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Has the Usage of Precision Agriculture Technologies Actually Led to Increased Profits for Nebraska Producers?

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HAS THE USAGE OF PRECISION AGRICULTURE TECHNOLOGIES ACTUALLY LED TO INCREASED PROFITS FOR NEBRASKA PRODUCERS?

by

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HAS THE USAGE OF PRECISION AGRICULTURE TECHNOLOGIES ACTUALLY LED TO INCREASED PROFITS FOR NEBRASKA PRODUCERS?

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An ever-increasing global demand for food, coupled with increasingly volatile commodity prices have charged producers with the task of becoming more efficient. As such, technologies aimed at producing more with less are continually being developed and marketed to producers. However, whether or not these expensive new technologies have resulted in improved profitability is still unknown, as the vast majority of studies showing their impact on profitability have been performed using hypothetical farms and simulations. These studies have shown the potential for increases in profitability from use, but their impact in the real world is still uncertain.

This project uses various fixed effect panel data models to examine the realized economic impact of using precision agriculture technologies amongst a sample of producers across Nebraska using financial data from 1995-2014. Results of the study show the existence of a strong, positive relationship between number of technologies used and net farm income, indicating that precision agriculture use is associated with higher profitability. However, whether use is driving profitability or profitability is driving use remains somewhat unclear. Pre-and-post analysis among users of the technologies suggest profitability has in fact increased from use, but the result is not

statistically significant. This may be a consequence of mixed results among users, with many factors influencing the level of benefit achievable from use. Nonetheless, an obvious learning effect exists for users, with profitability increasing more as experience with the technologies increases. This would be expected due to the need to produce data regarding within-field variability on which to capitalize, along with the investment in learning the ideal use of these relatively complicated technologies. Overall, it is obvious that further research regarding the impact of these technologies is of great relevance.

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CHAPTER 1: INTRODUCTION

1.1 Statement of the Problem

As world population and incomes continue to rise, they have and will continue to be followed by an increased demand for agricultural commodities, with a limited amount of land to cultivate for production. As such, producers are faced with an increased pressure for efficiency. The world population reached approximately 7.3 billion as of 2015, meaning that the world population has increased by nearly one billion in the last twelve years (United Nations Department of Economic and Social Affairs, 2015). Furthermore, the UN Department of Economic and Social Affairs (2015) also predict the world population is estimated to reach over 9.7 billion by 2050. In addition to the increased demand from a rising world population, producers are also facing increased pressure for efficiency with the recent downturn in commodity prices and increases in production expenses (USDA ERS, 2015; Robertson et al., 2012). With commodity prices near and below breakeven levels, there is a great need for producers to decrease costs and thus lower their breakeven.

The answer to these problems may lie within technological advancements. For purposes of this study, precision agriculture refers to agricultural production technologies aimed at increasing operational efficiency and/or managing variability within the field. Examples of technologies attempting to improve operational efficiency examined in this study include global positioning system (GPS) guidance for farm machinery, either using a lightbar or autosteer, automated section control on a planter or sprayer (row shutoff for the planter, nozzle shutoff for the sprayer), and telematics. Technologies that allow one to manage variability within the field include yield monitors, site-specific soil sampling, variable-rate application of inputs, and various imagery technologies. These technologies are believed to have numerous benefits in production agriculture, with a potentially large economic impact. They are believed to be able to improve the efficiency of farm operations by lowering input costs and have been shown in prior studies to have the potential to increase net returns (Schimmelpfenning, 2016; Smith et al., 2013; Shockley et al., 2012; Shockley et al., 2011; Mooney et al. 2009; Dillon et al., 2007; Batte and Ehsani, 2006; Griffin et al. 2005). In addition to lowering input costs through improved accuracy of application, it is also believed that precision agriculture technologies will allow farmers to increase production due to the vast amount of information available to them; allowing them to produce more output with less input (Sustainable America, 2012). Furthermore, some of these technologies are thought to have the potential for reducing negative environmental impacts from agriculture by reducing the amount of chemical inputs applied (USDA NRCS, 2007). Zilberman et al. (1997) stated that promoting the use of precision agriculture technologies will be the key to sustainability in agriculture.

However, these technologies and potential benefits come at an increased cost. A recent survey of Nebraska producers showed that the number one reported reason for not using precision agriculture technologies in their operations was the cost of investment and that they believe the biggest issue regarding advancements in agriculture production technology in the future will be overall affordability and cost (Castle et al., 2015). Additionally, some studies have shown certain technologies to have mixed, or even negative returns (Boyer et al., 2011; Daberkow and McBride 2003). Lambert and Lowenberg-DeBoer (2000) reviewed over 100 studies that have examined the effects of precision agriculture technologies, typically individually, in hypothetical or experimental settings. They found that over 60% of such studies reported potential positive net returns associated with use, while about 10% reported losses and the rest produced mixed results. So, although precision agriculture technologies are viewed by many to have a great efficiency and profit increasing potential, there is minimal study as to its realized economic impact in the real world.

1.2 Objectives

The purpose of this study is to examine the whole-farm economic impact of adopting precision agriculture technologies for producers across the state of Nebraska. Although prior studies have shown specific precision agriculture technologies' potential to increase profits in an experimental setting through different simulations or experiments, to the knowledge of the authors, there has only been one limited study to actually examine whether or not this potential to increase profits has been realized amongst adopters (Olson and Elisabeth, 2003). The objectives of the study are as follows:

1. Survey Nebraska Farm Business, Inc. clientele in order to assess overall precision agriculture technology adoption.
2. Analyze the relationship between precision agriculture usage and profitability in order to determine whether adopters of the technologies have experienced greater profitability as compared to non-adopters.
3. Compare pre-and-post-adoption profitability measures for users of the technology in order to examine the realized economic impact of adopters over time.

1.3 Organization of Study

Chapter 2 provides an explanation of each of the ten precision agriculture technologies in question in the study. Chapter 3 provides a review of relevant literature regarding the impact of these technologies. Chapter 4 provides the methodology used in the study. It explains the methods used for collecting and preparing the necessary data, the econometric models used to perform the analysis, and the manipulations made to the models in order to produce interpretable results. Chapter 5 provides the various estimation results as well as a discussion and interpretation of the results. Finally, Chapter 6 contains the conclusions made from this study as well as implications of the results and suggestions for further research in the area.

CHAPTER 2: DESCRIPTION OF TECHNOLOGIES IN QUESTION

This study will examine the economic impact of the use of precision agriculture. In order to do so, producers are surveyed as to whether or not they use/have used ten different precision agriculture technologies in their farming operation. The technologies include: a yield monitor without GPS, a yield monitor with GPS, GPS guidance with a lightbar, GPS guidance with autosteer, automated section control (planter row shutoff or sprayer nozzle shutoff), grid or management zone soil sampling, imagery technologies (aerial, satellite, UAV), telematics (tracking of equipment; wireless data transfer), variable rate application of nutrients, and variable rate planting. As alluded to in the introduction, the different technologies serve different purposes; some improve the efficiency of farming operations and some help manage the variability within fields. Although each technology serves a different purpose, many are complementary in nature and cannot be used without others. For example, variable-rate application of inputs cannot be used properly without using soil sampling to identify high-and-low-productivity areas, yield monitors to generate yield maps, or both in order to determine the ideal distribution of inputs. Furthermore, some technologies are more complex than others; simply having a yield monitor affixed in a combine requires far less work and understanding than generating prescription maps for variable-rate application or scouting fields via use of an unmanned aerial vehicle (UAV).

The first two technologies studied are the use of a combine yield monitor without and with GPS. A yield monitor is a device that allows the producer to see on-the-go yield values throughout the field while harvesting (Risius 2014). Yield monitors used in the U.S. work by measuring the amount of grain per a given area by analyzing mass flow (impact) or weight (Hopkins 2009). Mass flow, or impact, yield monitors sense the amount of grain hitting a given device (impact plate, paddle, fork) against area covered, while a weigh-type yield monitor measures the weight of the grain taken in and thus calculates yield based on area covered (Risius 2014; Hopkins 2009). A yield monitor without GPS is used simply to give the producer more accurate yield measurements while harvesting as opposed to having to estimate yield after completion of a portion of a field and attempting to gather an understanding of the high-performing and low-performing areas of the field. A yield monitor with GPS is able to take this a step further by recording both yield and location within the field, which allows the ability to generate yield maps. Yield maps produce a visual display of the high-yielding and low-yielding portions of the field, typically with color-coding to display the variation. Yield monitors and their corresponding yield maps allow producers to manage the variability within the field by determining what areas should be managed more intensively and what areas should be managed less intensively. For instance, a yield map can show low spots that need improved drainage or terracing, less-fertile areas that should receive less inputs, and more-fertile areas that should receive more inputs. If the inputs usually used on the less-fertile areas could instead be used on the more-fertile areas, it could result in higher overall yields with the same amount of inputs. Overall, a combine yield monitor, with or without GPS, is a relatively simple precision agriculture technology to adopt that aids in managing within-field variability but won't necessarily increase profitability or production on its own; it is more of an information-producing technology that allows the producer to evaluate field management decisions and develop plans for improved management in the future (Risius 2014).

The next two technologies in question are GPS guidance systems that differ by the method of maintaining proper positioning of the equipment within the field. One is a GPS guidance system that uses a lightbar to help producers maintain position and the other uses automatic steering (autosteer). These guidance systems can be used for any typical field operation: planting, applying fertilizer, spraying, and harvesting. In the first time using either of the systems on a new field, the producer must manually drive one round around the edge of the field or pass through the field in order to establish the path to follow. After this is complete and the pattern is set, the GPS guidance systems can be used. Producers can then store the paths for each of their individual fields in order to utilize them once again in subsequent field operations and following years. The lightbar display indicates the correctness of the position of the equipment in the field with centered lights indicating proper positioning and off-centered lights showing the direction in which the positioning is off, allowing the driver to manually make adjustments to stay on the right path and thus reduce overlap of inputs. When using automated guidance, after making the first round around the edge of the field or pass through the field, the autosteer system actually allows the equipment to drive itself through the field, keeping it in the correct position and reducing the overlap of inputs. Both GPS guidance systems are designed to improve efficiency of operation by reducing overlap and skips of inputs, reducing input costs, increasing machinery field capacity, increasing yield through better stands, and lengthening the operator’s workday due to decreased physical stress from no longer having to maintain proper positioning manually (Karimi et al., 2012; Shockley et al., 2011; Griffin and Lowenberg-DeBoer, 2005). Unlike yield monitors, these technologies do allow for direct cost savings and potential increases in production.

However, because they come at an increased cost, their profitability is not guaranteed. Existing studies regarding GPS guidance systems will be discussed further in Chapter 3.

The next technology in question is automated section control (ASC). ASC systems are an effective tool for reducing overlap when planting and spraying; it is used in conjunction with GPS in order to track the area already covered by the planter or sprayer and prevent the planter/sprayer from applying the input to this area twice. When approaching an already-covered area from a different angle, such as in a point-row, the ASC system begins shutting off the respective planter rows/sprayer nozzles as they reach the previously-covered portion of the field, resulting in more complete coverage with reduced overlap. ASC is most effective when used on fields with irregular shape or in-field obstructions, as there is more opportunity for double-planting or skips when using traditional planting methods, as will be discussed further in Chapter 3 (Smith et al., 2013; Shockley et al., 2012). ASC on planters and sprayers is a technology that is meant to improve the efficiency of operations and thus lowers input cost and reduces the amount of time spent in the field. Additionally, using ASC for planting has the potential to improve yields by producing better stands from reduced overlap and skipped areas (Runge et al., 2014). When used for spraying, ASC has the potential to reduce plant damage from double-spraying and also reaching areas that may have been skipped in the process of attempting to avoid overlap manually. Overall, the usage of ASC has the potential to bring a lot of benefit to any row-crop operation, but whether its increased cost is offset by these benefits is somewhat unknown.

Grid and management zone soil sampling are technologies aimed at improving producers' management of the variability within the field. The difference between the two is the pattern in which the samples are taken. Grid soil samples are taken in fixed increments that form a grid and can be increased or decreased in frequency to form a more accurate picture of the field, whereas management zone sampling is more focused on sampling different areas in which certain spatial information is known, such as those with different soil types, slopes, cropping histories, etc. (University of Nebraska-Lincoln Cropwatch). Much like yield monitors, these soil sampling technologies are capable of producing maps that can show the high-and-low-performing areas of the field based on soil type. Having an understanding of soil variability within the field is vital from an agronomic perspective; different soil types respond quite differently to different inputs and management practices. Knowing which portions of the field to apply less inputs and which portions to apply more inputs gives the potential to target areas of need more efficiently and increase productivity through greater production or decreased inputs. Again like yield monitors, soil sampling does not directly increase profitability; it's the improved management practices that are derived from soil sampling that are the true benefit.

The next technology in question is imagery to monitor crop condition (UAV, satellite/aerial imagery). Monitoring crop progress is important in determining the timing and location of inputs, such as fertilizers and pesticides, as well as for identifying issues with plant health and the development of plant disease. The timing of field operations can be crucial; applying chemicals too early or too late can result in yield losses. When the crop is in its early stages of growth, identifying problem areas within the field is relatively easy, as they can mostly be seen from the edge of the field. However, as the crop progresses, the view from the edge of the field no longer suffices. So, the traditional methods of crop scouting involve having to physically walk out into the field, which can be extremely time-consuming and less than ideal, or to fly over the field, which can be expensive. Using imagery technologies may eliminate the need for doing this and can save the producer vast amounts of time and potentially deliver a sizeable economic benefit (Doering, 2014). Furthermore, some imagery technologies can actually detect the temperature and chlorophyll levels of the crop; much more agronomic information than simply walking out into the field or flying over it can provide. Use of these imagery technologies is similar to yield monitors and soil sampling in that they don't directly provide economic benefits, they provide information for improved management practices. However, the use of these technologies is not very widespread due to their large investment cost and the fact that regulation regarding their usage is still unsettled.

Gartner IT Glossary defines telematics as the use of wireless devices and "black box" technologies to transmit data in real time back to an organization. Broadly speaking, telematics are used in a large variety of settings, such as monitoring automobile maintenance requirements, observing driving performance for car insurance purposes, tracking shipping containers, and now even tracking agricultural equipment and transferring data on-the-go in the field. Telematics systems in farming offer equipment diagnostics, real-time equipment monitoring, and on-the-go wireless data transfer to/from the field (Hest, 2010). Additionally, the tracking of information such as speed of the equipment in the field and during transport as well as working time is now available to producers. When using a GPS-enabled yield monitor as discussed above, telematics systems allow the data produced by the yield monitor to be transferred to a separate computer in real-time. Furthermore, the tracking of equipment in-field allows for improved management by analyzing performance. Equipment monitoring allows producers to track things such as engine temperatures and fluid levels in order to diagnose and attempt to alleviate problems before they occur. It is also possible to track idle times in equipment in order to reduce fuel consumption in times it's not needed, etc. The full list of possibilities from using telematics systems is yet to be defined, but it is a high-cost and complex technology. Hest (2010) quotes Matt Darr, a precision agriculture specialist at Iowa State who stated: "(m)aking money with a telematics system requires persistence and a plan for making use of data. When you buy autosteer, you begin saving immediately. With telematics, unless you put effort into using the data, you aren't going to get much value from it. There is potential there, but you are going to have to go after it." This quote does a very good job of explaining the implications of telematics and other high-end technologies available today in farming. Although it is a very powerful technology developed to improve efficiency and profitability in farming, it takes a great deal of time and learning to put it to its full use and there is a good chance that many users fall short. As such, telematics is a particularly interesting technology for which to examine the economic impact; it has the potential to improve profitability, but at a high investment cost both monetarily and in terms of time.

The last technology in question is variable-rate application of inputs with an automated controller. The first use of variable-rate technology is the variable-rate application of nitrogen, phosphorous, potassium, and lime (the most common fertilizers used in agricultural production). The second use is variable-rate seeding when planting. As alluded to above, producers use other technologies to diagnose the variability within the field and generate prescriptions for the ideal rate of inputs to apply to each area of the field. Yield maps, soil maps, and imagery technologies all provide the information that allows producers to capitalize on the use of variable-rate application. With all of this information provided, the producer can determine what seeding population and/or amounts of fertilizer to apply to each area of the field. After the prescription map is generated, the producer can drive their equipment through the field and apply the inputs at different rates using an automated controller. The controller is programmed to apply differing amounts to various locations and automatically uses that programming to apply the prescribed rates to the designated areas. Variable-rate application is designed to allow producers to reduce their use of inputs on less-productive areas and shift them to areas with higher yield potential. For instance, more productive areas of the soil should be planted with a higher seed population because they are more likely to be able to support the higher plant population, whereas less-productive areas may not. Variable-rate application is designed to allow producers to become more efficient with their inputs by focusing on areas with greater potential. In theory, the use of variable-rate application may allow producers to reduce their input costs and improve their yields (Mooney et al., 2009). Furthermore, the variable-rate application of nutrients may have benefits for soil health that can be recognized for years to come. Variable-rate application has many theoretical benefits, but it is a very expensive technology to invest in. Not only does it come with the increased purchase and maintenance/support cost, creating optimal and effective prescription maps for variable-rate application requires a very large investment in terms of a producer’s time.

CHAPTER 3: REVIEW OF RELEVANT LITERATURE

Previous research has shown that producers' belief that precision agriculture technologies will bring increased profitability is an influential factor in the adoption of the technologies (Watcharaanantapong et al., 2014; Walton et al., 2008). Additionally, the survey of Nebraska producers previously discussed by Castle et al. (2015) showed that nearly 70% of respondent adopters believe their profits have increased due to the use of precision agriculture. There have been many studies attempting to measure the economic benefit of specific technologies, each looking at different factors affecting profitability. Many of these studies use hypothetical farms and/or simulations in order to determine the potential returns from precision agriculture. Such studies have shown potential for consistent increases in net returns under varying circumstances from multiple specific technologies, including GPS guidance, automated section control, and variable rate application of nutrients (Smith et al., 2013; Shockley et al., 2012; Shockley et al., 2011; Mooney et al., 2009; Dillon et al., 2007; Batte and Ehsani, 2006; Griffin et al., 2005). Plus, a recent study by the USDA's Economic Research Service found positive impacts on profitability measures associated with the use of soil and yield mapping, GPS guidance systems, and variable-rate application of inputs (Schimmelpfenning, 2016).

However, returns from these technologies are not consistent across all areas. Several studies have shown that field characteristics, such as size, shape, and in-field obstructions affect returns from use (Smith et al., 2013; Shockley et al., 2012; Batte and Ehsani, 2006). The literature shows that the more irregular the field shape, be it from hills, trees, waterways, obstructions, etc., the higher the potential for increased profit from using automatic section control on a planter or sprayer (Smith et al., 2013; Shockley et al., 2012; Batte and Ehsani, 2006). This is due to the fact that irregularly-shaped fields present a higher chance of overlap in applications, so the role of ASC becomes more important in reducing said overlap, whereas more square-shaped fields have a lesser chance for overlap and thus the usage of ASC is not as relevant. Conversely, the more irregular the field shape, the lower the potential benefits from GPS guidance alone (Smith et al., 2013). Smith et al. (2013) found that GPS guidance alone has the highest returns for more square-shaped fields and the lowest returns for irregularly-shaped fields. Using GPS guidance can help reduce overlap when compared to traditional methods of planting, but the overlap resulting from irregularities in field shape, such as point rows, is not reduced because the individual planter rows/sprayer nozzles do not shut off as they pass over already-covered areas. Shockley et al. (2012) found that field shape becomes less important when the size of the field increases. Furthermore, spatial variability within the field, such as in terms of varying soil type, has been shown to have an effect on the profitability of precision agriculture (Osei and Li, 2016). The greater the variability within the field, the greater the opportunity to tailor inputs at a site-specific level and the less variable the field, the lesser the need to vary inputs. Overall, the literature shows precision agriculture technologies' ability to capitalize on field variability and potentially increase profits through reduced levels of inputs and/or increased production.

Many studies have also shown that increasing the number of acres in the operation has a positive impact on the potential profitability of the technology, indicating that larger farmers have a higher incentive for use (Mooney et al., 2009; Dillon et al., 2007; Batte and Ehsani, 2006; Griffin et al., 2005). Schimmelpfenning (2016) found precision agriculture technologies to be used on a considerably higher proportion of crop acres than farms, indicating that larger farmers are more likely to adopt. This result is intuitive because larger farmers are able to spread the cost of the equipment over a larger number of acres. Furthermore, due to the high investment cost in adopting these technologies, relatively large producers may be the only ones for which investment in these technologies is feasible. Although differing field and operation characteristics have been shown to have an impact on returns from usage of precision agriculture, the use of GPS guidance and ASC have both been shown to bring increased returns to producers individually, but they are their most effective when used together (Smith et al., 2013).

Studying the economic impact of precision agriculture across Nebraska is of interest due to the enormous diversity in production regions and practices across the state. Smith et al. (2013) in their simulations examined part of this potential variation in profitability from usage, as their study included fields from the entire state of Kansas as well as the three southernmost agricultural districts in Nebraska and one district in Colorado. Their study showed the highest return on investment for GPS guidance alone for West Central Kansas, followed by Southeast Colorado, and Southwest Kansas; districts where fields are predominantly large and regularly-shaped. GPS alone had the lowest return on investment in East Central Kansas, followed by Southeast Nebraska, and then Southeast Kansas; districts with much smaller and more irregularly-shaped fields due to a more hilly terrain. In contrast, when examining the usage of ASC, the rankings are the exact opposite; the highest return on investment was in East Central Kansas, followed by Southeast Nebraska, and Southeast Kansas, while the lowest returns were in West Central Kansas, Southeast Colorado, and Southwest Kansas. However, when using both technologies together, the highest return on investment was in East Central Kansas, Southeast Nebraska, and Southeast Kansas. These results show that the benefits from use of ASC outweigh those of GPS guidance, and the districts with more hilly and tree-covered terrain have a higher potential benefit from use as compared to the much flatter and less tree-filled fields of the western portions of the states. With these results in mind, a study examining whether or not the large hypothesized economic impacts described have been realized by producers in Nebraska is of great relevance.

Although there are many studies showing considerable benefits from different GPS systems and automatic section control, the literature has shown mixed results when it comes to variable-rate application of nutrients. Boyer et al. (2011) studied whether or not variable-rate application of nitrogen would increase yields and profitability in wheat production at eight different test plot locations across the state of Oklahoma. These test plots were studied over a five-year period and produced mixed results; there were some instances in which the variable-rate application resulted in higher returns and some instances in which uniform application resulted in lower returns and no statistically significant difference was found between the treatments. Daberkow and McBride (2003) studied the impact of using remote sensing imagery to determine and use variable-rate nitrogen application on sugar beets in the Red River Valley of North Dakota and Minnesota and the impact of use was found not to be statistically significant as well. However, Lowenberg-DeBoer (1999) studied the usage of variable-rate application of phosphorus and potassium as a risk management strategy (reducing production risk) on grain farms in the Eastern Corn Belt. Their empirical evidence from on-farm trials supported the hypothesis that variable-rate application can have positive benefits by reducing production risk. Schimmelpfenning (2016) found variable-rate application use to be associated with increases to operating profits and net returns. However, it is of interest to note that these positive returns were the smallest of the three technology groups studied, at only 1.1%. Variable-rate application of nutrients, in theory, should be able to allow producers to increase yields while decreasing inputs and thus have a positive impact on profits, but the literature shows mixed results from on-farm trials, so studying benefits realized by adopters in the real world is of great relevance.

When it comes to yield monitors, the majority of studies are from an agricultural engineering perspective; many studies have examined the accuracy of yield monitors under varying conditions (Risius, 2014; Grisso et al., 1999; Colvin and Arslan). In a case study, Griffin et al. (2008) found producers who used yield monitors and received spatial analysis reports have increased confidence in on-farm trials and their subsequent management decisions. In their study, Griffin et al. (2008) also stated that prior studies have shown the length of time using yield monitors to be a factor in producers' perceived value of their use. Risius (2014) touches on this fact in mentioning the importance of the amount of data to yield monitors' value. He states: "(t)he more data a producer can obtain from each individual harvest season, the more evidence that individual has to evaluate how different factors affected the harvest results. From these results, producers can determine if the decisions made from the data were financially justified." This statement shows the true nature of yield monitoring in improving profitability; the producer can use the data produced to make improved management decisions and the following year's yield information can show the producer whether or not these different management decisions paid off. As such, it may be of interest to examine the effect of length of time using a yield monitor, as well as other technologies, on profitability. Overall, measuring the direct economic impact of yield monitors proves to be very difficult and studies of this nature are lacking. The recent study by Schimmelpfenning (2016) found GPS mapping (though including both yield and soil mapping) to have a positive impact on net returns and operating profits. These technologies were associated with the largest increases in profitability measures of those studied, but the increase was still relatively small. Schimmelpfenning's study may be confounded for the purposes of this review, however, as the use of yield and soil mapping are combined and thus it is unknown whether or not these increases are more associated with the use of yield mapping, soil mapping, or the combination of the two.

Studies on the benefits of grid or management zone soil sampling mostly focus on increased returns from the variable-rate application of nutrients based on the soil samples. As such, it's once again difficult to determine the impact of the soil sampling itself. As mentioned above, the 2016 study by Schimmelpfenning showed a positive impact on profitability from the use of GPS mapping, but yield and soil mapping were combined, making it difficult to comment on the profitability of soil mapping by itself. The main thought process is summarized well by Mallarino and Wittry (1999): "(a)n intensive soil sampling plan will not be cost-effective unless the intensive sampling and resulting change(s) in fertilization method or rates result in higher yields and/or lower rates." Yohn and Wickline (2008) performed a study attempting to determine the differences in cost of conventional soil sampling and precision soil sampling on case farms in the state of West Virginia. Of the eight fields studied, the precision soil sampling led to cost reductions in only three, while conventional soil sampling was cheaper in five. On average, the conventional soil sampling was cheaper by $8.62 per acre. The two methods of soil sampling suggested differing rates of applying nutrients in almost all instances. Despite the precision soil sampling being more expensive, the authors noted that it is unclear how plants respond to having optimum levels of nutrients applied. If the precision sampling resulted in improved application that increased yield, the investment may pay for itself, but again, these benefits would not be derived solely from improved soil sampling, rather a combination of soil sampling and variable-rate application.

Imagery technologies are also difficult to assess, as they don't provide direct benefits either, but rather provide the information for variable-rate application of inputs and the timing of operations. Due to this, their economic benefit is once again very hard to measure on its own. Tenkorang and Lowenberg-DeBoer (2008) summarized the existing studies on the usage of remote sensing and imagery in agriculture. Of the nearly 100 studies examined, the vast majority were focused solely on technical aspects of the technology and only twelve studies reported an estimated economic benefit from use. These studies gave widely-varied estimates of returns from use and were all based on returns from adjusting management practices, as with soil sampling. So, once again, the direct benefit of this technology is extremely difficult to measure as its benefit is realized when used in conjunction with other technologies.

The technology with the least amount of literature available is telematics. This is most likely a function of the fact that it is the newest of the precision agriculture technologies examined in this study and that its benefit is also extremely difficult to quantify. As of right now, there is no quantitative information available as to telematics' economic impact other than the cost of purchasing and maintaining available systems. However, producing data that allows for monitoring efficiency of operations may give producers the ability to save money in the long run by using resources more effectively, and machinery diagnostics may allow problems to be detected before breakdowns occur, saving money by preventing the need for major repairs (Martindale, 2014).

As discussed in Chapter 2, many of the technologies in question don't bring direct increases in profitability by themselves, they provide the information that allows for improved management practices through the use of other technologies. As such, it's not easy to isolate and measure the economic impact of using things like yield monitors, grid or management zone soil sampling, imagery, or telematics. This study aims to examine benefits of using multiple precision agriculture technologies as a system, allowing the overall economic impact of both information-producing technologies and direct-benefit technologies to be assessed.

There have been many studies examining the profit potential of specific precision agriculture technologies through simulations and/or on farm trials, but a thorough review of literature finds only one study attempting to examine the whole-farm profitability of using precision agriculture technologies. Olson and Elisabeth (2003) surveyed just over 200 producers associated with the Southwestern Minnesota Farm Business Management Association regarding their use of precision agriculture and these responses were then connected with financial data in order to examine the economic impact of use. In their study, Olson and Elisabeth (2003) first examined the adoption of precision agriculture and then its subsequent impact. To assess the impact of adoption, whole farm rate of return to assets was used. Their results showed that the usage of precision agriculture actually had a negative impact on return to assets for the entire group of farms, but had no significant impact when the farms were separated into subgroups, such as row crop farmers only and by size. However, these results may not be indicative of the true impact of use. Due to the fact that the study was performed using production data from the year 2000, precision agriculture as it is known today did not yet exist and use of any precision agriculture technology was very limited. Only 27.8% of their respondents reported using at least one precision agriculture technology in their operation and these were likely technologies not expected to have a direct impact on profitability themselves. This limited amount of use in the sample most likely hindered the results of the study and prevented Olson and Elisabeth from being able to perform any further analysis by breaking the observed sample into subgroups. Sample limitations aside, the methodology and thought process behind Olson and Elisabeth’s work is still quite novel and extremely relevant to this study.

CHAPTER 4: METHODOLOGY

4.1 Data Collection and Preparation

In order to examine the economic impact of using precision agriculture, producers' technology usage and financial data are needed. The financial data for this study come from Nebraska Farm Business Inc. (NFBI). A database containing anonymous financial information on producers across the state associated with NFBI is used in order to perform the analysis in this study. To produce the technology usage data needed, a UNL Institutional Review Board (IRB) approved survey was developed and distributed to producers associated with NFBI. Response to this survey was kept completely anonymous, as researchers were only given access to a farm ID number, not actual producer names or personal information. This farm ID also allows for linkage to the financial database given to the researchers by NFBI. The survey asks producers if they have ever used the ten technologies discussed above in their farming operation and, if yes, the year they began using the technology and year they stopped using the technology. A copy of the survey used for data collection is shown in Figure A.1 of the Appendix.

A total of 109 surveys were mailed out to producers associated with NFBI and fifty-nine responses were received, resulting in a relatively high response rate of 54.13%. A database of technology usage by year was created, containing the usage of each technology, as well as total technology usage, for each respective producer from 1990-2016. For the various analyses, the data was transformed into more workable forms, combining the technology usage and financial data. A summary of producers' technology usage and financial information is shown in Section 5.1.

4.2 Financial Variables Used in Study

As mentioned above, a database containing financial information for a number of producers across Nebraska was received from NFBI. This database contains a large number of different liquidity, solvency, profitability, repayment capacity, and financial efficiency measures. In order to examine the impact of precision agriculture usage on whole-farm profitability, several different profitability and financial efficiency measures were used. The first and most obvious financial measure to use in this study is net farm income (NFI). NFBI defines this measure as the return to a producer’s labor, management, and equity that they have invested in their business; the reward for investing unpaid family labor, management, and money in the business instead of elsewhere. It is a measure of profitability, as it is the difference between the value of goods produced and the cost of the resources used to produce them. Net farm income in the database is calculated as:

$$NFI = Gross\ Cash\ Farm\ Income - Total\ Cash\ Farm\ Expenses$$
$$+/-\ Inventory\ Changes - Depreciation$$

There are two different versions of NFI available in this database: market-based and cost-based. For purposes of this study, cost-based net farm income is used, as it is the more accurate, reliable measure of the two. The difference between them is mostly the calculation of depreciation. For cost-based NFI, a set, consistent management depreciation is used (10% for machinery and equipment, 5% for buildings). For market-based NFI, the producer is able to choose the value of their equipment with a relatively high degree of flexibility, resulting in less consistency in depreciation values, as producers can manipulate their levels of depreciation and asset values in order to lower their income tax burden. Thus, cost-based NFI is the more accurate and consistent measure, making it the preferred choice for this study.

The next financial measures used are financial efficiency measures. NFBI states that these measures show how effectively a farm uses assets to generate income, making these measures very suitable for the purposes of this study. The financial efficiency measures used are ratios which show how gross farm income is used. The first measure used is the net farm income ratio (NFIR), which compares profit to gross farm income. This shows how much is left after all farm expenses, except for unpaid labor and management, are paid. Net farm income ratio is a very good measure for this study, as it shows a farm's efficiency in turning gross income into net income, i.e. profits. Furthermore, this efficiency measure is effective in eliminating potential size bias; net farm income will likely be higher for larger producers, whereas net farm income ratio will not necessarily be higher for larger producers, just for more efficient producers. The ratio is calculated as follows:

$$NFIR = \frac{Net\ Farm\ Income}{Gross\ Farm\ Income}$$

The second ratio used in analysis is the operating expense ratio (OER). This ratio shows the proportion of farm income used to pay operating expenses, not including principal or interest. Due to the fact that many studies have shown various precision agriculture technologies to decrease operating expenses, this ratio should, in theory, be lower for technology users. The operating expense ratio is:

$$OER = \frac{Total\ Farm\ Operating\ Expenses\ Excluding\ Interest\ \&\ Depreciation}{Gross\ Farm\ Income}$$

4.3 Methods Used for With/Without Analysis

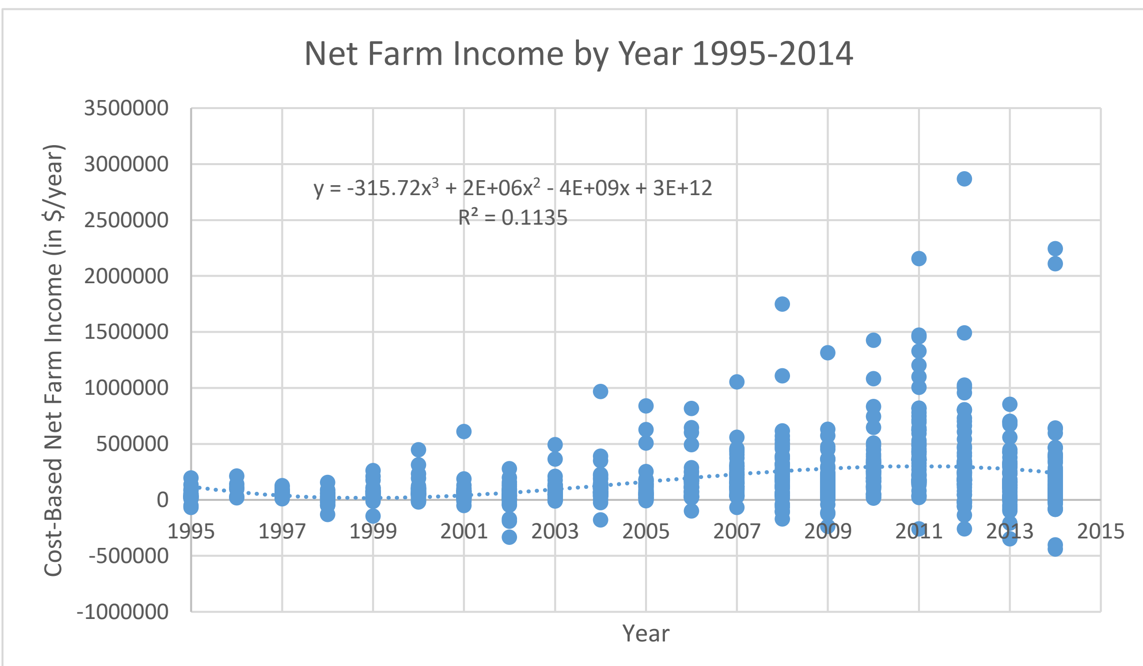
4.3.1 Initial With/Without Analysis

The first analysis performed in the study examines the differences in profitability between users and non-users of precision agriculture technologies in order to determine the relationship between technology usage and profitability. However, because only three of the fifty-nine respondents had never used any of the technologies, comparing strictly those using any technologies and those using none is not feasible. Rather, the total number of technologies used becomes the independent variable of interest, acting as a measure of the extent of precision agriculture technology use. The high rate of technology usage in the sample is most likely due to the fact that the producers associated with NFBI are more progressive than the typical producer. Just becoming a client of such an organization is an indication that they are inclined to be managerially-focused and thus are more likely to be early adopters of technology, resulting in a very low number of complete non-adopters.

The data of interest in this study take the form of panel data. Panel data is defined by Hilmer and Hilmer (2014) as data collected for a number of individuals, countries, firms, etc., over many different time periods, also known as longitudinal data. In this case, the panel data set consists of technology adoption and financial data for fifty-nine different individual farms in Nebraska over a twenty-year span, from 1995-2014. As such, basic regression methods used for cross-sectional data cannot be used and instead a panel data methodology is needed.

The two main issues with the data are the potential existence of a time-trend in the profitability measures and the potential for bias resulting from consistently high-or-low-performing farms. Due to the boom in farm incomes in the five-to-ten years prior to 2014, then large fall in 2014, a relatively large time-trend was expected to be found in the financial data. So, net farm income (NFI) was plotted by year from 1995-2014, as shown below in Figure 4.1. Various trend lines were fitted to the data and a third-order polynomial was found to be the best fit, as it shows a slight decrease through the late 1990s and a gradual rise until peaking around 2012, then a decrease again. To determine whether or not this time-trend was of significance, a regression was performed for the third-order polynomial and was found to be significant at the α=1% level. The time-trend regression results can be found in Figure A.2 of the Appendix.

Figure 4.1: Chart of NFI by Year from 1995-2014



In addition to the time-trend, there is also concern regarding bias in the results due to consistently high-performing and low-performing farms. For example, if some farms have consistently higher incomes, simply regressing technology usage versus income does not suffice, because these farms will have relatively higher incomes regardless of their level of technology usage. Additionally, when using NFI as the dependent variable, there is an obvious size bias that exists, as larger farms are most likely going to have larger NFI and smaller farms are going to have smaller NFI. Once again, simply regressing technology usage versus NFI will give a distorted response, because the larger farms may have a higher NFI than smaller farms regardless of whether or not the technologies used by the large farm have caused them to gain or lose money.

In order to address these two potential issues, a fixed-effect panel data model with T-1 year dummy variables was used (for the T=20 years from 1995-2014). The year dummy variables control for the time-trend by separating the effects of each year from the effect of the number of technologies used. The fixed-effect model is a method of removing the time-invariant component of the error term in panel data, in this case removing the bias of consistently high-and-low-performing farms (and size bias when regressing NFI). The fixed-effect model removes the individual effect α_i by applying a within-transformation to (or "demeaning") the data and then estimating the quasi-differenced regression by ordinary least squares (Hilmer and Hilmer, 2014). The within-transformation is performed by subtracting each individual's mean value for both the independent and dependent variables from each of the individual observations for each individual. For further explanation of this method, see Hilmer and Hilmer, 2014.

The first with/without analysis requires the use of one main independent variable (the number of precision agriculture technologies used, shown below as x_1) and year dummy variables to control for the existing time-trend (shown below as Φ_T). The year dummy variables take on a value of 1 in year T and a value of 0 if the observation is for any other year. So, each dummy variable used takes on a value of 1 only one time for each individual producer. Thus, our original model prior to the within-transformation can be written for $i = 1, 2, \ldots, N$ producers across $t = 1, 2, \ldots, T$ years as follows:

Equation 4.1: $$y_{it} = \beta_1 x_{1,it} + \Phi_T + \tilde{\varepsilon}_{it}$$

Where:

y_{it} = Various financial measures to be examined (NFI, NFIR, OER).

Applying the fixed-effect model to equation 4.1 transforms each variable, then OLS regression is performed to produce parameter estimates. This model was then estimated for the various y_{it} variables using the free, open-source technology software "R". Results of the regression can be found in the Results and Discussion section.

4.3.2 Extended With/Without Analysis

After performing the initial analysis to determine the relationship between the extent of precision agriculture technology usage and profitability, the analysis was taken a step further. Due to the fact that not all of the ten technologies are expected to have a direct impact on profitability, the independent variable was split into two groups of technologies in order to further examine these technologies' impact. The two groups are: 1) those technologies whose purpose is to provide information which can allow for improved management decisions, but do not themselves have a direct impact on profitability and 2) those technologies whose purpose is to directly increase profitability by reducing inputs and/or increasing production. The differences between these two types of technologies were detailed in Chapter 2, explaining why the technologies were assigned to their respective groups.

The group of information-producing technologies include: combine yield monitor (without GPS), combine yield monitor (with GPS), grid or management zone soil sampling, imagery, and telematics. The group of technologies with a direct impact on profitability include: GPS guidance with a lightbar, GPS guidance with autosteer, ASC, variable-rate application of nutrients, and variable-rate seeding. Thus, instead of an independent variable with values ranging from 0-10 technologies used, this analysis uses two separate independent variables with values ranging from 0-5 technologies used for each category and equation. The resultant model can be written as follows:

Equation 4.2: $$y_{it} = \beta_1 x_{1,it} + \beta_2 x_{2,it} + \Phi_T + \tilde{\varepsilon}_{it}$$

Where:

y_{it} = NFI of producer *i* in year *t*.

$x_{1,it}$= Number of information-producing technologies used by producer *i* in year *t*.

$x_{2,it}$ = Number of direct-impact technologies used by producer *i* in year *t*.

Once again, applying the fixed-effect model to equation 4.2 transforms each variable, then OLS regression is performed to produce parameter estimates. The results of this regression analysis are shown in the Results and Discussion.

4.4 Methods Used for Before/After Analysis

4.4.1 Initial Before/After Analysis

The second half of the analysis performed in the study examines the differences in profitability before and after adopting precision agriculture. Due to the fact that this analysis focuses solely on users of the technology, the three producers not using any of the technologies are removed from the data, resulting in a sample of fifty-six producers as opposed to the full fifty-nine responses received. As was the case in the with/without analysis, these data take the form of panel data, with financial and technology usage on the fifty-six individual producers each year from 1995 – 2014. This analysis allows for examination of whether or not usage of the technology has actually resulted in increased profitability as compared to non-use.

In order to perform this analysis, a binary dummy variable was created for use of precision agriculture, taking on a value of zero in years of non-use and a value of one in years of use; allowing for the before and after comparison. Precision agriculture use was defined as using any of the ten technologies in question. So, each producer's value was zero in each year prior to adopting a precision agriculture technology, then equaled one in the year of adoption and each subsequent year. Typically, the first technology adopted was a yield monitor, grid soil sampling, or a GPS guidance system. Multiple technologies could be adopted at once, but the dummy variable for use still takes on a value of one.

Due to the fact that there is a learning curve expected to be present when adopting a new technology, an interaction term of technology usage and years of use was created to capture this potential effect. To create this interaction term, time t=0 was set to be the initial year of use, with each year after taking on a value of t+1, t+2, …, t+k for all k years of use. So, a producer who adopted their first technology in 2013 would have a years after value of 1 in 2014, whereas a producer who adopted their first technology in 1995 would have a years after value of 19. This years of use value was then multiplied by the precision agriculture usage dummy variable, resulting in values of zero for years of non-use and values equal to the years of use for each year in which a technology is being used. It should be noted that a few producers started using precision agriculture technologies prior to the first year for which financial data is available. Adoption data is available starting in 1990, but financial data is not available until 1995. Thus, producers who adopted a precision agriculture technology in this period simply have a t=0 in a year prior to the beginning of their financial data, resulting in a positive value for the interaction term for all years of financial data. For those who had adopted precision agriculture prior to 1990, it is instead assumed that 1990 is their first year of use. These individuals then had an interaction term value of 5 at the start of the available financial data.

Because the dependent variable remains the same as in the with/without analysis, the same existence of a time-trend and individual performance bias is expected and must be addressed. Again, year dummy variables (Φ_T) are used to control for the time trend, and a fixed effect panel data model is used, applying within transformations and demeaning the data to remove any performance bias. However, in this model, there are now two main independent variables of interest: technology usage (x_1) and the interaction term between usage and length of usage ($x_1 * y_A$). The resultant model can be written as:

Equation 4.3: $$NFI_{it} = \beta_1 x_{1,it} + \beta_2(x_{1,it} * y_{A,it}) + \Phi_T + \tilde{\varepsilon}_{it}$$

Again, applying the fixed-effect model transforms each of the variables in Equation 4.3. The database was then uploaded to R and this model was estimated using NFI as the dependent variable. Results of the regression analysis can be found in the Results and Discussion.

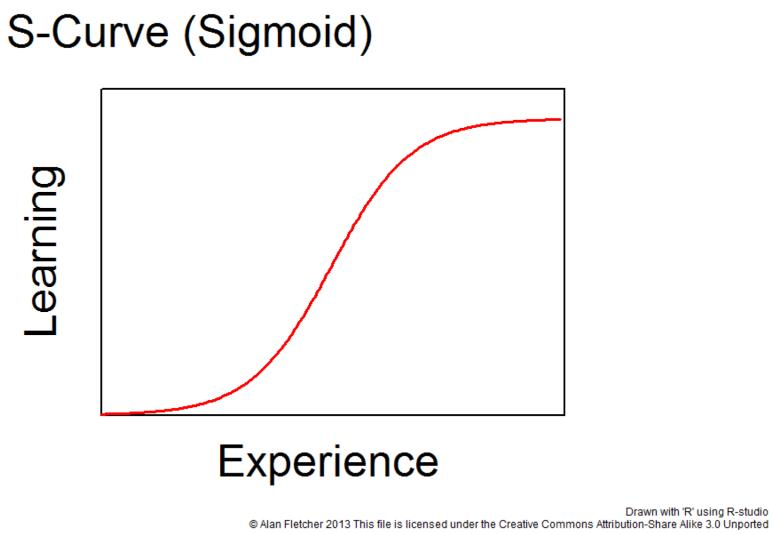
4.4.2 Extended Before/After Analysis

As alluded to above, a learning curve is expected for the realized benefits of using precision agriculture technologies. Due to the fact that some of these technologies are quite complex and the average producer is relatively older and may be less technologically-savvy, it is expected to take some time to optimally use the technology and thus take some time to realize the maximum benefit from use. So, it is hypothesized that as the number of years of use increases, increases in profitability should increase as well, which is the purpose of using the interaction term in the first analysis. However, the first model assumes this relationship to be linear, which may not be the case.

In his 2011 book, M. Jaber discusses the enormous number of different learning curves in existence, the majority of which are non-linear. Jaber (2011) notes that modeling changes in performance as a function of experience has often been done using non-linear forms such as S-curves and exponential functions. The author provides two early papers (Wright, 1936; Yelle, 1979) in operations management literature that discuss this issue. Jaber (2011) then describes a 1998 study by Ployhart and Hakel in which the cubic (S-shaped) curve is used to model the individual productivity of salespeople. The cubic function's S-shaped curve has been used to model learning in various circumstances. Daller, Turlik, and Weir (2013) performed a review of different learning curves as they related to vocabulary skills and provide multiple examples of studies in which a cubic function has been shown as best to capture the effect of learning. Although these studies are not from agricultural economics literature, their concept is still applicable to this study.

Due to the fact that this analysis examines the growth in financial performance (NFI) by individual farms using new technologies, this model seems quite relevant. The beginning stages of the S-shaped learning curve represent the time in which a person is becoming familiar with a task and begin to slowly improve. This is followed by a rapid ascent in performance, as the person gains experience and is able to start improving very quickly, until reaching a ceiling and their performance begins to plateau. This may very well be the case when it comes to precision agriculture usage, as the first few years are spent learning the features and proper uses of the technology, as well as collecting the necessary data to make improved management decisions, resulting in very slow increases or even decreases in profitability until they become familiar with the technology and have sufficient data on which to act. Furthermore, because many producers' first technology adopted was an information-producing technology such as a yield monitor or grid soil sampling, the first few years may actually show decreases in profitability due to the fact that they have paid for the technology but are not expected to receive any immediate, direct benefit to profitability from use. Once they have discovered the best uses of the technology and have an adequate amount of data collected, they are able to make rapid improvements to management decisions and experience large increases in profitability until ultimately reaching a ceiling and achieving near-maximum benefit from use. A generic form of the S-shaped (sigmoid) learning curve is shown in Figure 4.2 below.

Figure 4.2: Generic Sigmoid Learning Curve



In order to test for the existence of a non-linear learning factor, new polynomial interaction terms are added to the original fixed-effect panel data model as independent variables, resulting in the following:

Equation 4.4:

$$NFI_{it} = \beta_1 x_{1,it} + \beta_2 (x_{1,it} * {y_{A,it}}^3) + \beta_3 (x_{1,it} * {y_{A,it}}^2) + \beta_4 (x_{1,it} * y_{A,it}) + \Phi_T + \tilde{\varepsilon}_{it}$$

Where:

NFI_{it} = NFI for producer *i* during year *t.*

$x_{1,it}$ = Dummy variable for precision agriculture usage for producer *i* in year *t*; equal to 1 when producer using at least one technology, equal to 0 when not using any.

$y_{A,it}$ = Years of use of precision agriculture for producer *i* in year *t*, as defined above.

$x_{1,it} * y_{A,it}{}^{k}$ = Interaction term between precision agriculture usage and years of use raised to the k^{th} power, ranging from k=1 to k=*3* making up the third-order polynomial attempting to examine the existence of a cubic relationship for learning; equal to the value of $y_{A,it}{}^{k}$ during years in which producer *i* is using a precision agriculture technology and equal to 0 during years in which no technologies are used.

Again, applying the fixed-effect model transforms each of the variables in Equation 4.4. The database including the cubed and squared interaction terms was then uploaded to R and the model was run in order to produce interpretable parameter estimates. The results of this regression analysis can be found in the Results and Discussion section. However, these parameter estimates by themselves are not sufficient to make conclusions; further analysis is required.

4.4.3 Determining Significance of Parameter Estimates

The significance levels on the individual parameter estimates for the polynomial interaction terms do not provide any interpretable value by themselves. Instead, the significance of the marginal impact of years of use is of interest. The marginal impact of years of use shows the impact that adding an additional year of experience will have on NFI. If the marginal effect of years of use in a given year is positive and statistically significant, it is an indication that adding an additional year of experience with the technology will increase NFI further, while years in which the marginal effect is not statistically significant indicate that an additional year of experience will not have any further impact on NFI.

Differentiating Equation 4.3 with respect to years of use results in a marginal effect of:

Equation 4.4.1

$$Marginal\ Effect = \frac{\partial NFI_{it}}{\partial y_{A,it}} = 3\beta_2\left(x_{1,it} * y_{A,it}{}^2\right) + 2\beta_3\left(x_{1,it} * y_{A,it}\right) + \beta_4\left(x_{1,it}\right)$$

Due to the fact that $x_{1,it}$ = 1 during years of use, the marginal effect of years of use becomes:

Equation 4.4.2

$$Marginal\ Effect\ During\ Use = \frac{\partial NFI_{it}}{\partial y_{A,it}} = 3\beta_2\left(y_{A,it}{}^2\right) + 2\beta_3\left(y_{A,it}\right) + \beta_4$$

A t-statistic for this equation is then calculated in R for each year (year 1 to 25, indicating the maximum possible years of use in the data from 1990-2014). Each individual year's t-statistic is then used to calculate the corresponding p-value in R, determining for which years the marginal effect of years of using the technology on NFI is and is not statistically significant. The results of the tests for significance in each year can be seen in Table 5.2 in the Results and Discussion.

CHAPTER 5: RESULTS AND DISCUSSION

5.1 Summary of Sample Financial and Technology Usage Information

As mentioned above, a total of fifty-nine responses were received. A summary of the averages of the financial measures in question of these fifty-nine respondents can be seen by year in Table 5.1 below.

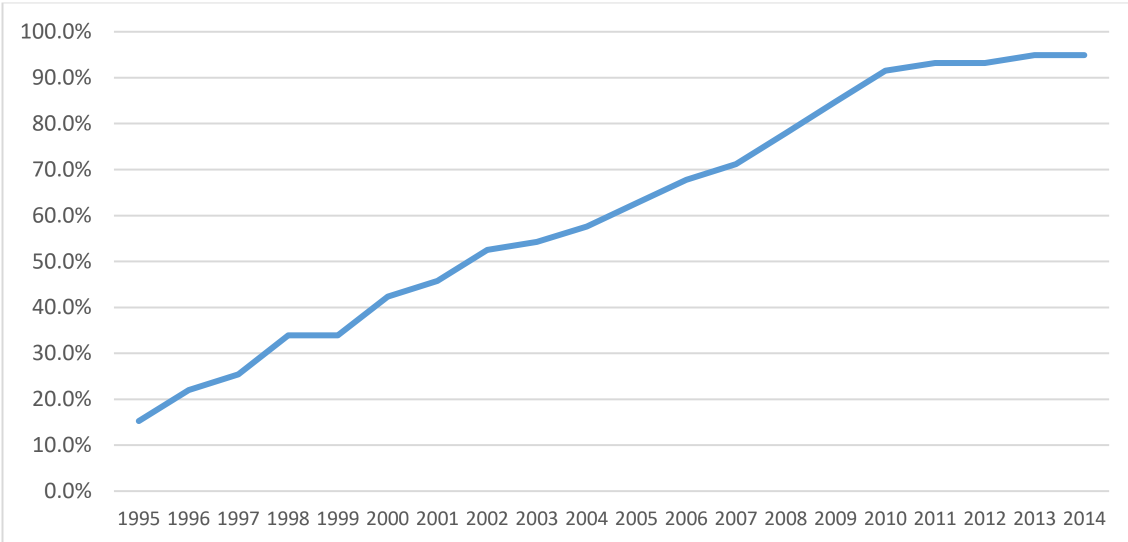
Table 5.1: Average Financial Measures of Sample by Year

Year	Avg. NFI	Avg. NFIR	Avg. OER
1995	$42,246.11	17.49	68.17
1996	$102,065.83	25.13	61.08
1997	$62,699.09	22.70	63.14
1998	$18,740.69	8.22	76.30
1999	$66,373.19	19.03	66.57
2000	$96,004.40	22.33	63.85
2001	$71,273.62	16.25	70.42
2002	$32,140.44	7.67	79.19
2003	$94,540.95	19.83	67.77
2004	$124,035.50	20.76	66.30
2005	$128,170.05	18.19	69.15
2006	$159,993.59	23.16	63.98
2007	$219,767.96	30.06	58.40
2008	$241,678.74	26.05	62.07
2009	$180,519.57	21.12	66.65
2010	$290,020.28	29.81	59.51
2011	$481,470.09	38.26	52.77
2012	$366,000.32	24.10	65.62
2013	$184,520.98	19.68	69.80
2014	$215,847.32	12.32	75.86

As can be seen in the table, the average NFI, NFIR, and OER are quite variable over the period, mainly because of the huge run-up in commodity prices from 2007 – 2012 and subsequent drop in 2013 – 2014. The variability in these measures over the time period serve to further highlight the need to control for a time trend using the year dummy variables, as explained in the methodology section. Due to the fact that the clients of NFBI are all active farmers whose main income source is farming, their income levels are likely to be a considerable amount higher than an average of producers across the state as would be reported by a USDA agency such as the National Agricultural Statistics Service (NASS). The averages typically reported by such agencies are an average of all farms, including hobby farmers and those whose main source of income is made outside of farming, causing it to be lower than an average of producers making their living entirely from farming. Regardless, the trends remain the same for all producers in the state, having experienced the same variability in commodity prices throughout the time period.

As alluded to in the review of relevant literature, one of the main issues with the only other whole-farm economic impact study on precision agriculture by Olson and Elisabeth (2003) was the low usage of precision agriculture in the sample in question. In their study, only 27.8% of respondents reported using at least one precision agriculture technology in their operation. Fortunately, that is not the case in this study, as by 2014, 94.9% (56 of 59 respondents) were using at least one precision agriculture technology, as can be seen in Figure 5.1 below. This provided the data needed to actually examine the realized impact of the technologies.

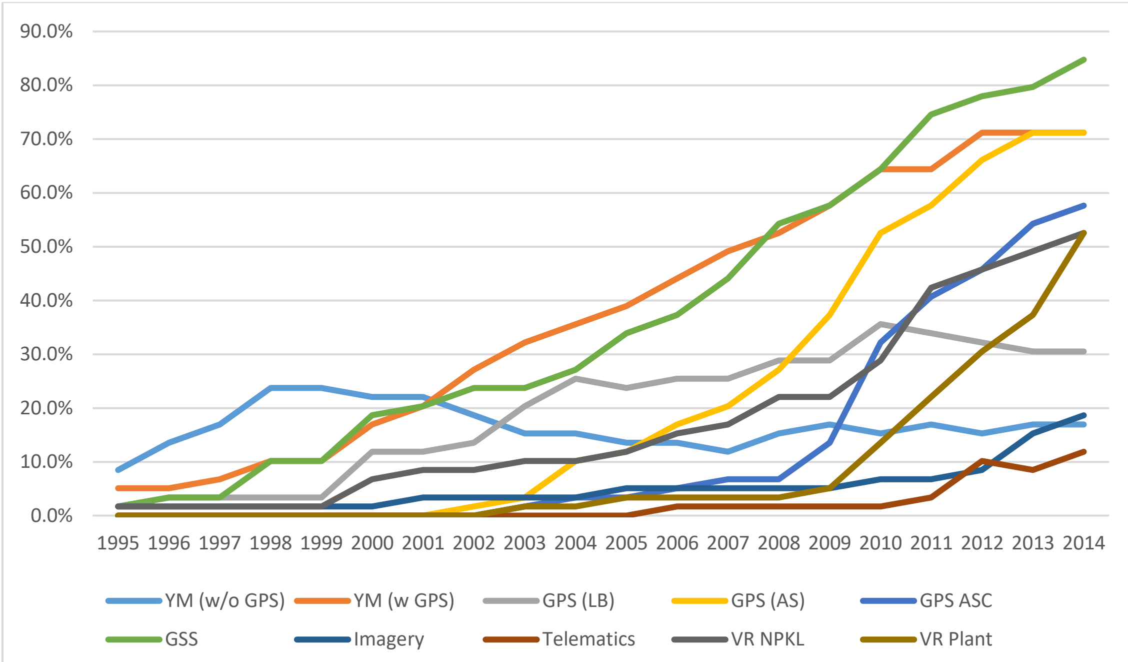
Figure 5.1: Percentage of Sample Using at Least One Technology by Year



As shown in Figure 5.1, precision agriculture usage increased quite steadily throughout the period studied, moving from only 15.3% users in 1995 to 94.9% users in 2014. Adoption of the technologies takes the form of a slight S-curve, as would be expected with the adoption of new technology, with slow rises in adoption after introduction by those ahead of the curve, followed by rapid adoption by the majority, and finally a tapering off as all of those who intend to adopt the technology have done so.

However, use of at least one technology isn't the only adoption characteristic of interest; which technologies are being used is also a very relevant aspect of overall usage. Figure 5.2 below shows the percentage of the sample using each of the individual technologies by year from 1995-2014.

Figure 5.2: Percentage of Sample Using Each Individual Technology by Year



As can be seen, grid soil sampling is the most widely used technology by the sample, with nearly 85% of respondents reporting use as of 2014, followed by GPS-enabled yield monitors and autosteer GPS guidance at 71.2% apiece. It's not a huge surprise to see these technologies at the top of the list, as they are relatively simple to use and do not require as much effort to produce benefits. The next-highest-used technologies as of 2014 are ASC at 57.6%, followed by variable-rate application of nutrients and variable-rate planting, tied at 52.5% each. These technologies are relatively new and have all seen use increase very rapidly since around 2008. Imagery and telematics are two of the least-used technologies with only 18.6% and 11.9% of the sample using them as of 2014, respectively. These two technologies not only require a relatively high amount of work to learn to use properly and receive benefit from, but they have both undergone very recent advancements and will thus take some time to catch on. GPS guidance systems with a lightbar and yield monitors without GPS are also relatively less-used as of 2014, with 30.5% and 16.9% use, respectively. These two technologies have both been around for a relatively long period of time and have actually begun to experience a decrease in use by the sample, as other technologies may have superseded them in usage.

This graph provides more than just the adoption of each technology over the time period in question; it presents an interesting picture regarding the dynamics of use, with new technologies coming out at differing times and being adopted and abandoned at varying rates. For instance, yield monitors without GPS, one of the earliest precision agriculture technologies, initially gained a significant amount of adopters, but their use peaked in the late 1990s and has decreased ever since. Their peak in the late 1990s and subsequent decrease is obviously due to the boom in popularity of yield monitors with GPS, the newer and superior technology. As can be seen in the graph, the non-GPS yield monitor's peak and decline coincides with the start of a large increase in GPS-enabled yield monitor use. A similar story is shown in the graph in terms of GPS guidance systems. GPS guidance via lightbar was made available to producers several years prior to autosteer systems. Lightbar usage saw considerable increases through the late 1990s and early 2000s, but reached a bit of a peak in 2004. From 2004 to 2014, usage of lightbars basically stagnated, while usage of autosteer exploded in a very obvious S-shaped pattern, showing another example a new technological advancement replacing existing technology.

5.2 Results and Discussion of With/Without Analysis

5.2.1 Initial With/Without Analysis

As explained in Chapter 4, a fixed-effect panel data model was used to examine the effect of the number of technologies used on the given profitability measures, with year dummy variables controlling for the time trend. These regressions were run in R in order to produce parameter estimates and interpretable results.

A summary table of the results of the initial with/without analysis is shown below in Table 5.2. As can be seen in the table, number of technologies used is estimated to have a positive and statistically significant relationship with net farm income, indicating that higher technology usage is associated with higher profitability.

Table 5.2: Initial With/Without Regression Results

Dependent Variable	Parameter Estimate	Standard Error	t-Value	P-Value
NFI	43,616.0305***	10,495.5200	4.1557	<0.0001
NFIR	1.0399	0.6964	1.4932	0.1359
OER	-1.0404*	0.5736	-1.8140	0.0701

Note: Each row represents the results of each respective regression. Parameter estimates indicate the estimated change in the given dependent variable from the use of an additional precision agriculture technology. Year dummy variables were also included in each regression to control for the time trend. *** indicates statistical significance at the α=1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

The parameter estimate of 43,616.03 indicates that the use of an additional precision agriculture technology is associated with an increase in net farm income of

\$43,616.03, with a p-value well within significance at the α = 1% level. These results show very clearly the existence of a large, positive relationship between extent of technology usage and NFI. The parameter estimate for number of technologies used is 1.04, indicating that each additional precision agriculture technology used is associated with an increase in net farm income ratio of approximately 1%. This result would be consistent with hypotheses, as the technology use is expected to improve efficiency and profitability, which would make one expect a very clear relationship between use and NFIR. However, this parameter estimate falls just outside of statistical significance, with a p-value of 0.136. As such, it is difficult to come to any conclusions regarding the relationship between the variables. The results of the OER regression show that the number of technologies used has a parameter estimate of -1.04, with statistical significance at the α = 10% level. This indicates that using an additional precision agriculture technology is associated with a 1.04% decrease in operating expense ratio, meaning that the use of precision agriculture is associated with lower operating expenses relative to gross farm income. This could be an indication of decreased operating cost from more efficient use of inputs (such as reduced overlap, etc.), increased gross farm due to greater production, or a combined effect of both.

Overall, the results of the initial with/without analysis show the existence of a strong relationship between higher levels of precision agriculture usage and higher profitability. This is evidenced by the positive and statistically significant relationship between number of technologies used and NFI, the negative and statistically significant relationship between number of technologies used and OER, and the positive but not quite statistically significant relationship between number of technologies used and

NFIR. However, this half of the analysis only proves the two are related; it does not definitely prove that usage of precision agriculture increases profitability. It may be the case that producers have adopted the technologies simply because they had the money to do so. Thus, whether use drives profitability or profitability drives use remains in question at this point in the analysis.

5.2.2 Extended With/Without Analysis

After performing the initial analysis to determine the relationship between the extent of precision agriculture usage and profitability, the analysis was taken a step further. As explained above, the independent variable from the initial with/without analysis is split into two categories of technologies. The first group of technologies are those not expected to have a direct impact on profit and instead are used to produce information with which producers can make improved decisions. The second group of technologies are those expected to have a direct impact on profits. NFI is used as the dependent variable. The results of the extended with/without analysis are shown below in Table 5.3.

Table 5.3: Extended With/Without Regression Results

Variable	Parameter Estimate	Standard Error	t-Value	P-Value
Direct Impact Techs. Used	60,792.60***	13,420.50	4.5298	<0.0001
Info. Producing Techs. Used	10,578.20	19,245.40	0.5496	0.5827

Note: Parameter estimates indicate the estimated change in NFI from the use of an additional technology in the respective categories. Year dummy variables were also included to control for the time trend. *** indicates statistical significance at the α=1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

The analysis was separated this way in order to further examine the relationship between technology usage and profitability. As seen in Table 5.3, the number of information-providing technologies used has a parameter estimate of 10,578.20, indicating that use of an additional information-providing technology is associated with an increase in NFI of $10,578.20. However, with a p-value of 0.5827, this result is not close to statistical significance. The number of direct-impact technologies used has a considerably larger parameter estimate of 60,792.60 and achieves statistical significance at the $\alpha = 1\%$ level. This means the use of an additional direct-impact technology is associated with an increase in NFI of nearly $61,000.

The large difference in parameter estimates and significance between the two groups of technologies helps to further make the case for demonstrating increased profitability from use of precision agriculture. The direct impact technologies' much larger and statistically significant parameter estimate relative to the information-producing estimate makes a great deal of sense, as the direct-impact technologies are expected to be the ones actually leading to increased net farm income. However, this analysis does not provide all of the evidence necessary to conclude that use of these technologies has led to increased profitability. The fact that the information-providing technologies have a much smaller parameter estimate could be due to them being cheaper and thus a lower level of profitability being needed to adopt them, whereas the more expensive direct-impact technologies may just require a higher level of profitability to adopt, resulting in their large estimate. Overall, the results of the extended with/without analysis illustrate that the direct-impact technologies drive the strong, positive relationship between the extent of precision agriculture usage and profitability (as would be expected), but whether or not use drives profitability or profitability drives use remains in question.

5.2.3 Summary of Results of With/Without Analysis

Overall, the results of the with/without analysis show the existence of a strong, positive relationship between precision agriculture usage and higher profitability. This relationship is being largely driven by the technologies expected to have a direct impact on profitability, not the information-producing technologies. However, the with/without analysis only proves that the two are related. To determine whether use of precision agriculture has led to higher profitability or the higher profitability has led to the use of precision agriculture, a pre-and-post adoption (before/after) analysis is performed on the profitability of users of precision agriculture to examine its realized economic impact over time.

5.3 Results and Discussion of Before/After Analysis

5.3.1 Initial Before/After Analysis

As in the with/without analysis, a fixed-effect panel data model was developed to examine the impact of using precision agriculture on profitability, again using year dummy variables to control for the existing time trend. Interaction terms between the use of precision agriculture and length of use are also used, attempting to examine the impact of learning on the benefit received from use. The results of the initial before/after analysis are shown in Table 5.4 below.

Table 5.4: Initial Before/After Regression Results

Variable	Parameter Estimate	Standard Error	t-Value	P-Value
Tech. Use	15,263.5140	38,327.5500	0.3982	0.6906
Tech. Use * Years Used	13,931.4420**	5,899.2740	2.3615	0.0185

Note: Year dummy variables were also included to control for the time trend. *** indicates statistical significance at the α=1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

As can be seen in the table, technology usage has a positive parameter estimate of 15,263.51, indicating that the usage of precision agriculture is estimated to have increased users' NFI by $15,263.51. However, with a p-value of 0.69, this result is quite far from being statistically significant and thus no conclusion regarding the benefit of using precision agriculture can be made based on this regression. On the contrary, the parameter estimate for the interaction term between precision agriculture usage and years of use is significant at the α = 5% level, with its p-value of 0.0185. The interaction term has a parameter estimate of 13,931.44, meaning that each additional year of using precision agriculture is estimated to increase NFI by nearly $14,000. The value of the parameter estimate itself is not necessarily the item of interest, but rather its sign. The fact that there is a positive and significant parameter estimate on the interaction term shows that the longer precision agriculture is used, the larger the increases in profitability experienced. This shows the existence of a learning effect in using these technologies, as expected.

5.3.2 Extended Before/After Analysis

As was detailed previously, the before/after analysis was taken a step further as polynomial interaction terms were added to the model in order to test for the existence of a non-linear learning relationship between length of usage and net farm income. The results of the extended before/after regression can be seen below in Table 5.5 and the results of the test for significance of the marginal effect for each year is shown in Table 5.6.

Table 5.5: Extended Before/After Regression Results

Variable	Parameter Estimate	Standard Error	t-Value	P-Value
Tech. Use	70,696.8965	45,397.3018	1.5573	0.1199
Tech. Use * Years Used	-11,855.3350	13,426.5875	-0.8830	0.3776
$(\text{Tech. Use * Years Used})^2$	2,634.6804*	1,372.3366	1.9199	0.0553
$(\text{Tech. Use * Years Used})^3$	-67.9060	42.4804	-1.5985	0.1104

Note: Year dummy variables were also included to control for the time trend. *** indicates statistical significance at the α=1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

Using the formulation, technology usage once again has a positive, but much larger, parameter estimate; now 70,696.90 as opposed to 15,263.51 in the previous regression. Additionally, a huge improvement in p-value is seen on the parameter estimate, falling just outside of statistical significance, right around a value of 0.12, preventing the ability to make any conclusion regarding the financial benefits realized from using precision agriculture. However, this is an indication that the model including the polynomial interaction terms has more explanatory power for the effect of precision agriculture usage on NFI.

In terms of the learning effect, the parameter estimates and significance of the interaction terms don't necessarily provide any interpretable results individually, as explained in Section 4.4.3. The true measure of interest is the significance of the marginal effect of years of use on the equation as a whole. As such, the value of the marginal effect is calculated for each year for twenty-five years after adopting a producer's first precision agriculture technology by plugging in the value of each year after adoption of the first technology ($y_{A,it}$) into equation 4.3.2. The statistical significance of the marginal effect in each respective year is then calculated, as explained in Section 4.4.3. The results of the tests of marginal effect by year are shown in Table 5.6 below.

Table 5.6: Estimated Marginal Effect of Years of Using Precision Agriculture

Year of Use	Marginal Effect	t-Stat	P-Value
1	-6,789.693	-0.607	0.728
2	-2,131.487	-0.228	0.590
3	2,119.283	0.789	0.215
4	5,962.617	0.868	0.193
5	9,398.515*	1.492	0.068
6	12,426.977**	2.036	0.021
7	15,048.003***	2.441	0.007
8	17,261.593***	2.720	0.003
9	19,067.747***	2.909	0.002
10	20,466.465***	3.041	0.001
11	21,457.747***	3.135	0.001
12	22,041.593***	3.192	0.001
13	22,218.003***	3.203	0.001
14	21,986.977***	3.141	0.001
15	21,348.515***	2.976	0.002
16	20,302.617***	2.687	0.004
17	18,849.283**	2.289	0.011
18	16,988.513**	1.831	0.034
19	14,720.307*	1.376	0.085
20	12,044.665	0.964	0.168
21	8,961.587	0.612	0.270
22	5,471.073	0.319	0.375
23	1,573.123	0.079	0.469
24	-2,732.263	-0.118	0.547
25	-7,445.085	-0.281	0.611

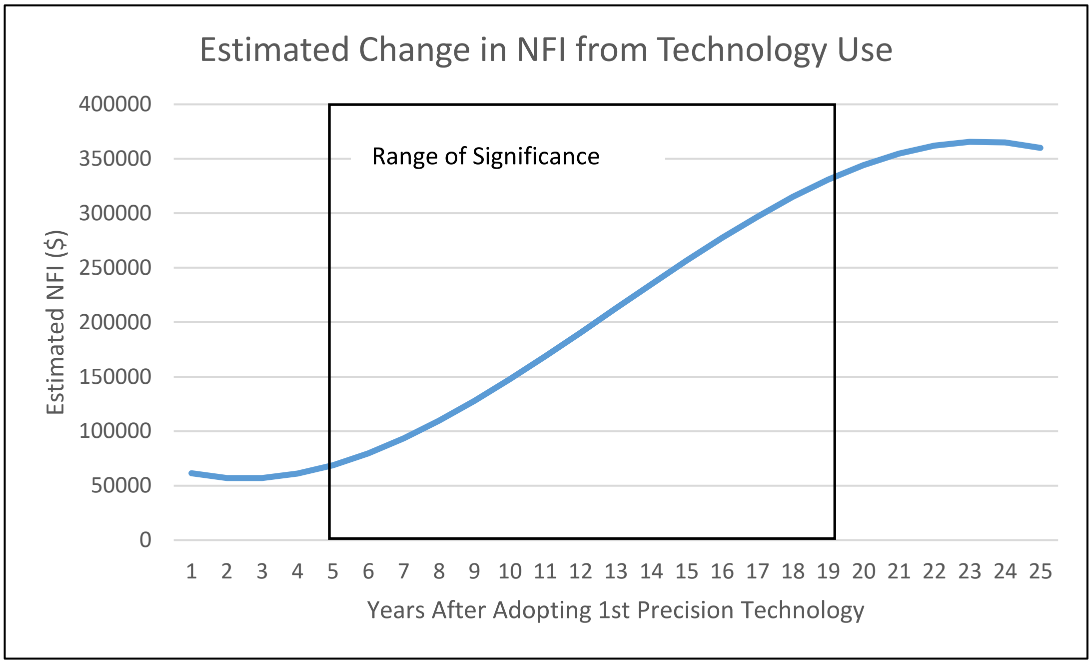
Note: Marginal effect indicates estimated effect an additional year of experience with precision agriculture will have on NFI. *** indicates statistical significance at the α=1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level.

The values for the marginal effect in the table indicate the estimated change in NFI that would result if an additional year of experience was added in that given year. For example, the estimated marginal effect in the first year indicates that NFI is expected to decrease by $6,789.69 when going from one year of experience with precision agriculture to two years of experience. The negative marginal effects in years one and two indicate that NFI is actually expected to decrease in the beginning years of using precision agriculture. This may be the result of producers typically adopting information-producing technologies first, such as yield monitors or site-specific soil sampling. These technologies don't provide any increases to profitability by themselves, as was shown in Table 5.3 and subsequently discussed. Their purpose is to gather data that the producer will be able to act on in the future. So, the producer is paying to purchase and maintain these technologies without receiving any real benefit until enough information is gathered on which to act; possibly explaining the negative marginal effects in the beginning. The marginal effect turns positive after three years of use, indicating that, after three years, an additional year of use would increase NFI by $2,119.28. After this, marginal effect remains positive and increases at a decreasing rate until reaching a peak in year 13. During this span, NFI is expected to continue growing with increased experience, indicating rapid growth from learning the technologies and acquiring actionable data. After reaching the peak in year 13, the marginal effect remains positive but the estimates decrease until ultimately turning negative once again between the 23rd and 24th year after beginning use. This is indicative of diminishing marginal returns from use of the technology, as the maximum benefit is approached.

Nonetheless, the marginal effect of years of use only achieves statistical significance beginning five years after adoption and remains significant through 19. The lack of statistical significance in the first four years after use means that adding an additional year of experience with precision agriculture is not expected to change profitability during this time. This is most likely a combination of both a lag in benefit due to lack of actionable data as well as a learning effect. In the first few years, it is not surprising to see a lack of improvements to profitability from use, especially if only using information-producing technologies. The estimate for the marginal effect is positive in all of the years in which statistical significance is achieved, showing that in these years, profitability is continually increasing with experience. This is indicative of a learning effect, with producers becoming better with the technologies over time and most likely adopting more of them during this span. Additionally, more and more years of data should be expected to result in more and more increases to profitability, as the producer is able to become increasingly better at managing within-field variability with the improved information. The final marginal effect of statistical significance indicates that adding an additional year of experience will increase profitability after 19 years of use, but not 20. Thus, moving from 19 years of use to 20 is expected to increase profitability, but moving from 20 years to 21 is not. This may be an indication of maximum benefit being achieved, showing that an additional year of experience is not going to provide any further improvements to profitability.

A graph of the parameter estimates for technology use is shown below in Figure 5.10. The range of years in which the marginal effect achieves statistical significance is indicated by the black box in the figure.

Figure 5.3: Graph of Extended Before/After Parameter Estimates



As can be seen, the graph takes the form of an S-curve, relatively similar to the generic learning curve seen in Figure 4.2. However, the longer, more gradual rise from beginning to end is an indication that learning the proper usage of precision agriculture and thus receiving maximum benefit takes a relatively long time, as a more shallow learning curve is indicative of a difficult-to-learn task, despite the common phrasing of "steep learning curve" (Givens, 2014). This point is further driven home by the fact that the marginal effect remains positive and statistically significant until year 20, indicating a rather lengthy investment of time to achieve maximum benefit. This result is intuitive both because it takes time to produce the data on which to act and because some of these technologies can be quite complex and should be expected to require a relatively long time to learn to use optimally.

5.3.3 Summary of Results of Before/After Analysis

Overall, the before/after analysis results in positive but not statistically significant estimated effects on NFI from usage of precision agriculture. The second model, resulting in an S-shaped learning curve effect is shown to be the better fit, but technology usage itself still does not achieve significance. As such, precision agriculture's realized effect on profitability remains somewhat unclear. However, a significant learning effect is shown to exist in both models, proving that profitability from using precision agriculture technologies increases with time. This learning effect is expected to take the form of a relative S-curve; likely a combination of needing to gather usable data in early years, as well as taking the time to learn the optimal use of the technologies.

CHAPTER 6: CONCLUSIONS AND DIRECTIONS FOR FUTURE RESEARCH

6.1 Conclusions from Study

Various fixed-effect panel data models were used to examine the realized whole-farm economic impact of using precision agriculture among producers in Nebraska. Necessary data for this study come from surveying producers across the state associated with NFBI regarding their adoption of precision agriculture from 1990-2014. Financial data for these producers from 1995-2014 was made available through collaboration with NFBI. The analysis was separated into two halves; the first examining the relationship between extent of technology usage and profitability and the second examining pre-and-post effects of technology usage over time among adopters.

The first half of the analysis found a positive and significant relationship between extent of technology usage and profitability. Thus, we are able to conclude that higher levels of technology usage are associated with higher profits. However, this result alone does not prove that using precision agriculture has resulted in higher profitability; producers could just be adopting the technology in times of high profitability. The second half of the analysis attempts to address this issue and determine whether use is driving profitability or profitability is driving use. The two different models used in the before/after analysis resulted in positive estimated effects on NFI due to precision agriculture usage, suggesting that use of the technologies has in fact increased profitability. However, these positive estimates are not statistically significant. As such, we are unable to conclude that the usage of precision agriculture has led to increased profitability; the picture remains unclear.

From the analysis, we are able to conclude that profitability increases with experience using the technologies, as both models examining the pre-and-post adoption relationships produced positive and significant parameter estimates for the interaction term(s) between precision agriculture usage and years of use. Overall, the model including polynomial interaction terms is a better fit than the model using a linear interaction term, indicating the existence of a non-linear learning effect from use, with the curve taking on a relative S-shape. This result makes sense, with producers not receiving much benefit from use while needing to collect actionable data and learn the optimal use of the technologies in the first few years, followed by a relatively long-term span of improvements in profitability before ultimately reaching the near-maximum benefit to profitability from use.

Overall, the results of this study prove that farms with higher profits have been using more precision agriculture technologies but it remains unclear whether they have achieved this profitability from using the technologies or have begun using the technologies because of the profitability. There is likely a mix of both going on with producers, as there are many different factors affecting the profitability of these technologies (as explained in Chapter 3) and differing levels of technological-savviness. It is clear that further study regarding the economic impact of these technologies is needed, as the investment in precision agriculture is quite costly, both monetarily and in terms of time spent learning proper use, but whether or not its use has paid off for adopters remains unclear.

6.2 Limitations of Study and Directions for Future Research

While this study produces interesting results, it faces many limitations. The most obvious improvement to the study would be increasing sample size. Although the response rate for the survey was quite high at over 54%, a sample of only 59 producers limits the amount of data available for analysis. Increasing sample size using the given NFBI population of interest would be an improvement and collecting other sources of data representing more producers would also be very desirable.

Although this study makes the most of the available technology adoption and financial data, the model is still limited. The year dummy variables attempt to control for changes in the farm economy over the time period and the fixed effect model attempts to control for any time-invariant bias among individuals. However, there are other factors that exist that could be addressed to build a more comprehensive model, including off-farm income, cropping patterns, production practices, field characteristics and variability, producer characteristics, etc. Including these variables could help to create a clearer picture of the impact precision agriculture has had and which factors have influenced its profitability. Doing so would require a considerably larger sample, however, as splitting the already limited sample even further would lessen explanatory power.

It would also be of interest to take the families of technologies examined in this study a step further and examine the realized economic impact of the technologies individually in order to determine which have shown the highest/lowest benefit. Though the results of the study show the direct-impact technologies to be driving the strong positive relationship that was found between higher levels of precision agriculture usage and higher profitability, it would be of interest to know which specific technologies are driving this relationship. Knowing which technologies have had the highest and lowest impacts on profitability would be of great interest to row crop producers in making their investment decisions in times of such tight margins.

Examining the learning curve associated with use of these technologies further would also be of interest. The extensive review of literature shows that there have been no prior studies investigating this learning effect, so all such subsequent study would be of great relevance. Though this study shows the existence of a learning effect from use, it assumes this learning effect to be the same for all producers. With different producers having different levels of experience with technology, education, etc., the learning curve is likely not the same for everyone. Thus, it would be of interest to explore these potential differences, perhaps determining the relative steepness/shallowness of the learning curve by different producer characteristics and for different technologies.

Overall, this study serves as a foundation for examining the realized economic impact of precision agriculture technology. As mentioned, studies using real-world financial data to examine the realized impact of precision agriculture are extremely limited at this point, making the methods and results of this study quite novel. Furthermore, this study provides a framework for examining the learning effect experienced by producers adopting precision agriculture technologies; a previously un-researched topic that should be expanded upon.

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APPENDIX

Figure A.1: Survey Used for Data Collection

NFBI Client,

This brief survey is asking for information regarding your usage of precision agriculture technologies in your operation. Your response to this survey is very important and will help provide an understanding of the costs and benefits associated with using these technologies. There will be no monetary compensation or direct benefits available for participation. However, the results of this study will be made available to the public, which may help producers like you make decisions regarding technology usage in the future.

Your response to this survey is voluntary and will be kept completely confidential. A farm ID number is asked for in order to link survey responses to selected farm financial data collected by NFBI in order to examine the realized economic impact of using these technologies over time. Researchers will only have access to the data and the anonymous farm ID number; only NFBI will have access to the information linking this ID number to individual producers. NFBI will control the data given to researchers and remove any information identifying individual producers. Individual data will not be made public; only aggregated data will be published. There are no known risks in participating in this study.

Your decision whether or not to participate in this survey will not affect your relationship with the University of Nebraska-Lincoln or NFBI in any way. This study is being conducted for a UNL graduate thesis and is not being conducted by NFBI. Completion of this survey implies your consent to participate in this research project, while not completing this survey implies that you do not consent to participating. With this in mind, please be as honest as possible when answering the following questions.

This survey should take no longer than five minutes to complete. Once the survey is completed, please send it back in the pre-paid envelope provided to you. We thank you in advance for your participation.

Sincerely,

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NFBI Consultant ______________________________

Farm ID ______________________________________

Precision Ag Technology	Have You Ever Used This Technology? (Yes/No)	If Yes, Year Began Using	If Stopped Using, Year Ended Using
Combine Yield Monitor (without GPS)			
Combine Yield Monitor (with GPS)			
GPS Guidance (Lightbar)*			
GPS Guidance (Autosteer)*			
GPS Automated Section Control (auto boom or row shutoff)*			
Grid Soil Sampling (<5 acre grids) or Management Zone Sampling (by soil or other defined zone)			
Imagery (aerial, satellite, UAV)			
Telematics (tracking of equipment; wireless data transfer)			
Variable Rate N, P, K, or Lime with Automated Controller*			
Variable Rate Seeding*			

*Indicates farm-level equipment only (do not include custom applicators)

Figure A.2: Results of Third-Order Polynomial Time Trend Regression

Regression Statistics	
Multiple R	0.336881991
R Square	0.113489476
Adjusted R Square	0.109866136
Standard Error	277082.8886
Observations	738

ANOVA

	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	7.21418E+12	2.40473E+12	31.32178459	4.64769E-19
Residual	734	5.63528E+13	76774927134		
Total	737	6.3567E+13			

	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	2.54436E+12	5.85733E+11	4.343895124	1.5968E-05
Time	-3807255303	876357980.9	-4.344406494	1.59318E-05
Time^2	1898977.317	437059.3711	4.34489555	1.58973E-05
Time^3	-315.7201578	72.65681363	-4.345362011	1.58644E-05