

**MINIMUM TILLAGE ADOPTION:
AN EXAMINATION OF THE
CANADIAN PRAIRIE PROVINCES**

A Thesis Submitted to the College of Graduate Studies and Research
In Partial Fulfillment of the Requirements for the
Degree of Master of Science in the Department of Agricultural Economics
University of Saskatchewan
Saskatoon

By
Kelly A. Davey

© Copyright Kelly A. Davey, August 2006. All Rights Reserved.

PERMISSION TO USE

In presenting this thesis in partial fulfillment of the requirements for a Postgraduate degree from the University of Saskatchewan, I agree that the Libraries of this University may make it freely available for inspection. I further agree that permission for copying of this thesis in any manner, in whole or in part, for scholarly purposes may be granted by the professor or professors who supervised my thesis work or, in their absence, by the Head of the Department or the Dean of the College in which my thesis work was done. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition will be given to me and the University of Saskatchewan in any scholarly use that may be made of any material in this thesis.

Requests for permission to copy or to make other use of the material in this thesis in whole or part should be addressed to:

Head of the Department of Agricultural Economics
University of Saskatchewan
Saskatoon, Saskatchewan S7N 5A8

ABSTRACT

Davey, Kelly A., M.Sc. University of Saskatchewan, Saskatoon, August 2006.
Minimum Tillage Adoption: An Examination of the Canadian Prairie Provinces
Supervisor: Dr. W.H. Furtan.

The use of minimum tillage technology reduces the quantity of tillage required to produce a crop, thereby reducing soil degradation. The reduced tillage results in increased soil organic matter and a reduction in soil and water erosion. Producers, researchers, and farm implement manufacturers have reduced land degradation through innovative farming practices and equipment. An example is the innovation of minimum tillage equipment and farming practices which is designed to reduce damage caused by increased tilling of the land. Minimum tillage maintains more of the previous crop's residue on the surface of the soil, thereby reducing the damaging effects of wind and water erosion. Some Prairie producers have chosen to adopt minimum tillage technology, while others continue to use conventional tillage. The objective of this thesis is to determine which socio-economic, farm, and regional characteristics are influential in determining whether minimum tillage technology and practices are adopted.

The theoretical framework for this thesis is based on an agriculture producer's objective function. A lexicographic utility function is used, which means that each element of the utility function must be satisfied in order of rank with the highest level of utility achieved when the greatest number of elements has been satisfied. For the empirical analysis a Probit model is used to model the decision of whether to adopt minimum tillage technology. A number of socio-economic, farm, and regional characteristics, such as age, education, farm size, soil type, weather, and location of a

research farm, were included as explanatory variables. The primary data source for the empirical analysis was farm level data from the Agriculture and Population Census data from 1991, 1996, and 2001, which resulted in over 42,000 observations in the data set.

A number of model specifications and sensitivity analyses were run and the results obtained were consistent with one another, thus the findings presented in this thesis are robust. A number of socio-economic, farm, and regional characteristics are significant in determining whether minimum tillage is adopted. These variables include: Alberta dummy variable, summerfallow, age, total farm area, gross farm sales, black, brown, and dark gray soils, corporate operating structure, time, average maximum April and June temperature, and total June precipitation.

ACKNOWLEDEMENTS

I am grateful to a number of people who supported me throughout my research and thesis writing. Firstly, I would like to extend a sincere thank you to my supervisor, Dr. W. Hartley Furtan for his guidance and professional insight he gave me throughout the past two years. As well, I would like to thank my committee members Dr. Richard Gray and Dr. Kamar Ali for their guidance and timely feedback throughout my thesis research and writing. I would also like to thank my external examiner, Dr. O.W. Archibold from the Department of Geography at the University of Saskatchewan, for his insights during my defense.

I would like to thank BIOCAP for funding my research. As well, I would like to thank Statistics Canada Agriculture Division for allowing me to use their data and providing funding to travel to Ottawa to complete my empirical work.

Finally, I would like to thank my parents, Allen and Laura, for encouraging me to follow my dreams and being there to support me in whatever I choose to do. I would also like to thank my brothers, Blaine, Lorne, and Adam, for being there for me.

TABLE OF CONTENTS

CHAPTER ONE: INTRODUCTION.....	1
1.1 Objective.....	5
1.2 Hypotheses	5
1.3 Use of a large micro-data set	6
1.4 Thesis Overview.....	6
CHAPTER TWO: LITERATURE REVIEW.....	8
2.1 Adoption of Agricultural Innovations	8
2.2 Technology Adoption Process	9
2.3 Technology Adoption Life Cycle.....	12
2.4 Theoretical Models for Technology Adoption	14
2.5 Adoption of Minimum Tillage Technology	15
2.6 Economic Comparison of Minimum Tillage and Conventional Tillage.....	16
2.7 Influence of Producer Characteristics on Adoption	18
2.7.1 Age	18
2.7.2 Education	19
2.7.3 Off-Farm Employment Income.....	19
2.7.4 Gender	20
2.7.5 Producer Perceptions	20
2.8 Influence of Farm Characteristics on Adoption	21
2.8.1 Land Tenure	21
2.8.2 Farm Size – Acres and Gross Sales.....	22
2.9 Influence of Regional Characteristics on Adoption	22
2.10 Knowledge Spillovers	23
2.11 Risk and Learning Costs of Adopting New Technology	24
2.12 Environmental Considerations	25
2.13 Problems with Previous Adoption Studies	26

2.14 Chapter Summary	27
CHAPTER THREE: THEORETICAL FRAMEWORK	28
3.1 The Objective Function.....	28
3.2 Technology Diffusion Theories.....	31
3.3 Modeling the Adoption of Minimum Tillage Technology	33
3.4 Aggregated versus Micro-data	35
3.5 Chapter Summary	35
CHAPTER FOUR: PROBIT MODEL SPECIFICATION.....	37
4.1 Explanatory Variables	37
4.2 Analysis Region.....	38
4.3 Data Sources	38
4.4 Data Sorting	40
4.5 Model	41
4.6 Description of Explanatory Variables	43
4.7 Hypothesized Coefficient Signs	48
4.8 Descriptive Statistics	50
4.9 Chapter Summary	53
CHAPTER FIVE: RESULTS AND DISCUSSION	54
5.1 Hypothesis	54
5.2 Interpretation of Models.....	54
5.3 Comparison of Model Results	57
5.4 Model Results.....	58
5.5 Significance of t-Statistics versus Significance of Variables.....	62
5.6 Explanation of Significant Variables	63
5.6.1 Gross Farm Sales (Sales)	63

5.6.2 Residence Dummy Variable (Residence)	63
5.6.3 Summerfallow Dummy Variable (Summerfallow)	64
5.6.4 Corporate Operating Structure (OpStruc)	64
5.6.5 Alberta Dummy Variable (AB)	65
5.6.6 Soil Variables	65
5.6.7 Weather Data	67
5.6.8 Research Farm (RFarm).....	69
5.6.9 Time	69
5.7 Sensitivity Analysis.....	70
5.8 Some Additional Explanation of Significant Variables from Sensitivity Analysis	79
5.8.1 Total Acres Farmed.....	79
5.8.2 Age	80
5.8.3 Post Secondary Education	81
5.9 Technology Adoption Life Cycle.....	81
5.10 Hypothesis Results.....	84
5.11 Chapter Summary	84
 CHAPTER SIX: SUMMARY AND CONCLUSIONS	 86
6.1 Summary	86
6.2 Implications for Public and Private Sectors	87
6.3 Implications for Academic Literature	88
6.4 Study Limitations	88
6.5 Future Minimum Tillage Adoption Research.....	89
 REFERENCES.....	 91

LIST OF TABLES

Table 4.1: Description and Source of Data	41
Table 4.2: Expected Relationships between the Adoption of Minimum Tillage and Explanatory Variables	48
Table 4.3: Comparison of Adopter and Non-Adopter Means	51
Table 5.1: Comparison of Different Data Sets	57
Table 5.2: Preferred Specification Results	59
Table 5.3: Results from Stacked Data with Total Gross Sales	71
Table 5.4: Results from Stacked Data with Total Acres Farmed	73
Table 5.5: Results from Stacked Data with Total Acres Farmed, Includes Transformed Variables	75
Table 5.6: Signs of Significant Variables from Tables 5.3 – 5.5	78

LIST OF FIGURES

Figure 2.1: Technology Adoption Life Cycle	13
---	----

CHAPTER ONE: INTRODUCTION

Prairie producers face a number of production challenges when growing a crop. Weather conditions change from year to year, for example one year it may be wet and cold and the next year it may be hot and dry. As well, some years the growing season is shortened by an early or late frost, while the next year there is a long growing season. In addition, producers face soil and nutrient problems. Producers must decide what nutrients to add to their soil and what amount. Soil erosion through wind and water are an additional production challenge as erosion removes valuable topsoil. In addition, producers must decide on seeding rates which is based on expected germination rates.

Land degradation from soil erosion and the depletion of soil organic matter is a concern for many Prairie producers. Continuous cultivation of the land disturbs the soil, thus leaving it open and susceptible to wind and water erosion. Planting a crop requires nutrients which can be obtained from the soil; however, long term cultivation of the land depletes these nutrients and soil organic matter (Zentner et al., 2002). The long term result is a decrease in crop yield and/or a decrease in crop quality.

On average much of the Canadian Prairie region benefits from additional soil moisture. Since crops are already grown in these regions, a small increase in soil moisture can provide tangible benefits to the crop and to the long term viability of the soil.

Producers, researchers, and farm implement manufacturers have been working to reduce the impact of soil erosion through innovative farming practices and the development of new tillage equipment. One example of innovation is the development and adoption of minimum tillage technology and associated farming practices which are designed to reduce damage caused by extensive tillage of the land and to preserve soil moisture. Minimum tillage, also known as reduced tillage, was first experimented with in the 1960's. Producers began seeding their crops into the previous crops residue without first tilling the land. In addition, producers adapted their equipment so as not to disturb the soil as much as compared with conventional tillage.

Minimum tillage is a tillage practice that does not completely turn over the soil. In some cases the soil is not turned over at all, this is known as zero tillage. By leaving the land less disturbed the soil is able to retain more soil moisture, as compared with land that is cultivated under conventional tillage. As well, the previous crops residue is left on the soil surface which allows it to be broken down into the soil which increases soil organic matter. The residue also acts as a canopy for the growing crop, maintaining the soil at a cooler temperature and allowing it to retain more soil moisture. In addition, minimum tillage reduces the number of times that the land must be cultivated. Producers are able to directly plant their crop into the previous crops residue, this provides economic and efficiency benefits.

With the implementation of the Kyoto Accord¹ on February 16, 2005, agriculture, and in particular crop production, is being looked to by the government, to help with the reduction of greenhouse gas emissions by sequestering carbon. Carbon

¹ In 2006 the Canadian Government announced that less emphasis will be placed on the Kyoto Accord.

credits are being sold, companies which cannot meet their emission targets buy the credits and organizations, such as agriculture producers, sell the credits.

In this thesis minimum tillage is defined as tillage that retains most of the previous crops residue on the surface, this includes zero tillage (2001 Agriculture Census Questionnaire)². Minimum tillage is also referred to as conservation tillage. Conventional tillage is defined as tillage that incorporates most of the previous crop's residue into the soil (2001 Agriculture Census Questionnaire)². Minimum tillage technology reduces the number of tillage operations before seeding a crop, thereby leaving the land less disturbed compared to conventional tillage. Minimum tillage also removes the requirement for the land to be left fallow once every two-to-three years because of the need to preserve moisture. By leaving more of the previous crop's residue on the surface of the land, more carbon is able to be sequestered; thereby reducing greenhouse gas emissions. An increased amount of residue on the soil surface significantly reduces the effects of wind and water erosion. Finally, the additional surface trash helps to maintain the soil moisture increasing the potential crop yield.

A producer will adopt a new technology if they perceive it benefits them in some manner. Economists argue that a producer will maximize their utility subject to a set of constraints, and any action that increases the level of utility will be viewed as positive by the individual producer. For illustration purposes, suppose the producer views a larger profit margin, *ceteris paribus*, as better or more desirable than a smaller profit margin.

² This definition of minimum tillage was used because it is the definition given on the Canadian Agriculture Census questionnaire, which is where the data are drawn from for this analysis. Various other definitions are used in other studies.

This means that an increase in the profit margin will have a positive effect on the level of utility.

Profit margins on a farm are influenced in a number of ways. On the input side, the required quantity of an input can increase or decrease depending on the technology used. As well, the quantity of output produced can either increase or decrease depending on the chosen technology. Together these changes in input and output quantities can influence a producer's profit margin.

The effect of minimum tillage on the farmer's profit margin will occur in a number of ways. Soil quality is influenced by wind and water erosion. A decrease in erosion leaves valuable top soil on the surface, which is necessary for proper crop development. An increase in soil organic matter enhances nutrient availability for crop growth. Similarly, an increase in the moisture level in the soil has the potential to increase crop yields, which also increases the profit margin. Thus there are a number of reasons a producer would adopt minimum tillage practices.

A number of reports have been completed which examine why individuals adopt new technologies, other studies have focused on the adoption of agricultural innovations, and finally a few have analyzed the adoption of minimum tillage technology. These studies will be reviewed in the Literature Review chapter of this thesis. The major shortcoming of many of these studies, and thus one reason for this thesis, is their analysis is static rather than dynamic. As well, the majority of studies use some form of aggregated data for the analysis instead of micro-level or individual producer data, which means that individual socio-economic and farm characteristics are not available as explanatory variables. In this thesis a number of socio-economic and farm

characteristics are included as explanatory variables in explaining the minimum tillage technology adoption decision.

1.1 Objective

The objective of this thesis is to determine which, if any socio-economic, farm, and regional characteristics are influential in determining whether minimum tillage technology is adopted. In addition, a test is carried out to determine whether the adoption of minimum tillage technology follows the technology adoption bell curve.

The results obtained from this research have the potential to benefit both the private and public sectors. Private corporations will be able to utilize information regarding the socio-economic, farm, and regional characteristics which significantly influence the adoption of innovative technology, and from this develop specific marketing strategies for different groups of producers and for different geographic regions. In addition, the results will help determine which groups of producers toward which a firm could target particular innovative technologies. The public sector has the potential to benefit by understanding how producers view environmental concerns in their decision of whether to adopt new technology. From this they will be able to develop useful and effective policies which help reduce negative environmental effects.

1.2 Hypotheses

H1: The adoption of minimum tillage technology is based on profitability, socio-economic factors, farm characteristics, and regional characteristics (such as extension and research services).

H2: The adoption of minimum tillage technology follows the bell curve of the technology adoption life cycle.

1.3 Use of a large micro-data set

A number of studies have examined the adoption of minimum tillage technology however, few have used micro-level data for the empirical work. Without micro-level data it is impossible to use socio-economic factors as explanatory variables, thus leaving out possible significant characteristics which are influential in the decision of whether to adopt minimum tillage technology. This study uses a combination of socio-economic, farm, and regional characteristics to model the decision of adopting minimum tillage technology. The data were retrieved from various Statistics Canada data files. In total just over 42,000 individual observations were available.

1.4 Thesis Overview

Chapter two provides an overview of the research previously done regarding the adoption of technological innovations. It reviews literature done on the adoption of technology, the adoption of minimum tillage technology, and the adoption of innovative agriculture technology. In addition, the benefits and drawbacks of using minimum tillage technology and practices are examined. Variables which have been used to examine the adoption of tillage technology will be discussed in detail.

Chapter three contains the theoretical framework for this analysis. The chapter begins with a producer's utility maximization function and leads into the Probit model, which is used for the empirical work in Chapter five. As well, technology diffusion theories are discussed.

The model specification for the empirical work of this analysis is found in Chapter four. The variables which are chosen as explanatory variables are discussed, as well as their expected influence on the adoption of minimum tillage technology. In addition, descriptive statistics for each of the explanatory variables are included.

Chapter five provides results for the empirical work in this analysis, along with a discussion of the significant variables and reasons for their significance. Marginal effects for each of the variables were found, however, only the significant variables are analyzed in detail. In addition, alternative model specifications and sensitivity analyses are analyzed.

Finally, chapter six provides a summary of the thesis. Limitations of this study are also discussed. As well, it provides insight into future research regarding the adoption of minimum tillage technology.

CHAPTER TWO: LITERATURE REVIEW

This chapter provides a review of the literature of the technology adoption process, as well as the findings of previous studies done regarding the adoption of minimum tillage technology³. Results from these studies provide useful background information for this research. The agronomic benefits (improvement of crop through increased yield or quality) of minimum tillage farming systems have been extensively researched and can be easily observed. On the other hand, the economic benefits (profit) of minimum tillage farming systems are not easily recognizable; however a number of economic studies on the adoption of minimum tillage technology and practices have been completed. In addition, the benefits and drawbacks of minimum tillage technology and practices are discussed.

2.1 Adoption of Agricultural Innovations

The adoption process of agricultural innovations is similar to that of other industries, however, there is one significant difference and that is the decision to adopt agricultural innovations lies with individual households rather than large corporate firms (Feder and Umali, 1993). The decision of whether to adopt a new technology is made in the context of an individual or firm's economic environment, which can vary

³ In some of the studies they refer to reduced till or no-till technology, depending on the exact definition the tillage equipment may differ. However, the studies are included in the literature review because the objectives of adopting the technology are similar.

significantly amongst different producers (Goel and Rich, 1997). For example, each farmer faces a slightly different interest rate depending on their level of outstanding debt, value of capital assets for collateral, and earning forecast over the loan time period. Thus, the decision to adopt minimum tillage technology is dependent on a producers socio-economic characteristics.

2.2 Technology Adoption Process

The decision of whether to adopt a new technology requires the producer to go through a thorough decision making process. Astebro (2004) lists three main decisions that must be made prior to the actual adoption of the new technology. The first decision is whether to adopt the new technology, this includes determining the new technology's potential influence on the firm's profit margin both in the short-term and over the long-term. The second decision is the depth of adoption, which is how much the firm wants to exploit the new technology. The third and final decision is the speed at which old technology is replaced by the new technology (Astebro 2004).

Astebro (2004) suggests three stylized facts about firms which adopt new technologies: i) large firms are more likely to adopt new technology, ii) once technology is adopted large firms will learn about and utilize the new technology more than small firms, and iii) the replacement speed of old with new technology is inversely related to firm size. These three stylized facts are consistent with the existence of the sunk costs that are associated with adopting new technology. Large firms have a greater output to spread the cost of the new technology over; therefore it is more economically viable for them to adopt the technology earlier as compared with a small firm, *ceteris paribus*. Large firms are better able to exploit the benefits of the new technology because they are

dealing with a larger quantity of output, therefore they will use the technology more often thereby exploiting more of its features. The speed at which firms replace capital equipment is inversely related to firm size. This occurs because when a small firm adopts a new technology they will replace the one or two machines that they use, whereas a large firm may try the new technology by replacing one machine and continuing to use the old technology as well until they have determined whether the new technology is a good fit for their firm. This implies that the adoption of new technology represents a far larger adjustment to a small firm's capital stock as compared with larger firms (Astebro 2004).

Astebro (2004) states that producers do not adopt new technology every time something new is developed, rather they will only adopt when it is beneficial for them to do so. This occurs when their capital stock is sufficiently far from optimal. This will generally occur through some combination of capital stock depreciation, positive developments of technological change, and through cumulative shocks that have moved them from their optimal region (Astebro 2004). This means that the majority of firms will only adopt a new technology when there are significant benefits for them to gain, they will not adopt new technology just for the sake of adopting new technology.

The decision as to whether to adopt a new technology can take a number of years to make. Doraszelski (2004) found that it takes an average of 9.04 years to decide whether to adopt a new technology, this is from the time the technology is available on the market until the average firm has adopted it. He states that a lot of the delay can be credited to firms waiting for the technology to undergo significant improvements before deciding to adopt. When a new technology is developed it generally has a number of flaws which will be improved once the early adopters have used the technology and

provided the manufacturer with feedback to improve future models. Therefore, the majority of firms have an incentive to delay adoption of a new technology until most of the first flaws have been corrected. This theory explains why the middle 68% of adopters represent the majority of firms that will adopt the new technology (Doraszelki 2004).

Jaffe et al. (2002) outline the development of technological change by following a three step process: invention, innovation, and diffusion. This process is the same for all industries and can take a number of years to complete. During the invention stage prototypes are developed and experimental tests are carried out. Once a suitable and usable prototype or process is developed the new technology can be placed on the market, this is called innovation. This is also the start of the technology adoption life cycle, which will be discussed in detail later. The final step in the development of technological change is diffusion, where the new technology or process is sold to the mass market (Jaffe et al., 2002).

Batz et al. (1999) suggest that the characteristics of new technology have significant influence on whether the technology will be adopted, as well as the rate and speed of adoption. In particular, technologies which reduce the perceived risk level as compared with traditional technologies tend to be adopted (Batz et al., 1999). This means that there is a need for the development of risk reducing technologies that are easier to operate than traditional technology. Batz et al. (1999) assumed that technology adoption decisions made by farmers are based on the following four technology characteristics: relative profitability, relative risk, initial costs, and relative complexity (Batz et al., 1999).

Goel and Rich (1997) found that the more competitive an industry is, the more likely the firm's in that industry are to adopt innovative technology. In order to succeed in a competitive industry a firm must adopt the new technology quickly to achieve competitive advantages. There may be first mover advantages associated with the adoption of innovative technology (Goel and Rich, 1997).

Finally, Feder and Umali (1993) state that, the longer an innovation has been on the market, the more the price of it declines. This means that the early adopters of the technology will pay a higher price to obtain the technology as compared with those firms who adopt later. Some producers may choose to wait for the price of the new technology to decrease before adopting it. In other words, it may not be economical for a firm to adopt a new technology when it first becomes available on the market. However, once the innovation has been on the market for a while it may become more profitable for a large majority of firms to adopt the technology (Feder and Umali, 1993).

2.3 Technology Adoption Life Cycle

The technology adoption life cycle follows an innovation from the time it becomes available on the market, until it is widely used by the majority of consumers. An illustration of the technology adoption life cycle is illustrated below in Figure 2.1.

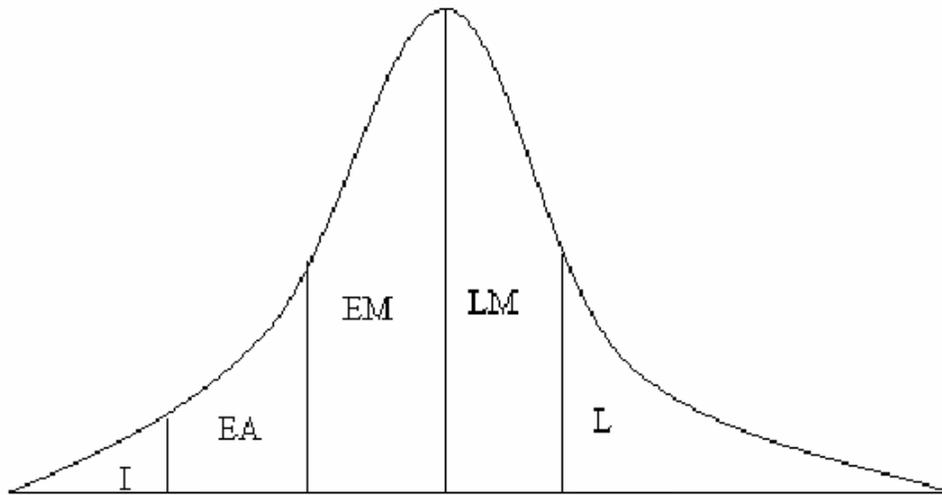


Figure 2.1: Technology Adoption Life Cycle

Source: <http://ist-socrates.berkeley.edu/~fmb/articles/lifecycle/>

The cycle forms a bell curve, where few firms adopt the new technology in the beginning followed by an increased number of firms adopting the technology, and finally the firms who wait until later to adopt the new technology. Moore (1991) summarized the technology adoption life cycle: beginning with when a new technology is first developed, the innovators will be the first to adopt the new technology; this area is labeled I in the figure. Innovators are the technology enthusiasts who like technology for its own sake and not just because it will increase their profitability. Innovators represent about 2.5% of potential consumers. Next to adopt the new technology are the early adopters who represent about 13.5% of potential consumers. The early adopters are labeled as EA in Figure 2.1. Early adopters are those firms who adopt new technology early in the products life cycle, as soon as they realize that it will provide them with an opportunity. Pragmatists are next, and they are divided into two groups,

the early majority and the late majority, each representing about 34% of potential consumers. EM and LM represent the early majority and late majority respectively in the figure 2.1. The early majority are the financially stable firms who do not like the risks of being the first to adopt a new technology, but they are ready to see the advantages in tested technologies. Early majority pragmatists are the beginning of the mass market for the new technology. The late majority dislikes new innovations and prefers old technology over drastic innovations. They adopt new technology reluctantly and do not expect to like it. The final group in the technology life cycle is the laggards representing 16% of the population. The laggards represent the area labeled L in the figure below. Laggards do not adopt new technology unless no other alternatives are available (Moore 1991). The technology adoption life cycle holds for the adoption of a new innovation in any industry.

2.4 Theoretical Models for Technology Adoption

Adesina and Zinnah (1993) outline three different theories which attempt to explain technology adoption, they are: the innovation-diffusion model, economic constraint model, and adopter perception model. The innovation-diffusion model states that access to information about new technology is significant in determining whether a new technology will be adopted or not. Those who support the innovation-diffusion model stress the importance of extension services, on-farm trials, and opinions of local and media opinion leaders. The economic constraint model states that economic constraints which are reflected by asymmetrical distribution patterns of resource endowments such land and capital are determining factors in whether new technology will be adopted. Finally, the adopter perception model states that the perceived

attributes of a new technology determine whether or not it will be adopted (Adesina and Zinnah, 1993).

2.5 Adoption of Minimum Tillage Technology

Minimum tillage farming systems reduce the number of times the land is cultivated, thereby reducing the potential for wind and water erosion. According to Ribera et al. (2004), the use of a minimum tillage farming system conserves soil moisture and reduces fuel, labor, and machinery costs. In addition, a reduction in wind and water erosion provides significant environmental benefits (Ribera et al. 2004).

Ribera et al. (2004) summarize the agronomic benefits to a minimum tillage farming system. In minimum tillage farming systems less organic matter is oxidized and lost to the atmosphere as compared with conventional tillage farming systems. In addition, minimum tillage farming systems provide a number of other benefits, including increased soil organic matter (SOM) and an increase in favorable types of microbial activity. Soils which are under minimum tillage management are less compact than those under conventional tillage farming practices, thereby allowing them to maintain soil moisture longer. The ability for less compact soils to hold moisture longer was shown during a drought in Texas, where soils farmed using minimum tillage farming practices were able to hold soil moisture for two weeks longer than soils farmed using conventional tillage (Ribera et al., 2004).

Crop rotations play a key role in the decision making process of whether to adopt minimum tillage technology. Different crop rotations have different levels of risk attached to them and different rotations are better suited to different tillage systems (Ribera et al., 2004). When a minimum tillage farming system is adopted, the

importance of a diverse crop rotation increases (Ribera et al., 2004). Therefore, under a minimum tillage farming system more time must be spent planning an appropriate crop rotation.

According to Parsch et al. (2001) the use of minimum tillage farming systems is decreasing in some areas, including Iowa. Some crops such as sorghum may do better under a conventional tillage farming system as compared with a minimum tillage farming system. They also note that the crop rotation is more important in a minimum tillage farming system as compared with a conventional tillage farming system. The adoption of minimum tillage technology is a long term decision because of the initial decrease in yield. In the beginning there is a decrease in chemical costs with a minimum tillage farming system, however, as weeds build up resistance chemical costs often increase (Parsch et al., 2001).

There have been no studies that examine the adoption of minimum tillage in Canada. This is, in itself a surprising result, given the importance and prevalence of the technology on the Canadian Prairies. This thesis starts to fill this gap by comparing the producer, farm, and regional characteristics of adopters and non-adopters of minimum tillage technology.

2.6 Economic Comparison of Minimum Tillage and Conventional Tillage

Many producers who are considering adopting minimum tillage technology and practices will compare expected profits of conventional tillage to minimum tillage; in addition they will consider the agronomic benefits and drawbacks to each (Ribera et al., 2004). Ribera et al. (2004) state the importance of considering the three areas which affect profits when evaluating new tillage technology, they are: changes in the cost per

acre, changes in the yield per acre, and the impact on net income risk (Ribera et al., 2004).

Economic studies that compare profits in a minimum tillage farming system to conventional tillage are often inconclusive. The studies agree that a minimum tillage farming system reduces the following input costs: fuel, labor, and machinery repair and depreciation costs. However, there is an increase in herbicide costs with a minimum tillage farming system. Therefore, some studies find that a minimum tillage farming system is more profitable as compared with conventional tillage, while other studies find the opposite result.

In Ribera et al. (2004), they study the economics of a Texas producer's adoption of a reduced tillage system. They concluded that under risk neutral rankings reduced tillage was preferred over conventional tillage in three of the five scenarios. However, when they assumed a risk averse producer reduced tillage was preferred over conventional tillage for all scenarios (Ribera et al., 2004).

Janosky et al. (2002) found that conventional tillage and minimum tillage are economically equivalent, however, they report that environmental disadvantages exist in conventional tillage farming systems. Wind erosion and blowing dust on conventionally tilled land reduces soil productivity and can contribute to poor air quality, both of which lead to long-term environmental damage. Since minimum tillage farming systems represent best management practices there is an incentive to change tillage methods even though there is no economic difference between minimum tillage and conventional tillage farming systems (Janosky et al., 2002).

Many studies which compare the economic viability of a minimum tillage farming system with a conventional tillage farming system neglect to consider the

business risk involved in the adoption of minimum tillage technology. The 2004 study by Ribera et al. did consider the business risk involved in adopting minimum tillage technology. Certainty equivalents (CE) were used, which allowed them to rank risky decisions (the adoption of minimum tillage technology) for the different levels of risk of the decision makers (Ribera et al., 2004).

2.7 Influence of Producer Characteristics on Adoption

2.7.1 Age

Lichtenberg (2001) suggests two different theories for the influence of age on the adoption of minimum tillage technology. The first theory he states is that older producers are nearing the end of their farming career and operating horizon, thus they have less time to earn a positive return from a capital investment. This makes them less likely to adopt minimum tillage technology. The second theory he states is that because older producers have a shorter planning horizon, as compared with younger producers, they may be more willing to sacrifice short term returns in order to increase the resale or rental value of the land, therefore they may be more likely to invest in soil conserving technology as compared with their younger counterparts (Lichtenberg, 2001).

Feder and Umali (1993) found that older producers are less likely to adopt soil conservation technology because of their shorter planning horizons as compared with younger producers. Lapar and Pandey (1999) found age to be significant in determining whether soil conservation technology will be adopted. In Westra and Olson (1997), Adesina and Zinnah (1993), and Uri (1998) age was found to be not significant in determining whether conservation technology will be adopted.

2.7.2 Education

Feder and Umali (1993) found that higher educational attainment levels and recognition of a soil erosion problem has a significant positive influence on the adoption of soil conservation technology. They also found that on average younger producers are more educated and more involved with innovative farming practices and technology as compared with their older counterparts (Feder and Umali, 1993). Westra and Olson (1997) and Uri (1998) found education to be not significant, but that the recognition of a soil erosion problem to be significant. Rahm and Huffman (1984) report that producers with higher levels of education are more likely to make an economically correct decision, rather than just adopt the new technology. Feder and Umali (1993) found that factors such as neighbor effects play a more important role during the later stages of technology diffusion.

2.7.3 Off-Farm Employment Income

Gould et al. (1989) provided two theories on the influence of off-farm jobs on the adoption of minimum tillage technology. The first theory was that the adoption of minimum tillage technology decreased as off-farm work hours increased because time spent on the agriculture operation decreased; therefore the producer was not as involved with the operation and was less likely to adopt new technology and practices as rapidly as someone who works full-time on their agriculture operation. Their second theory was that the probability of adopting minimum tillage technology increased as off-farm work hours increased because fewer hours are spent on the agriculture operation, therefore they need to adopt technology which cuts back on their labor hours (Gould et al., 1989).

Ervin and Ervin (1982) introduce an interpretation for the significance of off-farm income on the adoption of minimum tillage technology. In previous research off-farm income was found to be a significant explanatory variable. They interpret this as meaning that as off-farm income increases so does the ability to overcome financial constraints imposed by implementing new technology for soil conservation. This means that as off-farm income increases, so does the probability of adopting minimum tillage technology (Ervin and Ervin, 1982). Norris and Batié (1987), state that financial constraints are the biggest obstacle for those farmers not adopting minimum tillage technology (Norris and Batié, 1987). This means that off-farm income can ease the burden of financial constraints.

2.7.4 Gender

Doss and Morris (2001) studied the adoption rates by gender of modern varieties of maize in Ghana. They found that males and females adopted new varieties at different rates. In particular, they found that female headed households were slower at adopting new varieties compared to male headed households. They reported that women tended to lack the complementary inputs required to adopt modern maize varieties. Extension visits was another variable which they found to be significant. Male farmers received more visits from extension agents compared to their female counterparts (Doss and Morris, 2001).

2.7.5 Producer Perceptions

Many studies concerning the adoption of agricultural innovations have ignored producers' perceptions of the new technology and how it could benefit their operation.

Adesina and Zinnah (1993) considered producers' perceptions as an explanatory variable for the adoption of mangrove rice varieties. They found producers' perceptions to be a significant explanatory variable for the adoption of mangrove rice varieties (Adesina and Zinnah, 1993).

Lynne et al. (1995) examined the perceived and actual control over the adoption of new technology. They found that producers were more likely to adopt new technology if they perceived that they have control over the adoption, rather than being forced into adoption (Lynne et al., 1995).

2.8 Influence of Farm Characteristics on Adoption

2.8.1 Land Tenure

Soule et al. (2000) found that land tenure significantly influenced the adoption of conservation practices. Land renters have little security therefore they have little incentive to maintain soil quality for the long term. However, a distinction must be made between share-croppers and cash renters. Share-croppers are those who pay the landowner a share of the lands profits each crop year, whereas cash renters pay the landowner a fixed price each year. Landowners tend to be more actively involved in the management of the land under share leases; this means that soil conservation is more likely under a share lease agreement. They found that landowners were most likely to adopt soil conservation practices, followed by share-croppers, while cash renters were least likely to adopt soil conservation practices (Soule et al., 2000). Feder and Umali (1993) found that renters were less likely to invest in soil conservation technology; however, in the study done by Lee and Stewart they found that full owners were less

likely to adopt soil conservation technology as compared with renters (Feder and Umali, 1993 and Lee and Stewart, 1983).

2.8.2 Farm Size – Acres and Gross Sales

Total acres farmed and total sales are positively correlated, that is as total acres farmed increases so do total sales, *ceteris paribus*. As net income increases, a producer's ability to afford new capital equipment also increases. In addition, an increase in the number of acres farmed can lead to the need for new larger equipment. Feder and Umali (1993) found that a positive relationship existed between total acres farmed and income and the adoption of soil conservation technology. Westra and Olson (1997) also found that an increase in farm size lead to greater adoption rates of soil conservation technology. On the other hand, Adesina and Zinnah (1993) and Uri (1998) found farm size to be not significant in determining whether a producer will adopt soil conservation technology.

2.9 Influence of Regional Characteristics on Adoption

A number of regional characteristics, such as topography, rainfall, temperature, soil texture, land quality, and access to an extension agent have been included in previous soil conservation adoption studies. Uri (1998) found topography to be a significant variable where landowners whose land has an increased slope are more likely to adopt soil conservation technology in order to reduce the impact of erosion. In addition, soil texture was found to be not significant in Uri's model (Uri, 1998). Gould et al. (1989) found that land quality plays an important role in the adoption of any soil conservation technique. Producers whose land was more likely to experience the

negative effects of soil erosion are more likely to recognize that they have a problem and therefore are more likely to adopt technology which minimizes the negative impact of soil erosion (Gould et al., 1989). Westra and Olson (1997) found physical characteristics of the farm to be a significant variable. Uri (1998) found average rainfall, but not average temperature to be significant. Westra and Olson (1997) found the availability of support for conservation tillage and the quality of information available to be not significant. Adesina and Zinnah (1993) found contact with an extension agrologist to be not significant in explaining the adoption of soil conservation technology.

2.10 Knowledge Spillovers

Thornton and Thompson (2001) provide an overview of knowledge spillovers and the research which has been done regarding them. Knowledge spillovers occur when knowledge obtained from something previously done can be applied to something new. Knowledge spillovers can occur in a number of different ways. To begin with there are both internal and external knowledge spillovers. Internal knowledge spillovers are those spillovers which occur within the firm. While external knowledge spillovers are those spillovers which occur from outside the firm. In addition there are three other types of knowledge spillovers, including: intergenerational, within the same product class, and different product classes. Many theoretical studies have been completed which support the existence of knowledge spillovers. The theoretical literature on knowledge spillovers suggests that external knowledge spillovers have long term impacts on market growth, market structure, and industrial policy. Results from empirical studies of knowledge spillovers have varied significantly. Some studies have

found that knowledge spillovers exist, while others have found no existence (Thornton and Thompson, 2001).

2.11 Risk and Learning Costs of Adopting New Technology

The adoption of a new innovation includes both risk and uncertainty in the decision making process. Each producer has an individual level of risk aversion, which means that the adoption process and point of adoption for each producer will vary. Abadi Ghadim and Pannell (1999) found that older producers were more risk averse as compared with younger producers (Abadi Ghadim and Pannell, 1999). This is because older producers are generally closer to retirement, therefore their planning horizons are shorter, thereby making long-term capital intensive investments unfeasible. Uncertainty comes from the fact that the affect on long term profitability is unknown at the time of adoption. With time and the use of the innovative technology the degree of uncertainty will decrease as producers see how the early adopters have adjusted (Abadi Ghadim and Pannell, 1999).

When a firm adopts new technology the employees will go through a learning curve. Pindyck and Rubinfeld (2001) describe the learning curve as the relationship between a firm's cumulative output and the labor hours required to make each additional unit of output. The learning curve has a downward slope, meaning that as cumulative output increases the time required to produce an additional unit of output decreases. In addition, there will be learning costs associated adopting new technology. These costs are incurred because employees must learn how to use the new technology once it is implemented. Therefore, when the decision is being made to adopt a new technology, the learning cost associated with the new technology must be considered and spread over

the expected output. Learning costs come in the form of decreased productivity, in the beginning it takes longer to produce the old level of output until employees become familiar with the new technology after which time productivity should increase. If productivity does not increase after a reasonable adjustment period the new technology will not become widely accepted and adopted. In the case of adopting minimum tillage technology learning costs are not significant because the use of the technology does not differ significantly from that of conventional tillage. Therefore, learning costs will not be explored further in this research (Pindyck and Rubinfeld, 2001).

2.12 Environmental Considerations

The implementation of environmental policies such as the Kyoto Accord creates constraints for firms, therefore creating an incentive to make technological developments in order to meet the new regulations or emission targets. This means that there will be an incentive to create farming equipment or develop innovative farming practices which will decrease greenhouse gas emissions (Jaffe et al., 2002).

To date the adoption of minimum tillage technology has been on a voluntary basis. Therefore, it must be economically profitable or provide soil conservation benefits for a producer in order for them to adopt it. With the implementation of Kyoto it is expected that some producers will adopt minimum tillage technology and practices in order to make money from selling carbon credits; to what extent is unknown at this time. Because the commitment period for Kyoto is short, 2008 – 2012, it is expected that this will not cause a large increase in the adoption of minimum tillage technology. Thus, when producers are adopting minimum tillage technology in order to capture carbon credits, it must remain profitable after 2012 when the Kyoto commitment period

has expired (Weersink et al., 2005). In addition, much of the adoption of minimum tillage technology took place long before the implementation of the Kyoto Accord. This means that producers who adopted the technology did so because of other incentives such as, soil conservation or increased profitability.

2.13 Problems with Previous Adoption Studies

Many of the previous studies done regarding the adoption of new agriculture innovations contain flaws. These problems included: the failure to consider the adoption process as a dynamic problem, biases from omitted variables, poor model specification, and failure to relate hypotheses to a concrete conceptual framework (Abadi Ghadim and Pannell, 1999).

Feder and Umali (1993) describe how early studies regarding the adoption of new technology used static models to analyze the problem; however, more recent studies have used dynamic models to analyze the problems. Dynamic models yield significantly different results as compared with static models. The main differences come from the fact that dynamic problems consider the effects today's decisions have on future time periods, thus an innovation that may not be feasible to adopt for one time period may be feasible to adopt for the long term. With dynamic problems it is acceptable if the project has net costs during the first few time periods so long as it provides positive benefits over the project or equipment's expected life (Feder and Umali, 1993).

The majority of technology adoption studies for agriculture have used aggregated data, particularly studies that analyze a large geographic region. Studies which use farm level data are limited. The use of farm level data instead of aggregate data can lead to significantly different conclusions (Rahm and Huffman, 1984). Farm level observations

eliminate potential problems that may arise with aggregation bias and allow a greater number of human capital variables such as experience, health, and private and public information to be evaluated. The paper by Rahm and Huffman (1984) uses micro-data to analyze the adoption of minimum tillage technology by Iowa corn producers (Rahm and Huffman, 1984).

2.14 Chapter Summary

Much research has been done on the adoption of new technology, as well studies have been done on the adoption of minimum tillage technology. A number of variables have been found to have an impact on the adoption decision. These variables include: age, education, physical characteristics of the farm, off-farm income, land tenure, and farm size. A major shortcoming of previous minimum tillage adoption research is the use of aggregated data rather than micro-data.

CHAPTER THREE: THEORETICAL FRAMEWORK

This chapter presents the theoretical framework which is used to determine the particular influence that socio-economic, farm, and regional characteristics have in determining whether minimum tillage technology is adopted by an agricultural producer. This chapter briefly examines the von Neumann – Morgenstern (1944) expected utility hypothesis and then discusses a lexicographic utility function. For this thesis the lexicographic specification is chosen to represent the producer's decision making process when considering the adoption of minimum tillage technology. The empirical specification of the adoption decision follows.

3.1 The Objective Function

The utility function of a farm producer includes among other factors expected profit, risk, and attitude toward the environment. Risk can be included in the utility function in a number of ways. For example, the von Neumann – Morgenstern (1944) hypothesis of expected utility examines the mean-variance tradeoff of income from a particular action. Depending upon the individual's preference for risk, measured in terms of the mean and variance of income, the individual chooses those actions that maximize utility.

Utility functions can also be expressed as a lexicographic ordering of elements that provide the decision maker utility. The individual orders the elements in the

utility function, and then chooses a particular action depending upon a satisfying criterion. Each element of the utility function must be satisfied in order of rank with the highest level of utility achieved when the greatest number of elements has been satisfied. When the results of a particular action are such that the satisfaction of the first element is exceeded, the additional utility gained from a higher quantity of that good or service is less than the utility from an action that results in the second ordered element being satisfied, even with a lower quantity of the first element being achieved.

Little is known about the structure of a lexicographic utility function for the adoption of new technologies. Sociologists and economists have focused on the adoption decision rather than the demand for a new innovation (likewise this thesis focuses on the adoption decision). However, two important elements of an agricultural producer's utility function when faced with the decision to adopt minimum tillage technology will be expected profits and risk aversion. A third element of the utility function may be stress associated with falling profits, due in the case of this thesis to the decline in soil quality. Producers may view a decline in soil quality as a precursor to lower productivity and thus falling profitability. The notion that a producer may react to stress when making the decision to adopt a new technology was well summarized by Rosenberg (1969, p.23)...

... It is possible, furthermore, that threats of deterioration or actual deterioration from some previous state are more powerful attention-focusing devices than are vague possibilities for improvement. There may be psychological reasons why a worsening state of affairs, or its prospect, galvanizes those affected into a more

positive and decisive response than do potential movements to improved states...

Stress may be seen as caused by declining profits due to the loss of soil quality, low output prices, high input prices, or weather conditions. In this thesis stress will refer to a loss in soil quality. Reducing stress can then be thought of as being associated with the adoption of minimum tillage technology, and thus a powerful motivator in the adoption decision. Thus the decision to adopt minimum tillage technology is not only directly related to increased profitability, but also to the reduced stress of observing a decline in soil quality.

If stress operates as a focusing device it must be included as an element in the utility function, either implicitly or explicitly. The importance of reducing the stress from falling profits may be so large that it dominates the impact of expected profits. In such a case it could be included explicitly in the utility function as:

$$LU[\Pr(\pi \geq 0) = \alpha, E(\pi) \geq 0, \max E(\pi)] \quad (3.1)$$

where $\Pr(\pi \geq 0) = \alpha$ is the probability of profits being positive and equal to alpha (a risk parameter), $E(\pi) \geq 0$ is the need to reduce stress from falling profits, and $\max E(\pi)$ is the maximization of profits.

One aspect of the decision to adopt a new technology that the producer must consider is the future stream of benefits and costs associated with the decision. The profit element can be thought of as the discounted stream of net benefits over the life of

the new technology. Thus, although not explicitly mentioned in the objective function the impact of the dynamic nature of the adoption decision is included.

In previous studies regarding the adoption of minimum tillage technology it has been found that there was no economic difference between conventional and minimum tillage, therefore there was no economic incentive to switch technologies (Janosky et al., 2002). This may be due to the role stress played in the objective function as described above. However, if it is opportune for a producer to make a capital investment decision they may have an incentive to switch to minimum tillage technology because of the environmental benefits it offers. Another point to consider is the search costs involved with the purchase of new capital equipment. Whenever a capital investment is made the producer must conduct research into the latest technology and consider costs and what technology is the best fit for the operation.

3.2 Technology Diffusion Theories

Both internal and external learning sources help to shape the technology diffusion process. Internal learning is learning by doing, that is as you gain experience with a new technology you become better able to capture the benefits from using it and are able to do tasks more quickly and able to complete more tasks using the new technology. On the other hand, external learning is learning from others, this is the case when one observes things from other firms and what they are doing. By observing others using new technologies one then can change one's own practices. Internal learning relies on exogenous sources for information when what the neighbors are doing cannot be observed.

The adoption of new technology follows an 'S' shaped growth curve, which applies to the adoption of minimum tillage. The 'S' shaped growth curve is a form of the logistic growth function. A logistic growth function is used for the adoption of new technology; as more people adopt the new technology, an increased number of people are exposed to it, resulting in more people adopting the new technology. This is true up until a certain point, at which time everyone who will adopt the new technology has or the technology has reached the end of its useful life. Like any capital purchase, technology has a useful lifespan after which time it is replaced by new innovative technology.

The Bass Diffusion Model, developed in the 1960s by Frank Bass, was developed as an extension to the Logistic Growth Model. The Bass Model takes into account both innovator and imitator behaviors, while the Logistic Growth Model considers only imitator behaviors (Feder and Umali, 1993).

The Bass Model was first developed to deal with population heterogeneity. It classifies the population into two separate groups, innovators and imitators. Innovators are those firms that adopt new technology independently of others; their decision to adopt new technology is based on exogenous information. On the other hand imitators are those firms who are influenced by those who have already adopted the technology.

In the case where there are no innovators the Bass Model is reduced to the Logistic Growth Model. This means that there is no difference between the Logistic Growth Model and the Bass Diffusion Model. Based on statistical evaluation (R^2 , correlation between actual and predicted values, and long term forecasting efficacy), it

has been found that the Bass Diffusion Model yields little improvement over the Standard Logistic Growth Model.

3.3 Modeling the Adoption of Minimum Tillage Technology⁴

When producers are confronted with a decision to adopt minimum tillage technology they have less than full information about the future, they face uncertainty. In this case producers are assumed to make the decision by choosing the action that maximizes the individual producer's utility. It is assumed that a discrete variable T is used to denote if the producer adopts the new technology, such that $T=1$ if the decision is adopt and $T=0$ if the decision is to not adopt. Following Rahm and Huffman (1984) we let the utility function $U(R_{Ti}, A_{Ti})$ rank the i^{th} firm's preference for the technology where R_T are the moments that describe the distribution of the discounted net returns from adoption, and A_T are other attributes of the new technology. The values of R_{Ti} and A_{Ti} are unobservable in the data because the technology has not yet been adopted by the producer. However, it is postulated there is a linear relationship between the firm's ranking and the choice of adoption based upon some observable characteristics of the firm. The linear equation is specified as:

$$U_{Ti} = X_i \alpha_T + e_{Ti} \quad (3.2)$$

where X_i are specific observable firm characteristics such as, farm size, education, and age, $T = 0, 1$, $i = 1, 2, \dots, n$ (firms), and e_{Ti} the error term.

⁴ This section follows the model developed by Rahm and Huffman (1984).

Producers are assumed to choose the technology which gives them the highest level of utility. Thus the i^{th} firm will adopt minimum tillage technology if U_{1i} is greater than U_{0i} . We define a variable Y_i such that:

$Y_i = 1$ if $U_{0i} < U_{1i}$, the producer adopts minimum tillage technology

$Y_i = 0$ if $U_{0i} \geq U_{1i}$, the producer does not adopt minimum tillage technology

The conditional probability of the occurrence of Y_i given a vector of regressors X_{ij} is given by the following:

$$\begin{aligned} f(Y_i = 1 | X_{ij}; \theta_0) &= F(X'_{ij} \theta_0) \\ f(Y_i = 0 | X_{ij}; \theta_0) &= 1 - F(X'_{ij} \theta_0) \end{aligned} \quad (3.3)$$

Where X_{ij} is a vector of regressors specific to each producer (i) and characteristic (j), θ_0 is the technology variable, and $F(X'_{ij} \theta_0)$ is the cumulative distribution function of the standard normal distribution.

We can write the probability of $Y_i=1$ as a function of the firm specific characteristics.

$$\begin{aligned} P_i &= \Pr(Y_i = 1) = \Pr(U_{0i} < U_{1i}) \\ &= \Pr(X_{ij}\alpha_0 + e_{0i} < X_{ij}\alpha_1 + e_{1i}) \\ &= \Pr[e_{0i} - e_{1i} < X_{ij}(\alpha_1 - \alpha_0)] \\ &= \Pr(\mu_i < X_{ij}\beta) = F(X_{ij}\beta) \end{aligned} \quad (3.4)$$

where $\Pr(\cdot)$ is a probability function, $\mu_i = e_{0i} - e_{1i}$ is a random disturbance term, $\beta = \alpha_1 - \alpha_0$ is a coefficient vector, and $F(X_{ij}\beta)$ is the cumulative distribution function for μ_i evaluated at $X_{ij}\beta$. Therefore, the probability of the i th firm adopting minimum tillage technology is the probability that the utility of conventional tillage technology is less than the utility of minimum tillage technology or the cumulative distribution

function F evaluated at $X_{ij}\beta$. The exact distribution of F depends on the distribution of the random term $\mu_i = e_{01i} - e_{1i}$. If μ_i is normal, then F is a cumulative normal distribution; and if μ_i is uniform, then F is triangular.

The marginal effect of a variable X_{ij} on the probability of adopting minimum tillage technology is $\partial P_i / \partial X_{ij} = f(X_{ij}\beta) \cdot \beta_j$, where $f(\cdot)$ is the marginal probability density function of μ_i . The direction of the marginal effect is determined by the sign of β_j ; β_j represents coefficient differences $\alpha_{1j} - \alpha_{0j}$. Thus, β_j is expected to be positive (negative, zero) if α_{1j} is positive and greater than (less than, equal to) α_{0j} .

3.4 Aggregated versus Micro-data

The use of a large micro-data set for the empirical work of this analysis may yield new information about the adoption of minimum tillage technology as compared with the results obtained from the use of more aggregated data. Using micro-data eliminates the aggregation bias. In addition, a wider variety of variables are able to be examined, in particular human capital variables are able to be considered. It is thought that human capital variables play a significant role in determining whether minimum tillage technology is adopted. (Rahm and Huffman 1984)

3.5 Chapter Summary

The adoption of minimum tillage technology and practices is a dichotomous problem, meaning that a producer will either use the technology or they will not. A

Probit model, adapted from the work done by Rahm and Huffman (1984) will be used for the empirical work of this research.

As examined in the previous chapter there are several socio-economic, farm, and regional characteristics which play a role in determining whether minimum tillage technology is adopted. Several of these variables are included in the empirical work for this research. In addition, several other variables are also included which are thought to play an influential role in the adoption of minimum tillage technology decision.

CHAPTER FOUR: PROBIT MODEL SPECIFICATION

This chapter sets up the Probit model that is used in Chapter Five for the empirical work of this analysis. In addition, the basic characteristics of the data set will be discussed, including the descriptive statistics for each of the explanatory variables employed in the model.

The objective of this thesis is to determine which socio-economic, farm, and regional characteristics are influential in determining whether a producer adopted minimum tillage technology. In addition, this analysis tests whether the adoption of minimum tillage technology follows the technology adoption bell curve.

4.1 Explanatory Variables

The explanatory variables in the model have been chosen based on a number of journal articles discussed in the literature review regarding technology adoption in agriculture. Some additional explanatory variables are included that have not been included in previous studies. This was made possible because of the availability of micro-data, for example, the variables chosen for the model represent the socio-economic, farm, and regional characteristics that have been found to influence or that are hypothesized to influence agriculture technology adoption.

4.2 Analysis Region

Data from Alberta, Saskatchewan, and Manitoba are used for the empirical analysis. The three Prairie Provinces were chosen because of their similar mix of agriculture production, meaning that their growing conditions, crop rotations, and tillage practices are similar. Agriculture in other parts of Canada is different from that on the Prairies, for example British Columbia has more orchards and vineyards while Ontario and Quebec have more dairy farms.

4.3 Data Sources

The primary data source for this study is the Canadian Agriculture Census for the years 1991, 1996, and 2001. However, additional data from the Census of Population, Prairie Farm Rehabilitation Administration (PFRA), Agriculture and Agri-Food Canada (AAFC), and the Soil Science Department at the University of Saskatchewan are used. The combination of data sources allows for the inclusion of producer, farm, and regional characteristics in the analysis.

Tillage practice data from the 1991, 1996, and 2001 Agriculture Censuses is used to test whether the adoption of minimum tillage technology and practices follow the bell curve of the technology adoption life cycle. Tillage data prior to 1991 are not available. This creates some problems in testing whether the adoption of minimum tillage technology follows the bell curve of the technology adoption life cycle, since the adoption of minimum tillage technology began prior to 1991.

The Agriculture and Population Censuses are conducted by Statistics Canada every five years. The Agriculture Census is completed by everyone who has, or has the potential to have farm income; this includes hobby farmers with less than a quarter

section of land to corporate farmers with hundreds of quarter sections of land. If there is more than one producer on a farm only the primary operator completes the Agriculture Census, thus each operation is only reported once. The Population Census has two forms, a short form and a long form. The short form is completed by 80% of households in Canada, while the remaining 20% fill out the long form. Linkages between the Agriculture Census and the long form of the Population Census were required for the analysis; therefore the data set represents 20% of all farms in Alberta, Saskatchewan, and Manitoba.

Farm level data cannot be linked from one census year to another due to government confidentiality restrictions. This means variables for a particular farm cannot be lagged from one census year to another, however, some variables, such as gross sales and weather are lagged because of how the question is asked. The inability to link particular operations between census years is a problem, however it is one that will have to be dealt with in another study.

Weather data were obtained from Prairie Farm Rehabilitation Administration (PFRA). This data contained average maximum temperature and total precipitation for the months of April, May, June, and July. Data for the following years were collected: 1990, 1995, and 2000. The data were broken down by weather stations, often there is more than one weather station in each census division (CD). The raw weather data were modified in the Canada Rural Economy Research Lab (C-RERL), where with the use of Geographic Information Systems (GIS) an average weather observation was found for each CD using all weather stations within the CD.

Soil data were obtained from the Department of Soil Science in the College of Agriculture at the University of Saskatchewan. Due to government confidentiality

restrictions with the Census data, soil data cannot be linked with each producer's land, therefore soil type percentages were used for each CD. For each CD the percentage of gray, dark gray, dark brown, brown, black, and unknown soils was calculated.

Research farm data were obtained from Agriculture and Agri-Food Canada. Physical addresses were taken and then plotted in the C-RERL lab using GIS technology. A dummy variable was created where one, means that a research farm was located in a particular CD while a value of zero, means that no research farm was located in a particular CD.

The models are run using panel data, meaning that a combination of cross-sectional and time series data is used for the analysis. Panel data allows us to see if there is a time trend in the data.

4.4 Data Sorting

The Agriculture and Population Census data were cleaned by eliminating those farms that were not primarily grain based or had an 'unusual' operating structure, such as corporate farms and Hutterite colonies. As well, those farms that were deemed to be 'small' were also eliminated, that is farms that were less than 160 acres in size were eliminated from the data set. This was done because farms smaller than 160 acres are not using the land for growing crops that can be farmed under minimum tillage practices.

4.5 Model

Equation 4.1 below depicts the Probit model that was estimated with the data set(s).

$$\begin{aligned}
 F[\text{Prob}(\text{MinTill}_{t,i,j})] = F[P(Y = 1|X)] = F[\beta_0 + \beta_1 AB_{t,j} + \beta_2 Labor_{t,i} + \beta_3 Young_{t,i} + \\
 \beta_4 Male_{t,i} + \beta_5 Post_{t,i} + \beta_6 NWork_{t,i} + \beta_7 Resid_{t,i} + \beta_8 Sfallow_{t,i} + \beta_9 \ln Age_{t,i} + \beta_{10} \ln TFArea_{t,i} + \\
 \beta_{11} \ln Own_{t,i} + \beta_{12} \ln ValMch_{t,i} + \beta_{13} \ln ValBOwn_{t,i} + \beta_{14} \ln ValBRnt_{t,i} + \beta_{15} RFarm_{t,j} + \\
 \beta_{16} \ln Black_{t,j} + \beta_{17} \ln Brown_{t,j} + \beta_{18} \ln DarkGray_{t,j} + \beta_{19} \ln DarkBrown_{t,j} + \beta_{20} \ln Gray_{t,j} + \\
 \beta_{21} OpStruc_{t,i} + \beta_{22} \ln Age_{t,i}^2 + \beta_{23} \ln TFArea_{t,i}^2 + \beta_{24} Time + \beta_{25} \ln AprMax_{t-1,j} + \\
 \beta_{26} \ln Apr Precip_{t-1,j} + \beta_{27} \ln MayMax_{t-1,j} + \beta_{28} \ln May Precip_{t-1,j} + \beta_{29} \ln JunMax_{t-1,j} + \\
 \beta_{30} \ln Jun Precip_{t-1,j} + \beta_{31} \ln JulMax_{t-1,j} + \beta_{32} \ln Jul Precip_{t-1,j} + \beta_{33} \ln Precip_{t-1,j} + \varepsilon_{ij}]
 \end{aligned}
 \tag{4.1}$$

Where: t = time period, i = farm/producer, and j = CD.

Table 4.1 below gives a description of each of the variables included in the econometric model together with the source of the data.

Table 4.1: Description and Source of Data

Variable	Description	Source
MinTill	Use of minimum tillage technology and practices; $Y = 1$ if minimum tillage is used and $Y = 0$ if minimum tillage is not used	Agriculture Census
AB	Dummy variable = 1 if Alberta	N/A
Labor	Dummy variable = 1 if more than one operator	Agriculture Census
Young	Dummy variable = 1 if there is an operator younger than 35 involved in the operation	Agriculture Census
Male	Dummy variable = 1 if primary operator is male	Agriculture Census
Post	Dummy variable = 1 if primary farm operator obtained more than grade 12 education	Census of Population
NWork	Dummy variable = 1 if primary operator spends more than 20 hours per week at off-farm work	Agriculture Census
Resid	Dummy variable = 1 if primary producer resides on the operation	Agriculture Census

Table 4.1 Continued: Description and Source of Data

Variable	Description	Source
Summerfallow	Dummy variable = 1 if summerfallow is practiced on the operation	Agriculture Census
Age	Age of primary farm operator (years)	Census of Population
TFArea	Total farm area (acres)	Agriculture Census
Sales	Gross Sales (dollars)	Agriculture Census
Own	Proportion of total farm area that is owned	Agriculture Census
ValMch	Value of machinery (dollars)	Agriculture Census
ValBOwn	Value of buildings owned (dollars)	Agriculture Census
ValBRnt	Value of buildings rented (dollars)	Agriculture Census
RFarm	Dummy variable = 1 if research farm in located within CD	AAFC
Black	Proportion of black soil in CD	Soil Science Department
Brown	Proportion of brown soil in CD	Soil Science Department
Dark Gray	Proportion of dark gray soil in CD	Soil Science Department
Dark Brown	Proportion of dark brown soil in CD	Soil Science Department
Gray	Proportion of gray soil in CD	Soil Science Department
OpStruc	Dummy variable = 1 if operation has a corporate operating structure	Agriculture Census
Time	Variable to account for technological change that occurs with time (1 = 1991, 2 = 1996, 3 = 2001)	N/A
AprMax	April average maximum temperature (Celsius)	PFRA
AprPrecip	Total April precipitation (millimeters)	PFRA
MayMax	May average maximum temperature (Celsius)	PFRA
MayPrecip	Total May precipitation (millimeters)	PFRA
JunMax	June average maximum temperature (Celsius)	PFRA
JunPrecip	Total June precipitation (millimeters)	PFRA
JulMax	July average maximum temperature (Celsius)	PFRA
JulPrecip	Total July precipitation (millimeters)	PFRA
Precip	Total precipitation for April to July (millimeters)	PFRA

Source: Author

4.6 Description of Explanatory Variables

A location dummy variable for Alberta was created to measure the province affect. The goal of this dummy variable is to capture the affect of policies implemented by a particular province that either encourages or discourages the adoption of minimum tillage technology and practices. In addition, the dummy variable captures any regional differences that are not captured by the other explanatory variables. It was hypothesized that Saskatchewan and Manitoba remain as one group because they rely heavily on agriculture, whereas Alberta receives a large portion of its income from oil and gas revenue.

When there is more than one operator on an operation, each operator is able to specialize in specific tasks. This allows them to gain additional knowledge on the most recent technology innovations and practices in their area of expertise. The end result is an operation that is able to make a more informed decision more quickly on new innovations and practices. This does not mean that an operation with a single operator cannot make an informed decision, rather it is easier for an operation with more than one operator to do so.

A ‘young’ dummy variable was included in the model to account for the presence of a young operator in a multi-generational operation. If there was a producer on the operation aged 35 or younger, the operation is considered to have a young operator. In multi-generational farms each of the operators has input into operational decisions, therefore even if the primary farm operator is older, the young operator(s) may have significant influence on technology adoption decisions. As well, multi-generational operations have a longer planning horizon as compared with a single operator farm whose primary producer is older.

A higher level of education attainment is hypothesized to enable producers to deal with new information at a faster rate than those with lower levels of education (Schultz, 1982). This does not mean that a higher level of education attainment increases the probability of adopting minimum tillage technology; rather it means that the producer makes a more informed decision more quickly on whether the adoption of new technology will benefit the operation. Producers with higher levels of education are better able to weigh the pros and cons of new technology and practices before adopting them (Schultz, 1982). In the model a post secondary dummy variable was created for producers who had obtained an education certificate past grade 12, that is they had a post secondary certificate, diploma, or degree.

Hours of non-farm work per week was included to measure the amount of time a producer spends away from their agriculture operation each week at other paid employment. An increase in the hours of non-farm work can lead to an increased probability of adopting minimum tillage technology to reduce the number of times the land must be worked. On the other hand, it can be that the producer does not rely as heavily on farm income for household income, thus they are not as likely to adopt the latest technology to improve the economic and environmental viability of the farm. In the model non-farm work is measured with a dummy variable, if a producer spends more than 20 hours per week at paid off-farm work they are considered to work off the farm. A dummy variable was used instead of a continuous variable because the Agriculture Census question was separated into twenty hour segments.

Producers who reside on the farm are often more devoted to the farm and follow the most recent trends in technology and practices, whereas a producer residing off the farm may not rely as heavily on the agriculture operation for household income. Thus, the

residence of the primary producer can be influential in determining how much effort a producer puts into their operation.

Age of the primary farm operator is included in the model because it is thought that age plays a determining role in ones perception of new technology. Older producers are nearing the end of their farming careers and are looking to retire. Given their shorter planning horizons it is not economically viable for them to adopt a new technology if they are unable to recapture the capital cost of the equipment. Therefore, older producers are less likely to adopt new technology and practices.

Total farm area is measured using acres farmed. Total acres farmed is an important explanatory variable because the more acres cultivated, the greater gross farm sales, which results in more financial resources to make capital purchases. In addition, larger farms are more likely to achieve economies of scale because of their larger output. As well, equipment does not come in small sizes. A squared farm size variable is included to test whether large farms adopt minimum tillage technology at a different rate than smaller farms.

As the value of gross sales increase for an operation so does net income (assuming a fixed net return per acre); therefore the operation has more money to put towards the purchase of new capital equipment. Total acres farmed and gross sales move in the same direction; this means *ceteris paribus* an increase in acres farmed causes an increase in gross sales. In addition, an increase in gross sales caused by an increase in acres farmed can lead to an increased need for new and/or additional equipment. Since gross sales and total acres farmed are highly correlated only one will be included in the model at a time.

Land tenure has an impact on whether soil conservation technology is adopted. It has been found that land owners are most likely to adopt soil conserving technology and practices, while cash renters are least likely to adopt it (Soule et al., 2000). Sharecroppers fall somewhere between land owners and cash renters. In this model land tenure is measured by the proportion of total farm area that is owned.

The value of capital assets owned by a particular operation plays a determining role in accessing credit. As the value of capital assets increases so does ones collateral, thus the ability to borrow money for the purchase of new capital equipment increases.

Research farms play an influential role in a producer's decision making process. Often research farm employees are the first to tell producers about the most recent innovations in farming practices and technology. If not research farm employees then it is often farm implement dealers and chemical and/or other input representatives. In this model, access to a research farm is based on the location of a research farm within the same CD as the farm.

Different soil types respond differently to minimum tillage technology and practices. This means that minimum tillage technology is better suited to some soil types, therefore it is not an ideal tillage technology for all soil types. To capture the differences in soil types, the proportion of each black, brown, dark gray, dark brown, and gray soil in each CD was calculated.

Having a corporate operating structure can be an indication of how a producer views corporate tax advantages, i.e. lower tax rates and the ability to depreciate capital assets. An operation that is profit driven analyzes new technology and practices as they become available and consider the benefits to their operation. Since having a corporate operating structure involves a cost and extra book keeping an operation will be

incorporated when it is profitable for them to do so, therefore this is an indication of how the operator views the benefits of various tax provisions. Operations that have a corporate operating structure are separated from those operations that are sole-proprietorships or partnerships.

A time dummy variable is included to measure the effect that time and technological change has on the adoption of minimum tillage technology. As time increases it is thought that adoption will increase because producers have seen the technology in use by their neighbors and their own equipment may be nearing the end of its useful life. Values of 1, 2, and 3 were assigned to 1991, 1996, and 2001 respectively.

A decrease in soil temperature caused by an increase in residue on the surface of the soil is a benefit of using minimum tillage technology and practices. Since average air temperatures have a direct impact on soil temperatures, average maximum temperatures for April, May, June, and July are included in the model. The inclusion of average maximum temperatures allows for regional comparisons. Agriculture areas that have problems with cooler soil temperatures are less likely to adopt minimum tillage technology because it would be detrimental to their crop's development.

One of the benefits of minimum tillage technology and practices is increased retention of soil moisture, therefore a precipitation variable is included in the model. Total precipitation for each of the growing season months (April, May, June, and July) is included, as well as total precipitation for the four months combined. It is critical that producers receive the appropriate amount of precipitation over the growing season in order to produce good crops.

An environmental damage variable was not included in the model because no variable was available. As well, no proxy variable was available. This means that

actual environmental damage or a producer’s perception of environmental damage is not included in this analysis.

4.7 Hypothesized Coefficient Signs

Table 4.2 below reports the hypothesized sign of the explanatory variables included in the empirical model. An explanation of the hypothesized coefficient sign is also included.

Table 4.2: Expected Relationships between the Adoption of Minimum Tillage and Explanatory Variables

Variable	Expected Sign	Explanation
Research Farm	+	If a research farm is located within the same CD as a producer’s operation the more likely the producer is to learn of new developments, both in terms of technology and practices.
Age of primary farm manager	-	As the age of the primary farm operator increases it is expected that the probability of adopting minimum tillage technology and practices decreases, since the adoption of minimum tillage technology is a long term planning decision.
Total Farm Area	+	The greater the number of acres farmed the more likely an operator is to adopt minimum tillage technology. A larger farm has more acres to spread the capital cost over, as well they have to replace their equipment more often because of wear.
Precipitation (April, May, June, July, and Total)	-	It is expected that as precipitation over the growing season increases the adoption of minimum tillage technology and practices will decrease. This is because soil moisture is not a significant concern when adequate precipitation is received. In addition, too much moisture is bad for proper crop development.
Average Maximum Temperature (April, May, June, and July)	+	As average maximum temperatures increase the adoption of minimum tillage technology will also increase. This is because the increased residue on the soil surface will keep the soil cooler, which is beneficial.

Table 4.2 Continued: Expected Relationships between the Adoption of Minimum Tillage and Explanatory Variables

Variable	Expected Sign	Explanation
Education Attainment	Priori Unknown	As education attainment levels increase, producers are able to make more informed decisions. Since minimum tillage technology and practices are not suitable under all scenarios, the expected sign is unknown.
Total Gross Farm Sales	+	An increase in gross farm sales is expected to increase the probability of adopting minimum tillage technology and practices, since producers now have a larger income to afford the capital cost of new technology.
Labor	+	The more operators an operation has the more opinions and thoughts that go into a decision making process. Therefore, if minimum tillage technology is beneficial to an operation it is more likely they will adopt it. As well, an increase in the number of operators on an operation means an increase in total acres farmed.
Young	+	Younger operators are more likely to act favorably towards new technology, therefore they are more likely to adopt. In addition, young farmers have longer planning horizons in order to spread the capital cost over.
Summerfallow	-	A negative relationship is expected between the adoption of minimum tillage technology and summerfallow. In most cases land under minimum tillage management does not incorporate summerfallow into the crop rotation.
Own	+	Land owners benefit from an increase in land quality when they sell or rent their land. Since minimum tillage technology and practices maintain or increase the quality of soil a positive relationship is expected.
Capital Assets	+	As the value of capital assets increases, so does collateral and the ability to borrow money for future capital purchases.
AB	Priori Unknown	N/A
NFWork	-	As the number of hours a producer spends at off-farm employment increases the less likely they are to be dependent on farm income to support the household, thus the less likely they are to keep up to date on the latest developments in technology and practices.

Table 4.2 Continued: Expected Relationships between the Adoption of Minimum Tillage and Explanatory Variables

Variable	Expected Sign	Explanation
OpStruc	+	Operations that are incorporated are expected to have less capital restraints, thus they will keep up to date on the latest technology and practices and adopt whenever it is beneficial for them to do so.
Resid	+	A producer who lives on their operation sees it everyday and may be more aware of the operation. As well, they may be more reliant on the farm for household income.
Black, Dark Brown, Gray, and Dark Gray	+	Most years farms located in the black, dark brown, gray, and dark gray soil zones receive an adequate amount of precipitation during the growing season to grow a crop; however, the increase in the amount of residue on the soil surface can benefit the crops by providing extra moisture to grow a better crop. In addition, these soils are able to maintain higher levels of soil organic matter, which is beneficial to crop development.
Brown	-	Farms located in CD's with a large proportion of brown soil are prone to water shortage problems. These problems are so great that even the benefits provided by minimum tillage technology and practices are not enough to offset the water shortage.
Time	+	As time goes on (measured by year in this model) more producers are expected to adopt minimum tillage technology. This happens for a number of reasons, including: technological improvements, the neighbor effect, and need to replace old equipment with new.

Source: Author

4.8 Descriptive Statistics

Descriptive statistics for the variables included in the models can be found in Table 4.3 below. The descriptive statistics in this table are for the entire stacked data set (1991, 1996, and 2001 censuses) and includes both adopters and non-adopters. t-statistics were run on the explanatory variables to compare the difference in means between adopters and non-adopters. If the difference between the two group's means

was significant at the 95% level, the variable is expected to be significant in the model. The variable is expected to not be significant if there was little or no difference between the two group's means. The total sample size is 42,573, consisting of 7,903 adopters and 34,670 non-adopters. Due to the large sample size (more than 42,000 observations) any t-value greater than 1.96 in absolute terms is considered significant at the 95% confidence level. As illustrated in Table 4.3 below, there are a number of variables with significant differences between the adopters and non-adopters of minimum tillage technology and practices.

Table 4.3: Comparison of Adopter and Non-Adopter Means

Variable	Adopters		Non-Adopters		t-value
	Mean	Standard Deviation	Mean	Standard Deviation	
Alberta dummy variable	0.18	0.84	0.29	1.00	-20.10
Labor dummy variable	0.31	1.01	0.27	0.98	6.94
Young dummy variable	0.20	0.87	0.18	0.84	4.85 ⁵
Male dummy variable	0.96	0.44	0.96	0.44	-1.06
Post Secondary Education dummy variable	0.50	1.09	0.53	1.10	-4.18 ⁵
Non-Farm Work dummy variable	0.25	0.95	0.26	0.97	-2.05 ⁵
Residence dummy variable	0.79	0.89	0.80	0.89	-1.27
Summerfallow dummy variable	0.61	1.06	0.61	1.07	0.42
Age (years)	48.5	29.7	50.9	31.80	-13.81

⁵ The difference between the adopters and non-adopters mean value is small at 0.02, however, the t-statistic is significant. Each of these has small standard deviation values, which result in a large t-statistic.

Table 4.3 Continued: Comparison of Adopter and Non-Adopter Means

Variable	Adopters		Non-Adopters		t-value
	Mean	Standard Deviation	Mean	Standard Deviation	
Total Farm Area (acres)	1,521	2853	967	2,130	42.58
Total Sales (dollars)	150,694	360,745	86,372	273,554	38.65
Proportion of Owned Land	0.68	0.71	0.74	0.71	-14.75
Machinery Value (dollars)	220,618	487,491	141,285	356,868	36.17
Value of Owned Buildings (dollars)	410,127	1,021,349	280,998	827,437	26.12
Value of Rented Buildings (dollars)	197,404	875,910	107,905	672,432	21.96
Research Farm dummy variable	0.34	1.03	0.24	0.9440	17.80
Proportion of Black Soil	0.31	0.70	0.37	0.7355	-14.80
Proportion of Brown Soil	0.23	0.74	0.13	0.62	25.98
Proportion of Dark Gray Soil	0.05	0.23	0.10	0.29	-26.36
Proportion of Dark Brown Soil	0.31	0.68	0.19	0.62	32.35
Proportion of Gray Soil	0.10	0.42	0.19	0.58	-31.07
Operating Structure dummy variable	0.14	0.77	0.07	0.56	21.15
Time dummy variable	2.19	1.72	1.84	1.75	35.09
Average Maximum Temperature of Previous April (Celsius)	9.39	5.15	8.76	5.38	20.92
Total Precipitation of Previous April (millimeters)	29.10	21.94	29.87	23.84	-5.75
Average Maximum Temperature of Previous May (Celsius)	17.57	2.29	17.35	2.50	15.94
Total Precipitation of Previous May (millimeters)	45.69	50.54	44.51	51.68	4.03

Table 4.3 Continued: Comparison of Adopter and Non-Adopter Means

Variable	Adopters		Non-Adopters		t-value
	Mean	Standard Deviation	Mean	Standard Deviation	
Average Maximum Temperature of Previous June (Celsius)	22.25	4.35	22.39	4.24	-5.75
Total Precipitation of Previous June (millimeters)	76.21	56.59	80.30	65.84	-11.17
Average Maximum Temperature of Previous July (Celsius)	24.83	3.06	24.10	3.24	40.14
Total Precipitation of Previous July (millimeters)	74.60	71.94	79.37	68.58	-12.09
Total Precipitation for April to July of Previous year (millimeters)	225.57	114.15	234.05	116.41	-1.28

Source: Statistics Canada, PFRA, and University of Saskatchewan Soil Science Department

4.9 Chapter Summary

This chapter outlines the empirical model that is used to test the objectives of this analysis. Each of the explanatory variables is discussed. Descriptive statistics were run on the stacked data set containing both adopters and non-adopters; in addition t-statistics comparing the two groups were run. A number of variables had significant t-statistics, therefore a number of variables are expected to be significant in the empirical model.

CHAPTER FIVE: RESULTS AND DISCUSSION

The objective of the empirical work for this analysis is to test the predictions of the theoretical model. It was hypothesized that the adoption of minimum tillage technology and practices is dependent on a number of socio-economic, farm, and regional characteristics. A number of different model specifications and sensitivity analyses were run, however, only the results from the preferred model are discussed in detail.

5.1 Hypothesis

H1: The adoption of minimum tillage technology is based on profitability, socio-economic factors, farm characteristics, and regional characteristics (such as extension and research services).

H2: The adoption of minimum tillage technology follows the bell curve of the technology adoption life cycle.

5.2 Interpretation of Models

The dependent variable for all models is the use of minimum tillage technology. Data cannot be linked from one census year to another without going through a long government security approval process, which was not feasible given the time limitations of this research. Therefore, the dependent variable is 'use'. Thus, it cannot be

determined if the farm had adopted the technology since the previous census or if they were long time users of minimum tillage technology and practices.⁶

To determine the ‘best’ Probit model the log likelihood value was analyzed. The larger the log likelihood value, the better the model fit. One important point to consider is that as the sample size increases the log likelihood value decreases. This means that the log likelihood values cannot be compared between different data sets because of the influence sample size has on the value.

A constant model, a model that contains a constant term and no explanatory variables, was run on each of the different data sets. This is done to compare the log likelihood values of the constant model with models that contain explanatory variables. A large log likelihood value is preferred. It is expected that a model containing explanatory variables will have a larger log likelihood value as compared with a constant model; otherwise the chosen explanatory variables do not have a significant influence on the dependent variable.

The percent correctly predicted was used to measure how often the model correctly predicted adoption or non-adoption. In addition, weighted averages of the percent correctly predicted were found⁷, this was done to eliminate the effects of when a

⁶ This means that producers who are using minimum tillage technology in the current time period, but adopted the technology in previous time periods do not have the same set of characteristics that they had at the time of adoption. For example, if they adopted the technology ten years prior to the census they would have been ten years younger, possibly had a smaller land base, less gross farm sales, and so forth. This means that the significance of some variables may be over or under stated.

⁷ If $F(\alpha + \beta X_{ij}) \geq 0.5$ then set it equal to 1; if $F(\alpha + \beta X_{ij}) < 0.5$ set it equal to 0. Then the weighted average percent correctly predicted can be found by using the following formula:
$$[[(\Pr(Y_i = 1) / N) * \Pr(Y_i = 1 | F(.) \geq 0.5) + (\Pr(Y_i = 0) / N) * \Pr(Y_i = 0 | F(.) < 0.5)] / N] * 100$$

model incorrectly predicts an outcome of 0. Therefore, the percent correctly predicted and weighted average percent correctly predicted are better for the analysis of the different model specifications and sensitivity analyses as compared with the log likelihood value, particularly when the same data are not always used.

The estimated coefficients from a Probit model do not have a direct economic interpretation, therefore they must be manipulated in order to analyze the results. To do this marginal effects are calculated to determine the effect each variable has on the probability of adoption. Marginal effects measure the percentage change in the probability of adoption given a one unit change in the independent variable, while holding all other explanatory variables constant. Marginal effects for dummy variables are calculated at their modal values. While marginal effects for other variables are calculated at their mean values.

The census data came with weights for each observation because the data represents a 20% sample of Prairie farms. The weight variable represents the number of farms in the entire sample (100% of Prairie farms) with those particular characteristics. The weight variable is calculated whenever a data set is created from a sample of the population. The majority of models run in this analysis included the weighted variable, although some were run without to analyze the impact of it on parameter estimates. The log likelihood value increased when the weight variable was not included in the model, however, there was no change in the percent correctly predicted. Since results between the models run with the weight variable and without did not differ significantly, it was concluded that the weight variable did not play a significant role.

5.3 Comparison of Model Results

A model (specification to be discussed later in this chapter) was run on 1991 data, 1996 data, 2001 data, and finally a stacked data set with all three census years included. Log transformed data were used to reduce the variance amongst the observations whenever it was possible to do so. Results from these four regressions can be found in Table 5.1.

Table 5.1: Comparison of Different Data Sets

	% Correctly Predicted	Weighted Average % Correctly Predicted	Log Likelihood Value⁸	Constant Log Likelihood Value
1991	88.54%	79.63%	-24,638	-33,812
1996	81.18%	67.69%	-29,787	-33,546
2001	75.21%	54.92%	-29,623	-27,550
Stacked	81.87%	68.00%	-85,832	-97,799

Source: Author's Calculations

The weighted averages of the percent correctly predicted were all less than the percent correctly predicted values, however, all were still acceptable levels. The percent correctly predicted for the models ranged between 75 and 88%, which is considered a good prediction rate. With the exception of the 2001 data, the log likelihood values of the regressions with explanatory variables were an improvement over the constant model. The log likelihood value of the 2001 regression with explanatory variables was worse than that of the constant model.

⁸ This column shows the log likelihood values from regressions that were run with explanatory variables.

As can be seen in Table 5.1 above the 1991 data fit the model best, followed by the 1996 and stacked data sets, and finally the 2001 data set fits the data 'poorest'. From these initial results, the stacked data set was chosen to use in future models. This decision was made because the stacked data contains all the data and thus the results are more meaningful and relevant with its inclusion. By using only the 1991 data the results are 15 years old, thus their impact on today's and future decisions is limited. As well, using the stacked data set allows for the analysis of the impact of time on the decision of whether to adopt minimum tillage technology and practices. The use of the stacked data makes this analysis relevant to business and policy decisions that are being made today.

As illustrated in Table 5.1 above the model's ability to correctly predict adoption declines as time goes on, that is the 1991 model had the best percent correct prediction while the 2001 model had the 'poorest' percent correct prediction. This provides tentative support for the technology adoption life cycle, which is as time goes on less producers are adopting minimum tillage technology and practices for the first time.

5.4 Model Results

A total of twelve different model specifications and sensitivity analyses were run using the stacked data set. Results from all of these models are not included because all had a good fit and the results did not vary significantly between different model specifications. Percent correctly predicted by these different model specifications and sensitivity analyses ranged from a low of 81.63% to a high of 82.07%. As can be seen from the percent correctly predicted, the ability of the different models to correctly predict adoption did not vary significantly. The majority of the models had the same significant variables, such as Alberta dummy variable, summerfallow, age, farm size,

black, brown, and dark gray soils, corporate operating structure, time average maximum April and June temperature, and total June precipitation, thus yielding consistent results amongst the different models. This gives the results more support in the decision making process as to when producers adopt minimum tillage technology. The preferred specification results are presented below in Table 5.2, while results from other models are presented in Tables 5.3 to 5.5.

Table 5.2: Preferred Specification Results

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Intercept	-2.8665	n/a	1.5109	0.0803
AB	-0.3931	-0.0844	0.0307	<0.0001
Labor	0.0070	0.0017	0.0173	0.6979
Young	0.0267	0.0063	0.0261	0.3348
Male	-0.1258	-0.0315	0.0384	0.0017
Post Secondary Education	-0.1040	-0.0246	0.0746	0.1833
NFWork	0.0060	0.0014	0.0200	0.7735
Residence	-0.0505	-0.0121	0.0195	0.0142
Summerfallow	-0.1794	-0.0432	0.0171	<0.0001
Age	1.0706	0.2527	0.5361	0.0682
Sales	0.1843	0.0435	0.0110	0.5530

Table 5.2 Continued: Preferred Specification Results

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Own	0.0093	0.0022	0.0152	<0.0001
ValMch	-0.0022	-0.0005	0.0053	0.6824
ValBOwn	0.0065	0.0015	0.0031	0.0394
ValBRnt	0.0063	0.0015	0.0019	0.0010
RFarm	0.3279	0.0837	0.0806	0.0001
Black ⁹	0.0792	0.0187	0.0085	<0.0001
Brown	-0.1448	-0.0342	0.0134	<0.0001
Dark Brown	-0.0071	-0.0017	0.0050	<0.0001
Dark Gray	0.0276	0.0065	0.0058	0.1989
Gray	-0.0248	-0.0059	0.0102	0.0234
OpStruc	0.0788	0.0192	0.0255	0.0028
AgeSqd	-0.1972	-0.0466	0.0750	0.0156
Time	0.3575	0.0844	0.0455	<0.0001
Farm Post	-0.0110	-0.0026	0.0350	0.7657
Age RFarm	0.0032	0.0007	0.0012	0.0107
Age Post	0.0012	0.0003	0.0012	0.3653
Apr Max	0.3198	0.0755	0.0472	<0.0001
Apr Precip	0.0222	0.0052	0.0239	0.3734

⁹ The proportion of black soil in a particular CD was logged, however, the value should not have been logged because values of proportions of 0 and 1 were then treated the same. Due to time and location circumstances the model cannot be re-run. Of the total data set 0.7% of the observations are affected, thus this is not a significant problem for the final results. The result of using the logged value is that the significance of black soil in the decision to adopt minimum tillage will be understated, but since the variable is significant the problem is not of major concern.

Table 5.2 Continued: Preferred Specification Results

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
May Max	-0.3316	-0.0783	0.1717	0.0646
May Precip	0.0654	0.0154	0.0205	0.0028
Jun Max	0.8456	0.1997	0.2306	0.0003
Jun Precip	-0.1723	-0.0407	0.0291	<0.0001
Jul Max	-0.9295	-0.2194	0.3142	0.0039
Jul Precip	-0.0390	-0.0092	0.0237	0.1201
Precip	-0.1041	-0.0246	0.0389	0.0120
TFArea Time	0.0000136	3.20e-06	4.30e-06	<0.0001
Post Time	0.0809	0.0191	0.0223	0.0005
AgeTime	0.0014	0.0003	0.0008	0.0713
RFarm Time	-0.0139	-0.0328	0.0222	<0.0001
Black Time	-0.1504	-0.0355	0.0211	<0.0001
Brown Time	0.0101	0.0024	0.2213	0.6648
Dark Gray Time	-0.4343	-0.1025	0.0402	<0.0001

Source: Author's Calculations

Gross farm sales and total farm area move together, that is as acres farmed increase so does gross sales, *ceteris paribus*. To prevent collinearity total acres farmed and total gross sales are not included in the same model. Therefore, some models were specified with total acres farmed as an independent variable and others were specified with gross farm sales. Results from the models did not vary significantly. The preferred model uses gross sales as an explanatory variable.

Heteroscedasticity was not a large problem in the models, possibly due to the large sample size. However, even though it was not a large problem precautions were taken and the robust command in STATA was used. Results between SAS and STATA were identical, this means that the standard errors in all models presented do not have heteroscedastic errors.

Multicollinearity was not a major problem in this research. Before any models were run correlation tables for all independent variables were created, after careful examination of these tables it was determined that collinearity was not a problem with any of the explanatory variables. Another point which illustrates that multicollinearity was not a problem was when models were run using only the significant variables the models were still significant. In addition, there were always a large number of variables which were significant in all the models.

5.5 Significance of t-Statistics versus Significance of Variables

As hypothesized the significant variables in the model had significant t-statistics when comparing the mean of adopters and non-adopters. However, there were three exceptions: gender, residence, and summerfallow. They were significant in the model, however, the t-statistics comparing the means of adopters and non-adopters were not significant. The gender variable was significant because 95% of producers are male, the large majority. The reasons for residence and summerfallow being significant variables, even though their t-statistics were not, are discussed later in this chapter.

5.6 Explanation of Significant Variables

5.6.1 Gross Farm Sales (Sales)

Gross farm sales is a significant variable when determining whether a producer will adopt minimum tillage technology and practices; Feder and Umali (1993) also obtained this result in their work. The result is substantiated by the fact that producers who use minimum tillage technology have average gross sales of \$150,694, while the average gross sales of non-adopters are \$86,372. As gross farm sales increase so does the ability of the producer to purchase new equipment, that is he/she is better able to afford the capital investment cost. For every one unit increase in log gross farm sales the probability of adopting minimum tillage technology increased 4.35%.

5.6.2 Residence Dummy Variable (Residence)

Residence was a significant variable; a producer who resided on the farm was less likely to adopt minimum tillage technology and practices as compared with a producer whose residence was not on the agriculture operation. This is due to at least two different reasons. First, a producer who does not live on the operation may have only a small number of acres; therefore they may have custom operators carry out the farm operations. Custom operators manage a large number of acres, thus they have the resources to adopt the latest technology if it is beneficial to their operation. Secondly, the operator who lives in town may be more likely to attend meetings where the latest technology and practices are presented and discussed as compared with a producer who must travel a long distance. A producer residing on the agriculture operation is 1.21%

less likely to adopt minimum tillage technology as compared with a producer who resides off the operation.

5.6.3 Summerfallow Dummy Variable (Summerfallow)

Producers who included summerfallow in their crop rotation were less likely to adopt minimum tillage technology. The use of minimum tillage technology and practices eliminates the need for summerfallow in the crop rotation. Based on the t-statistic which compared the difference in means between adopters and non-adopters, the variable was not expected to be significant. A producer who includes summerfallow in their crop rotation was 4.32% less likely to adopt minimum tillage technology and practices.

5.6.4 Corporate Operating Structure (OpStruc)

Farms with a corporate operating structure are more likely to adopt minimum tillage technology. There is a cost associated with incorporation, as well as some increased annual costs such as auditing and board meetings. However, for large profitable farms there is a tax incentive to incorporate as earnings are taxed at a lower rate. Another incentive with incorporation is limited liability; that is the individual farmer will lose only those assets which are part of the company rather than everything they own including personal assets. The positive sign on the corporate operating structure variable is what was hypothesized. When a farm has a corporate operating structure they are 1.92% more likely to adopt minimum tillage technology as compared with farms that are structured as partnerships or sole-proprietorships.

5.6.5 Alberta Dummy Variable (AB)

The Alberta dummy variable was a significant explanatory variable in all the model specifications and sensitivity analyses. Based on the t-statistic comparing the mean of adopters and non-adopters the variable was expected to be significant. Producers in Alberta are less likely to adopt minimum tillage technology as compared with their counterparts in Saskatchewan and Manitoba. The marginal effect of the Alberta dummy variable is -0.0845, this means that a producer living in Alberta is 8.45% less likely to adopt minimum tillage technology and practices as compared with a producer living in Saskatchewan or Manitoba. Agriculture in certain regions of Alberta is different than that in Saskatchewan and Manitoba. Differences include: large scale irrigation in southern areas of the province, Peace River area of production, and government programs and/or oil and/or natural gas revenue.

5.6.6 Soil Variables

Three of the five soil zone variables were significant in determining whether a producer would adopt minimum tillage technology and practices. This finding is supported by Gould et al. (1989) who found land quality to be a significant variable in determining tillage adoption. In this research the black, brown, and dark gray soil zones were significant. Having a large proportion of black and dark gray soil in a CD increased the probability of adopting minimum tillage technology, while having a large proportion of brown soil in a CD decreased the probability. These coefficients had the same sign as was hypothesized. In the brown soil zone lack of soil moisture is a severe problem; even though minimum tillage technology and practices increase soil moisture, it does not increase it enough for crops to properly develop. As well, farms located in

the brown soil zone are exposed to severe wind and water erosion problems. It has been found that summerfallow in the brown soil zone is more effective at retaining moisture for crops as compared with minimum tillage technology and practices (Alberta Agriculture, Food and Rural Development, 2006). Lack of moisture problems tend to not be as prevalent in the black and dark gray soil zones, therefore the use of minimum tillage technology and practices is able to build soil moisture to adequate amounts in order for a crop to properly develop. Therefore, it is unnecessary to incorporate summerfallow into the crop rotation if minimum tillage technology and practices are used in the brown and dark gray soil zones. The dark brown soil variable was not significant in all the models. Adoption of minimum tillage technology in the dark brown soil zone is based on the individual producer's preferences; since it lies between the brown and black soil zones and producers in the brown soil zone are less likely to adopt, while producers in the black soil zone are more likely to adopt. There is little evidence to suggest that it is an improvement over conventional tillage.

Black Soil (Black)

Being located in a CD with a large percentage of black soil increases the probability of adopting minimum tillage technology and practices. For a 1unit increase in the log proportion of black soil in a CD the probability of adopting minimum tillage technology and practices increases by 1.87%.

Brown Soil (Brown)

Being located in a CD with a large percentage of brown soil decreases the probability of adopting minimum tillage technology and practices. For a 1unit increase

in the log proportion of brown soil in a CD the probability of adopting minimum tillage technology decreases 3.4%.

Dark Gray Soil (Dark Gray)

Being located in a CD with a large proportion of dark gray soil increases the probability of adopting minimum tillage technology. For a 1 unit increase in the log proportion of dark gray soil in a CD the probability of adopting minimum tillage technology increases 0.65%.

5.6.7 Weather Data

A number of the weather variables were significant in the different model specifications and sensitivity analyses that were run. The significant weather variables include: average April maximum temperature, average June maximum temperature, and total June precipitation. June is a critical month for crop development; therefore it was expected that both average maximum temperature and total precipitation for June to be significant.

Average Maximum Temperature for April (Apr Max)

The probability of adopting minimum tillage technology increases as the average maximum temperature for April increases. As the air temperature increases the soil temperature also increases; thus the soil will not be too cold to seed into and for the seed to properly germinate and develop. Therefore, the increased residue on the soil surface is not a hindrance to crop development. The sign on the average maximum temperature coefficient for the previous April was the same as hypothesized. For every one unit

increase in the log April average maximum temperature the probability of adopting minimum tillage technology increased 7.55%.

Average Maximum Temperature for June (Jun Max)

The average maximum temperature for the previous June was significant in the model. The probability of adopting minimum tillage technology and practices increases as the average maximum temperature for June increases. The increased residue on the soil surface is beneficial to good crop development because it prevents the crop from drying up. As well, in a drought the residue provides protection for the crop. The sign on the maximum June temperature was the same as was hypothesized. For every one unit increase in the log average maximum daily temperature of the previous year's June the probability of adopting minimum tillage technology increased by 19.97%.

Total June Precipitation (Jun Precip)

Total precipitation for June was a significant variable; as total June precipitation increased the probability of adopting minimum tillage technology and practices decreased. If a crop has adequate moisture for development through precipitation there is little incentive for a producer to adopt minimum tillage technology and practices. This is because their crop does not yield significantly more or obtain a better grade quality to justify the capital cost of adopting minimum tillage technology. The sign of the June precipitation coefficient was the same as was hypothesized. This makes sense because as precipitation increases the need for increased drought protection decreases. For every one unit increase in the previous June's log precipitation the probability of adopting minimum tillage technology decreased 4.07%.

Uri (1998) found average rainfall to be significant; in the empirical work of this thesis June precipitation from the previous year was significant, however, average precipitation for April through July was not significant. In addition, Uri (1998) found average temperature to be not significant, while the empirical work for this thesis found average April and June average maximum temperatures to be significant.

5.6.8 Research Farm (RFarm)

The probability of adopting minimum tillage technology and practices increases if a research farm is located in the same CD as a producer. Producers who farm in a CD with a research farm are able to observe the benefits of new technology and practices more easily first hand. In addition, producers who farm in a CD with a research farm have less distance to travel and thus easier access to attend field days that are put on by the research farm. A producer who resides in a CD with a research farm is 8.37% more likely to adopt minimum tillage technology and practices as compared with a producer whose farm is in a CD with no research farm. This result is contrary to Adesina and Zinnah (1993) who found access to an extension agent to be not significant in determining whether a producer will adopt a new technology.

5.6.9 Time

The probability of adopting minimum tillage technology and practices increases as time passes. This result was expected because as time passes and the innovation has gained a reputation for itself on the market more producers are likely to use the technology. This also follows the theory of the technology adoption life cycle. As well, in this analysis the measure for minimum tillage was 'use', which means that there is a

cumulative effect on the variable. The sign on the time variable was the same as the hypothesized sign. For every increase in time period, in this case every five census years, the probability of adopting minimum tillage technology increased by 8.44%.

5.7 Sensitivity Analysis

For the sensitivity analysis a number of interactive variables were created including:

- Research farm and post secondary education
- Age and research farm
- Age and post secondary education
- Total farm area and time
- Education and time
- Age and time
- Research farm and time
- Black soil and time
- Brown soil and time
- Dark gray soil and time

These variables were included in all the estimated equations as a sensitivity test.

Below are the results from alternative model specifications and sensitivity analyses. The results amongst the different models did not vary significantly, which provides support for the results. Table 5.3 shows the results of the model run using the stacked data set and total gross sales to represent the size of the operation. Only three transformed interaction variables were included in this model. The percent correctly

predicted was 81.83% and the weighted average percent correctly predicted was 68.47%.

Table 5.3: Results from Stacked Data with Total Gross Sales

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Intercept	-4.4811	n/a	1.0447	<0.0001
AB	-0.3595	-0.0771	0.0293	<0.0001
Labor	0.0050	0.0012	0.0187	0.7896
Young	0.0209	0.0049	0.0271	0.4403
Male	-0.1586	-0.0399	0.0413	0.0001
Post secondary Education	0.0660	0.0154	0.0609	0.2785
NFWork	0.0269	0.0063	0.0230	0.2422
Residence	-0.0758	-0.0181	0.0212	0.0003
Summerfallow	-0.1327	-0.0315	0.0179	<0.0001
Age	-0.3119	0.0498	0.0175	<0.0001
Own	0.0090	0.0021	0.0164	0.5836
Sales	0.2096	0.0490	0.0094	<0.0001
ValMch	0.0005	0.0001	0.0055	0.9294
ValBOwn	0.0081	0.0019	0.0033	0.0143
ValBRnt	0.0068	0.0016	0.0020	0.0006
RFarm	0.0743	0.0177	0.0700	0.2882
Black	0.0679	0.0159	0.0084	<0.0001

Table 5.3 Continued: Results from Stacked Data with Total Gross Sales

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Brown	-0.1824	-0.0426	0.0129	<0.0001
Dark Brown	-0.0023	-0.0005	0.0054	0.6689
Dark Gray	0.0443	0.0104	0.0057	<0.0001
Gray	0.0083	0.0019	0.0106	0.4362
OpStruc	0.1405	0.0348	0.0276	<0.0001
AgeSqd	-0.1560	-0.0365	0.0250	<0.0001
Time	0.4243	0.0992	0.0232	<0.0001
RFarm Post	0.0112	0.0026	0.0355	0.7528
Age RFarm	0.0026	0.0006	0.0012	0.0331
AgePost	0.0010	0.0002	0.0012	0.4137
Apr Max	0.5143	0.1202	0.0473	<0.0001
Apr Precip	0.1589	0.0372	0.0230	<0.0001
May Max	-0.6671	-0.1560	0.1754	0.0001
May Precip	0.0391	0.0091	0.0213	0.659
Jun Max	1.6869	0.3944	0.2356	<0.0001
Jun Precip	-0.1863	-0.0436	0.0309	<0.0001
Jul Max	-0.5192	-0.1214	0.2872	0.0707
Jul Precip	-0.0092	-0.0022	0.0251	0.7132
Precip	-0.1497	-0.0350	0.0423	0.0004

Source: Author's Calculations

Table 5.4 provides results from the model run using the stacked data set and total acres farmed as the operation size variable. As well, only three transformed interaction variables were included in this model. The percent correctly predicted was 81.87% and the weighted average percent correctly predicted was 68%.

Table 5.4: Results from Stacked Data with Total Acres Farmed

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Intercept	-4.9172	n/a	0.9861	<0.0001
AB	-0.2957	-0.2731	0.0278	<0.0001
Labor	-0.0035	0.0032	0.0177	0.8445
Young	0.0145	0.0134	0.0255	0.5697
Male	-0.1379	-0.1274	0.0389	0.0004
Post Secondary Education	0.0863	0.0797	0.0574	0.1326
NFWork	0.0222	0.0205	0.0216	0.3050
Residence	-0.0780	-0.0720	0.0199	<0.0001
Summerfallow	-0.2272	-0.2098	0.0173	<0.0001
Age	-0.3148	-0.2907	0.0468	<0.0001
Own	0.0230	0.0212	0.0155	0.1378
TFArea	0.3348	0.3092	0.0133	<0.0001
ValMch	0.0011	0.0010	0.0052	0.8244
ValBOwn	0.0030	0.0028	0.0032	0.3507
ValBRnt	0.0014	0.0013	0.0019	0.4647

Table 5.4 Continued: Results from Stacked Data with Total Acres Farmed

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
RFarm	0.1110	0.1025	0.0661	0.0931
Black	0.0729	0.0673	0.0078	<0.0001
Brown	-0.1841	-0.1700	0.0122	<0.0001
Dark Brown	-0.0032	-0.0030	0.0051	0.5294
Dark Gray	0.0368	0.0340	0.0054	<0.0001
Gray	0.0008	0.0007	0.0099	0.9393
OpStruc	0.1253	0.1157	0.0262	<0.0001
AgeSqd	0	n/a	n/a	n/a
TFAreaSqd	0	n/a	n/a	n/a
Time	0.4635	0.4281	0.0218	<0.0001
RFarm Post	0.0076	0.0070	0.0336	0.8207
Age RFarm	0.0028	0.0026	0.0012	0.0183
Age Post	0.0008	0.0007	0.0011	0.4572
Apr Max	0.4690	0.4332	0.0445	<0.0001
Apr Precip	0.1316	0.1215	0.0217	<0.0001
May Max	-0.5069	-0.4682	0.1641	0.0020
May Precip	0.0557	0.0514	0.0201	0.0056
Jun Max	1.9085	1.7627	0.2215	<0.0001
Jun Precip	-0.1567	-0.1447	0.0293	<0.0001
Jul Max	-0.7090	-0.6548	0.2697	0.0086

Table 5.4 Continued: Results from Stacked Data with Total Acres Farmed

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Jul Precip	-0.0312	-0.0288	0.0237	0.1893
Precip	-0.1360	-0.1256	0.0399	0.0007

Source: Author's Calculations

Table 5.5 provides results from the model run using total acres farmed to represent farm size. It also includes all the transformed interaction variables that were created. The percent correctly predicted was 81.92% and the weighted average percent correctly predicted was 68.49%.

Table 5.5: Results from Stacked Data with Total Acres Farmed, Includes All Transformed Variables

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Intercept	-0.6596	0	1.6322	0.6861
Alberta	-0.3722	-0.0744	0.0310	<0.0001
Labor	-0.0090	-8.60e-06	0.0178	0.6133
Young	0.0319	0.0056	0.0276	0.2474
Male	-0.1250	-0.0267	0.0389	0.0013
Post Secondary Education	-0.0914	-0.0238	0.0752	0.2244
NFWork	0.0091	0.0002	0.0221	0.6800
Residence	-0.0677	-0.0138	0.0200	0.0007
Summerfallow	-0.2517	-0.0602	0.0178	<0.0001
Age	0.8786	0.2713	0.5487	0.1093

Table 5.5 Continued: Results from Stacked Data with Total Acres Farmed, Includes Transformed Variables

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
Own	0.0228	0.0042	0.0155	0.1426
TFArea	-0.2660	-0.0154	0.1512	0.0785
ValMch	0.0036	0.0002	0.0052	0.4872
ValBOwn	0.0041	0.0009	0.0032	0.2031
ValBRnt	0.0024	0.0006	0.0019	0.2213
RFarm	0.3389	0.0884	0.0818	<0.0001
Black	0.0768	0.0189	0.0087	<0.0001
Brown	-0.1646	-0.0368	0.0136	<0.0001
Dark Brown	-0.0033	-0.0014	0.0054	0.5383
Dark Gray	0.0289	0.0063	0.0059	<0.0001
Gray	-0.0206	-0.0052	0.0106	0.0523
OpStruc	0.1101	0.0210	0.0266	<0.0001
TFAreaSqd	0.0455	0.0071	0.0121	0.0002
AgeSqd	-0.1733	-0.0487	0.0764	0.0233
Time	0.4228	0.0992	0.0491	<0.0001
RFarm Post	-0.0296	-0.0033	0.0356	0.4056
Age RFarm	0.0035	0.0008	0.0012	0.0035
Age Post	0.0018	0.0003	0.0012	0.1478
Apr Max	0.3219	0.0776	0.0469	<0.0001
Apr Precip	0.0137	0.0080	0.0243	0.5731
May Max	-0.3976	-0.0701	0.1720	0.0208

Table 5.5 Continued: Results from Stacked Data with Total Acres Farmed, Includes Transformed Variables

Variable	Coefficient	Marginal Effect	Standard Error	Pr>Chi-Square
May Precip	0.0772	0.0146	0.0213	0.0003
Jun Max	1.1821	0.2734	0.2313	<0.0001
Jun Precip	-0.1599	-0.0341	0.0300	<0.0001
Jul Max	-1.2367	-0.2505	0.3124	<0.0001
Jul Precip	-0.0684	-0.0127	0.0244	0.0050
Precip	-0.1055	-0.0224	0.0400	0.0084
TFArea Time	-1.31e-05	-3.104e-06	4.36e-06	0.1495
Post Time	0.0704	0.0195	0.0223	0.0016
Age Time	0.0012	0.0003	0.0008	0.1243
RFarm Time	-0.1309	-0.0306	0.0228	<0.0001
Black Time	-0.0956	-0.0246	0.0214	<0.0001
Brown Time	0.0327	0.0052	0.0224	0.1445
Dark Gray Time	-0.3161	-0.0874	0.0397	<0.0001

Source: Author's Calculations

In this analysis a number of models were estimated to test the sensitivity of the results to specification change. The results were very robust as the signs on the majority of significant variables matched expectations. Table 5.6 compares the signs of the significant variables for the models presented in Tables 5.3 to 5.5, NS means that the variable was not significant in that particular model.

Table 5.6: Signs of Significant Variables from Tables 5.3 – 5.5

Variable	All Var with Total Gross Sales (Table 5.3)	All Var with Total Farm Area (Table 5.4)	All Var with Total Farm Area plus Transformed Variables (Table 5.5)
Alberta	-	-	-
Male	-	-	-
Residence	-	-	-
Summerfallow	-	-	-
LAge	-	-	NS
LSales/LTFArea	+	+	NS
LValBRnt	+	NS	NS
RFarm	NS	NS	+
LBlack	+	+	+
LBrown	-	-	-
LDarkGray	+	+	+
OpStruc	+	+	+
Time	+	+	+
AgeRFarm	NS	NS	+
LApr1Max	+	+	+
LApr1Precip	+	+	NS
LMay1Max	-	NS	NS
LJun1Max	+	+	+
LJun1Precip	-	-	-

Table 5.6 Continued: Signs of Significant Variables from Tables 5.3 – 5.5

Variable	All Var with Total Gross Sales (Table 5.3)	All Var with Total Farm Area (Table 5.4)	All Var with Total Farm Area plus Transformed Variables (Table 5.5)
LJul1Max	NS	-	-
LPrecip	-	-	NS
PostTime	NS	NS	+
RFarmTime	NS	NS	-
BlackTime	NS	NS	-
DarkGrayTime	NS	NS	-

Source: Author's Calculations

As illustrated in Table 5.6 above the signs of the significant variables remained the same throughout the different models. The only difference was that some variables were significant in some models while not significant in others. The variables that were significant in only some models are discussed in section 5.8.

5.8 Some Additional Explanation of Significant Variables from Sensitivity Analysis

5.8.1 Total Acres Farmed

When total acres farmed was included as an explanatory variable instead of gross sales, it was significant in determining whether a producer would adopt minimum tillage technology and practices. This result is supported by Feder and Umali (1993) and Westra and Olson (1997). The models were not sensitive to using total acres farmed and gross sales interchangeably; results between the models did not differ significantly from one another. The larger the total operation size the more likely the farm is to use

minimum tillage technology and practices. This result is supported by the average farm size of adopters versus the average farm size of non-adopters. The average farm size of adopters is 1,521 acres, while the average farm size of non-adopters is 967 acres. This implies that there are economies of scale with the adoption of minimum tillage technology, meaning that it is more profitable to spread the cost of minimum tillage technology over a large number of acres versus a small number of acres. This result makes intuitive sense since hobby farms tend to be smaller in size; therefore they are less likely to adopt the most recent products and techniques. In comparison larger farms rely more heavily on the farm for household income, therefore they are more likely to look for opportunities to improve their operation and increase profits.

5.8.2 Age

The age and age squared variables were not significant in the preferred model; however, they were significant in some of the other model specifications and sensitivity analyses. When only the age variable was included in the model the coefficient was negative, meaning that as a producers age increases the probability of adopting minimum tillage technology decreases. However, when age squared was added to the model the age coefficient became positive while the age squared variable was negative. This means that the very young did not adopt the technology, probably because they were not farming or did not have enough experience and/or capital to adopt the technology. At the same time older farmers did not adopt the technology either. The adoption of minimum tillage technology increases as age increases to a certain point at which time it begins to decrease. Younger producers are more likely to adopt new technology because they have longer planning horizons in which to earn the money back

on their investment. As well, younger producers react more favorably to technological change. Previous research has found the age variable to be both significant and not significant. In Westra and Olson (1997), Adesina and Zinnah (1993), and Uri (1998) found age to be not significant in explaining tillage adoption. On the other hand, age was a significant explanatory variable in Feder and Umali (1993) and Lapar and Pandey (1999).

5.8.3 Post Secondary Education

The post secondary education variable was not significant in any of the models, which was also found in Westra and Olson (1997) and Uri (1998). The post secondary education variable being insignificant raises an interesting issue about the adoption of minimum tillage technology and practices that is, the adoption of minimum tillage technology and practices is based on a neighbor effect, rather than an educated analysis of the producer's own operation. As well, this provides evidence of a knowledge spillover, in that people follow what others do.

5.9 Technology Adoption Life Cycle

Due to data constraints the technology adoption life cycle curve of minimum tillage technology was not able to be calculated. Tillage data has only been collected since the 1991 Agriculture Census, meaning that only three years of data was available. In addition, the question on the census asks what type of tillage technology the farm is currently using; therefore it is unknown if they have adopted the technology since the previous census or if they have been using the technology for a number of years. As well, there has been a decrease of over 20% in the total number of farms in the Prairie

Provinces between 1991 and 2001, which resulted in a decrease in the total number of farms using minimum tillage technology even though as a percentage of total farms the use of minimum tillage technology has increased.

In 1991, 31% of producers in the Prairie Provinces used minimum tillage technology. Between 1991 and 1996 there was a significant increase in the use of minimum tillage technology, by 1996 42% of Prairie Producers were using minimum tillage technology. By 2001 the use of minimum tillage technology had increased once again and 48% of Prairie Producers were using minimum tillage technology. The adoption of minimum tillage technology will never reach 100% because the technology is not suited to all agriculture regions in the Prairie Provinces. As well, a significant capital cost is involved with purchasing the technology, therefore the farm must be large enough to justify the capital cost to purchase it.

More producers in Saskatchewan have adopted minimum tillage technology compared with their counterparts in Alberta and Manitoba. In the 1991 Agriculture Census 36% of Saskatchewan Producers reported using minimum tillage technology, while only 23% of Alberta Producers and 33% of Manitoba Producers reported using the same technology. Between 1991 and 1996 Saskatchewan and Alberta saw a significant increase in the use of minimum tillage technology. In Saskatchewan the use of minimum tillage technology increased by 13 percentage points to 49%, while Alberta increased 11 percentage points to 34%. Manitoba saw a slight increase of 3 percentage points to 36%. Between 1996 and 2001 Alberta saw another significant increase in the use of minimum tillage technology, increasing 10 percentage points to 44%. Both Saskatchewan and Manitoba saw small increases of 4 percentage points and 3 percentage points respectively. So by 2001 53% of Saskatchewan Producers were using

minimum tillage technology, while 39% of Manitoba Producers were using the technology. Regional differences account for the different adoption rates amongst the provinces. Alberta has a couple of agriculture regions which are different than other regions in the Prairie Provinces, these regions are: the Peace River area in northern Alberta and the irrigated land in parts of southern Alberta. Soil in the Peace River area is rich; as well it is prone to late frost in the spring and early frost in the fall. Lack of soil moisture in southern Alberta is not a problem as they are able to easily irrigate. Manitoba has a fusarium problem in the Red River region; one way to prevent the spread of the disease is to till the land.

From the available tillage data the adoption of minimum tillage technology and practices appears to follow the technology adoption life cycle curve. However, because tillage data was not kept prior to 1991 the actual adoption curve cannot be analyzed. Based on adoption rates between 1996 and 2001 adoption is slowing, particularly in Saskatchewan and Manitoba. In 2001, 48% of operations in the Prairie Provinces used minimum tillage technology; it is also known that less than 100% of operations will adopt the technology and practices. Therefore, the adoption of minimum tillage technology is somewhere along the downward sloping portion of the technology adoption life cycle curve. The early adopters have adopted, along with the early majority and even some of the late majority. It is unknown at what proportion adoption will top out, but it is expected to be soon as the technology and practices are not suitable for a number of producers due to their regional, farm, and/or socio-economic characteristics.

5.10 Hypothesis Results

The first hypothesis of this analysis was that the adoption of minimum tillage technology is based on profitability, socio-economic factors, farm characteristics, and regional characteristics. Based on the empirical work of this analysis this hypothesis is not rejected, which means that the adoption of minimum tillage technology is based on profitability, socio-economic factors, farm characteristics, and regional characteristics. The second hypothesis was that the adoption of minimum tillage technology follows the bell curve of the technology adoption life cycle. From the empirical work of this analysis this hypothesis is not rejected, which means that given the data set used the adoption of minimum tillage technology is following the technology adoption life cycle curve.

5.11 Chapter Summary

A number of model specifications and sensitivity analyses were run using the stacked data. Results between these models did not differ significantly, both in terms of their ability to correctly predict adoption and in terms significant variables. The consistency in model results provides support for the conclusions which are drawn from this research. There were a number of variables which were significant in all the models, including: Alberta dummy variable, summerfallow, age, total farm area, gross farm sales, black, brown, and dark gray soils, corporate operating structure, time, average maximum April temperature, average maximum June temperature, and total June precipitation. From the model results the hypothesis that the adoption of minimum

tillage technology is based on profitability, socio-economic factors, farm characteristics, regional characteristics, and environmental benefits which help in the reduction of the effects of climate change cannot be rejected.

Due to a lack of tillage data prior to 1991, the complete curve of the technology adoption life cycle was unable to be analyzed. However, from the available data adoption of minimum tillage technology appears to follow the bell curve of the technology adoption life cycle. Thus, the hypothesis that the adoption of minimum tillage technology follows the bell curve of the technology adoption life cycle cannot be rejected.

CHAPTER SIX: SUMMARY AND CONCLUSIONS

This chapter provides a summary of the major findings of this analysis. As well, the objectives and hypotheses of the analysis are revisited and answered. Implications for the public and private sectors of the results from the empirical work are discussed. Finally, the chapter concludes with suggestions for future studies on the adoption of minimum tillage technology.

6.1 Summary

The objective of this thesis was to determine the socio-economic, farm, and regional characteristics that play a significant role in determining whether minimum tillage technology is adopted. After reviewing previous research and doing empirical work it was found that a number of socio-economic, farm, and regional characteristics play an influential role in determining whether an operation adopts minimum tillage technology. Variables which play an influential role include: total gross farm sales, total farm area, age, soil type, location of a research farm within a CD, Alberta dummy variable, operating structure of the farm, time, average maximum temperature for April, June, and July, and precipitation for June. Given these results, the first hypothesis that the adoption of minimum tillage technology is based on profitability, socio-economic factors, farm characteristics, and regional characteristics cannot be rejected.

In addition, this research examined whether the adoption of minimum tillage technology followed the bell curve of the technology adoption life cycle. Since tillage practice data was not available prior to 1991 and the adoption of minimum tillage technology began prior to 1991, the complete technology adoption life cycle was not able to be analyzed. From the available data it appears that adoption of minimum tillage technology follows the technology adoption life cycle. From this analysis it can be concluded that over half of Prairie producers who will ever use the technology have adopted it. As well, it can be concluded that adoption is currently on the downward sloping portion of the bell curve of the technology adoption life cycle. This is based on the fact that in 2001 48% of Prairie farms were using minimum tillage technology. In addition, adoption rates slowed considerably from 1996 to 2001. For example, in Saskatchewan there was a 4% increase from 1996 to 2001, while there was a 13% increase from 1991 to 1996. Given these results the second hypothesis that the adoption of minimum tillage technology follows the bell curve of the technology adoption life cycle cannot be rejected.

6.2 Implications for Public and Private Sectors

It is possible private companies can use the results reported in this thesis to design and implement marketing strategies for minimum tillage technology to target specific segments of the market. Minimum tillage technology marketing efforts targeted towards younger producers are beneficial, although not the very young as they do not have the experience and capital resources to readily adopt new technology. As well, marketing efforts can be concentrated in the black and dark gray soil zones, where producers are most likely to adopt minimum tillage technology. Marketing efforts targeted to large

farms, both in terms of total acres farmed and total gross sales, are beneficial as these operations have the financial resources to afford the cost of the new technology.

Policy makers can use this analysis to design and implement policies that focus on soil conservation and the reduction of greenhouse gas emissions. The majority of producers who have adopted minimum tillage technology did so before the implementation of the Kyoto Accord. This illustrates the fact that an environmentally friendly practice, such as minimum tillage technology, that provides tangible benefits to a producer is more likely to be adopted even without policy incentives.

6.3 Implications for Academic Literature

This analysis provides an in-depth analysis of minimum tillage adoption throughout the Prairie Provinces. The data set used for the empirical work contained data for over 42,000 producers, the largest data set analyzed for the Prairie Provinces. As well, the linkages created between the Population and Agriculture Censuses allowed for an extensive analysis of the influence socio-economic and farm characteristics play in the minimum tillage technology adoption decision.

6.4 Study Limitations

Since the tillage practice question on the Agriculture Census is vague in its wording, producers may have inadvertently checked off the incorrect tillage practice. This means that the minimum tillage variable may not be correct for a particular observation, which would lead to variables being significant or not significant when in reality they are not.

The tillage data were based on the use of minimum tillage, rather than if producers had adopted the technology since the last census. This means that a producer using the technology may have made that decision several years ago when their operation was different as compared to the particular census year. For example, the socio-economic and farm characteristics may not be representative of what they were when the decision to adopt minimum tillage technology was made.

The most recent data available for this analysis were the 2001 census, which is five years old. Thus, the model results may be out-dated and new adoption trends may be emerging.

6.5 Future Minimum Tillage Adoption Research

The use of growing degree days (GDD) or frost free days may be more useful as an independent variable as compared with average monthly maximum temperatures. The use of minimum tillage technology and practices decreases the soil temperature, which in areas with limited GDD or frost free days has a significant negative impact on crop development. For example, frost damages the crop before it is fully mature. It is expected that areas with limited GDD or frost free days are less likely to adopt minimum tillage technology and practices. GDD or frost free days were not included in this analysis because of time constraints to gather the data and have it plotted in the GIS lab.

A different definition of post secondary education may change the significance of the variable. Rather than using a broad definition of post secondary education, such as used in this analysis, it may be useful to separate the different levels of post secondary education. For example, certificate, diploma, degree, and advanced degree could each be assigned different values.

In approximately one year, results from the 2006 Agriculture Census and Population Census will be available, thus it will be useful to include these data in the stacked data set and then analyze how the adoption of minimum tillage technology has changed between 2001 and 2006.

Linking results from one census year to another would provide useful insight into how a particular operation has changed. For example, did the total acres increase which caused demand for new equipment. This was not feasible for this analysis because the administrative process that must be done in order to link census results from one census to another is expected to take at least one year, which did not work with the timelines for this research.

To better answer the question of the adoption of minimum tillage technology following the technology adoption life cycle curve; it may be useful to track the sale of new minimum tillage equipment. This technique would raise a number of other questions as well including, what is the useful life of minimum tillage equipment. At some point the equipment will wear out and a producer would need to replace it.

REFERENCES

- Abadi Ghadim, Amir K. and David J. Pannell. 1999.** *A Conceptual Framework of Adoption of an Agricultural Innovation.* Agricultural Economics. Volume 21. pp. 145 – 154.
- Adesina, Akinwumi A. and Moses M. Zinnah. 1993.** *Technology characteristics, farmers' perceptions and adoption decisions: A Tobit model application in Sierra Leone.* Agricultural Economics. Volume 9. pp. 297 – 311.
- Agriculture and Agri-Food Canada. 2006.** Accessed at: <http://www.agr.gc.ca>.
- Alberta Agriculture, Food and Rural Development. 2006.** Accessed at: www1.agric.gov.ab.ca.
- Ástebro, Thomas. 2004.** *Sunk Costs and the Depth and Probability of Technology Adoption.* The Journal of Industrial Economics. Volume LII. Issue 3. pp. 381 – 399.
- Batz, F.J., K.J. Peters, and W. Janssen. 1999.** *The influence of technology characteristics on the rate and speed of adoption.* Agricultural Economics. Volume 21. pp. 121 – 130.
- Binger, Brian R. and Elizabeth Hoffman. 1998.** *Microeconomics with Calculus.* Second Edition. Addison-Wesley. United States of America.
- Berkeley website. 2005.** Accessed at: <http://ist-socrates.berkeley.edu/~fmb/articles/lifecycle/>
- Doraszelski, Ulrich. 2004.** *Innovations, Improvements, and the Optimal Adoption of New Technologies.* Journal of Economic Dynamics and Control. Volume 28. pp. 1461 – 1480.
- Doss, Cheryl R. and Michael L. Morris. 2001.** *How does gender affect the adoption of agricultural innovations? The case of improved maize technology in Ghana.* Agricultural Economics. Volume 25. pp. 27 – 39.
- Ervin, Christine A. and David E. Ervin. 1982.** *Factors Affecting the Use of Soil Conservation Practices: Hypotheses, Evidence, and Policy Implications.* Land Economics. Volume 58. Number 3. pp. 277 – 292.
- Feder, Gershon and Dina L. Umali. 1993.** *The Adoption of Agricultural Innovations A Review.* Technological Forecasting and Social Change. Volume 43. pp. 215 – 239.

- Goel, Rajeev K. and Daniel P. Rich. 1997.** *On the Adoption of New Technologies.* Applied Economics. Volume 29. pp. 513 – 518.
- Gould, Brian W., William E. Saupe, and Richard M. Klemme. 1989.** *Conservation Tillage: The Role of Farm and Operator Characteristics and the Perception of Soil Erosion.* Land Economics. Volume 65. Number 2. pp. 167 – 182.
- Hadwen, Trevor. 2006.** Prairie Farm Rehabilitative Administration.
- Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 2002.** *Environmental Policy and Technological Change.* Environmental and Resource Economics. Volume 22. pp. 41 – 69.
- Janosky, Jeffrey S., Douglas L. Young, and William F. Schillinger. 2002.** *Tillage.* Agronomy Journal. Volume 94. pp. 527 – 531.
- Lapar, Ma. Lucila A. and Sushil Pandey. 1999.** *Adoption of soil conservation: the case of the Philippine uplands.* Agricultural Economics. Volume 21. pp. 241-256.
- Lee, L.K. and W.H. Stewart. 1983.** *Land Ownership and the Adoption of Minimum Tillage.* American Journal of Agricultural Economics. Volume 65. Issue 2. pp. 256 – 264.
- Lichtenberg, Erik. 2001.** *Adoption of Soil Conservation Practices: A Revealed Preference Approach.* Department of Agricultural and Resource Economics, The University of Maryland, College Park, Working Paper 01-12.
- Lynne, Gary D., C. Franklin Casey, Alan Hodges, and Mohammed Rahmani. 1995.** *Conservation Technology Adoption Decisions and the Theory of Planned Behavior.* Journal of Economic Psychology. Volume 16. pp. 581
- Moore, Geoffrey A. 1991.** *Crossing the Chasam: marketing and selling technology products to mainstream customers.* Harper Business. New York, N.Y.
- Norris, Patricia E. and Sandra S. Batie. 1987.** *Virginia Farmers' Soil Conservation Decisions: An Application of Tobit Analysis.* Southern Journal of Agricultural Economics. Volume 19. pp. 79 – 90.
- Parsch, Lucas, Terry C. Keisling, Patricia A. Sauer, Lawrence R. Oliver, and Nathan S. Crabtree. 2001.** *Production Agriculture.* Agronomy Journal. Volume 93. pp. 1296 – 1304.
- Pindyck, Robert S. and Daniel L. Rubinfeld. 2001.** *Microeconomics.* Fifth Edition. Prentice Hall. Upper Saddle River, New Jersey. Pp. 232 – 237.

- Rahm, Michael R. and Wallace E. Huffman. 1984.** *The Adoption of Reduced Tillage: The Role of Human Capital and Other Variables.* American Journal of Agricultural Economics. Number 66. pp. 405 – 413.
- Ribera, Luis A., F.M. Hons, and James W. Richardson. 2004.** *Tillage and Cropping Systems.* Agronomy Journal. Volume 96. pp. 415 – 424.
- Rosenberg, N. 1969.** *The Direction of Technological Change: Inducement Mechanisms and Focusing Devices.* Economic Development and Cultural Change. Number 18. pp. 1 – 24, quote on pp. 23.
- Schultz, Theodore W. 1982.** *Investing in People: The Economics of Population Quality.* University of California Press. United States of America.
- Soule, Meredith J., Abebayehu Tegene, and Keith D. Wiebe. 2000.** *Land Tenure and the Adoption of Conservation Practices.* American Journal of Agricultural Economics. Volume 82. Issue 4. pp. 993 – 1005.
- Statistics Canada.** Census Data for 1991, 1996, and 2001.
- Thornton, Rebecca Achee and Peter Thompson. 2001.** *Learning from Experience and Learning from Others: An Exploration of Learning and Spillovers in Wartime Shipbuilding.* The American Economic Review. Volume 91. Number 5. pp. 1350 – 1368.
- University of Saskatchewan, Soil Science GIS Lab.** Soil Data.
- Uri, Noel D. 1998.** *Conservation Tillage and the Use of Energy and Other Inputs in US Agriculture.* Energy Economics. Volume 20. pp. 389 – 410.
- Von Neumann, J. and Morgenstern, O. 1944.** *Theory of Games and Economic Behavior.* Princeton University Press. Princeton, NJ.
- Weersink, Alfons, David Pannell, Murray Fulton, and Andreas Meyer-Aurich. 2005.** *Agriculture's Likely Role in Meeting Canada's Kyoto Commitments.* Canadian Journal of Agricultural Economics. Volume 53. pp. 425 – 441.
- Westra, John and Kent Olson. 1997.** *Farmers' Decision Processes and Adoption of Conservation Tillage.* Department of Applied Economics, College of Agricultural, Food, and Environmental Sciences, University of Minnesota, Staff Paper pp.97-9.
- Zentner, Robert P., David D. Wall, Cecil N. Nagy, Elwin G. Smith, Doug L. Young, Perry R. Miller, Con A. Campbell, Brian G. McConkey, Stewart A. Brandt, Guy P. Lafond, Adrian M. Johnston, and Doug A. Derksen. 2002.** *Economics of Crop Diversification and Soil Tillage Opportunities in the Canadian Prairies.* Agronomy Journal. Volume 94. pp.216 – 230.

