017*	0.009	0.010	0.012
November	-0.047***	0.017	-0.059***	0.018	0.025	0.017	0.006	0.020
December	-0.062***	0.018	-0.072***	0.019	0.024	0.020	0.006	0.021
January	-0.068***	0.017	-0.077***	0.019	0.023	0.020	-0.001	0.022
February	-0.077***	0.021	-0.086***	0.022	0.027	0.024	0.007	0.025
March	-0.094***	0.024	-0.106***	0.025	0.013	0.025	-0.003	0.026
April	-0.103***	0.025	-0.120***	0.026	0.011	0.027	-0.010	0.028
May	-0.120***	0.028	-0.133***	0.029	0.008	0.031	-0.015	0.034
June	-0.127***	0.027	-0.149***	0.029	-0.001	0.031	-0.025	0.033
constant	3.521*	1.887	2.488	1.646	1.436	1.561	1.387	1.894
r-sq within	0.501		0.475		0.511		0.445	
between	0.189		0.068		0.385		0.399	
overall	0.308		0.224		0.361		0.371	
number of observations	688		698		589		589	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Years Hedged = 5				Years Hedged < 5			
	ln(Satisfy Price)		ln(Goal Price)		ln(Satisfy Price)		ln(Goal Price)	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
ln(first price- FP)	0.147	1.084	0.572	0.970	-0.947	0.983	-0.328	1.133
ln(current price- CP)	0.189**	0.085	0.175**	0.085	0.078	0.087	0.166	0.095
ln(highest price- HP)	0.250*	0.148	0.233	0.167	0.172	0.176	0.245	0.181
ln(lowest price- LP)	0.066	0.146	0.074	0.126	-0.545	0.141	-0.613***	0.141
ln(weighted price- WP)	0.116	0.121	0.082	0.113	0.611***	0.183	0.528**	0.210
expectations (E)	0.017	0.011	0.010	0.013	0.027**	0.011	0.027*	0.015
increasing price sequence (IPS)	-0.022	0.026	-0.022	0.028	0.046*	0.026	0.016	0.034
sequence after an increasing sequence (AI)	0.007	0.011	0.011	0.013	0.003	0.012	0.002	0.015
sequence after a decreasing sequence (AD)	-0.040*	0.022	-0.055***	0.020	-0.037	0.025	-0.009	0.024
October	0.002	0.010	0.000	0.011	-0.022*	0.011	-0.034**	0.012
November	0.000	0.019	-0.007	0.019	-0.035**	0.017	-0.063***	0.018
December	-0.008	0.020	-0.015	0.020	-0.043**	0.020	-0.068***	0.021
January	-0.016	0.020	-0.024	0.020	-0.043*	0.021	-0.072***	0.021
February	-0.011	0.024	-0.024	0.024	-0.055**	0.026	-0.073***	0.024
March	-0.028	0.026	-0.038	0.026	-0.069**	0.027	-0.090***	0.026
April	-0.035	0.028	-0.045	0.028	-0.074**	0.027	-0.105***	0.028
May	-0.042	0.031	-0.055*	0.032	-0.089***	0.031	-0.113***	0.030
June	-0.052	0.031	-0.067**	0.033	-0.095***	0.030	-0.132***	0.030
constant	0.613	2.033	-0.031	1.866	3.257*	1.820	2.117	2.187
r-sq within	0.482		0.458		0.493		0.474	
between	0.285		0.247		0.232		0.207	
overall	0.342		0.309		0.304		0.290	
number of observations	728		728		528		538	
number of producers	41		41		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(φs) coefficients are statistically distinguishable for satisfy subsamples

(φg) coefficients are statistically distinguishable for goal subsamples

	Certainty Equivalent ≥ 50				Certainty Equivalent < 50			
	ln(Satisfy Price)		ln(Goal Price)		ln(Satisfy Price)		ln(Goal Price)	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
ln(first price- FP)	-0.537	0.801	-0.093	0.912	-0.366	1.243	-0.368	0.980
ln(current price- CP) (ϕ_g)	0.109	0.074	0.150*	0.079	0.183	0.108	0.194*	0.111
ln(highest price- HP)	0.256*	0.142	0.298*	0.160	0.096	0.195	0.068	0.205
ln(lowest price- LP)	-0.482***	0.131	-0.365***	0.136	0.216	0.205	0.056	0.175
ln(weighted price- WP)	0.518***	0.152	0.389**	0.171	0.092	0.161	0.107	0.163
expectations (E) (ϕ_s)	0.018**	0.009	0.009	0.013	0.032***	0.012	0.035***	0.009
increasing price sequence (IPS)	0.034	0.022	0.016	0.026	-0.007	0.029	0.000	0.026
sequence after an increasing sequence (AI)	0.011	0.011	0.017	0.012	0.005	0.012	-0.004	0.012
sequence after a decreasing sequence (AD) (ϕ_g)	-0.052**	0.022	-0.042*	0.022	-0.037	0.025	-0.051**	0.022
October	-0.017*	0.009	-0.021*	0.011	0.009	0.013	0.000	0.011
November	-0.034**	0.016	-0.046**	0.018	0.019	0.023	0.001	0.021
December	-0.047***	0.017	-0.052***	0.019	0.018	0.026	-0.004	0.023
January	-0.049***	0.017	-0.057***	0.019	0.012	0.026	-0.011	0.023
February	-0.060***	0.021	-0.067***	0.022	0.021	0.031	-0.001	0.028
March	-0.074***	0.023	-0.082***	0.025	0.002	0.033	-0.018	0.030
April	-0.088***	0.023	-0.096***	0.026	0.005	0.036	-0.024	0.032
May	-0.102***	0.025	-0.107***	0.029	0.002	0.042	-0.029	0.038
June	-0.111***	0.025	-0.123***	0.030	-0.007	0.042	-0.042	0.038
constant	2.315	1.545	1.394	1.792	1.659	2.248	2.021	1.832
r-sq within	0.533		0.489		0.418		0.401	
between	0.344		0.228		0.138		0.172	
overall	0.410		0.317		0.222		0.256	
number of observations	772		782		505		505	
number of producers	46		46		29		29	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Age ≥ 50				Age < 50			
	ln(Satisfy Price)		ln(Goal Price)		ln(Satisfy Price)		ln(Goal Price)	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
ln(first price- FP) (ϕ_s)	-2.170**	0.890	-1.665**	0.784	1.756*	0.940	1.684	1.072
ln(current price- CP)	0.135	0.087	0.167*	0.087	0.132	0.091	0.151	0.090
ln(highest price- HP)	0.166	0.159	0.088	0.169	0.216	0.156	0.343**	0.165
ln(lowest price- LP)	-0.336**	0.153	-0.396**	0.155	-0.050	0.148	-0.058	0.149
ln(weighted price- WP)	0.457***	0.154	0.449**	0.169	0.249	0.158	0.164	0.181
expectations (E)	0.037***	0.009	0.030**	0.012	0.014	0.009	0.014	0.013
increasing price sequence (IPS) (ϕ_g)	0.039*	0.021	0.046*	0.024	-0.031	0.020	-0.047*	0.025
sequence after an increasing sequence (AI)	-0.016	0.012	-0.010	0.013	0.032**	0.014	0.029*	0.014
sequence after a decreasing sequence (AD) (ϕ_g)	-0.022	0.016	-0.034*	0.018	-0.059**	0.022	-0.041*	0.022
October	-0.005	0.011	-0.013	0.012	-0.007	0.010	-0.014	0.012
November	-0.020	0.019	-0.035**	0.019	-0.005	0.018	-0.024	0.021
December	-0.024	0.021	-0.039*	0.021	-0.019	0.020	-0.035	0.021
January	-0.026	0.021	-0.046**	0.021	-0.027	0.019	-0.043**	0.020
February	-0.027	0.025	-0.042*	0.025	-0.030	0.023	-0.047*	0.024
March	-0.042	0.027	-0.065**	0.028	-0.045*	0.025	-0.055**	0.026
April	-0.052*	0.028	-0.079***	0.029	-0.048*	0.028	-0.063**	0.029
May	-0.067**	0.032	-0.093***	0.033	-0.053*	0.031	-0.067**	0.032
June	-0.080**	0.031	-0.103***	0.033	-0.055*	0.031	-0.084**	0.033
constant	5.398***	1.650	4.717***	1.529	-2.326	1.764	-2.238	2.034
r-sq within	0.506		0.467		0.505		0.472	
between	0.258		0.267		0.188		0.151	
overall	0.330		0.339		0.277		0.240	
number of observations	673		673		604		614	
number of producers	39		39		38		38	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Education ≥ Post Secondary				Education < Post Secondary			
	ln(Satisfy Price)		ln(Goal Price)		ln(Satisfy Price)		ln(Goal Price)	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
ln(first price- FP)	-1.629	0.982	-1.155	0.909	0.698	1.022	0.303	1.118
ln(current price- CP)	0.181**	0.072	0.220***	0.075	0.095	0.099	0.112	0.100
ln(highest price- HP)	0.360**	0.146	0.355**	0.160	0.090	0.175	0.160	0.192
ln(lowest price- LP)	-0.208	0.181	-0.195	0.134	-0.207	0.148	-0.252	0.168
ln(weighted price- WP)	0.215	0.166	0.117	0.166	0.456***	0.150	0.426**	0.167
expectations (E) (ϕ_g)	0.029***	0.009	0.022**	0.011	0.018	0.011	0.025*	0.015
increasing price sequence (IPS)	0.017	0.022	-0.002	0.023	0.001	0.035	0.023	0.041
sequence after an increasing sequence (AI)	0.003	0.011	-0.004	0.012	0.012	0.015	0.016	0.015
sequence after a decreasing sequence (AD)	-0.036	0.025	-0.024	0.017	-0.043*	0.021	-0.052**	0.023
October	-0.014	0.010	-0.020*	0.011	-0.002	0.011	-0.011	0.013
November	-0.026*	0.016	-0.038**	0.015	-0.005	0.021	-0.027	0.024
December	-0.030*	0.017	-0.039**	0.016	-0.018	0.024	-0.042	0.027
January	-0.032*	0.018	-0.042**	0.017	-0.024	0.024	-0.051*	0.026
February	-0.038*	0.022	-0.041**	0.020	-0.025	0.028	-0.055*	0.030
March	-0.056**	0.024	-0.063***	0.022	-0.039	0.029	-0.065*	0.033
April	-0.064**	0.025	-0.076***	0.022	-0.044	0.032	-0.075**	0.035
May	-0.080***	0.029	-0.092***	0.027	-0.047	0.035	-0.079*	0.039
June	-0.085***	0.029	-0.102***	0.027	-0.060*	0.034	-0.096**	0.040
constant	4.113**	1.797	3.387*	1.702	-0.077	1.969	0.681	2.208
r-sq within	0.482		0.412		0.479		0.497	
between	0.396		0.190		0.191		0.247	
overall	0.427		0.271		0.250		0.317	
number of observations	655		665		622		622	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	September Price Expectations \geq \$9				September Price Expectations $<$ \$9			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
positive incremental price change (ϕ_s) (ϕ_g)	0.377***	0.061	0.357***	0.060	0.505***	0.074	0.514***	0.090
negative incremental price change (ϕ_s) (ϕ_g)	-0.163**	0.063	-0.194***	0.067	-0.339***	0.058	-0.288***	0.088
expectations (E) (ϕ_g)	0.088	0.055	0.083*	0.047	0.089*	0.045	0.113**	0.054
increasing price sequence (IPS)	0.042	0.032	0.039	0.036	0.111**	0.042	0.094*	0.052
sequence after an increasing sequence (AI)	0.005	0.024	-0.008	0.030	0.030	0.035	0.049	0.042
sequence after a decreasing sequence (AD)	0.007	0.038	-0.008	0.035	-0.032	0.046	-0.004	0.050
constant	-0.109***	0.028	-0.097***	0.027	-0.129***	0.042	-0.170***	0.049
R-sq within	0.165		0.147		0.361		0.242	
between	0.197		0.218		0.001		0.001	
overall	0.162		0.146		0.308		0.206	
number of observations	748		758		529		539	
number of producers	43		43		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Break-Even Price \geq \$5.50				Break-Even Price $<$ \$5.50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
positive incremental price change (ϕ_s) (ϕ_g)	0.314***	0.057	0.297***	0.059	0.562***	0.067	0.569***	0.083
negative incremental price change (ϕ_s) (ϕ_g)	-0.209***	0.062	-0.195**	0.072	-0.293***	0.068	-0.293***	0.083
expectations (E)	0.064	0.052	0.075	0.050	0.100**	0.045	0.113*	0.057
increasing price sequence (IPS)	0.034	0.041	0.060	0.039	0.104***	0.032	0.063	0.045
sequence after an increasing sequence (AI)	-0.005	0.028	0.013	0.024	0.021	0.032	0.015	0.044
sequence after a decreasing sequence (AD)	0.027	0.050	0.009	0.045	-0.044	0.030	-0.031	0.034
constant	-0.082**	0.033	-0.119***	0.031	-0.129***	0.033	-0.125***	0.038
R-sq within	0.158		0.119		0.347		0.276	
between	0.058		0.040		0.201		0.141	
overall	0.153		0.111		0.310		0.254	
number of observations	688		698		589		599	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Years Hedged = 5				Years Hedged < 5			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
positive incremental price change (ϕ_s) (ϕ_g)	0.451***	0.058	0.444***	0.068	0.399***	0.081	0.390***	0.085
negative incremental price change (ϕ_s) (ϕ_g)	-0.241***	0.058	-0.210***	0.054	-0.268***	0.075	-0.296***	0.107
expectations (E)	0.062	0.042	0.019	0.043	0.120**	0.056	0.191***	0.052
increasing price sequence (IPS)	0.041	0.033	0.027	0.042	0.114***	0.041	0.118***	0.034
sequence after an increasing sequence (AI)	0.000	0.029	-0.002	0.037	0.022	0.030	0.026	0.029
sequence after a decreasing sequence (AD)	0.015	0.041	0.018	0.042	-0.037	0.043	-0.046	0.028
constant	-0.088***	0.027	-0.085***	0.029	-0.143***	0.042	-0.180***	0.043
R-sq within	0.258		0.193		0.237		0.205	
between	0.227		0.263		0.037		0.026	
overall	0.252		0.195		0.198		0.159	
number of observations	728		728		528		548	
number of producers	41		41		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Certainty Equivalent ≥ 50				Certainty Equivalent < 50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
positive incremental price change (ϕ_s) (ϕ_g)	0.464***	0.061	0.462***	0.072	0.374***	0.074	0.362***	0.070
negative incremental price change (ϕ_s) (ϕ_g)	-0.225***	0.059	-0.274***	0.064	-0.277***	0.075	-0.184*	0.100
expectations (E) (ϕ_s)	0.081*	0.045	0.068	0.047	0.089*	0.049	0.140**	0.052
increasing price sequence (IPS)	0.099**	0.039	0.092**	0.041	0.035	0.032	0.041	0.041
sequence after an increasing sequence (AI)	0.012	0.028	0.006	0.031	0.009	0.030	0.028	0.042
sequence after a decreasing sequence (AD)	-0.030	0.041	-0.039	0.035	0.004	0.048	0.016	0.046
constant	-0.130***	0.031	-0.124***	0.031	-0.074**	0.033	-0.125***	0.042
R-sq within	0.246		0.208		0.238		0.162	
between	0.121		0.098		0.086		0.108	
overall	0.220		0.190		0.231		0.152	
number of observations	772		782		505		515	
number of producers	46		46		29		29	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Age ≥ 50				Age < 50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
positive incremental price change (ϕ_s) (ϕ_g)	0.456***	0.073	0.405***	0.076	0.404***	0.058	0.440***	0.070
negative incremental price change (ϕ_s) (ϕ_g)	-0.225***	0.061	-0.218***	0.080	-0.267***	0.068	-0.261***	0.070
expectations (E)	0.138***	0.050	0.139**	0.058	0.022	0.042	0.048	0.045
increasing price sequence (IPS)	0.105***	0.030	0.078*	0.043	0.018	0.041	0.048	0.039
sequence after an increasing sequence (AI)	0.042	0.027	0.046	0.043	-0.026	0.029	-0.017	0.025
sequence after a decreasing sequence (AD)	-0.038	0.026	-0.012	0.032	0.040	0.053	-0.005	0.049
constant	-0.166***	0.035	-0.172***	0.045	-0.054*	0.029	-0.082***	0.021
R-sq within	0.228		0.156		0.271		0.240	
between	0.010		0.046		0.156		0.161	
overall	0.172		0.130		0.267		0.236	
number of observations	673		683		604		614	
number of producers	39		39		38		38	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Education ≥ Post Secondary				Education < Post Secondary			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
positive incremental price change (ϕ_s) (ϕ_g)	0.445***	0.073	0.428***	0.074	0.418***	0.058	0.422***	0.072
negative incremental price change (ϕ_s) (ϕ_g)	-0.280***	0.067	-0.225**	0.087	-0.215***	0.063	-0.245***	0.068
expectations (E)	0.086**	0.042	0.128***	0.036	0.087	0.056	0.059	0.072
increasing price sequence (IPS)	0.025	0.032	0.070*	0.041	0.102**	0.040	0.037	0.044
sequence after an increasing sequence (AI)	-0.027	0.030	-0.003	0.040	0.051**	0.023	0.043	0.030
sequence after a decreasing sequence (AD)	0.017	0.044	-0.031	0.038	-0.029	0.044	0.015	0.044
constant	-0.067*	0.034	-0.120***	0.038	-0.140***	0.030	-0.118***	0.039
R-sq within	0.259		0.181		0.226		0.200	
between	0.154		0.028		0.050		0.143	
overall	0.253		0.161		0.184		0.194	
number of observations	655		665		622		632	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	September Price Expectations \geq \$9				September Price Expectations $<$ \$9			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
month (increasing price sequence) (ϕ_g)	-0.030**	0.013	-0.037**	0.016	0.003	0.011	-0.034**	0.017
month (decreasing price sequence) (ϕ_s) (ϕ_g)	-0.063***	0.014	-0.064***	0.015	-0.058***	0.017	-0.084***	0.023
positive total price change ($\Delta P(p)$) (ϕ_s) (ϕ_g)	0.401***	0.063	0.398***	0.079	0.565***	0.061	0.588***	0.083
negative total price change ($\Delta P(n)$)	-0.131	0.120	-0.156	0.119	-0.393***	0.129	-0.229	0.167
expectations (E)	0.101	0.112	0.085	0.108	0.203***	0.074	0.114	0.109
sequence after an increasing sequence (AI)	0.027	0.083	-0.076	0.131	-0.014	0.121	0.084	0.178
sequence after a decreasing sequence (AD)	0.019	0.147	-0.021	0.152	0.001	0.135	0.321*	0.163
constant	0.029	0.075	0.061	0.085	0.014	0.064	-0.078	0.101
R-sq within	0.381		0.362		0.638		0.511	
between	0.383		0.304		0.393		0.209	
overall	0.363		0.319		0.544		0.439	
number of observations	748		748		529		539	
number of producers	43		43		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Break-Even Price \geq \$5.50				Break-Even Price $<$ \$5.50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
month (increasing price sequence)	-0.029**	0.011	-0.048***	0.013	-0.001	0.014	-0.024	0.020
month (decreasing price sequence) (ϕ_s) (ϕ_g)	-0.066***	0.015	-0.091***	0.018	-0.051***	0.016	-0.052***	0.017
positive total price change ($\Delta P(p)$) (ϕ_s) (ϕ_g)	0.404***	0.060	0.442***	0.074	0.556***	0.074	0.544***	0.101
negative total price change ($\Delta P(n)$)	-0.130	0.130	-0.027	0.136	-0.378***	0.138	-0.344**	0.151
expectations (E)	0.121	0.103	0.053	0.099	0.144**	0.068	0.093	0.125
sequence after an increasing sequence (AI)	-0.043	0.079	-0.047	0.087	-0.002	0.128	0.015	0.208
sequence after a decreasing sequence (AD)	0.059	0.203	0.202	0.199	-0.050	0.103	0.003	0.128
constant	0.055	0.070	0.013	0.094	0.038	0.074	0.037	0.092
R-sq within	0.429		0.437		0.564		0.408	
between	0.314		0.146		0.447		0.400	
overall	0.396		0.333		0.490		0.395	
number of observations	688		698		589		589	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Years Hedged = 5				Years Hedged < 5			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
month (increasing price sequence)	-0.026**	0.010	-0.043***	0.016	-0.008	0.015	-0.027	0.017
month (decreasing price sequence) (ϕ_s) (ϕ_g)	-0.055***	0.016	-0.067***	0.018	-0.064***	0.016	-0.082***	0.020
positive total price change ($\Delta P(p)$) (ϕ_s) (ϕ_g)	0.451***	0.065	0.391***	0.079	0.495***	0.068	0.606***	0.083
negative total price change ($\Delta P(n)$) (ϕ_s)	-0.258*	0.129	-0.226*	0.132	-0.291*	0.169	-0.168	0.181
expectations (E)	0.039	0.078	-0.161	0.097	0.233**	0.100	0.300**	0.119
sequence after an increasing sequence (AI)	-0.047	0.107	-0.089	0.165	0.039	0.091	0.071	0.107
sequence after a decreasing sequence (AD)	0.098	0.159	0.087	0.170	-0.128	0.141	0.081	0.148
constant	0.097	0.061	0.201**	0.079	-0.029	0.087	-0.202*	0.114
R-sq within	0.474		0.385		0.502		0.515	
between	0.480		0.312		0.312		0.192	
overall	0.463		0.363		0.416		0.379	
number of observations	728		728		528		538	
number of producers	41		41		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Certainty Equivalent ≥ 50				Certainty Equivalent < 50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
month (increasing price sequence) (ϕ_g)	-0.021*	0.012	-0.033**	0.016	-0.011	0.012	-0.034**	0.013
month (decreasing price sequence) (ϕ_g)	-0.078***	0.012	-0.089***	0.014	-0.028	0.021	-0.051**	0.024
positive total price change ($\Delta P(p)$) (ϕ_s) (ϕ_g)	0.537***	0.063	0.563***	0.077	0.373***	0.064	0.374***	0.080
negative total price change ($\Delta P(n)$)	-0.171	0.116	-0.169	0.125	-0.376**	0.157	-0.169	0.167
expectations (E)	0.118	0.077	-0.042	0.109	0.201**	0.096	0.242***	0.085
sequence after an increasing sequence (AI)	0.023	0.108	-0.050	0.158	-0.077	0.077	-0.005	0.124
sequence after a decreasing sequence (AD)	-0.060	0.127	0.015	0.129	0.041	0.212	0.099	0.216
constant	0.046	0.073	0.074	0.102	0.051	0.060	-0.013	0.053
R-sq within	0.529		0.488		0.409		0.309	
between	0.360		0.246		0.374		0.312	
overall	0.456		0.398		0.405		0.319	
number of observations	772		782.000		505		505	
number of producers	46		46.000		29		29	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Age \geq 50				Age < 50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
month (increasing price sequence) (ϕ_g)	-0.012	0.011	-0.046**	0.019	-0.026*	0.014	-0.030**	0.012
month (decreasing price sequence) (ϕ_s) (ϕ_g)	-0.066***	0.014	-0.087***	0.018	-0.049***	0.017	-0.053***	0.018
positive total price change ($\Delta P(p)$) (ϕ_s) (ϕ_g)	0.563***	0.067	0.564***	0.089	0.375***	0.063	0.434***	0.076
negative total price change ($\Delta P(n)$) (ϕ_s)	-0.224*	0.125	-0.150	0.138	-0.294*	0.153	-0.267*	0.151
expectations (E)	0.228***	0.079	0.105	0.111	0.042	0.093	0.030	0.103
sequence after an increasing sequence (AI)	0.099	0.089	0.212	0.155	-0.127	0.105	-0.236*	0.128
sequence after a decreasing sequence (AD)	-0.102	0.111	0.026	0.129	0.120	0.192	0.155	0.201
constant	-0.039	0.066	-0.053	0.109	0.114	0.083	0.086	0.075
R-sq within	0.533		0.413		0.438		0.462	
between	0.253		0.234		0.395		0.284	
overall	0.408		0.343		0.430		0.412	
number of observations	673		673		604		614	
number of producers	39		39		38		38	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%
(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples
(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Education \geq Post Secondary				Education < Post Secondary			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
month (increasing price sequence) (ϕ_g)	-0.028**	0.013	-0.044***	0.016	-0.009	0.011	-0.036**	0.016
month (decreasing price sequence) (ϕ_s) (ϕ_g)	-0.046***	0.016	-0.064***	0.020	-0.073***	0.014	-0.081***	0.016
positive total price change ($\Delta P(p)$) (ϕ_s) (ϕ_g)	0.473***	0.070	0.474***	0.085	0.472***	0.060	0.509***	0.087
negative total price change ($\Delta P(n)$)	-0.251	0.162	-0.181	0.142	-0.248**	0.114	-0.197	0.146
expectations (E)	0.120	0.085	0.066	0.075	0.214**	0.086	0.129	0.158
sequence after an increasing sequence (AI)	-0.093	0.090	-0.142	0.134	0.060	0.106	0.156	0.170
sequence after a decreasing sequence (AD)	0.115	0.174	0.088	0.175	-0.100	0.151	0.074	0.168
constant	0.073	0.078	0.091	0.088	0.019	0.067	-0.043	0.108
R-sq within	0.445		0.403		0.531		0.445	
between	0.370		0.139		0.361		0.459	
overall	0.417		0.309		0.443		0.436	
number of observations	655		665		622		622	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%
(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples
(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	September Price Expectations \geq \$9				September Price Expectations $<$ \$9			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
expectations (E)	-0.034	0.031	-0.029	0.035	-0.043	0.041	-0.045	0.046
current price (CP) - reference price (RP) (ϕ_s) (ϕ_g)	0.042**	0.016	0.038**	0.017	0.098***	0.020	0.072***	0.015
(E) * (CP - RP)	-0.009	0.015	-0.006	0.016	-0.030	0.030	-0.018	0.027
increasing price sequence (IPS)	0.031	0.020	0.034	0.023	0.036	0.028	0.046*	0.026
sequence after an increasing sequence (AI)	0.020	0.014	0.018	0.014	0.029*	0.014	0.030**	0.014
sequence after a decreasing sequence (AD)	-0.008	0.015	-0.004	0.015	-0.019	0.037	-0.017	0.035
October	-0.009	0.020	-0.008	0.020	0.001	0.024	-0.003	0.024
November	0.012	0.029	0.010	0.029	-0.014	0.025	-0.018	0.024
December	-0.045**	0.018	-0.047**	0.018	-0.063***	0.020	-0.066***	0.020
January	-0.027	0.021	-0.029	0.021	-0.058***	0.019	-0.064***	0.019
February	-0.049**	0.023	-0.050	0.023	-0.043*	0.021	-0.048**	0.022
March	-0.030	0.021	-0.031**	0.021	-0.041	0.027	-0.044	0.027
April	-0.029	0.023	-0.030	0.022	-0.052**	0.022	-0.063***	0.022
May	-0.010	0.021	-0.011	0.020	-0.037	0.028	-0.049*	0.028
June	0.021	0.030	0.019	0.029	0.015	0.037	0.002	0.035
constant	0.141***	0.032	0.148***	0.040	0.181***	0.028	0.187	0.030
R-sq within	0.104		0.103		0.173		0.164	
between	0.383		0.454		0.020		0.013	
overall	0.129		0.141		0.093		0.096	
number of observations	748		748		529		539	
number of producers	43		43		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Break-Even Price \geq \$5.50				Break-Even Price $<$ \$5.50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
expectations (E)	-0.088*	0.044	-0.089**	0.043	-0.014	0.024	-0.013	0.030
current price (CP) - reference price (RP) (ϕ_s) (ϕ_g)	0.062***	0.017	0.054***	0.017	0.053***	0.019	0.045***	0.015
(E) * (CP - RP)	-0.035	0.022	-0.028	0.020	-0.012	0.022	-0.008	0.021
increasing price sequence (IPS) (ϕ_s)	0.037*	0.019	0.033	0.022	0.041*	0.024	0.050**	0.023
sequence after an increasing sequence (AI)	0.030**	0.013	0.024	0.014	0.014	0.012	0.018	0.012
sequence after a decreasing sequence (AD)	-0.023	0.019	-0.010	0.020	-0.016	0.024	-0.015	0.023
October	0.017	0.018	0.015	0.018	-0.027	0.024	-0.027	0.024
November	0.044	0.025	0.041	0.025	-0.044	0.029	-0.047	0.029
December	-0.024*	0.013	-0.028**	0.013	-0.080***	0.023	-0.081***	0.024
January	-0.015	0.015	-0.018	0.016	-0.064**	0.024	-0.067**	0.025
February	-0.016	0.016	-0.018	0.017	-0.080***	0.028	-0.082***	0.028
March	0.002	0.022	-0.001	0.022	-0.074***	0.023	-0.074***	0.024
April	-0.002	0.020	-0.007	0.020	-0.081***	0.023	-0.083***	0.023
May	0.004	0.019	-0.001	0.019	-0.055*	0.028	-0.057**	0.028
June	0.071*	0.036	0.062*	0.034	-0.039	0.024	-0.041*	0.024
constant	0.135***	0.030	0.153***	0.040	0.177***	0.028	0.178***	0.029
R-sq within	0.146		0.143		0.134		0.132	
between	0.057		0.066		0.279		0.341	
overall	0.111		0.114		0.142		0.164	
number of observations	688		698		589		589	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Years Hedged = 5				Years Hedged < 5			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
expectations (E)	-0.026	0.024	-0.027	0.028	-0.019	0.025	-0.025	0.031
current price (CP) - reference price (RP) (ϕ_s)	0.066***	0.014	0.065***	0.013	0.044*	0.022	0.034	0.020
(E) * (CP - RP)	-0.027	0.019	-0.019	0.016	0.005	0.019	-0.001	0.021
increasing price sequence (ϕ_s)	0.035*	0.019	0.032	0.019	0.044*	0.026	0.053*	0.027
sequence after an increasing sequence (AI)	0.036**	0.014	0.037**	0.014	0.010	0.013	0.007	0.015
sequence after a decreasing sequence (AD)	-0.034	0.024	-0.040	0.024	0.002	0.023	0.013	0.020
October	-0.001	0.020	-0.001	0.020	-0.009	0.024	-0.009	0.024
November	-0.006	0.024	-0.009	0.025	0.015	0.034	0.012	0.033
December	-0.062***	0.017	-0.065***	0.017	-0.036	0.023	-0.037	0.023
January	-0.055***	0.018	-0.057***	0.018	-0.016	0.024	-0.020	0.025
February	-0.053**	0.021	-0.058***	0.021	-0.033	0.026	-0.033	0.026
March	-0.052***	0.019	-0.057***	0.019	-0.022	0.027	-0.023	0.027
April	-0.051**	0.022	-0.056**	0.021	-0.023	0.025	-0.027	0.025
May	-0.019	0.026	-0.025	0.025	-0.027	0.022	-0.028	0.022
June	0.009	0.028	0.001	0.027	0.013	0.034	0.011	0.034
constant	0.160***	0.026	0.192***	0.027	0.133***	0.035	0.126	0.042
R-sq within	0.147		0.157		0.115		0.111	
between	0.165		0.229		0.136		0.103	
overall	0.113		0.130		0.110		0.114	
number of observations	728		728		528		538	
number of producers	41		41		32		32	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Certainty Equivalent ≥ 50				Certainty Equivalent < 50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
expectations (E)	-0.039	0.039	-0.059	0.049	-0.056**	0.025	-0.040	0.028
current price (CP) - reference price (RP) (ϕ_s) (ϕ_g)	0.065***	0.018	0.063**	0.019	0.056***	0.018	0.043**	0.015
(E) * (CP - RP)	-0.034	0.021	-0.035	0.023	-0.003	0.017	0.010	0.018
increasing price sequence (IPS)	0.067***	0.023	0.069**	0.026	0.003	0.019	0.006	0.019
sequence after an increasing sequence (AI)	0.012	0.014	0.011	0.014	0.035***	0.013	0.032**	0.012
sequence after a decreasing sequence (AD)	-0.042	0.026	-0.034	0.027	-0.006	0.016	-0.005	0.014
October	-0.001	0.021	-0.002	0.021	-0.013	0.021	-0.013	0.021
November	-0.003	0.027	-0.007	0.027	0.009	0.027	0.008	0.027
December	-0.050***	0.017	-0.053***	0.017	-0.054**	0.022	-0.056**	0.022
January	-0.040**	0.017	-0.043**	0.018	-0.041	0.024	-0.044*	0.025
February	-0.049**	0.022	-0.051**	0.022	-0.042*	0.022	-0.044*	0.024
March	-0.027	0.023	-0.030	0.023	-0.042*	0.022	-0.042*	0.022
April	-0.035	0.022	-0.039*	0.021	-0.046*	0.023	-0.051**	0.024
May	-0.013	0.023	-0.017	0.022	-0.038	0.025	-0.042	0.026
June	0.034	0.033	0.025	0.032	0.001	0.030	-0.004	0.030
constant	0.150***	0.029	0.175***	0.039	0.176***	0.033	0.177***	0.036
R-sq within	0.126		0.134		0.169		0.155	
between	0.230		0.292		0.092		0.095	
overall	0.111		0.123		0.109		0.114	
number of observations	772		782		505		505	
number of producers	46		46		29		29	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Age ≥ 50				Age < 50			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
expectations (E)	-0.061	0.044	-0.049	0.051	-0.009	0.026	-0.017	0.030
current price (CP) - reference price (RP) (ϕ_s) (ϕ_g)	0.050*	0.025	0.034*	0.020	0.073***	0.015	0.073***	0.015
(E) * (CP - RP)	-0.020	0.026	-0.005	0.025	-0.004	0.022	-0.013	0.018
increasing price sequence (IPS)	0.030	0.018	0.036*	0.019	0.044	0.027	0.048	0.030
sequence after an increasing sequence (AI)	0.015	0.010	0.017	0.010	0.041**	0.018	0.039**	0.019
sequence after a decreasing sequence (AD)	-0.002	0.014	0.000	0.013	-0.045	0.030	-0.036	0.033
October	0.008	0.022	0.007	0.022	-0.020	0.020	-0.021	0.020
November	-0.011	0.025	-0.012	0.025	0.013	0.030	0.009	0.030
December	-0.035*	0.019	-0.036*	0.020	-0.072***	0.018	-0.075***	0.019
January	-0.027	0.021	-0.030	0.022	-0.054***	0.019	-0.056***	0.019
February	-0.025	0.023	-0.027	0.023	-0.072***	0.022	-0.075***	0.021
March	-0.023	0.025	-0.026	0.026	-0.051**	0.021	-0.049**	0.020
April	-0.039*	0.020	-0.044**	0.020	-0.044*	0.026	-0.044	0.026
May	-0.037	0.022	-0.041*	0.023	-0.008	0.026	-0.008	0.025
June	0.041	0.034	0.038	0.033	-0.008	0.034	-0.017	0.031
constant	0.147***	0.038	0.144***	0.044	0.175***	0.028	0.196***	0.031
R-sq within	0.119		0.115		0.155		0.162	
between	0.101		0.126		0.135		0.202	
overall	0.102		0.115		0.120		0.129	
number of observations	673		673		604		614	
number of producers	39		39		38		38	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples

	Education \geq Post Secondary				Education $<$ Post Secondary			
	Reference Price = Satisfy Price		Reference Price = Goal Price		Reference Price = Satisfy Price		Reference Price = Goal Price	
	coefficient	std. error	coefficient	std. error	coefficient	std. error	coefficient	std. error
expectations (E)	-0.007	0.023	-0.015	0.031	-0.091*	0.047	-0.074*	0.043
current price (CP) - reference price (RP) (ϕ_s) (ϕ_g)	0.050***	0.016	0.047**	0.019	0.077***	0.023	0.059***	0.015
(E) * (CP - RP)	0.007	0.016	-0.002*	0.019	-0.053**	0.025	-0.033	0.021
increasing price sequence (IPS) (ϕ_g)	0.039*	0.020	0.039*	0.023	0.036	0.021	0.046**	0.021
sequence after an increasing sequence (AI)	0.027**	0.010	0.024**	0.010	0.019	0.014	0.019	0.014
sequence after a decreasing sequence (AD) (ϕ_g)	0.025	0.018	0.032*	0.017	-0.050**	0.023	-0.043*	0.023
October	0.013	0.021	0.011	0.021	-0.022	0.021	-0.022	0.021
November	0.016	0.026	0.011	0.026	-0.009	0.029	-0.012	0.030
December	-0.037**	0.018	-0.041**	0.019	-0.062***	0.020	-0.065***	0.020
January	-0.019	0.017	-0.024	0.019	-0.056**	0.022	-0.060**	0.023
February	-0.036*	0.019	-0.038*	0.020	-0.051*	0.026	-0.056**	0.026
March	-0.041**	0.020	-0.044**	0.020	-0.024	0.026	-0.026	0.026
April	-0.031	0.020	-0.035*	0.020	-0.045*	0.025	-0.050*	0.025
May	0.008	0.027	0.004	0.026	-0.053***	0.019	-0.05*	0.019
June	0.038	0.033	0.032	0.031	0.002	0.034	-0.005	0.033
constant	0.124***	0.031	0.146***	0.042	0.201***	0.035	0.190***	0.032
R-sq within	0.155		0.159		0.125		0.113	
between	0.338		0.388		0.037		0.032	
overall	0.178		0.189		0.068		0.076	
number of observations	655		665		622		622	
number of producers	39		39		36		36	

***statistically significant at 1%, **statistically significant at 5%, *statistically significant at 10%

(ϕ_s) coefficients are statistically distinguishable for satisfy subsamples

(ϕ_g) coefficients are statistically distinguishable for goal subsamples