THE IMPACT OF COVER CROPS ON FARM FINANCE AND RISK: INSIGHTS FROM INDIANA FARM DATA USING ECONOMETRIC AND STOCHASTIC METHODS

by

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A Thesis

Submitted to the Faculty of Purdue University

In Partial Fulfillment of the Requirements for the degree of

Master of Science in Agricultural Economics

Department of Agricultural Economics

West Lafayette, Indiana

August 2019

THE PURDUE UNIVERSITY GRADUATE SCHOOL
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ACKNOWLEDGMENTS

I would like to acknowledge the help and support of my committee, Dr. Wallace Tyner, Dr. Michael Langemeier, and Dr. Otto Doering. Their help and guidance has been invaluable. Each has given significant advice and assistance in the research process. Additionally, each has offered friendship and personal support along the way. Several other faculty also helped me understand concepts and answered questions in their areas of expertise, most notably Dr. Timothy Baker.

I am grateful for partial funding support for this research received from the Natural Resource Conservation Service via a sub-contract with the Farm Foundation. The Farm Foundation contract number is 693A7516007. However, I am solely responsible for the contents of this thesis.

I was also fortunate to have excellent classmates and friends in the department, each of whom were a pleasure to work with and provided a team which helped one another. In particular, I would like to thank Jeremiah Stevens and Jonathan Lawing for their contributions to my thesis and experience at Purdue. We spent many hours working together on homework, discussing research ideas, or debating issues. Lest I give the impression that life was all serious, there was also an occasional basketball game (played and watched) or movie mixed in as well.

I also would like to acknowledge my parents for the role they played in my education and helping me in any way they could. I want to thank my sweet wife for her support and encouragement. I don’t know what I would have done without her love and assistance. She also contributed many valuable suggestions in terms of readability and spent significant effort proof reading for spelling and punctuation. I thank her for her contributions and support.

Lastly, I want acknowledge the strength I have received through prayer and faith. I feel that I have been blessed with the ability to finish this project.

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ABSTRACT

Author: Anderson, Andrew, E. MS
Institution: Purdue University
Degree Received: August 2019
Title: The Impact of Cover Crops on Farm Finance and Risk: Insights from Indiana Farm Data Using Econometric and Stochastic Methods
Committee Chair: Dr. Wallace E Tyner

For agricultural soils to be perpetually productive, farmers must maintain and improve the physical, chemical, and biological properties of the soil. The loss of soil to erosion is a major challenge to soil health, contributing to farmland loss and declines in productivity. This is a long-term problem for agriculture because there is a limited amount of topsoil available. Another costly loss happens when residual nitrogen is lost to leaching or carried away in runoff. This is a particular problem in the fall and winter months when fields lie fallow, and there are no plants to take up excess nitrogen. Losing nitrogen is a problem for both the nutrient content of the soil as well as a serious concern in terms of water contamination. Cover crops provide a way to at least partially address each of these and many other agronomic and soil health issues. Although there has been a steady increase in cover crop use, adoption has been relatively slow. This is likely due to a lack of economic information and understanding of the associated risk. To address this problem, field level data was gathered from farmers across central and northeastern Indiana. The data included information on cash crop yield, cover crops grown, fertilizer use, among many other variables. The sample was trimmed based on the estimated propensity to cover crop, in order to reduce selection bias. Using this data, the effect of cover crops on the mean and variation of the subsequent cash crop yield was estimated using regression analysis. This information was combined in a stochastic analysis of a farm enterprise budget. The effects of cover crops on farm finance and risk were evaluated. These final analyses provide agricultural producers with more information to make informed decisions regarding the adoption of cover crops. The information may also provide insight to policy makers, who may wish to understand more completely the private economics of cover crops. The results indicated that cover crops have the ability to provide economic benefits when grown prior to corn in our study region. These include increased yield, reduced need for nitrogen fertilizer, and increased temporal yield stability. These benefits translate into higher revenue from the sale of the grain, lower input costs, and lower risk and uncertainty. However, the results for soybeans showed cover crops had a negative, albeit statistically insignificant, effect on desirable measures. This led to lower projected revenue, higher projected costs, and increased expected risk. Even so, the average corn-soybean contribution margin with cover crops was nearly equal to the baseline scenario. Furthermore, the analysis of risk showed that the corn-soybean two-year average would be preferred by farmers with moderate to high risk aversion. The difference between the effect of cover crops in corn and soybeans may be due to differences in the crop's inherent nitrogen needs and the difficulty of cover crop establishment after corn in the region.

CHAPTER 1 INTRODUCTION

1.1 Soil Health

The rapidly growing human population relies almost completely on food from agriculture. About 99.7% of calories consumed by humans originate from the land, with less than 0.3% coming from oceans and other bodies of water (Pimentel, 2006). This places the burden of feeding the world squarely on the productive capacity of the soil. Virtually every kind of land-based food production system relies directly on plants grown in soil. The ability of the soil to support life is vital to the survival and progress of society. Soil degradation is considered to be an important factor in the decline of past civilizations (Lowdermilk, 1953). In modern intensive agriculture, soil resources worldwide are often used more far more quickly than they are replenished (Nearing, Xie, Liu, & Ye, 2017). Present levels of soil loss and degradation are unsustainable in the long run and appear to be a threat to food production and food security in some areas of the world, even in the short run (Scherr, 1999).

Most farmers in the US already understand the importance of soil fertility and have a program to monitor and address chemical imbalances. But maintaining healthy soil requires balancing the management of multiple characteristics. For agricultural soils to be perpetually productive, farmers must maintain and improve the physical, chemical, and biological properties of the soil (Andrews, Karlen, & Cambardella, 2004). Soil physical properties include topsoil depth, soil structure, water retention, and soil temperature. Examples of relevant chemical properties are nutrient status, soil pH, and soil organic carbon. Perhaps the most important soil functions result from biological properties involving microbial activity, earthworms, and other organisms. Nutrient cycling and other vital processes could not take place without the extensive biological activity that occurs in the soil (Lehman et al., 2015).

Intensive modern agriculture has had widespread and sometimes harmful effects on soil quality. Soil erosion on agricultural lands is slowing but still continues at unsustainable rates (Nearing et al., 2017). This is a long-term challenge for agriculture because there is a limited amount of topsoil available. Additionally, erosion can alter soil physical properties very quickly, making the ground less productive (Alberts, Moldenhauer, & Foster, 1980; Chepil, 1957; Colazo & Buschiazzo, 2015). Runoff carries nutrients that are dissolved in the water or attached to soil particles in addition to the soil itself, depleting the nutrient status of the soil (Sharpley et al., 1994). The soil that is removed through water erosion often finds its way into rivers and streams causing the water to become polluted. Most of the nitrogen (N) and phosphorus (P) in waterways was transported by means of soil erosion (Nearing et al., 2017). Soil removed by wind degrades air quality and causes damage to buildings and vehicles. The loss of soil to erosion is a major factor contributing to farmland loss and declines in productivity (Pimentel, Harvey, Resosudarmo, & Sinclair, 1995).

In its atmospheric form, N is not available to plants until it has been fixed into a usable form. N fixing mostly occurs through industrial or biological fixation. Arable cropland receives both biologically fixed N and fertilizer, as well as organic waste including manure and plant residue that contain organic N. However, the organic N incorporated into the soil must be mineralized by soil microbes before it is available to crops. Microbes also assist in nitrification, which transforms fertilizers and mineralized organic N from ammonium (NH_4^+) to nitrate (NO_3^-) which is more available for plants. However, NO_3^- as well as most soils are negatively charged, so NO_3^- is not retained well in the soil. If NO_3^- is not taken up by plants, it is susceptible to leaching or being carried away in runoff. This is a particular problem in the fall and winter months when fields lie fallow, and there are no plants to take up NO_3^-. Seasonal precipitation typically increases during this time creating moist soils. These conditions in addition to fall cultivation promote microbial activity which accelerates mineralization of organic N in the soil and crop residues (Di & Cameron, 2002; G. S. Francis, Haynes, & Williams, 1995). Mineralized NH_4^+ is then transformed relatively quickly by nitrification into NO_3^-. Approximately 50 to 75% of NO_3^- that has built up by the end of autumn in the soil profile is leached throughout the winter (Di & Cameron, 2002). Most nitrogen losses in the Midwest due to leaching—as much as 95%—take place in the period from November to May when there is no vegetative cover on fields (Cambardella, Moorman, Jaynes, & Hatfield, 1999; Drury, Tan, Gaynor, Oloya, & Welacky, 1996). Losing such large amounts of N is a problem for both the nutrient content of the soil as well as a serious concern in terms of water contamination.

Nitrate originating from agricultural cropland is a major contributor to nutrient contamination of surface waterways in the Midwestern United States (Alexander et al., 2008; Burkart & James, 1999; David, Drinkwater, & McIsaac, 2010). The enrichment of waterways with too many nutrients (eutrophication) causes algae to grow and creates hypoxic conditions (shortage of oxygen), blocks sunlight, and can cause the collapse of underwater ecosystems. Phosphorus accelerates eutrophication and is usually the limiting factor in most US freshwaters (Sharpley et al., 1994). Seasonal hypoxia in the Gulf of Mexico has been indirectly linked to the load of nutrients supplied by rivers that empty into the Gulf, in particular the Mississippi River (Turner & Rabalais, 1994). The cultivation of corn and soybeans alone contributes approximately 52% to the total nitrogen yield in waterways in the Mississippi River basin (Alexander et al., 2008). Eutrophication and resulting hypoxia of waterways cause numerous economic costs (Dodds et al., 2008).

Cover crops provide a way to at least partially address each of the previously mentioned soil health and environmental concerns that are faced by modern agriculture. While each of these issues will not be entirely solved by using cover crops, using such a system could assist farmers in managing these concerns. Often there is some difficulty assigning an explicit economic value to many benefits of cover crops, particularly those that are external to the farm business. However, there could be an observable impact on profitability through any direct changes in costs and any impact on yields. Although there has been a significant increase in cover crop use in the recent past, farmers have been slow to adopt cover cropping in the Midwest. In fact, only about 8.6% of farms in the US use cover crops and cover cropped land represents a mere 2.6% of total cropland (USDA, 2014). This is likely due to the uncertainty of economic benefit to the farm business, as details about the economic viability of cover crops are still lacking (CTIC, 2017; S. M. Lira & Tyner, 2018; Singer, Nusser, & Alf, 2007). Farmers who have not yet adopted cover crops into their cropping system are also concerned about the contribution of cover crops on production risk (CTIC, 2017). Furthermore, since many farmers have short term time horizons, long-term benefits may be less relevant in the decision to adopt cover crops (Napier, Tucker, & McCarter, 2000). There is a need to quantify the costs, benefits, and impact on production risk for farmers and policy makers. With better information and analysis, decisions on adoption and promotion can be more informed and productive.

The problem is that while cover crops assist in managing soil health and environmental concerns, farmers are slow to adopt them. This is likely because of a lack of authoritative economic information and particularly risk analysis. Policy makers also need additional economic information on which to base improved promotion programs.

1.2 Objectives

The objective of this study is to provide better information to help farmers to make informed production choices about cover crops. If the direct (private) benefits of using cover crops are greater than the direct (private) costs, then adoption by farmers is an economically attractive choice. This study may also provide policy makers with additional cost-benefit differential information to structure any policy needed to promote the use of cover crops. The analysis of risk should also be considered in connection with crop insurance risk assessment when cover crops are grown. Perhaps reduced premiums could double as an incentive for the adoption of cover crops as a conservation practice. Our study is focused on central and northeastern Indiana, but the conclusions could be relevant across the Midwest.

1.3 Methodology

Data were collected from corn and soybean farmers in 37 counties in central and northeast Indiana. These counties were selected because they share a similar climate and growing conditions. The data set included farms that have used cover crops as well as those that have not. Information for the cash crop includes yields, seeding rates, herbicide use, and fertilizer applications. Also, information was gathered for the cover crop; in many cases, this included the cost of establishment and termination.

Participation in the study was voluntary so there is the potential for bias based on the farmers who chose to participate in the study. Because the data was observational farm data, the assignment of cover crop fields was not random. This has the potential to cause selection bias if there are reasons a field might be systematically chosen for cover cropping. To correct for this bias, an accepted method from econometrics was used to trim the sample. This sample trimming was done based on an estimated propensity of a field to be cover cropped.

First, we built on the work of S. M. Lira and Tyner (2018), to examine the effect of cover crops on the mean of the subsequent cash crop yield. Yield changes are important to the farmer's adoption decision because they make a direct and observable impact on revenue. This analysis was done using regression analysis, including year fixed effects and several interactions. For corn, the projected yields were plotted over nitrogen application to observe the yield response.

Second, we tested the impact of cover crops on the variation of the cash crop yield. Variation in yield is a measure of production risk. Since risk reduction can be valued, this may represent a potential additional benefit to the farmer. This analysis was done by collapsing the data over the temporal dimension and performing a regression analysis. This method helped to estimate the effect of cover crops on the temporal cash crop yield variability.

Finally, the financial and risk analyses brought the economic value of all of the previous analyses together. The financial analysis evaluated private financial benefits and costs. The risk analysis ranked competing alternatives in terms of their relative economic attractiveness given the risk they carry. The financial analysis was done by creating a farm enterprise budget in @Risk that showed the costs and revenue of producing either corn or soybeans. These budgets had several stochastic inputs, including yields, prices, and selected costs. The predicted yields and yield standard deviations defined the stochastic yield distributions. The budgets—one for corn and one for soybeans—were estimated using Monte Carlo simulation. From the simulated budget financial comparisons were made between cover crop scenarios and the baseline. The main measure that was calculated and compared was the contribution margin. The output distributions for the contribution margin from the simulation were compared for first- and second-degree stochastic dominance. Using the output data and an assumed utility function, certainty equivalence was estimated and compared. The budgets provide specific financial values and a basic ranking. The stochastic dominance and certainty equivalence analyses provide a ranking with preference for risk accounted for. These final analyses could provide agricultural producers with more information to make increasingly optimal decisions regarding the adoption of cover crops. The information may also provide insight to policy makers, who may wish to understand more completely the private economics of cover crops.

1.4 Road Map

Following this introduction, chapter 2 contains a review of the literature on related topics. It includes studies that discuss the challenges of soil erosion and nutrient loss. Additionally, the research surrounding many of the agronomic and soil health benefits of cover crops is explored. Lastly, the previous literature regarding the economics of cover crops will be reviewed. Chapter 3 contains a detailed explanation of the data collected in this project. Chapter 4 explains the methods and theory used in this analysis. Chapter 5 reports the results of this study and provides discussion of the findings and their implications. Chapter 6 summarizes the results and draws conclusions from this study as well as limitations and suggestions for future research.

CHAPTER 2 LITERATURE REVIEW

2.1 Introduction

In this chapter, we review the academic literature that is relevant to our study of cover crops. To begin, we examine literature relating to two especially significant environmental concerns facing Midwestern agriculture. These are (1) soil loss and degradation, and (2) nutrient contamination of waterways. For some time, cover crops have been proposed as at least part of the solution to these problems. Consequently, we will then briefly review basic cover crop management by discussing establishment and termination. We also review the options for different cover crops and their merits. Next, we turn our attention to the considerable literature on the environmental impact and agronomic benefits of cover crops. These include their impact on nutrient loss, soil erosion, soil properties, as well as weeds, pests, and diseases. The impact of cover crops on cash crop yields has a direct effect on profitability, and there are many studies that have analyzed this. We summarize the body of literature related to both average yields and yield variability. Finally, we provide an overview of research on the profitability and economics of cover crops. In conclusion, we summarize what this study is anticipated to add to the existing body of knowledge.

2.2 Environmental Concerns for Midwestern Agriculture

To begin our exploration of the literature on cover crops we discuss two main environmental concerns for agriculture, especially in the Midwest. Understanding these problems will underscore the significant environmental and agronomic services provided by cover crops.

2.2.1 Soil loss and degradation

There are two kinds of water erosion that typically impact agricultural cropland, rill, and inter-rill erosion. Rill erosion takes place in small rivulets where water flow becomes concentrated where it dislodges soil particles and transports them away. Inter-rill erosion, also known as sheet erosion, takes place on soil surfaces where falling water droplets displace and transport soil to wherever the water is flowing, usually to the rills. The formation of rills is undesirable because they have greater capacity to displace soil. Rill erosion also displaces larger soil particles than inter-rill erosion does (Alberts et al., 1980). Other types of erosion such as gully or streambank erosion are less common on cultivated land but are still possible.

Wind erosion can also impact agricultural lands especially during dry conditions when soil is left bare. Tillage causes the breakdown of soil aggregates leaving them more susceptible to wind erosion. Wind erosion tends to “sort” the soil material, removing the smaller and lighter particles while leaving behind larger components such as sand (Chepil, 1957). This process, if sustained over time, can increase the sandiness of the soil, diminish water holding capacity, reduce soil organic matter, deplete the nutrient status of the soil, and generally cause a decline in soil productivity (Colazo & Buschiazzo, 2015).

Soil erosion creates costs for farmers and others. The soil that is removed through water erosion often finds its way into rivers and streams causing the water to become polluted. Soil that is removed by wind degrades air quality and causes damage to buildings and vehicles. The loss of the soil itself is a major long-term problem for each farm since soil erosion is a major factor contributing to farmland loss and declines in productivity (den Biggelaar, Lal, Wiebe, & Breneman, 2001). These issues can raise costs for the farm business as it attempts to compensate for the loss of soil to wind and surface erosion. It is estimated that 10% of the total energy used in all of U.S. agriculture in 1995 was spent to offset losses of nutrients (Pimentel et al., 1995).

Research indicates that soil is more susceptible to erosion when soybeans are the main cash crop, as well as the year after soybeans have been grown (Alberts, Wendt, & Burwell, 1985). In fact, soybeans fields lose soil at about twice the rate that corn fields do. This is likely due to the fact that corn produces more residue that is left on the soil surface and corn residue decays more slowly than soybean residue does (Alberts et al., 1985). Soybean production has been increasing steadily for the last few decades, with more farmers utilizing a corn-soybean rotation. This increase demonstrates the need for management tools to control erosion and highlights the particular challenge of keeping Midwestern soil out of waterways.

Between 1982 and 2012 soil erosion rates on cultivated cropland in the United States declined from 9.3 to 6.7 metric tons per ha per year (Nearing et al., 2017). This reduction coincided with widespread adoption of erosion control practices such as no-till, conservation tillage, and residue management practices. This is significant progress and shows that conservation efforts have made a widespread impact. However, average soil losses are still well above the average soil formulation rate of about 2 metric tons per ha per year (Nearing et al., 2017).

Eroded sediment from farmland carries with it large amounts of nitrate, phosphorus, and other agricultural chemicals into waterways. In fact, soil erosion is the vehicle for around 73% of the total nitrogen and 80% of the total phosphorus that is delivered to waterways in the United States (Nearing et al., 2017).

2.2.2 Pollution of waterways

Multiple studies have concluded that nitrate originating from agriculture has become a primary source for nutrient pollution of surface waterways. Alexander et al. (2008) estimate that agriculture contributes more than 70% of the N and P that is delivered to the Gulf of Mexico from the Mississippi River basin, with corn and soybeans alone contributing around 52%. In a large study that modeled the nitrogen runoff for the whole Mississippi River basin, David et al. (2010) found that the N export to rivers ranged from 5% in the lower basin to 30% in the upper basin of net N inputs on agricultural land. Their results also suggested that the interaction of fertilizer application and runoff volume was the largest predictor of N losses to rivers. Tile drainage also explained 17% of the spatial variation in riverine nitrate yield in the winter and spring.

Nutrient load in the Mississippi River has been shown to be the primary cause of seasonal hypoxia in the Gulf of Mexico (Turner & Rabalais, 1994). Nitrates are typically discussed as the problem, yet P is also an important contaminant leading to eutrophication and hypoxic conditions as well. In fact, P is a limiting factor whose absence slows this process (Sharpley et al., 1994). The eutrophication of waterways creates multiple economic costs. The damage to aquatic life affects regions that rely on water-based ecosystems for recreation or commercial fishing. Less obvious economic costs such as decreased property values are also significant (Dodds et al., 2008).

2.3 Overview of Cover Crop Management Practices

Cover crops have gained increasing attention for their potential assist in the agricultural issues that we have thus far discussed. We now turn our attention to studies that have examined alternative management practices.

2.3.1 Establishment

Cover crops are typically planted in the fall close to the harvest of the cash crop. The seed may be broadcast, drilled, or aerially seeded. In order to successfully establish a quality stand in the upper Midwest, cover crops should be planted as early as possible (Stute & Posner, 1993). One review of different establishment methods compared drilling cover crops with broadcast seeding (not including aerial broadcasting or inter-seeding). They concluded that drilling required fewer resources than broadcasting because they made an additional pass to incorporate the broadcast seed, with an implement such as a disk, harrow, or cultivator. This analysis also indicated that at a given seeding rate, drilled cover crops had important attributes like greater uniformity and more rapid emergence (Brennan, 2014).

Alternately, some farmers choose to inter-seed into an existing crop. While this lengthens the growing season for the cover crop, it also must compete with the cash crop until it is harvested which may reduce quality of establishment (Stute & Posner, 1993). Similarly, other farmers broadcast seed aerially before harvest to give the cover crops more time grow before cold weather sets in (Blanco-Canqui, Sindelar, Wortmann, & Kreikemeier, 2017). In a field trial completed in Iowa, aerial seeding led to higher average biomass in both fall and spring than drilled cover crops. This is probably due to timing of establishment. However, aerial seeding often has higher variability in biomass (Carlson, 2012). This may be a result of several factors that can interfere with the establishment of the cover crop. Thus there exists a tradeoff between getting the crop in earlier for better establishment and higher variability in the quality of establishment.

2.3.2 Termination

If cover crops are not winter-killed, they need to be chemically or mechanically terminated. Alternatively, the cover crop could be harvested for forage in the spring (Jewett & Thelen, 2007). If cover crops are not effectively killed in the spring, they can become a weed and reduce yields of the subsequent cash crop (Palhano, Norsworthy, & Barber, 2018). Ineffective termination may also create extra costs for additional passes and could delay planting of the cash crop.

Chemical termination is the most common and typically the most effective method of terminating cover crops. The cover crop may be terminated before or after the planting of the cash crop, but most farmers kill cover crops before planting (CTIC, 2017). Many herbicides may be utilized to kill cover crops, but some chemicals are more effective than others for differing varieties. A study in Arkansas evaluated different chemical options for killing cover crops before planting the cash crop. Cereal cover crops were easily controlled with a pre-plant application of glyphosate. On the other hand, the most effective way to terminate legumes was shown to be applying a pre-plant mixture of glyphosate with glufosinate, 2,4-D, and dicamba (Palhano et al., 2018). Alternatively, another study suggested that a pre-plant application of 2,4-D followed by a post-emergence treatment of dicamba was adequate to terminate legume cover crops (Teasdale & Rosecrance, 2003).

The mechanical method is typically to use some form of tillage, such as disking, to destroy the cover crop. However, other methods are available such as a mechanical roller-crimper, flail mower, or corn stalk chopper. Yet, none of these methods provide as effective control of cover crops as chemical termination methods or heavy tillage (Teasdale & Rosecrance, 2003). The advantage of these alternative methods is that they allow cover crops to be terminated without the use of chemicals or tillage. This could be particularly useful to organic or low-input farmers who use a no-till system. The difficulty with the roller-crimper is that it has low kill rates when the cover crops are in earlier stages of development, but works well as the cover crop matures (Ashford & Reeves, 2009). The roller-crimper also is more effective for some varieties than others (Wayman et al., 2015).

The method chosen can impact soil nutrient levels. Termination through spring tillage can encourage more rapid mineralization of residual nitrogen that was taken up and stored in the cover crop biomass (Di & Cameron, 2002). On the other hand, removing the cover crop for forage would reduce the amount of nitrogen returned to the soil profile (Jewett & Thelen, 2007).

Another concern regarding termination is the timing of termination. While the exact date of termination does not typically have much effect on biomass production (Wayman et al., 2015), it may have several other important implications. The timing can affect corn seedling disease, growth, and eventual yield. One study evaluated experiments in which a rye cover crop was grown and followed by corn. Differing termination dates were used ranging from 25 days before planting to 2 days after planting corn. The corn seedlings grew more slowly in treatments where the cover crops were terminated within 10 days of the planting date. These same treatments also had reduced corn yield following cover crops. In contrast, plots where the cover crops were terminated more than ten days prior to planting did not experience these problems (Acharya, 2017). The timing of termination also has an impact on the levels of soil nutrients available to the newly planted cash crop. The cover crop takes up excess nitrogen, which is returned to the soil when it is terminated. However, the nitrogen must be mineralized from its organic state before it can be used by the following cash crop. The timing of termination affects the amount of nitrogen that is mineralized and available for the cash crop. Different varieties of cover crops release nitrogen into the soil at differing rates, so some varieties should be terminated earlier than others (Lacey & Armstrong, 2014).

2.3.3 Common Cover Crops

One of the most important management choices for farmers who adopt cover crops is variety selection. Common cover crops include species in the following categories: (1) cereal grains, (2) brassicas and mustards, (3) legumes, (4) non-legume annuals, (5) mixes (CTIC, 2017).

Farmers may use a wide variety of plants as a cover crop, or they may choose to mix two or more species. The choice of cover crop variety rests on the management goals of the farmer and the weather and climate conditions they face. The cost of seed, planting, and termination is also an important consideration when selecting a cover crop.

Cereal grains

Included in this category are common cover crops such as cereal rye, oats, winter wheat, triticale, and winter barley. Cereal rye is, by a wide margin, the most commonly used cover crop from any category (CTIC, 2017). Cereal grains have several qualities that make them a good choice. They are very effective at scavenging residual nutrients, particularly nitrogen from the soil (Rasse, Ritchie, Peterson, Wei, & Smucker, 2000). Additionally, they have extensive root systems to mitigate erosion, and they produce substantial biomass that can help add organic matter to the soil (Appelgate, Lenssen, Wiedenhoeft, & Kaspar, 2017; Poffenbarger et al., 2015; Snapp et al., 2005). Cover crops in this group are better at adding carbon to the soil than legumes because they decompose more slowly (Blanco-Canqui, Holman, Schlegel, Tatarko, & Shaver, 2013) One challenge with cereal grains as cover crops, particularly rye, is that the nitrogen that has been taken up by the plant is slow to mineralize after termination in the spring and is thus less available for the following cash crop (Lacey & Armstrong, 2014). In corn, this can reduce yields if the rye is not terminated long enough before planting (Crandall, Ruffo, & Bollero, 2005). There are also concerns with pest and disease management, because these varieties are related to several cash crops like corn and wheat, they may provide winter habitat for pests and diseases (Acharya, 2017; Acharya, Kasper, Moorman, Lenssen, & Robertson, 2016; Bakker, Acharya, Moorman, Robertson, & Kaspar, 2016).

Brassicas and mustards

This category of cover crops includes varieties like radish, rapeseed, turnip, and canola (CTIC, 2017). These crops have taproots that can break into hard soils and improve permeability for water and air (Chen, Weil, & Hill, 2014). Brassicas and mustards can help control certain types of weeds (Björkman et al., 2015). Brassicas scavenge as much nitrogen in the fall as rye but are prone to winter kill, so they may not perform as well in the spring for nitrogen uptake. Additionally, if the cover crop winter kills, the residue will be releasing mineral nitrogen into the soil, which may be lost if another crop is not planted early enough to capture it (Dean, 2009). On the other hand, the early release of nitrogen may allow more plant-available nitrogen to be in the soil when the following cash crop is planted and beginning to grow. Additionally, it has been shown that radish cover crops release mineralized nitrogen into the soil at a faster rate, even when terminated at the same time (Lacey & Armstrong, 2014). Another prominent challenge for this category of cover crops in the cooler regions of the Midwest is that they are typically difficult to establish in the late fall following grain harvests (Appelgate et al., 2017; Björkman et al., 2015).

Legumes

Several varieties of legume cover crops are commonly planted. Some of the most popular include crimson clover, hairy vetch, winter pea, cowpea, red clover, as well as other clovers and vetches (CTIC, 2017). It is common for farmers to plant legumes as a cover crop because of their ability to fix nitrogen in the soil to be used by the subsequent cash crop (Balkcom & Reeves, 2005; Ebelhar, Frye, & Blevins, 1984; Stute & Posner, 1993). However, the ability of each legume to provide biologically fixed nitrogen varies among varieties (Coombs, Lauzon, Deen, & Van Eerd, 2017). Legumes produce good amounts of above and below ground biomass and have stronger helpful impacts than most other cover crops on soil chemistry, microbial populations, and enzyme activity (Maltais-Landry, 2015; Mullen, Melhorn, Tyler, & Duck, 1998). There is also evidence that some legumes improve water infiltration when compares to cereals (McVay, Radcliffe, & Hargrove, 1989).

Non-legume annuals

Common non-legume annuals that are grown as cover crops are millet, buckwheat, and sorghum sudangrass (CTIC, 2017). Buckwheat grows quickly and thus is a good option for weed suppression and works well in cool climates where the fall growing season is short (Bulan, Stoltenberg, & Posner, 2015). Millet has been tested as a cover crop in soybeans with good results for suppressing weeds and did not reduce subsequent grain yields (Samarajeewa, Horiuchi, & Oba, 2006).

Cover crop mixes

Mixes are a good way to combine the unique strengths of multiple cover crops varieties. Many farmers who use cover crops design their own custom mixes to meet their needs (CTIC, 2017). For example, a farmer may wish to combine the nitrogen fixing attribute of a legume with the nitrogen scavenging ability of a cereal grain such as rye. Mixes can combine these or other attributes while increasing total biomass over what could have been achieved in a monoculture (Sainju, Whitehead, & Singh, 2005). There is some literature to suggest that cover crop mixes have a larger positive effect on corn yields, but the evidence is not necessarily conclusive (Miguez & Bollero, 2005). Because total cover crop biomass is usually increased, mixes have the potential to contribute more carbon to the soil than a single cover crop (Faé et al., 2009). However, some trials suggest that the advantage of mixes over a single cover crop may be limited (Appelgate et al., 2017). The proportion of each crop in the mix also has an effect on the performance of the mix for any particular attribute. For instance, hairy vetch alone has about two to four times the aboveground nitrogen content as rye by itself. Yet, in a mix of vetch and rye the total aboveground nitrogen content of the cover crop peaks between 50 and 100% hairy vetch (Poffenbarger et al., 2015).

2.4 Literature on Environmental and Agronomic Benefits of Cover Crops

When properly managed, cover crops can assist farmers by providing a partial solution to some of the biggest environmental and soil health challenges they face. In the following section, we will explore the research that has documented many agronomic and environmental benefits of cover crops as well as a few challenges cover crops may contribute to.

2.4.1 Reducing nutrient runoff and leaching

Losses of nutrients occur when fields lie fallow in the fall, winter, and spring as nitrogen mineralizes in the soil from crop residue and residual fertilizer. This mineralized nitrogen becomes vulnerable to leaching and runoff (Di & Cameron, 2002). Cover crops can be an effective mitigating strategy because they immobilize nitrogen by taking it up for plant growth. Research has shown that cover crops reduce soil mineral nitrogen during the fall by scavenging excess nutrients, which has the potential to diminish leaching and runoff losses throughout the winter (Ball Coelho, Roy, & Bruin, 2005; Coombs et al., 2017; Gaudin, Janovicek, Deen, & Hooker, 2015; Nance, Gibson, & Karlen, 2007; O'Reilly, Van Eerd, Robinson, & Vyn, 2011; Rasse et al., 2000). Even so, the amount of nitrogen uptake by cover crops—impacting their ability to slow losses—is dependent on growing conditions in the fall and early spring (Andraski & Bundy, 2005)

Nutrient runoff can contaminate waterways and increase fertilizer costs for the farmer. A study in Missouri found cover crops reduced dissolved nutrient runoff by 35 - 41% for ammonium, by 74 - 77% for nitrates, and by 7 - 63% for P due to runoff volume reduction. The analysis concluded that the use of cover crops significantly reduces nutrient runoff in no-till soybeans (Zhu, Gantzer, Anderson, Alberts, & Beuselinck, 1989).

Nitrate leaching occurs when nitrate leaves the soil in drainage water, contaminating groundwater or nearby surface waterways that receive the drainage. Research has demonstrated the ability of cover crops to reduce N leaching losses. One study used common rye and hairy vetch as cover crops in a continuous corn rotation. It was determined that both cover crops reduced nitrate leaching, but rye appeared to be the most effective (McCracken, Smith, Grove, MacKown, & Blevins, 1994). Another study tracked fields that were transitioning from pasture land to arable cropping. In this experiment, the reduction in leaching losses was attributed to uptake of nitrogen by the cover crops rather than reduction in drainage volumes. In fact, cover crops only reduced soil drainage by very small amounts, usually in the spring when transpiration demands by the crops increased. The results suggested that leaching loss reduction was positively related to the biomass of the cover crop, emphasizing the importance of good establishment for effective uptake of mineral N (G. Francis, Bartley, & Tabley, 1998). An additional study confirmed that cover crops reduced nitrate leaching after pastures were plowed to plant crops. A seven-year experiment was conducted to determine if tillage practices and cover crops had any impact on nitrate leaching. Before the transition leaching losses were low because pre-winter mineral N was relatively low, and the pasture continued to take up N throughout the winter. Much larger losses occurred under arable cropping. However, winter cover crops reduced the losses by approximately 50%. The average loss under a cover crop system was only 10 to 18 kg/ha/year. However, in years with very high winter precipitation, cover crops were less effective at reducing nitrate leaching (Fraser et al., 2013).

In some ways, nutrient losses through subsurface drainage are similar to traditional leaching problems, yet drainage systems represent a distinct means of transport for nutrients. A three-year trial in Minnesota evaluated the use of rye as a cover crop to reduce nitrate loss through subsurface drainage. The results showed that the cover crop reduced total drainage discharge by 11% and nitrate losses by 13% (Strock, 2004). In Iowa research was conducted to analyze the effectiveness of oat and rye cover crops in reducing nitrogen losses from subsurface drainage water. The plots that were used had subsurface (tile) drainage that was monitored for nitrate losses. The plots were evaluated over five years while cultivated in a corn-soybean rotation with treatments including oat cover, rye cover, and a control. There was no statistically significant difference among treatments for the volume of cumulative drainage. The rye cover crop reduced nitrate concentrations by 48%, while the oat cover was about half as effective. The difference is attributed to the fact that oats winterkilled and thus did not grow and take up nitrogen in the spring when much of the drainage occurs (T. C. Kaspar, Jaynes, Parkin, Moorman, & Singer, 2012). This result confirmed earlier analysis of rye cover crops. In a previous study under similar conditions, a rye cover reduced nitrate concentrations (amount of nitrate per unit of water) by 59% and loads (nitrate discharged over a given period) by 61% in drainage water. The result was attributed to nitrogen uptake of the rye, as the treatment did not significantly reduce average cumulative drainage (T.C. Kaspar, Jaynes, Parkin, & Moorman, 2007).

Cover crops have been shown to significantly reduce nitrogen runoff and leaching. However, these studies have shown the impact in experiments at a field or plot level. The impact of widespread adoption in the Midwest was simulated by Kladivko et al. (2014) for a successfully established, fall-planted rye cover crop. The simulation showed a 20% reduction in nitrates delivered to the Mississippi River. This demonstrates the significant potential impact that cover crops could make on total nutrient losses to waterways in the Midwest.

2.4.2 Reducing soil erosion

For decades research has shown than cover crops reduce water erosion in corn and soybeans. One early study from 1955 analyzed the results from a 10-year trial in which cover crop treatments using a mix of vetch and rye were compared to a control. The plots had up to an eight percent slope to simulate highly erodible land. The results showed that the control group had more than twice the average annual runoff and erosion compared to the cover crop treatment (Beale, Nutt, & Peele, 1955).

More recent studies have had similar findings when studying cover crops effect on water erosion. T C Kaspar, Radke, and Lafien (2001) studied the use of small grains such as oats and rye for water erosion and runoff control in Iowa. It was determined that oats and rye were effective in reducing erosion, particularly when the cash crop is soybeans, which have a greater potential for erosion. A study in Missouri used chickweed, downy brome, and Canada bluegrass as cover crops following soybeans to assess soil erosion. Average yearly soil losses from the chickweed, downy brome, and Canada bluegrass were decreased by 87, 95, and 96% respectively when compared to a control. Additionally, soil losses were significantly correlated with the degree of soil cover, underscoring the importance of effective establishment for cover crops for effective erosion control (Zhu et al., 1989).

Some of the reasons that cover crops are effective in reducing soil erosion are obvious while there are others that are more subtle. The most obvious is that cover crops protect the surface of the soil from being directly impacted by raindrops by creating a living cover or adding to residue cover. Cover crops also increase soil aggregate stability, which particularly helps curb rill erosion (Blanco-Canqui, Mikha, Presley, & Claassen, 2011; T C Kaspar et al., 2001). It has also been demonstrated that cover crops improve water infiltration and water holding capacity, which reduces the amount of runoff, limits inter-rill erosion, and helps to keep rills from forming in the first place (Blanco-Canqui et al., 2011; Haruna, Anderson, Nkongolo, & Zaibon, 2017). Cover crops have also been successfully used to restore eroded soils, reversing the effects of soil degradation (Wilson, Lal, & Okigbo, 1982).

2.4.3 Soil chemical, physical and biological properties

Legume cover crops have the ability to fix nitrogen in the soil, and potentially reduce the amount of nitrogen fertilizer that is needed to achieve good cash crop yields. The amount of nitrogen fertilizer that can be replaced by biological fixation by legume cover crops is the topic of much research. In field experiments under no-till corn with a hairy vetch cover crop, Ebelhar et al. (1984) estimated that the vetch provided the equivalent of 90 to 100 kg per ha of nitrogen fertilizer. McVay et al. (1989) measured the contribution of legume cover crops to soil nitrogen using a rotation of no-till corn and grain sorghum. The results indicated that hairy vetch and crimson clover could provide 123 and 99 kg per ha of plant-available nitrogen, respectively. Based on these results legume cover crops could contribute around 40% of the nitrogen needed for a central Indiana corn crop (Snyder, 2012).

Non-legume cover crops can also contribute to the soil nitrogen available to the following cash crop. As discussed previously in this chapter, other cover crops can reduce nitrogen losses throughout the winter and release them after termination in the spring. Although different varieties release nitrogen at differing rates (Ranells & Wagger, 1996). It is estimated that cereal rye can scavenge and hold up to 73 kg of nitrogen per ha (Ball Coelho et al., 2005). Kessavalou and Walters (1999) also estimated how much nitrogen cereal rye could scavenge and suggested adjusting the nitrogen application based on the approximate weight of cover crop dry matter. Their study concluded that a credit of 40 kg of nitrogen per metric ton of rye dry matter, should be applied when the following crop is corn (Kessavalou & Walters, 1999). Likewise, a study done in Wisconsin using oat, triticale, and rye, concluded that the economically optimal nitrogen rate was 32 kg per ha lower on average following cover crops. Thus, even non-legume cover crops have the potential to increase soil fertility and to reduce fertilizer applications significantly. Cover crops can also help improve cycling for other nutrients as well, including potassium, phosphorus, sulfur, and other micronutrients (Alford, 2015; Amini, 2011; Villamil, Bollero, Darmody, Simmons, & Bullock, 2006)

Soil organic carbon is a component of soil organic matter. Since cover crops return organic matter to the soil, it is reasonable to believe that they may also increase soil organic carbon. Research has shown that cover crops and associated management practices have a positive effect on soil organic matter and soil carbon (Ding et al., 2006; Villamil et al., 2006). In a meta-analysis of papers that quantified the ability of cover crops to sequester carbon, Poeplau and Don (2015) find that the average annual carbon sequestration into the soil is 0.32 metric tons per ha. The ability of cover crops to accumulate carbon in the soil is also influenced by tillage practices. Olson, Ebelhar, and Lang (2014) reported that no-till and cover crops increased soil organic carbon more than treatments of cover crops tilled with a chisel plow or moldboard plow. However, several short term studies have shown little or no measurable effect of cover crops on soil carbon (Acuña & Villamil, 2014; Blanco-Canqui et al., 2014; Rorick, 2016). Additionally, eroded soils that have lower amounts of carbon, previous to cover crops, have more potential to sequester carbon (Berhe, Harte, Harden, & Torn, 2007).

The impact of cover crops on soil physical properties has been widely studied for many years. It usually takes several years of successive cover cropping to realize the improvements in the physical structure of the soil (Benoit, Willits, & Hanna, 1962). Soil aggregate stability is the ability of soil aggregates to bind together and resist disruption from water. When soil aggregates breakdown during rainfall, the surface can crust, blocking additional water and air from entering (National Soil Survey Center, Soil Quality, & National Soil Tilth, 1996). Cover crops improve aggregate stability by increasing soil organic matter and by creating root networks in the soil (Blanco-Canqui et al., 2011; Villamil et al., 2006). Bulk density and penetration resistance are ways to measure soil compaction, which is reduced by using cover crops (Haruna & Nkongolo, 2015; Hubbard, Strickland, & Phatak, 2013). Cover crops also increase porosity and enhance water retention and conductivity in the soil (Blanco-Canqui et al., 2011; Hubbard et al., 2013; T C Kaspar et al., 2001; Villamil et al., 2006).

The biological properties of the soil provide several services that are vital for crops to grow and be productive. Soil microorganisms, as well as larger organisms like earthworms, are the driving force behind nutrient cycles, biological nitrogen fixation, building soil aggregates, improving porosity, and other important soil functions (Lehman et al., 2015). Cover crops can improve the soil biological properties in several different ways. A 15-year study was conducted on a winter wheat-grain sorghum rotation in eastern Kansas. The results showed that the soil under the cover crop treatment had six times as many earthworms when compared to the control (Blanco-Canqui et al., 2011). A different study examined the microbial population under cover crops. The findings showed that crimson clover between corn crops increased the populations of bacillus spp., actinomycetes, and total culturable bacteria. The crimson clover treatment also significantly increased enzyme activities as well as microbial biomass carbon (Kirchner, Wollum, & King, 1993). Yet another experiment used hairy vetch and winter wheat as cover crops in no-till continuous corn, concluding that “the use of cover crops significantly enhanced soil biological properties as measured by microbial numbers and enzyme activities” (Mullen et al., 1998). The same study also determined that hairy vetch was superior to wheat in its ability to increase microbial populations in the soil, likely because—as a legume—it fixed additional nitrogen as well as added more organic matter to the soil than wheat (Mullen et al., 1998). Soil biological properties in the early growing season are strongly affected by the existence and variety of early spring vegetation (Wortman, Drijber, Francis, & Lindquist, 2013).

2.4.4 Weed, pest, and disease management

Much interest has been shown in the potential of cover crops to suppress weeds within cropping systems. Cover crops could help limit weed populations in several different ways (Teasdale, Brandsæedter, Calegari, & Skora Neto, 2007). The first is by means of direct competition with weeds that are growing concurrently with the cover crop. Other ways that cover crops help manage weeds are through chemical inhibition, called allelopathy (Weston & Duke, 2003), or physical suppression by means of cover crop residue (Teasdale, Beste, & Potts, 1991). An indirect way that cover crops help to control weeds is altering the timing of nutrient cycles so that nutrients are not available to emerging weeds. A trial in Maryland, using forage radish as a cover crop found that winter annual weeds were nearly eliminated in the fall and spring, but the weed suppression did not continue into the growing season after the cover crop was terminated (Lawley, Weil, & Teasdale, 2011). However, rye was tested in another experiment in Pennsylvania for two years with only limited success (Mischler, Curran, Duiker, & Hyde, 2010). Similarly, other studies have tested multiple cereal and legume cover crops impact on weed density and biomass, with weak and sometimes mixed results (Appelgate et al., 2017; Reddy, 2001). Yet, rye has been credited with reducing the weed seed bank in the long term (Moonen, 2004). Cover crops are not necessarily a perfect substitute for herbicides, but they can assist as another tool in a weed management program (Teasdale, 1996).

Insect pests are part of an eco-system with a food chain and have natural predators to keep their populations in check. One way to manage insects that are harmful to crops is to promote the population of their natural predators. Cover crops may have the potential to assist in this by providing habitat for predators of insect pests (Baliddawa, 1985; Letourneau et al., 2011). An experiment investigating this line of reasoning examined the impact of using slender wheatgrass as a cover crop on the population of western corn rootworm in a corn-soybean rotation. The study concluded that the cover crop significantly reduced western corn rootworm populace by intensifying predation (Lundgren & Fergen, 2011). Similar results have been shown in other crops such as cotton (Tillman et al., 2004). However, other studies have concluded that cover crops have little impact on insect pests (Schipanski et al., 2014), or have even exacerbated pest problems (Bottenberg, Masiunas, Eastman, & Eastburn, 1997). In North Carolina, using a continuous corn rotation, House and Alzugaray (1989) found that southern corn rootworm populations increased following the use of legume cover crops. Cover crops may also increase damage to cash crops from some other kinds of insect pests. A study in Ohio found that cover crops could increase damage from seedcorn maggots. This was only a problem when a live cover crop was terminated just before planting by some form of tillage. The effect was largest if the cover crop was a legume (Hammond, 1990).

Cover crops can help reduce disease in some crops (Ratnadass, 2012). In Illinois, an experiment using soybeans as the cash crop, covers of cereal rye and rapeseed decreased numbers of soybean cyst nematode in the soil (Wen, Lee-Marzano, Ortiz-Ribbing, Hartman, & Eastburn, 2017). In that same study, a cereal rye cover crop also was associated with higher soybean yields when Rhizoctonia root rot was present (Wen et al., 2017). Conversely, growing a cover crop may also have the potential to provide a perpetual habitat for pathogens over the winter months (Ratnadass, 2012; Smiley, Ogg, & Cook, 1992). For example, rye can serve as a host for corn pathogens because it allows a "green bridge" between the soybean and corn crops. A study that examined this problem discovered that "radicle rot incidence, radicle disease severity, and Pythium incidence were greater… in corn following rye compared to no rye" (Acharya et al., 2016). However, it was also shown that the incidence of these diseases was reduced if the rye cover crop was terminated more than 10 days before planting (Acharya et al., 2016).

2.5 Literature on the Potential of Yield Effects of Cover Crops

Cash crop yields have a direct effect on profitability for farm businesses. Thus the question that must be answered before most farmers will adopt a management practice is: "how will it impact my yields?” This question has been thoroughly examined for decades in the literature. An overview is presented here.

2.5.1 Effect of cover crops on average yields

Research on the impact of cover crops upon average yield has been prolific and has generated mixed results. Some research found little or no evidence for any effect, some studies found a positive impact, while still other analyses found that cover crops reduced the yield in the subsequent cash crop. In a review of the published research on the effect of cover crops on yields, Blanco-Canqui et al. (2015) reviewed 17 studies. Out of those studies cover crops had increased yields of the following crop in nine, there was no change in yields for six papers, and two showed yields declining following cover crops (Blanco-Canqui et al., 2015). The impact of cover crops on yields likely varies by region and may be more positive where there is adequate precipitation, as suggested by Unger and Vigil (1998). It is also possible that cover crops may affect the yield of some cash crops and not others (Nkongolo & Haruna, 2015). Lastly, the impact of cover crops on the following cash crop yield could be influenced by field-specific attributes such as topography (Muñoz, Steibel, Snapp, & Kravchenko, 2014)

In field trials done in Iowa, T. C. Kaspar and Bakker (2015) used 12 different cultivars of rye, triticale, and winter wheat as cover crops in a corn-soybean rotation. The purpose of the study was to evaluate the impact of each cover crop on the following corn yields. Each of the three species had cultivars that, when used as a cover crop, reduced the following year’s corn yield. The negative effects took place in only two of the four years of the study (T. C. Kaspar & Bakker, 2015). Reduced yields in soybeans have also been experienced after using cover crops of hairy vetch, crimson clover, rye, oat, wheat, subterranean clover, and Italian ryegrass (Reddy, 2001).

S. M. Lira and Tyner (2018) conducted observational research to estimate the impact of cover crops on corn and soybean yields in central and northeastern Indiana. Their data followed 128 fields that were cover cropped as well as those that were not, for five consecutive years, allowing them to use a fixed effects regression model. By using a fixed effects identification strategy, many possible confounding variables should have been controlled for. The results did not show any statistically significant effect of cover crop use on the yield of the subsequent cash crop (S. M. Lira & Tyner, 2018). Other studies have similar results, showing no significant effect on yields (Olson et al., 2014; Ruffo, Bullock, & Bollero, 2004; Tonitto, David, & Drinkwater, 2006). However, this study is especially significant because it seeks to evaluate the impact of cover crops on yields at a scale much larger than the typical field trial. It also is more general by grouping all cover crops in search of a broad treatment effect.

On the other hand, there is a significant body of relevant literature that has demonstrated a yield increase, mainly for corn. Corn grain yields were analyzed after cereal rye for a long-term study in southern Ontario, Canada. Yields were higher following cover crops in six out of seven years when compared to a control (Ball Coelho et al., 2005). Andraski and Bundy (2005) conducted a three-year field trial in Wisconsin with cereal cover crops in continuous corn. The experiment evaluated the corn yield response to cover crops at different rates of nitrogen fertilizer application. For two of the three years, yields on the cover cropped plots were higher regardless of fertilizer rates, but in the remaining year the yield benefit of cover crops diminished as the fertilizer rate increased. The corn yield benefits were also similar for cover crops with and without the top growth removed. The results of this study suggest that the yield benefit of cover crops was not entirely due to nitrogen contributions (Andraski & Bundy, 2005).

In conclusion, a meta-analysis of 65 previous studies found a neutral to positive effect of winter cover crops on corn yields (Marcillo, 2017). On average grass cover crops had no detectable positive or negative effect on corn yields. However, they did observe a positive yield effect from legume cover crops when no nitrogen (N) fertilizer was applied, but it diminished with increased N application. In general, yield increases are attributed to improved soil physical properties and fertility status including increased rooting depth and access to water, soil organic carbon and N fixing or scavenging (Chen & Weil, 2011; Marcillo, 2017).

2.5.2 Effect of cover crops on yield stability

The impact of cover crops on average yields has been well studied. The impact of cover crops on yield stability, on the other hand, has not been so thoroughly investigated. Yet, there is research that indicates that increasing crop diversity has the potential to improve yield stability over time. A study using data from a long-term crop rotation and tillage trial in Ontario, Canada examined the impact of crop diversity on temporal yield stability over 31 years. The analysis concluded that more diverse crop rotations reduced yield variation for corn and soybeans and decreased the probability of crop failure (Gaudin, 2015). Several other studies have come to similar conclusions (Grover, Karsten, & Roth, 2009; Varvel, 2000). Cover crops could potentially provide similar benefits because they provide additional rotational diversity.

Ott and Hargrove (1989) analyzed the yields of corn after using legume, non-legume, and no cover crop. For each cover crop, multiple levels of nitrogen were applied. Broadly, they concluded that “legume cover crops increased both average corn yield and yield variance” (Ott & Hargrove, 1989). Yet, the analysis is limited because the trial was only three years in length. Because of its short duration, the study probably was not able to provide a complete picture of temporal variation across growing seasons.

The body of research that has examined the variance of cash crop yields following a cover crop is small. This may be due to the difficulty of evaluating yield variance since many cover crop studies are experments that lack the large number of observations that would be needed to draw very robust conclusions.

2.6 Literature on the Economics of Cover Crops

The economics of cover crops are discussed frequently in the literature, yet the conclusion remains unclear. Many researchers could not show that there was a direct economic benefit to the farmer while others found substantial benefit. Part of the ambiguity comes because there is not a strong consensus on which benefits should be valued and included. Additionally, it is difficult to assign a value to many long-term benefits of cover crops. However, even valuing these benefits, in some cases it may not justify the additional costs except on highly erodible land using favorable discount rates (Ervin & Washburn, 1981).

Mallory, Posner, and Baldock (1998) considered farm level data from collaborating farmers in the northern Corn Belt. The cover crops used were evaluated for their ability to provide an alternative to nitrogen fertilizer, thus reducing input costs. The results showed that cover crops were not an economically viable alternative to nitrogen fertilizer. Furthermore, the study concluded that the price of nitrogen fertilizer would have to more than triple for cover crop-supplied nitrogen to be as cost-effective as commercial fertilizer. This is an important example from the literature because it was done with real farm data under multiple management systems. Similar, but more recent farm level data from Midwestern farms confirmed that even with cost share payments, the average change in net revenue due to cover crop use was negative (Plastina, Liu, Miguez, & Carlson, 2018).

A long-term study by Roberts, Larson, Tyler, Duck, and Dillivan (1998) in western Tennessee discussed the economics of multiple cover crops in no-till corn. Over the nine-year study period, hairy vetch consistently returned the highest net revenue. Other studies have resulted in similar conclusions (Frye, Smith, & Williams, 1985). The system using a vetch cover crop had higher yields and lower applied nitrogen rates per acre than any other treatment. For all years no cover was second place for net revenue per hectare, with clover and wheat following after that. The cost of production was lowest for no cover followed by hairy vetch, clover, and wheat, respectively. The study also concluded that no reasonable reduction in seed price for wheat and clover would make those cover crops economically more attractive than no cover. Likewise, the price of vetch seed would need to triple to offset the economic advantage it created as a cover crop (Roberts et al., 1998). This study represents a very in-depth analysis over a long period of time, making the findings very relevant in the discussion of direct economic benefit to farmers.

In an analysis of the economics of cover crops, Ott and Hargrove (1989) studied the profitability and economic risk of using cover crops in no-till corn production. The study used test plots that were treated with cover crops of hairy vetch, crimson clover, winter wheat, or were left fallow over the winter. In order to test the sensitivity of the results to price changes, two different corn prices were combined with two different nitrogen prices. The risk analysis consisted of calculating and comparing the lower bound of the confidence intervals for profits at different confidence levels. This was done for each cover crop variety as well as the control. Doing this also required fitting probability distributions for the yield data. For each of the corn and fertilizer prices, crimson clover and hairy vetch were profitable. Hairy vetch was better than crimson clover, which was better than no cover for all nitrogen levels except the highest level of

224 kg per ha when no cover surpassed crimson clover, which overtook hairy vetch. Wheat was the least profitable in every case. Overall, the most profitable system was hairy vetch with no nitrogen applied and was not sensitive to price changes. The risk analysis confirmed that hairy vetch was the preferred cover crop generally. For risk-averse farmers hairy vetch with no nitrogen is the best option, while for risk-neutral farmers hairy vetch with 56 kg per ha of nitrogen is desirable (Ott & Hargrove, 1989). A similar study also concluded that hairy vetch was the best option when compared to crimson clover and wheat. However, it determined that the profit-maximizing rate of applied nitrogen was 168 kg per ha. Different from the research cited above, the risk analysis in this study indicated that risk increased if commercial fertilizer was replaced by legume fixed nitrogen (Larson, Roberts, Tyler, Duck, & Slinsky, 1998).

On the other hand, several studies have found that the costs of establishment and the extra pass for termination outweigh the benefits of cover crops. When evaluating the budget impacts of cover crops and no-till on soybeans, Reddy (2001) calculated net returns below zero for all cover crops in the study. Conversely, in this study, the no cover crop systems had significantly positive net returns for both no-till and conventional tillage. De Bruin, Porter, and Jordan (2005) assessed economic returns for soybeans following a cover crop of cereal rye in a corn-soybean rotation. They determined that while yields were not impacted, the net return per acre was reduced due to increased input costs. Roth, Ruffatti, Apos, Rourke, and Armstrong (2018) researched a case farm in Illinois to determine whether environmental and nitrogen cycling benefits could help to recover the additional costs associated with the use of cover crops. They concluded that benefits to the farmer from erosion control, mitigating nitrogen losses, timing of the nutrient cycle, could cover 33.4 to 86.1% of the cost of cover crops.

Some studies have attempted to use Monte Carlo simulations to model the impact of cover crops on profitability. (Gabriel, Garrido, & Quemada, 2013). Pratt, Tyner, Muth, and Kladivko (2014) used stochastic cost-benefit analysis to model the financial returns to farmers using cover crops. The authors estimated the value for benefits such as increased nitrogen, increased soil organic matter, reduced compaction, and reduced erosion. They conducted the simulation for mixes of 60% annual ryegrass-40% oilseed radish, 60% crimson clover-40% annual ryegrass, as well as annual ryegrass, cereal rye, crimson clover hairy vetch, oats, and oilseed radish. The largest net return was crimson clover with an $84.61 per ha and an approximately zero probability of loss. The cover crop that performed the worst was oilseed radish showing a net loss of $12.21 and a 77.3% probability of loss. Other cover crops were in between these extremes, and all had positive net returns, except hairy vetch and oilseed radish. Hairy vetch had substantial benefits, but the seed costs were so high that the costs outweighed the benefits. They concluded that the agronomic benefits of some cover crops could, by themselves, provide enough private economic benefits to make adoption an attractive option (Pratt et al., 2014).

2.7 Contribution of this Study to the Literature

This study will look at the impact of cover crops on cash crop yields at a large scale using farm level data. Using additional data we will add to the work of S. M. Lira and Tyner (2018), using a similar econometric analysis to observe any detectable treatment effect. This is an important contribution because it uses observational data at a large scale, as opposed to test plot experiments.

The variance analysis will build on work done by Ott and Hargrove (1989) as well as Larson et al. (1998) to determine any difference in yield variability when cover crops are used.

An economic risk analysis will also be conducted, as was done in these two studies. However, the data from these two experiments were quite limited, and this analysis can add insight at a larger scale using farm level observational data. Moreover, the body of literature covering the effect of cover crops on yield variability and risk is quite small and not necessarily conclusive.

The final analysis will be the creation of simulated farm budgets. These will add to the existing literature on the net returns for corn and soybeans, with and without cover crops. By using data to fit input distributions for crop yield we can utilize stochastic methods to analyze the distribution of net returns. A similar approach has been used in past research (Pratt, 2012; Pratt et al., 2014). This study will use more data-driven inputs than have been used previously. It will also look at an overall financial picture, rather than just the net benefit of cover crops. It will also value only the most relevant and direct benefits and costs of cover crops from the farmer perspective.

CHAPTER 3 DATA

3.1 Data Collection

This study uses an updated dataset that was used by S. M. Lira and Tyner (2018) in their research article and by S. Lira (2017) in the analysis for his master's thesis. The survey methodology that was used to collect this data was developed by Bounaffaa (2015) to collect data to analyze the benefits and costs of cover crops.

The data were collected from corn and soybean farmers in central and northeast Indiana. The full list of counties that were eligible to be included is contained in Table 3.1. These counties were selected because the soil types, weather conditions, and topography are similar. Data collection proceeded using the same survey data sheet as was used in the past. The attempt to recruit additional farmers only resulted in the addition of 3 new farms to the project.

Table 3.1 Indiana counties eligible to be included in the study

Adams	Allen	Benton	Blackford	Boone
Carroll	Clinton	Decatur	DeKalb	Delaware
Fayette	Grant	Hamilton	Hancock	Hendricks
Henry	Howard	Huntington	Jay	Johnson
Madison	Marion	Miami	Montgomery	Morgan
Noble	Putnam	Randolph	Rush	Shelby
Tippecanoe	Tipton	Union	Wabash	Wayne
Wells	Whitley			

Several additions and changes to the data should also be noted. In 2017 the Farm Foundation approved funding for soil tests for each of the farms in the study. Each farmer was mailed all of the materials and instructions necessary to complete and return soil samples from each field. However, participation in soil sampling was optional because it was not specified in the contract, so there was no incentive beyond a free soil sample. Likely as a result of this, not all of the farmers returned soil samples. Just 14 of 23 farmer participants returned soil samples despite repeated reminders. This represents only 65 of 109 fields that were in the study in 2017.

Another change to the data structure from the previous years of this project was the removal of weather data. The weather data included growing degree days, average monthly temperatures, and rainfall information. However, year and county dummies could be used to control for weather conditions. These dummy variables control for all year specific conditions at the county level, including the weather data that was removed from the dataset. Because this was the anticipated method of analysis, weather data at the county level was removed from the dataset. This different approach should have allowed the model to control for many different weather-related conditions.

The data that was used to develop the simulated farm budgets for cover crop and conventional farms was drawn from the real farm survey data as well as cost estimates from Purdue University and University of Illinois (Langemeier, 2018; Schnitkey & Lattz, 2017). The cost of cover crop seed and chemical termination came from farmer surveys. The nitrogen savings from cover crops were also estimated from farmer data. Other operating costs were estimates from extension services. The yield distributions were from simulated yields from a set of assumptions about the hypothetical farm that is being modeled. These estimates were generated based on a regression model using farmer data.

There is the potential for selection bias in the data since the sample was not randomly chosen. The bias could arise if there are important farm or farmer characteristics for the set of farmers who voluntarily joined the project that differed in a significant way from the overall population of farmers in the region.

An additional source of bias comes from the fact that choice by farmers to plant cover crops on a field is not random. The factors affecting this choice could cause bias in any analysis of the effect of cover crops on yield (Tucker, 2010). A propensity score trimmed sample, often referred to as a matched sample was also utilized to control for selection bias resulting from farmers choosing cover crop fields non-randomly (Imbens, Mitnik, Crump, & Hotz, 2009; Sanglestsawai, Rejesus, & Yorobe, 2014; Stürmer, Rothman, Avorn, & Glynn, 2010). Chapter 4 contains the details on how this sample was generated. The summary statistics for the trimmed samples are contained in appendix B.

3.2 Description of Variables

3.2.1 Main Dataset

After the data was collected it was consolidated into a dataset that included variables relevant to the analysis of yields, as had been done previously. The 2017 soil tests added data to the variable for soil organic matter, which had few existing observations as it was optional information in the farmer surveys. The soil tests further added several variables for other soil chemical properties. Each variable in the dataset is explained in detail below, including units of measure.

The data is of longitudinal structure, following specific fields over time. Because of this, it was important to have a marker for each individual field in the data. The field code identifies each field and the corresponding farm. The number before the decimal point indicates the farm number, which is randomly assigned to each participating farm. The number after the decimal indicates the field number within that farm. This variable is labeled “fieldcode” in the dataset. The digit before the decimal in the field code corresponds to the farm number. This farm identifier is also listed as another variable labeled “farmcode” in the dataset.

There is a variable for year. The only distinction that needs to be made is that this is the year in which the cash crop was grown. If a cover crop was grown, it was most likely planted the preceding fall. Thus, if a field has a cover crop listed in a particular year, the cover crop was most likely planted and established in the year prior to the year listed for that observation. This variable is labeled “year” in the dataset.

There is a variable for the county where the field is located. This is the primary location data for each observation. This variable is labeled “county” in the dataset.

The cash crop for each field is denoted by the variables “corn” and “soybean” in the dataset. Both of these variables are binary variables. The variable “corn” is 1 if the crop that year is corn and 0 otherwise. The variable “soybean” is 1 if the crop that year is soybeans and 0 otherwise. Since all of the data are from fields in a corn-soybean rotation, these variables are perfectly correlated. This could create a problem of multicollinearity if used simultaneously in the same regression model. However, rather than use these variables as independent regressors, they will be used to partition the data to be analyzed in separate models.

Each field has a variable for the yield of the cash crop in the year listed. This variable is measured by taking the average yield across the field. The units of this variable are bushels of corn or soybeans per acre. This variable is labeled “yield” in the dataset.

The field size is the number of acres for that field. This variable is labeled “acres” in the dataset. This is an important variable for weighting each observation. The field sizes vary greatly, and giving the same weight to each field is analogous to oversampling the small fields. This is important for correctly reporting the summary statistics, but may not be necessary for the regression analysis (Solon, Haider, & Wooldridge, 2015).

The variable labeled “slope” in the dataset is meant to report the average percent slope of the entire field. In the dataset this variable is reported in percentage points (i.e. if slope is 1 in the data then the average slope is 1%) to aid in interpretation. The farmers in the study gave a range for the slopes in each field, the midpoint was calculated and reported in this variable.

A set of dummy variables describes the tillage regime for each field in each year. The first two variables “mintill” and “notill” describe whether the field was cultivated using minimum tillage (e.g. vertical tillage) or no-till, respectively. The reference category is conventional tillage. The next two dummy variables that describe the tillage regime are related to the frequency of use for no-till. The first, an indicator for continuous no-till, is labeled “contnt” and signals that the field has been farmed with no-till practices for at least two consecutive years. The second identifies fields that are farmed using no-till every other year, it is labeled “evothernt” in the data.

The next group of variables is a set of binary indicators to indicate which crop was planted in the previous cropping year. The first is labeled “aftercorn” and signals the crop in the preceding year was corn. The second is labeled “aftersoy” and indicates the crop in the preceding year was soybeans.

Three variables describe the fertilizer application. The first variable in this category is total applied nitrogen, labeled “n_app” in the data. This variable measures the total pounds of elemental nitrogen applied per acre via fertilizer. The next variable is total applied phosphorus, measured by the total pounds of P_2O_5 applied per acre via fertilizer. This variable is labeled “p_app” in the data. The last variable is total applied potassium, measured by the total pounds of K_2O applied per acre via fertilizer. This variable is labeled “k_app” in the data.

Two variables relate to cash crop planting. The first is the seeding rate, measured in thousands of seeds planted per acre. This is labeled “seedrate” in the data. The second is a binary variable to indicate whether the seed was treated with any kind of seed treatment. This is labeled “treatment” in the data.

A dummy variable labeled “drain” is used to show whether the field had a drainage system for excess water. The most common system was pattern tile, although some fields had random tile, and a few were drained using drainage ditches.

The next group of variables in the data describes the cover crop use by the farmer. The first variable in this set is a dummy variable for cover crop use. This variable takes a value of 1 if the farmer cultivated a cover crop previous to the cash crop in the same field, and a value of 0 otherwise. This variable is labeled “covercrop” in the data. The next set of variables in this group are dummy variables indicating the variety of cover crops that were used. This set of variables includes all of the different cover crop varieties used by our farmers (with the exception of turnips, which were used only very few times). In the data the labels are: “ar” for annual ryegrass, “ccl” for crimson clover, “cr” for cereal rye, “oat” for oats, “rd” for tillage radishes, “rp” for rapeseed, “wt” for wheat. There is no risk of multicollinearity using this set of binary variables because each group is not mutually exclusive, due to the fact that many farmers plant two or more varieties in any given year. An additional variable is given to describe cover crop establishment, as determined subjectively by the farmers. For farmers who used cover crops, we asked them to rank the quality of their establishment, with a 1 being poor, 3 being average, and a 5 being excellent. This is reported for cover crop observations in the same scale in which it was reported, it is left blank for non-cover crop observations. This variable is labeled “ccrank” in the data. The last variable to describe cover crop use is a variable indicating the number of consecutive years cover crops have been used on the field, this is labeled “ccyear” in the data.

A variable indicating the region is included and labeled “ne” in the data. This variable is 1 if the farm is located in the northeast region of Indiana, and 0 if the farm is located in central Indiana. The farm is considered to be in the northeast part of the state if it is located in Adams, Allen, DeKalb, Huntington, Miami, Noble, Wabash, Wells, or Whitley counties.

A group of variables describes the soil order that is dominant in each field. In the data the labels are: “moll” for Mollisols, “incept” for Inceptisols, “hist” for Histisols, and “mix” for mixes of Mollisols with Alfisols. The default (reference category) is Alfisols, meaning that Alfisols dominate the field if all of the soil variables are equal to 0.

The next group of variables provides information about the farmers’ experience, education, and age. There is a variable labeled “farmexp” which reports the farmer’s years of practical experience in farming. The next variable is labeled “ccexp” which reports the farmer’s years of practical experience cultivating cover crops. There are two dummy variables relating to education, one for a bachelor’s degree (“undergrad”), and one for a graduate degree (“post”), with the reference category being high school graduation. The variable “age” reports the farmer’s age in years.

There is a group of variables relating to the farm associated with each observed field. These are measures of the farm size in acres (“fsize”), the number of acres consistently cultivated using cover crops (“ccacres”), and the number of persons that work on the farm (including the operator, family members, and hired labor). The variable for farm size may be particularly interesting as a proxy for skilled management. The correlation between farm size and skilled management is probably not perfect, but we hypothesize that is it strong. It also may be a cycle with positive feedback, where the managers who manage the most land become more skilled by the experience provided because they operate a larger farm.

The last group of variables all relates to soil chemical properties in the field. This data was gathered through the optional soil samples that were sent to the farmer participants in 2017, with the exception of some self-reported estimates of soil organic matter from previous years. For this reason, this information is not available for every field or every year. The variables in this group are percent soil organic matter (“som”), soil PH (“ph”), phosphorus in parts per million (ppm) (“p_ppm”), potassium in parts per million (“k_ppm”), magnesium in ppm (“mg_ppm”), and calcium in ppm (“ca_ppm”), the cation exchange capacity is in millequivalents per 100 grams of soil (meq/100g) (“cec”), percent potassium saturation (“k%”), percent magnesium saturation (“mg%”), and percent calcium saturation (“ca%”). The variable for soil organic matter provides a good proxy for overall soil health.

3.2.2 Farm Budget Data

The farm budget data included the cover crop seed cost and pounds of seed per acre for each cover crop mix used. From this information we can make a data-driven assumption about the cover crop mix and the seed cost. Chemical termination costs were also included in the farmer surveys. From this information, we can make a data-driven assumption about the cost of chemical termination. This additional cost is only relevant if the cover crops are not killed by the standard spring herbicide application, from the farmer survey we can calculate the probability of needing a second pass to kill the cover crop.

The reduced fertilizer cost from cover crops will be estimated using the farmer data. This data will be used to define stochastic input distributions for nitrogen, phosphorus, and potassium.

The yield distributions will provide the largest source of variation and make the largest difference in profitability. The data that define these distributions are simulated using the assumed characteristics of the model farm. These assumptions are used as inputs into a model that was created using a regression from the farmer data.

The operating costs are estimates from Purdue extension based on average productivity farmland and a 3000 acre farm with average soils (Langemeier, 2018). The data include estimates for the cost of fertilizers, pesticides, dryer fuel, machinery fuel, machinery repairs, hauling, interest, insurance, and miscellaneous costs. Additional costs for cover crop seed and chemical termination were taken from farmer data. The planting cost for cover crops is an estimate from University of Illinois extension (Schnitkey & Lattz, 2017)

3.3 Categorical Data Description

To begin with, the data are described categorically. This will give a sense of the sources of the data and some basic field and farmer characteristics. It will also help in the process of analyzing the potential sources of selection bias to which this study may be subject.

The number of fields that had a cover crop, sorted by cash crop is presented in table 3.2. Out of the 910 observations in the study, 235 were cultivated using a cover crop while 675 were cultivated without a cover crop. Each of those groups was nearly evenly split between corn and soybeans.

Table 3.2 Number of cover crop fields by cash crop

Cover crop	Soybeans	Corn	Total
No cover crop	347	328	675
Cover crop	120	115	235
Total	467	443	910

The number of fields split between corn and soybeans was similar in each year, this data is presented in table 3.3. When data collection began in 2016 each farmer was asked to contribute 5 years of historical data, which would have given their historical information back to 2011. However, several farmers gave data back as far as 2009, this is the reason there are fewer fields in 2009 and 2010. Additionally, several farmers did not submit their 2018 data before the time of this analysis and were thus excluded from the data.

Table 3.3 Number of fields by cash crop in each year

Year	Soybeans	Corn	Total
2009	22	18	40
2010	19	23	42
2011	55	43	98
2012	46	56	102
2013	59	50	109
2014	49	60	109
2015	64	46	110
2016	50	55	105
2017	65	44	109
2018	38	48	86
Total	467	443	910

The number of fields cultivated with and without a cover crop in each year of the study is presented in table 3.4. The number of cover cropped fields increased each year until 2018. In 2018 the number decreased as several farmers mentioned that a wet fall delayed harvest and left little time for cover crop establishment.

Table 3.4 Number of fields by cover crop in each year

Year	No cover crop	Cover crop	Total
2009	35	5	40
2010	35	7	42
2011	82	16	98
2012	80	22	102
2013	82	27	109
2014	81	28	109
2015	77	33	110
2016	70	35	105
2017	68	41	109
2018	65	21	86
Total	675	235	910

Not every county that was eligible for this study was represented in the data, and not every county had cover crop and non-cover crop observations. In table 3.5 the counties that were actually represented in the data are listed. Alongside each county, are reported the number of observations in the data from fields without a cover crop, fields with a cover crop, as well as the total number of observations from that county in the data. Also included is the percent of the total observations that each county represents. Of particular note are Howard and Tipton counties, which represent the location for 14.3 and 11.1 percent of the observations, respectively. Additionally, several counties have very few observations with a cover crop. Adams, Carroll, Henry, Howard, Madison, Montgomery, and Wabash counties had no fields recorded with cover crops, while Noble County had no observations without cover crops.

Table 3.5 Field-year observations by county

County	No cover crop	Cover crop	Total	Percent of Sample
Adams	49	0	49	5.38%
Allen	16	40	56	6.15%
Carroll	30	0	30	3.3%
Cass	19	1	20	2.2%
DeKalb	64	3	67	7.36%
Fayette	8	57	65	7.14%
Hancock	36	4	40	4.4%
Hendricks	7	2	9	0.99%
Henry	20	0	20	2.2%
Howard	130	0	130	14.29%
Johnson	17	18	35	3.85%
Madison	38	0	38	4.18%
Montgomery	9	0	9	0.99%
Noble	0	40	40	4.4%
Shelby	57	2	59	6.48%
Tippecanoe	11	16	27	2.97%
Tipton	92	9	101	11.1%
Union	14	31	45	4.95%
Wabash	35	0	35	3.85%
Wells	23	12	35	3.85%
Total	675	235	910	100.00

Figure 3.1 maps the sum of the acres within each county by cover crop. This is referred to here as acre-years because each acre is counted again each year it is in the study, and not all fields have data for the same years. Consequently, acre-years gives a picture of the sample taken by this project, and its spatial distribution. From these maps, it appears the cover crop observations are sparsely represented across the state. The county with the most cover crop fields is located in the northeast while the county with the most non-cover crop fields in in the central part of the state.

Figure 3.1 Maps of acre-years by county for fields with and without a cover crop
a) Without cover crops b) With cover crops

Each farmer who cultivated cover crops was asked to rank the quality of establishment on a scale of 1 through 5. While not every cover cropped field received a ranking, 222 out of 235 were assigned an establishment score. The number of cover crop fields in each category is listed in table 3.6. Most observations received a score of 3, which was meant to represent average establishment.

Table 3.6 Number of observations by category in cover crop establishment ranking

Cover crop rank	1	2	3	4	5	Total
Number of fields	6	27	121	46	22	222

3.4 Descriptive Statistics

The descriptive statistics for this dataset are presented and discussed in this section. As a result of the structure of the data, many of the statistics presented here are weighted where appropriate, using the acres for each field. This was done because the field sizes vary greatly and information about each one often represents an average over the field. Computing summary statistics using weights makes interpretation easier. For example, using weights, the mean yield is the average across the acres not the average across the fields. Using weights is also more accurate, because small fields are given less importance than larger fields (Solon et al., 2015). These statistics were calculated with analytic weights using the "aweights" option in STATA.

The descriptive statistics were grouped by subject. Because of this, some categorical binary variables are in the same tables as continuous variables. This is easily noted as the standard deviation, minimum, and maximum columns will be empty. The statistic presented in the mean column will be listed as a percentage and is the proportion of observations in that group that are marked with a 1 (true/yes) for that variable.

Each section presents the summary statistics for its respective group of variables. In general, the summary statistics are partitioned by cash crop and cover crop use. For reference, Appendix A contains tables summarizing the overall dataset by cash crop variety.

3.4.1 Cash Crop Yield

The cash crop yields were calculated using analytic weights as noted above. Therefore, the mean should be interpreted as the average acre in the data, and not the average field. The overall average yields were 180.97 bu/acre and 55.46 bu/acre for corn and soybeans, respectively. The summary statistics for the cash crop yield over the whole dataset are presented in table 3.7. On the whole, there are slightly more soybean observations than corn observations, as well as more acres devoted to soybeans over the years in this sample. The Minimum value for corn is considerably lower than would be expected for corn yields. However, this observation occurred in 2012, which was a drought year in Indiana (Schnitkey, 2012). In the analysis of mean yield, yearly conditions will be controlled for, so this should not present a problem.

Table 3.7 Corn and soybean yield

	Obs	Acres	Mean	SD	Min	Max
Soybean	467	29179	55.46	9.49	18.72	86.65
Corn	443	27282	181.26	41.91	20	270

The average soybean yield plotted over time is displayed in Figure 3.2, including a trend line. The slope of the trend line indicates that the mean soybean yield increased by just under a half bushel per year, on average. Such a trend suggests an increase in average yields of about 6% over the span of this study.

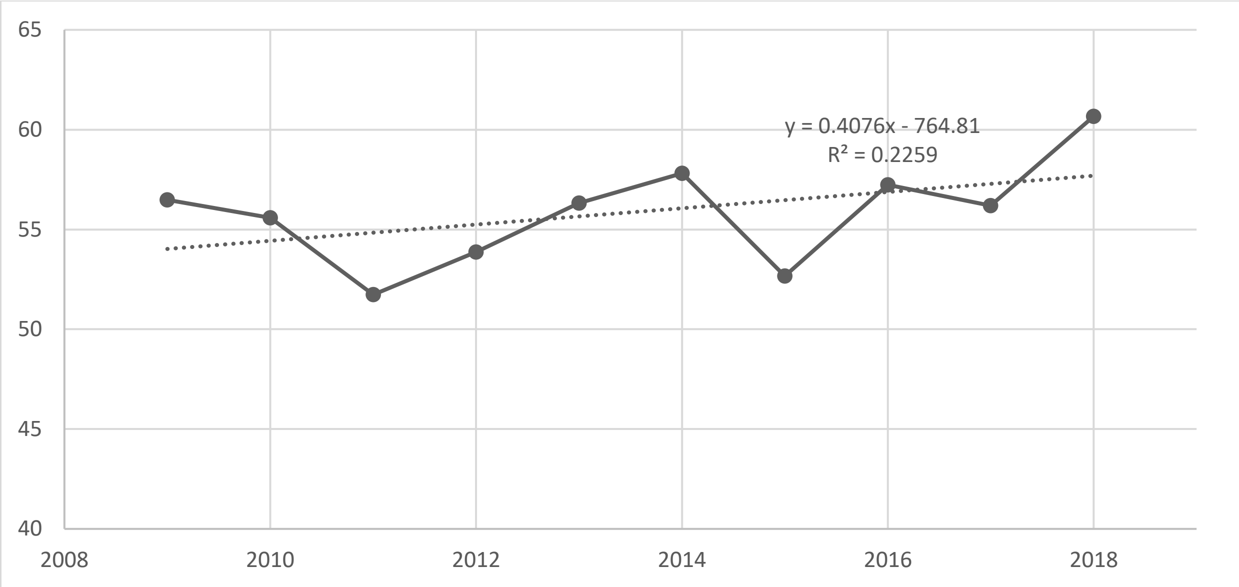

Figure 3.2 Soybean yield by year

The time trend for corn yields is shown graphically in figure 3.3 along with the yearly means over time. The slope of the trend line indicates that corn yields have risen 3.75 bu/acre per year, on average. This trend line indicates an average increase of 20.7% over the period of the study, or about 2.3% increase per year. The drought year 2012 has the lowest mean corn yield at 125.31 bu/acre of any year in the study. Another abnormal crop year for corn in our data was 2018, with an exceptionally high mean corn yield of 214.3 bu/acre. This is also likely a result of year specific weather conditions and is a reflection of record yields across the state (Hurt, 2018).

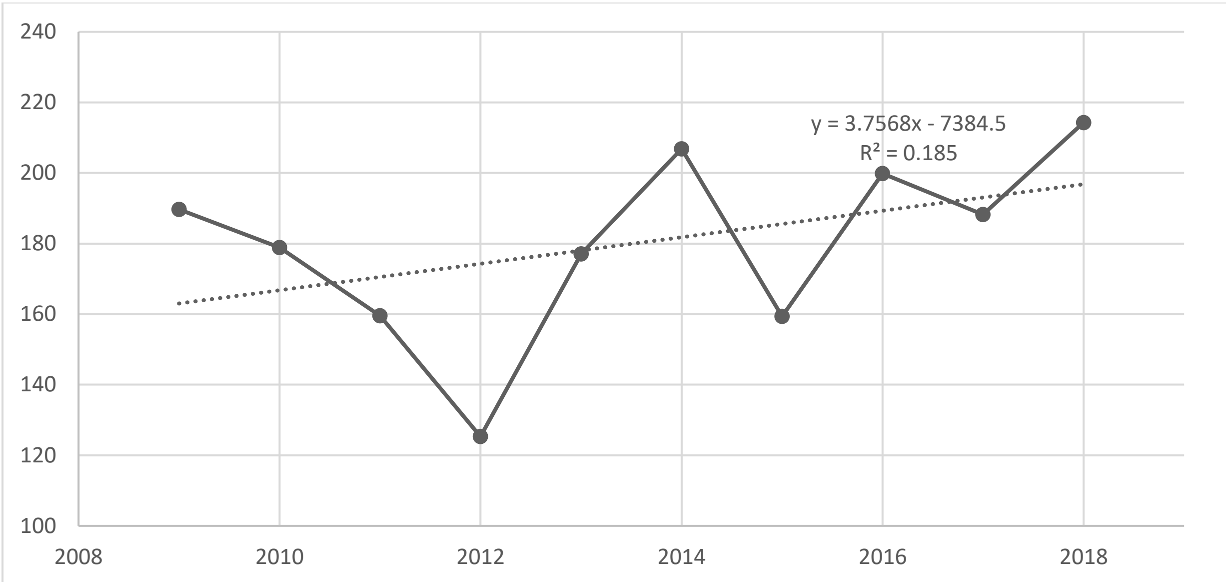

Figure 3.3 Corn yield by year

The summary statistics for soybean yield by cover crop use are presented in table 3.8. There were 29,179 acres devoted to soybeans over the span of the study, of these 22,112 were cultivated without a cover crop, while 7,078 were cultivated with a cover crop. The fields without cover crops had higher mean yields. Fields with a cover crop yielded an average of 51.99 bu/acre, and fields without cover crops yielded an average of 56.57 bu/acre.

Table 3.8 Soybean yield by cover crop use

	Obs	Acres	Mean	SD	Min	Max
Without cover crop	347	22112	56.57***	9.27	18.72	86.65
With cover crop	120	7068	51.99***	9.36	25	76

Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

Corn crop yields were also summarized by cover crop use over the whole dataset and displayed in table 3.9. Most of the corn acres over the duration in the study were not cultivated with a cover crop; only 6,781 acres had a cover crop compared to 20,501 that did not have a cover crop. The fields with a cover crop had a lower overall standard deviation of 30.51 bu/acre compared to 43.65 for fields without a cover crop. Similar to soybeans, fields without cover crops had higher yields with an overall average of 186.9 bu/acre. Fields with a cover crop yielded an average of 164.23 bu/ac over the whole dataset. This large difference may be due to many factors that are correlated with cover crop use. We explored this difference through further summary statistics as well as the correlation matrix.

Table 3.9 Corn yield by cover crop use

	Obs	Acres	Mean	SD	Min	Max
Without cover crop	328	20501	186.9***	43.65	20	270
With cover crop	115	6781	164.23***	30.51	47	246

Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

3.4.2 Yield Response to Nitrogen Application

The yield response to nitrogen will be an important modeling consideration later in this analysis. This section discusses the relationship based on scatter plots of the data with yield on the vertical axis and nitrogen application on the horizontal axis. The first factor to consider is the direction of the relationship, whether the correlation is positive or negative. The other important factor to note is the shape of the relationship. The relationship in corn is assumed to be non-linear and positive, which should be verified in these plots.

Soybean yield without cover crops is plotted against cash crop yield is figure 3.4. There appears to be little or no correlation between nitrogen application and yield for soybeans without a cover crop. For comparison, soybean yield with cover crops is plotted against cash crop yield in figure 3.5. There also appears to be no relationship between yield and nitrogen when cover crops are present. This was not unexpected since soybeans are a nitrogen-fixing legume. Most, if not all, of the nitrogen needs of soybeans are provided through nitrogen fixing symbiotic rhizobia bacteria contained in nodules on the plant's root system. Consequently, soybean yield is not very responsive to nitrogen fertilizer.

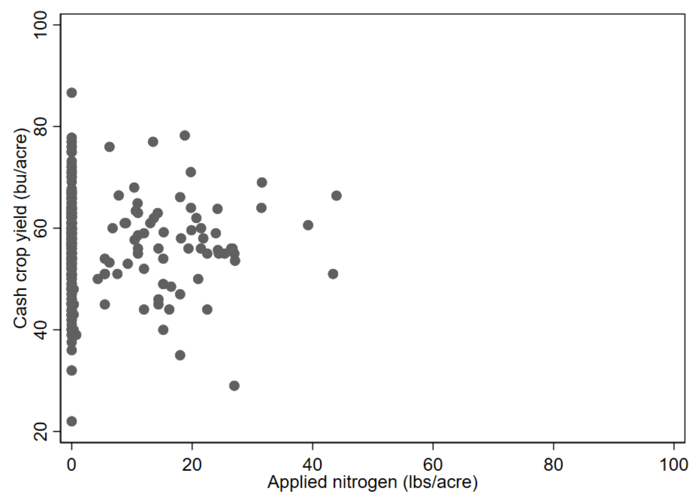

Figure 3.4 Soybean yield and nitrogen application without cover crops

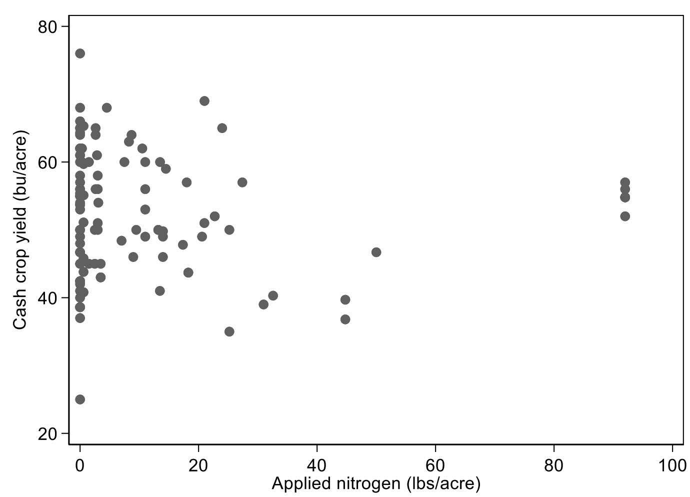

Figure 3.5 Soybean yield and nitrogen application with cover crops

The next set of scatter plots are for the relationship between corn yield and nitrogen fertilizer application. Figure 3.6 shows corn yield without cover crops plotted against nitrogen application. There appears to be a fairly strong positive relationship. The data also appear to have a concave pattern, which is especially noticeable at nitrogen application levels of 150 or more. This general shape implies decreasing marginal returns to nitrogen application. This shape also indicates a non-linear model should be used for the relationship between nitrogen and yield in corn. Cover crops affect nitrogen cycling, and thus should also be interacted with the non-linear nitrogen relationship in corn.

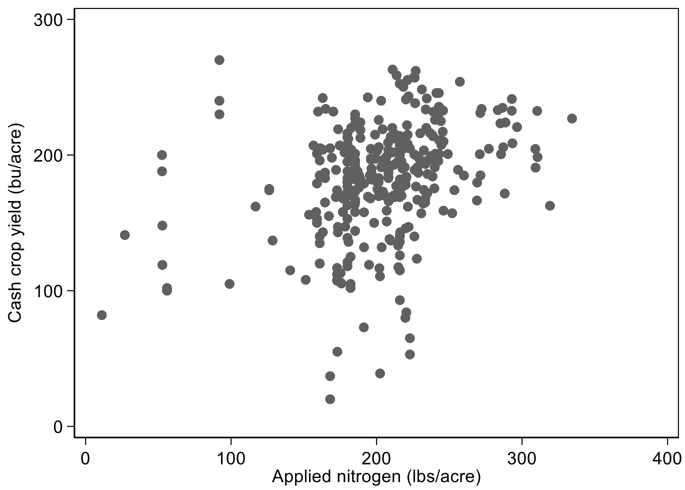

Figure 3.6 Corn yield and nitrogen application without cover crops

Figure 3.7 shows corn yield with cover crops plotted against nitrogen application. There appears to be a fairly strong positive relationship between 100 and 250 lbs of applied nitrogen, with a handful of high yields with less than 100 lbs of applied nitrogen. However, the shape of this relationship is not easily discernable based on this simple scatter plot.

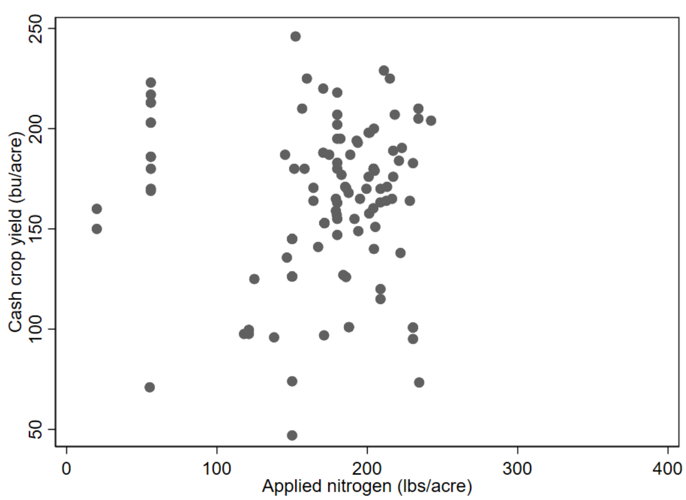

Figure 3.7 Corn yield and nitrogen application with cover crops

3.4.3 Farming Practices

Many of the farming practices that were used on the fields in this study are reported by the farmers in the data. These farming practices are grouped by type, and descriptive statistics are presented in tables in this section. All of these statistics are weighted by field size to reflect a per acre basis for interpretation. Many of the farming practices were recorded using dummy variables in which the value 1 means the practice was used, while the value 0 means the practice was not used. In these cases the only descriptive statistic reported is a simple proportion of the group that received the particular farming practice. In tables where there are both numeric and categorical variables summarized, the proportions and means will share a column, while the standard deviation, minimums, and maximums will be left out for dummy variables.

3.4.4 Tillage Practices

The tillage regime in each field is described in the data by three primary and two secondary variables. The first two binary variables for no-till and minimum tillage indicate whether these practices were used, if both are 0 then the field was tilled using conventional methods. These three tillage practices form a partition in the data, and their proportions sum to 100%. The other two variables that describe the tillage regime relate to the frequency of the use of no-till. Continuous no-till is for fields that have been farmed using no-till for at least two consecutive years, every other no-till is for fields that have used both conventional tillage and no-till in the last two years. This is usually because the farmer used rotational no-till—conventional for corn and no-till for soybeans. The every other year no-till variable contains fields that are in rotational no-till but are on their conventional tillage year. For this reason, the sum of these proportions is different than the proportion of no-till fields.

The summary statistics for tillage practices in soybeans by cover crop use are presented in table 3.10. In soybeans, 64.33% of the acres without a cover crop were cultivated using no-till. In comparison, 93.9% of the cover cropped soybean acres were cultivated using no-till. This difference shows a strong relationship between cover crops and no-till in soybeans. Both groups used no-till at a higher rate than the statewide average of 52% in 2017 (ISDA, 2017).

Table 3.10 Tillage practices in soybeans by cover crop use

Without cover crop	Proportion
Conventional Tillage	26.93%***
Minimum tillage	8.73%***
No-till	64.33%***
Continuous no-till	33.53%***
Every other no-till	28.77%***
With cover crop	
Conventional Tillage	4.93%***
Minimum tillage	1.17%***
No-till	93.9%***
Continuous no-till	89.4%***
Every other no-till	5.37%***

Without cover crop group included 347 observations and 22,112 acres
With cover crop group included 120 observations and 7,068 acres
Difference of means test (with vs without cover crops)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

The proportions for tillage practices in corn, grouped by cover crop use are listed in table 3.11. The cover crop acres devoted to corn had a very high rate of no-till cultivation, at 90.86%. This was primarily comprised of continuous no-till regimes, with only a small proportion of rotational no-till. This is compared to a proportion of just 31.39% of acres without a cover crop that were farmed using no-till. This shows that there is a strong connection between cover crops and no-till in corn as well. However, both of these figures are higher than the statewide average of 25% for no-till corn in 2017 (ISDA, 2017).

Table 3.11 Tillage practices in corn by cover crop use

Without cover crop	Proportion
Conventional Tillage	62.07%***
Minimum tillage	6.53%**
No-till	31.39%***
Continuous no-till	30.49%***
Every other no-till	34.37%***
With cover crop	
Conventional Tillage	8.62%***
Minimum tillage	0.52%**
No-till	90.86%***
Continuous no-till	89.70%***
Every other no-till	5.78%***

Without cover crop group included 328 observations and 20,501 acres
With cover crop group included 115 observations and 6,781 acres
Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

3.4.5 Fertilizer Application and Other Farming Practices

For the purpose of exploring the systematic differences in farming practices between observations with a cover crop and those without, fertilizer application and other farming practices were summarized by cover crop use in both corn and soybeans. Table 3.12 contains the descriptive statistics for farming practices by cover crop use for soybeans. One notable difference was higher fertilizer use when a cover crop was present in soybeans. This was driven by some farmers using chicken litter or other manure as fertilizer. This was likely for the purpose of adding phosphorus and potassium, but the nitrogen simply came along with the manure. It is also interesting that cover cropped acres used seed treatments at a far lower rate than those without a cover crop.

Table 3.12 Fertilizer application and other farming practices in soybeans by cover crop use

Without cover crop	Mean	SD	Min	Max
Applied nitrogen (lbs/acre)	4.21***	10.5	0	160.68
Applied phosphorus (lbs/acre)	13.72***	28.97	0	133.78
Applied potassium (lbs/acre)	34.12***	71.67	0	504.42
Seed Rate (thousands/acre)	172.95	26.24	120	225
Seed treatment	61.42%***	.	.	.
Previous crop-corn	92.44%*	.	.	.
Previous crop-soybeans	7.56%*	.	.	.
With cover crop				
Applied nitrogen (lbs/acre)	14.03***	27.79	0	92
Applied phosphorus (lbs/acre)	24.83***	37.55	0	138
Applied potassium (lbs/acre)	60.24***	70.79	0	209.89
Seed Rate (thousands/acre)	170.28	17.80	120	225
Seed treatment	46.27%***	.	.	.
Previous crop-corn	87.34%*	.	.	.
Previous crop-soybeans	12.66%*	.	.	.
Years of continuous cover crop	4.58	2.47	1	10

Without cover crop group included 347 observations and 22,112 acres
With cover crop group included 120 observations and 7,068 acres
Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

Farming practices in corn are summarized by cover crop use in table 3.13. The most notable difference between farming practices in cover cropped fields and those without a cover crop was the fertilizer use. Acres without cover crops received 206.9 lbs/acre of nitrogen fertilizer, while cover cropped acres only received 171.33 lbs/acre. There exist similarly large differences in applied phosphorus and potassium. These differences may be, at least partly, due to the farmer’s expectations of nutrient cycling benefits from growing cover crops. The difference also could be due to poorer quality soils in cover crop fields and farmer expectation of lower payoff from additional fertilizer.

With one exception, other farming practices appear to be similar between fields with and without a cover crop. That exception is the variable for seed treatment, which is lower for cover cropped fields. Seed treatment could significantly impact establishment and is likely positively correlated with yield.

Table 3.13 Fertilizer application and other farming practices in corn by cover crop use

Without cover crop	Mean	SD	Min	Max
Applied nitrogen (lbs/acre)	206.9***	41.04	11.18	334.37
Applied phosphorus (lbs/acre)	72.33***	47.83	0	208
Applied potassium (lbs/acre)	93.42***	74.96	0	330
Seed Rate (thousands/acre)	33.81**	2.48	26	63.05
Seed treatment	59.37%***	49.19%	0	1
Previous crop-corn	5.21%**	22.26%	0	1
Previous crop-soybeans	94.79%**	22.26%	0	1
With cover crop				
Applied nitrogen (lbs/acre)	171.33***	40.92	20.09	242.4
Applied phosphorus (lbs/acre)	29.53***	36.24	0	132.5
Applied potassium (lbs/acre)	37.95***	53.36	0	216
Seed Rate (thousands/acre)	33.25**	1.52	29	36
Seed treatment	42.89%***	49.71%	0	1
Previous crop-corn	0.22%**	4.75%	0	1
Previous crop-soybeans	99.78%**	4.75%	0	1
Years of continuous cover crop	4.13	2.44	1	10

Without cover crop group included 328 observations and 20,501 acres
With cover crop group included 115 observations and 6,781 acres
Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

3.4.6 Cover crop practices and varieties

Cover crop establishment, termination, and cultural practices varied across this sample. Planting was done by aerial broadcast, other broadcast, or drilling at various times before or after harvest. The variable for cover crop establishment in the data is meant to act as a proxy for the different combinations of establishment methods. Cover crop termination was done chemically by every farmer in our sample who used cover crops.

The selection of cover crop variety is an important management decision that must be made based on the needs of each field. Nine cover crop varieties were reported in farmer surveys as having been used. However, only seven were included in the data. Hairy vetch and turnips were not included as a category because they were used as part of a mix in just a very few observations. The proportions for each variety of cover crop are presented in table 3.14 as a percentage of total cover cropped acres. The percentages do not add up to 100% because cover crops were often planted in mixes. The proportions are interpreted as the percentage of cover crop fields that included this variety, alone or in a mix with other varieties.

Of the varieties used, cereal rye and tillage radish were nearly tied as the most popular being planted on 39.81% and 39.75% of the acres that were cultivated with a cover crop, respectively. Annual ryegrass was close behind with 37.34%. Crimson clover was also a very important variety in this sample, being planted on 31.53% of the cover cropped acreage.

Table 3.14 Cover crop varieties used on cover crop fields

Variable	Proportion
Annual ryegrass	37.34%
Crimson clover	31.53%
Cereal rye	39.81%
Oats	16.49%
Tillage radish	39.75%
Rapeseed	10.7%
Wheat	13.5%

The cover crop group included 235 observations and 13,848 acres

The distribution of the mixes is shown in figure 3.8. The different species of cover crops were grouped into four groups. A group was defined for cereal rye and annual ryegrass, another for other cereal cover crops including oats and wheat, another for other cover crops including tillage radish and rapeseed, and yet another for legume cover crops of which crimson clover was the only one. This figure shows the unweighted percentages, so they may differ from table 3.14.

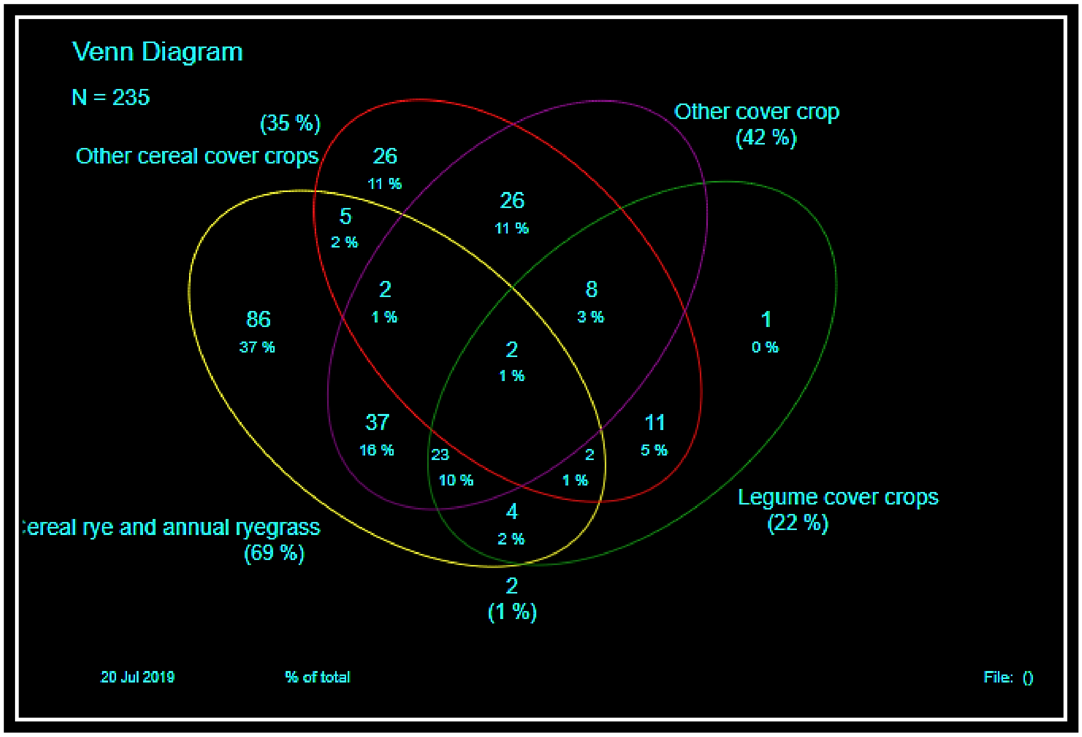

Figure 3.8 Distribution of cover crop mixes

3.4.7 Soil and Field Attributes

With the addition of optional soil tests to the project in 2017, new data became available that may help in understanding the soil profile in the fields from which this data come. Some data was already available on soil type and soil organic matter, but the soil test results add significantly to this information. Other field attributes can also carry information about the growing conditions and factors that may impact yield. Soil and field attributes that were observed are summarized in this section.

3.4.8 Field Attributes

The comparison of fields with cover crops and those without yielded some interesting differences. These differences are presented in table 3.15. Cover cropped fields are smaller on average, but only slightly. Fields with a cover crop average 58.93 acres, while fields without a cover crop are 63.13 acres. The average slope for cover crop acres is higher, at 3.17%, than the average slope of 1.83% for acres without a cover crop. This difference may be due to the use of cover crops to prevent erosion on steeper sloping fields, and these fields may already have eroded soils. A higher percentage of cover cropped fields were located in northeast Indiana.

Table 3.15 Field attributes by cover crop use

Without cover crop	Mean	SD	Min	Max
Field size (acres)	63.13*	49.35	6.6	271
Average slope (% grade)	1.83***	1.97	0	13
Drainage system	69.55%	46.05%	0	1
Northeast Indiana	26.72%***	44.28%	0	1
With cover crop				
Field size (acres)	58.93*	55.13	6.6	230
Average slope (% grade)	3.17***	1.93	0.5	9
Drainage system	68.63%	46.50%	0	1
Northeast Indiana	46.72%***	50.00%	0	1

Without cover crop group included 675 observations and 42,613 acres
With cover crop group included 235 observations and 13,848 acres
Difference of means test (with vs without cover crops)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.4.9 Soil Attributes

The differences in the soil attributes of fields with and without cover crops may be an important key in understanding the types of fields that are selected to be cultivated using cover crops. Farmers may choose less productive fields to plant cover crops for the purpose of improving soil health in that field. A field with similar attributes and more productive soils may be less likely to be selected as a cover crop field because the soil health does not need immediate improvement. This use of cover crops as a cure rather than preventative maintenance could drive selection of poor quality fields into the cover crop group of this study. This selection is a likely source of bias if not adequately controlled for in the analysis.

The soil profile is summarized by cover crop use in table 3.16. Fields that were cultivated without the use of cover crops were dominated by either Alfisols, Mollisols, or a mix of the two. Cover cropped fields have a much higher proportion of Alfisols than those without a cover crop, including far less Mollisol-Alfisol mixes. In the group of fields without a cover crop, one farm was dominated by Histosols, a rare soil order characterized by very high soil organic matter. For the purposes of comparing descriptive statistics across groups, soil organic matter was summarized with and without these observations and both sets of numbers were included in the table. However, the average for soil organic matter excluding Histisols is probably the most accurate comparison to make, as Histisols are rare and unique in this attribute. Cover cropped fields had higher soil organic matter at 3% than fields without a cover crop at 2.65% (excluding Histosols).

Another notable difference is the cation exchange capacity. This measure is fairly stable over time; it is a good measure of the inherent capacity of the soil to hold nutrients. Cation exchange capacity is determined by the parent material of the soil, as well as the organic matter present. Organic matter in the soil has a strong positive impact on the cation exchange capacity. The cation exchange capacity was much lower, at 10.67 meq/100g, in fields with a cover crop than those without a cover crop, which averaged 13.47meq/100g. This is a very interesting difference, especially given the fact that cover crop fields have higher organic matter.

Consequently, the difference in cation exchange capacity must be due to poorer parent material or severely eroded soils. This is strong evidence that the fields with poorer soils were more likely to be selected into the cover crop group.

Table 3.16 Soil profile by cover crop use

Without cover crops	Obs	Acres	Mean	SD	Min	Max
Alfisols	675	42613	34.29%***	.	.	.
Mollisols	675	42613	32.04%	.	.	.
Inceptisols	675	42613	0.54%	.	.	.
Mollisols/Alfisols mix	675	42613	31.97%***	.	.	.
Histisols	675	42613	1.16%	.	.	.
Soil organic matter (%)	465	27613	3.09	3.51	1.3	36.13
Soil organic matter (excluding Histisols, %)	449	27118	2.65***	0.59	1.3	5.23
Soil PH	425	26333	6.57**	0.35	5.83	7.53
Soil phosphorus (ppm)	425	26333	46.75**	31.68	8.33	169
Soil potassium (ppm)	425	26333	154.35***	50.45	65	270.33
Soil magnesium (ppm)	425	26333	270.52***	82.69	111.33	722.67
Soil Calcium (ppm)	425	26333	1864.99***	653.10	1028.5	4619
Cation exchange capacity	425	26333	13.17***	3.64	7.8	28.9
With cover crops	**Obs**	**Acres**	**Mean**	**SD**	**Min**	**Max**
Alfisols	235	13848	63.43%***	.	.	.
Mollisols	235	13848	30.76%	.	.	.
Inceptisols	235	13848	0%	.	.	.
Mollisols/Alfisols mix	235	13848	5.81%***	.	.	.
Histisols	235	13848	0%	.	.	.
Soil organic matter (%)	208	12599	3.0***	0.73	1.8	5.23
Soil PH	139	4820	6.47**	0.35	5.83	7.10
Soil phosphorus (ppm)	139	4820	38.84**	29.47	8.33	152
Soil potassium (ppm)	139	4820	135.59***	73.32	48	310.33
Soil magnesium (ppm)	139	4820	216.0***	73.31	111.33	373.67
Soil Calcium (ppm)	139	4820	1455.07***	290.08	1000	1929.33
Cation exchange capacity	139	4820	10.67***	2.52	6.5	15

Difference of means test (with vs without cover crops)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.4.10 Farm Operator Attributes

To summarize the variables that relate to the farmer and farm characteristics, the data were filtered to include only observations from 2017. This was done because it is the most recent year in which all of the farmers are represented in the data. Variables that described the operator of the farm were summarized by cover crop use in table 3.17. The farmers were classified as cover crop farmers if they were using cover crops or ever had grown cover crops. Farmers who used cover crops were older, had more farming experience, were less educated, and farmed smaller acreages. This is likely another source of selection bias that should be controlled for in the analysis.

Table 3.17 Operator characteristics in 2017 by cover crop use

Operators who had not used cover crops	Mean	SD	Min	Max
Operator farming experience	22.40***	13.66	9	49
High school	10%***	.	.	.
Bachelor's degree	50%**	.	.	.
Graduate degree	40%	.	.	.
Operator's age	47.8**	16.32	29	74
Total acres managed	2675.7***	2812.37	60	7500
Farm laborers	4.55***	3.72	1	10
Operators who had used cover crops				
Operator farming experience	36.31***	15.36	6	54
Operator cover crops experience	9.85	10.78	0	42
High school	54%***	.	.	.
Bachelor's degree	30.77%**	.	.	.
Graduate degree	15.38%	.	.	.
Operator's age	54.46**	15.1	24	72
Total acres managed	901***	797.96	190	2500
Total acres of cover crops	358.15	412.19	0	1500
Farm laborers	2.62***	1.71	1	7

There were 10 operators who had not ever used cover crops
There were 13 farmers who currently used cover crops or had done so in the past
Difference of means test (with vs without cover crops)
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

3.5 Correlation Matrices

Some of the most important things that the descriptive statistics can reveal are hints at the best identification strategy for the model. One simple way to identify variables that could cause endogeneity is to create a correlation matrix to identify variables that should or should not be included in the model. Table 3.18 is a modified correlation matrix. It includes all of the major variables listed as row titles against cash crop yield and cover crops in corn and soybeans as column titles. This was done for the purpose of determining which variables are correlated with both the dependent and independent variables of interest in our model.

Several interesting correlations exist in this data. One prominent relationship is the negative correlation between slope and yield for both corn and soybeans, as well as a strong positive relationship with cover crops. Similarly, no-till is negatively correlated with yield and positively correlated with cover crops. These variables would likely cause negative bias if not included in the regression model. Other variables that describe farming practices, farmer attributes, and soil health also show similar correlations and were controlled for in the analysis.

An interesting correlation in the data was the negative correlation between soil organic matter and yield in both corn and soybeans. Soil organic matter is often used as a broad measure of soil health. The assumption is often made that increased soil organic matter will lead to increased yield. Later in the analysis, this hypothesis will be tested.

Table 3.19 presents yield correlations by cash crop and cover crop use. The correlation between no-till and yield is different over cover crop use, suggesting an interaction effect. This is also the case for fertilizer use, where significant differences exist, especially in corn.

Table 3.18 Yield and cover crop correlation matrix

	Soybeans		Corn	
	Yield	Cover crop	Yield	Cover crop
Cash crop yield	1	-0.187	1	-0.21
Field size	0.056	-0.041	0.118	-0.031
Average slopes	-0.274	0.337	-0.244	0.343
Minimum tillage	-0.041	-0.084	-0.008	-0.079
No-till	-0.22	0.246	-0.204	0.4
Continuous no-till	-0.178	0.406	-0.197	0.382
Every other no-till	0.012	-0.223	-0.08	-0.175
Previous crop-corn	0.119	-0.057	0	-0.108
Previous crop-soybeans	-0.119	0.057	0	0.108
Applied Nitrogen	-0.117	0.221	0.282	-0.312
Applied phosphorus	0.041	0.172	0.085	-0.241
Applied potassium	0.084	0.15	0.098	-0.247
Seed rate	-0.075	-0.053	0.262	-0.184
Seed treatment	0.053	-0.148	0.186	-0.212
Drainage system	-0.004	-0.028	0.193	-0.105
Cover crop	-0.187	1	-0.21	1
Northeast Indiana	-0.327	0.155	-0.19	0.084
Mollisols	0.188	-0.079	0.157	-0.1
Inceptisols	0.014	-0.055	-0.02	-0.057
Alfisols/Mollisols mix	0.047	-0.201	0.166	-0.132
Histisols	-0.208	-0.082	-0.129	-0.075
Operator farming experience	-0.09	0.457	-0.067	0.438
Operator cover crops experience	-0.134	0.31	-0.096	0.463
Bachelor's degree	0.147	-0.224	0.087	-0.237
Graduate degree	-0.16	0.069	-0.289	0.119
Operator's age	-0.085	0.333	-0.101	0.338
Total acres managed	0.201	-0.297	0.277	-0.292
Total acres of cover crops	-0.077	0.419	-0.018	0.225
Farm laborers	0.118	-0.22	0.208	-0.236
Soil organic matter	-0.23	-0.086	-0.142	-0.066
Soil PH	0.096	-0.112	0.246	-0.147
Soil phosphorus	0.03	-0.129	0.028	-0.099
Soil potassium	-0.003	-0.169	-0.003	-0.106
Soil magnesium	0.019	-0.334	0.009	-0.295
Soil Calcium	-0.048	-0.337	0.158	-0.341
Cation exchange capacity	-0.062	-0.364	0.096	-0.358

Table 3.19 Yield correlations by cash crop and cover crop use

	Soybeans		Corn	
	Yield without cover crops	Yield with cover crops	Yield without cover crops	Yield with cover crops
Cash crop yield	1	1	1	1
Field size	0.066	0.001	0.137	0.054
Average slopes	-0.2	-0.311	-0.101	-0.443
Minimum tillage	-0.059	-0.06	-0.049	0.102
No-till	-0.2	-0.111	-0.144	-0.095
Continuous no-till	-0.117	-0.106	-0.137	-0.1
Every other no-till	-0.045	0.05	-0.143	-0.028
Previous crop-corn	0.154	-0.001	-0.009	-0.147
Previous crop-soybeans	-0.154	0.001	0.009	0.147
Applied Nitrogen	-0.145	0.006	0.323	-0.001
Applied phosphorus	0.044	0.152	0.067	-0.088
Applied potassium	0.073	0.274	0.018	0.195
Seed rate	-0.063	-0.176	0.237	0.221
Seed treatment	0.071	-0.119	0.163	0.098
Drainage system	0.034	-0.142	0.163	0.216
Northeast Indiana	-0.328	-0.253	-0.243	0.013
Mollisols	0.148	0.276	0.13	0.17
Inceptisols	0.005	0	-0.037	0
Alfisols/Mollisols mix	0.023	-0.083	0.128	0.215
Histisols	-0.261	0	-0.169	0
Operator farming experience	0.061	-0.183	0.166	-0.359
Operator cover crops experience	-0.05	-0.247	0.097	-0.194
Bachelor's degree	0.22	-0.276	0.101	-0.183
Graduate degree	-0.247	0.121	-0.291	-0.224
Operator's age	-0.017	-0.05	0.027	-0.256
Total acres managed	0.158	0.258	0.242	0.255
Total acres of cover crops	0.011	-0.022	0.033	0.02
Farm laborers	0.134	-0.31	0.235	-0.315
Soil organic matter	-0.295	-0.025	-0.183	-0.163
Soil PH	0.113	-0.072	0.207	0.272
Soil phosphorus	0.075	-0.254	0.164	-0.403
Soil potassium	0.038	-0.215	0.154	-0.33
Soil magnesium	-0.025	-0.106	0.027	-0.399
Soil Calcium	-0.115	-0.111	0.106	-0.01
Cation exchange capacity	-0.135	-0.13	0.061	-0.231

The last set of correlations that were explored were between cover crops, cover crop varieties, cover crop establishment, and manager experience against measures of soil health. This may give us information on whether cover crops improve soil health. If the measure of soil health is one that changes slowly, these correlations may give additional information on the type of fields that are chosen by farmers to grow cover crops. This set of correlations is presented in Table 3.20.

In general, nearly everything related to cover crops is negatively correlated with all of the soil health indicators. This is probably not because the cover crops are damaging the soil. It is likely due to the fact that improving soil health is a very slow process, and it appears that cover crops are planted on poor soils in an effort to improve them. This is evidenced by the variable for years of continuous cover cropping, which has a positive correlation with most of the soil health variables. This may suggest that cover crops improve soil health slowly, and many benefits may take years to be realized. However, this is not a controlled regression so causation cannot be assigned.

Table 3.20 Cover crop attributes and soil health correlations

	Soil organic matter	Soil PH	Soil phosphorus	Soil potassium	Soil magnesium	Soil Calcium	Cation exchange capacity
Cover crop	-0.077	-0.129	-0.114	-0.138	-0.314	-0.339	-0.360
Annual rye	-0.073	0.058	-0.176	-0.286	-0.323	-0.186	-0.259
Crimson clover	-0.042	0.041	-0.110	-0.146	-0.051	-0.064	-0.085
Cereal rye	-0.015	-0.142	-0.053	0.028	-0.114	-0.156	-0.141
Oat	-0.030	-0.048	-0.048	-0.083	-0.104	-0.135	-0.143
Radish	-0.049	-0.029	-0.041	-0.092	-0.138	-0.177	-0.191
Rapeseed	-0.018	0.004	-0.077	-0.093	-0.007	-0.068	-0.073
Wheat	-0.017	-0.092	0.043	0.035	-0.015	-0.147	-0.124
Cover crop establishment rank (1-5)	-0.025	-0.033	-0.041	-0.037	-0.191	-0.038	-0.075
Years of continuous cover crop	0.047	-0.057	0.121	0.049	0.097	-0.176	-0.063
Operator cover crop experience	-0.065	-0.199	-0.166	-0.173	-0.236	-0.395	-0.389
Total acres of cover crops	-0.161	-0.108	-0.406	-0.389	-0.382	-0.425	-0.467

CHAPTER 4 METHODOLOGY

4.1 Introduction

This chapter provides a description of the methods used to analyze the data gathered from farmers in the project. The focus of this study is to quantify the economic consequences of growing cover crops. The channels by which cover crops may impact the economic picture for individual farmers are investigated. Each of these analyses provides interesting insights individually. Their results are subsequently combined into stochastic farm budgets to provide a clear demonstration of the private financial implications to the farm business from growing cover crops.

The first analysis is a probit model to determine the factors that increase the likelihood of a field being selected into the cover crop group. This model is intended to help consider potential bias resulting from non-random selection into the cover crop group. This model will be used to generate a propensity score which will approximate the probability of a field being chosen to be cover cropped. The propensity score will then be used to identify observations that may potentially cause bias in the estimates and remove them. The estimated effect of cover crops on mean variability of cash crop yield will be calculated using a trimmed sample.

Section 4.2 is devoted to explaining the methods used in the analysis of the effect of cover crops on mean crop yield. The next analysis is focused on the effect of cover crops on crop yield variability. The models that were developed and used to estimate this effect are presented in section 4.3. The central analysis for this research is a stochastically simulated farm budget model, outlined in section 4.4. The previous analyses of mean yield and yield variation contribute as inputs to the financial analysis. This model examines the economic impact of cover crops on the farm business in terms of returns as well as risk. Several methods are used to rank competing alternatives based on both risk and reward.

4.1.1 Dataset configurations

In the analysis of the data, two different dataset configurations were used. The first was the original dataset without any changes. This data had a longitudinal structure, each observation was one field in one year of the study period. This data was used in the analysis of mean yields.

The second dataset configuration was the original data collapsed over time. Every observation consisted of one field. Each field had an observation for soybeans and an observation for corn so that the yield variability could be separated by crop. The variables within individual observations were averaged over time for the years in which its respective crop was grown. Three variables were also added: one for the temporal yield standard deviation, one for the yield coefficient of variation, and one for the standard deviation of nitrogen application. The modified data had a relatively small sample size because each observation was represented by one field averaged over time. However, this data structure was necessary for the analysis of yield variability.

4.1.2 Propensity score model for trimmed sample

The choice by farmers to plant cover crops on a field is not random. The factors affecting this choice could cause bias in any analysis of the effect of cover crops on yield (Tucker, 2010). The reasons for planting cover crops may be based on the attributes of the field. One hypothesis is that farmers choose to cover crop fields that have steeper slopes where cover crops might be selected as an erosion control method. Such fields may be less productive due to degraded soil from past erosion. Fields could also be selected systematically for other reasons. The farmer may choose a field simply because the soil is not particularly fertile. This might occur if the farmer sees cover crops as a way to restore or improve soil health and fertility. This non-random selection would cause bias in the analysis of yield response to cover crops. In our data, it appears that farmers systematically plant cover crops on lower-quality fields. Descriptive statistics show that cover cropped fields have higher slopes, lower fertility status, and lower nutrient holding capacity than fields without cover crops.

A common technique for reducing selection bias is to conduct the analysis on a propensity score trimmed sample (Imbens et al., 2009; Sanglestsawai et al., 2014; Stürmer et al., 2010). The idea behind this is to use field attributes to estimate the probability (propensity score) of a field being selected to be cover cropped (Rosenbaum & Rubin, 1985). This is intended to identify fields that are similar in ways that are important to the cover cropping decision and to do the analysis on these fields. The fields with similar probabilities are chosen to be part of the analysis, while other fields are removed from the sample. This is done by choosing a cutoff level α where observations with propensity scores outside the interval $[\alpha, 1 - \alpha]$ are excluded from the regression (Imbens et al., 2009).

The chosen method for estimating the propensity score was a probit model. The model is defined in equation 4.1. The dependent variable in this regression was the binary variable for cover crop use. The independent variables were average slope, drainage system, dummy variables indicating soil type, the size of the field and farm, dummy variables on the operator's education, and the operator's age. This model was estimated and the predicted valued calculated for the full dataset as well as the dataset for variation. The predicted values were used as the propensity score for cover crop use.

Equation 4.1 Probit model to generate propensity score

$$\mathrm{P}(covercrop) = \beta_0 + \beta_1 slope + \beta_2 drain + \beta_3 moll + \beta_4 mix + \beta_5 acres + \beta_6 fsize + \beta_7 undergrad + \beta_8 post + \beta_9 age + U$$

Coefficients for the model described in equation 4.1 are found in table 4.1. These results convey the direction of the marginal effect and have associated hypothesis tests. However, in a probit model, the coefficients do not represent the marginal effect as in ordinary least squares regression (Wooldridge, 2016). This model was intended for predicting the propensity score for cover crops, not necessarily for causal effects. Consequently, the coefficients should be interpreted with caution. In table 4.1, column (1) uses the full data set, while column (2) uses the adapted data used in the variation analysis.

Table 4.1 Marginal effects of probit model covariates on cover crop use

	Cover crop	Cover crop
Average slope	0.164***	0.178***
	(0.0570)	(0.0523)
Tile drain	-1.011*	-1.454***
	(0.520)	(0.255)
Farmer’s age	0.0244	0.00137
	(0.0169)	(0.00828)
Field Size	0.0103***	0.0108***
	(0.00381)	(0.00258)
Farm Size	-0.000759**	-0.000825***
	(0.000316)	(0.000155)
Bachelor’s degree	-0.861	-1.295***
	(0.597)	(0.291)
Graduate degree	-1.236*	-1.506***
	(0.677)	(0.304)
Mollisols	-0.289	-0.438*
	(0.393)	(0.248)
Alfisols/Mollisols	-0.679*	-0.266
	(0.395)	(0.413)
Constant	-0.652	1.586**
	(1.156)	(0.631)
Observations	886	213

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The estimated models described above were used to predict a propensity score for each observation in the respective datasets. Figure 4.1 is a histogram of the propensity for a field to be cover cropped using the original dataset. From the histogram, it is easy to see a concentration of observations with a propensity score of less than 0.1. On the other hand, there are very few observations that have a propensity score greater than 0.8. Random selection in treatment assignment would mean every field would have an equal probability of being cover cropped, independent of field attributes (Tucker, 2010). If this had been the case, we would expect the histogram to be relatively flat, reflecting equal probability. The trimmed sample will use only the middle section where the histogram appears relatively flat. The interval [0.2, 0.8] was chosen as the most uniform interval using a symmetric trim level.

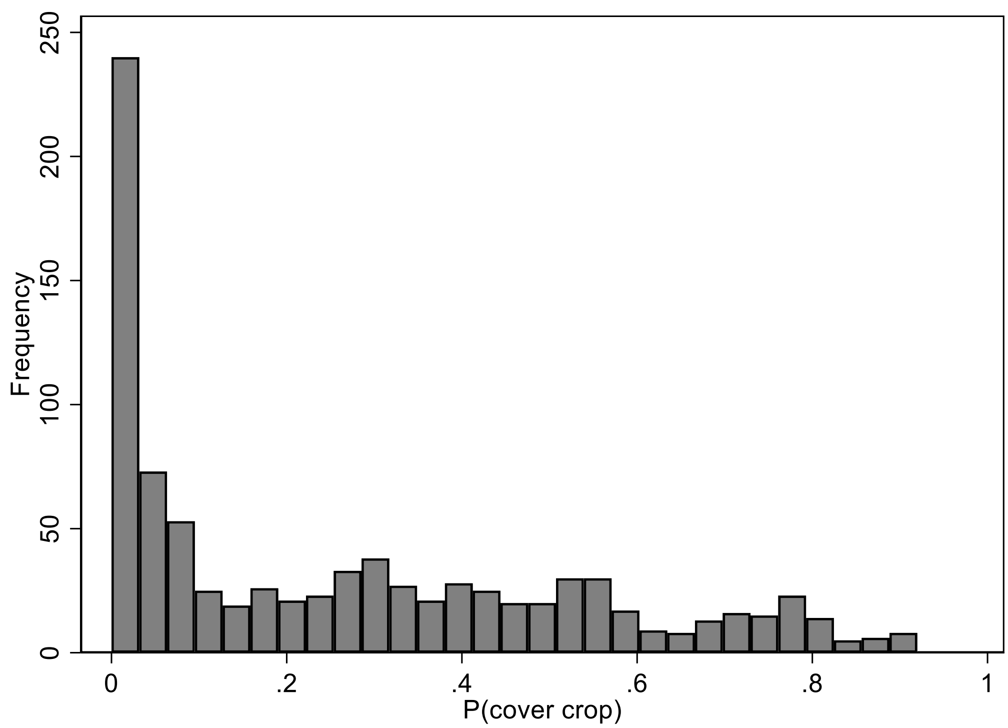

Figure 4.1 Histogram of cover crop propensity score using original dataset

As noted previously, the data that was gathered for this project suggest that cover crops are used on fields of lower average quality. If this was indeed the case, we would expect to see a negative correlation between the propensity score and crop yields. The correlations in table 4.2 show a strong negative relationship using the full sample. Trimming the sample should remove much of the correlation due to non-random selection-based field and farmer attributes. Using the trimmed sample does reduce this correlation dramatically, especially for soybeans. Even in corn the correlation is reduced by more than half. At least part of the remaining correlation in corn is probably driven by the lower nitrogen application by farmers with a high propensity to cover crop. The dramatic reduction in these correlations confirms that the trimmed sample is helping to compare fields of similar productive capacity.

Table 4.2 Correlations between yield and cover crop propensity score

	Full sample	20% Trimmed sample
Variable	Propensity score	Propensity score
Corn yield	-0.3424	-0.1363
Soybean yield	-0.3363	0.0001

The same process discussed above was used for the adapted dataset for the variation analysis. The results of the probit regression are presented in column 2 for table 4.1. From this model, the propensity score for the temporally consolidated dataset was predicted. The histogram of the cover crop propensity score for this dataset is displayed in figure 4.2. This figure shows a concentration of observations with a propensity score close to zero. It does not exhibit the thin right tail as was evident in the original data. The interval [0.1, 0.9] in this dataset is relatively flat in the histogram of propensity score frequency. For this reason, a 10% trimmed sample was used in the variance analysis.

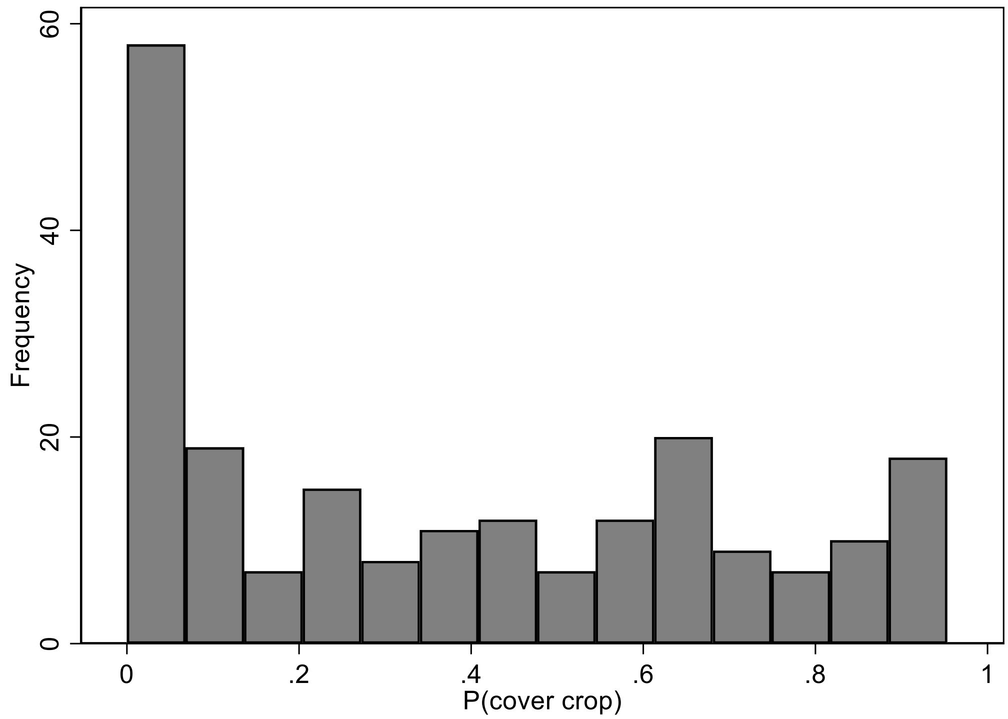

Figure 4.2 Histogram of cover crop propensity score using adapted dataset

As with the original dataset, in the modified dataset we expect a correlation between the cover crop propensity and field quality. As a result, there should be a positive correlation between the yield coefficient of variation and the propensity score. The correlations between the propensity score and the yield coefficient of variation are shown in table 4.3. As expected, a positive relationship exists. However, trimming the sample reduces the correlation by about half in both corn and soybeans. The reduction in these correlations confirms that the trimmed sample is providing fields of similar quality for analysis.

Table 4.3 Correlations between coefficient of variation and cover crop propensity score

	Full sample	10% Trimmed sample
Variable	Propensity score	Propensity score
Corn CV%	0.1095	0.1596
Soybean CV%	0.0594	0.0829

These results support the utilization of a trimmed sample. This was done throughout the analysis of mean yields and yield variation. These results also provide justification for the intervals selected to trim each dataset. For this study a 20% (α=0.2) trimmed sample was used in the analysis of mean yields, meaning observations with a propensity score inside the interval [0.2, 0.8] were included in the trimmed sample. For the analysis of yield variability, a 10% (α=0.1) trimmed sample was used; observations with a propensity score inside the interval [0.1, 0.9] were included in the trimmed sample.

4.2 The Impact of cover crops on average yields

From the data that we have gathered, the impact of cover crops on cash crop yields can be estimated. This will add significantly to the available knowledge on how cover crops may impact the farm business. This project will evaluate cover crop yields using econometric regression analysis with the intent of obtaining an unbiased estimate of the effect of cover crops on the subsequent cash crop yield. The methodology uses sound and accepted techniques in creative ways to accomplish this goal.

This analysis will follow a different methodology for testing the effect of cover crops on average yields than was used by S. Lira (2017), who used an older version of this same dataset with a similar objective. The data structure is longitudinal with each field being defined as a panel. This type of data is often analyzed using fixed-effects regression models that control for time-invariant characteristics within each field (Wooldridge, 2016). However, this data is not well suited to this type of model, because the treatment variable for cover crop use has very limited temporal variation within each panel. Thus controlling for time-invariant attributes at least partially controls for the effect of cover crops on yield.

The dependent variable in the yield model is the cash crop yield while the independent variable of interest is cover crop use. The control variables in these models are field, farm, and farmer attributes that are likely correlated with both yield and cover crop use. The models that will be used in this analysis are Ordinary Least Squares (OLS) regression models. For each different model, separate regressions will be estimated for corn and soybeans. Each model will be estimated using both the whole sample and the trimmed sample.

The regression models were not estimated using weights as were the summary statistics. The rationale for using weights comes from the fact that each field is a different size. The variables are an average across those acres and larger fields provide more precise averages. However, this is also the definition of heteroskedastic sample, which is easily corrected using robust standard errors (Solon et al., 2015). All models in this analysis were calculated using heteroscedasticity robust standard errors. Additionally, cluster robust standard errors at the farm level were considered. We believe that the error term is likely correlated within farms because of location and farmer management practices that are not observed. This method would not affect the point estimates for the coefficients but would adjust the standard errors to be more accurate (Cameron & Miller, 2015). However, since the data only contain 23 farms, this type of standard error may not be appropriate. Using clustered standard errors with too few clusters can lead to overfitting and may not fix the error term correlation issue because the asymptotics have not yet kicked in (Cameron & Miller, 2015). For this reason, clustered standard errors were not used.

In order to control for year-specific weather-related factors, year dummy variables are included. County-specific conditions are accounted for using county dummy variables. Field attributes may be important, and some soil-related variables are available in the data. The complication with using the soils data in the regression is that it reduces the sample to those fields for which data are available. Because cover crops have been shown to impact soil chemical properties, it is difficult to know which way the causality goes. Including soil quality variables would probably be over-controlling and would result in attenuation bias. For these reasons, the main models will not include soils data.

In general, functional forms for most variables in each model were assumed to be linear. The effect of cover crops on yield was expected to have interactions with soil moisture, nutrient application, and tillage. The effect of nitrogen on corn yield was assumed to be quadratic and was the only covariate modeled as having a nonlinear effect on yield. The specific functional form of each regression will be discussed for corn in section 4.2.2 and soybeans in section 4.2.3.

4.2.2 Corn yield regression models

The models for corn include the dependent variable for corn yield and the independent variable of interest, cover crops. Control variables were included for farming practices, field attributes, and fixed effects for county and year. The first three covariates were measures of fertilizer applied to the field. These are important because cover cropped fields received less fertilizer on average than fields without a cover crop. Fertilizer application would cause endogeneity if not included in the model. To model the heterogeneous effect of cover crops on yield over fertilizer use, cover crop use was interacted with each fertilizer application. This is done because cover crops affect nutrient cycling and losses and may impact yields through such changes. A quadratic term for nitrogen was used to model decreasing marginal returns to nitrogen.

The next group of variables related to other farming practices that differed by cover crop use. These variables included cash crop seed rate, cash crop seed treatment, average slope, no-till, drainage system, the set of dummy variables indicating soil type, and farm size. With the exception of farm size and field size, each of the above variables is correlated with cover crop use and could directly impact yields. Farm size may be a proxy for farm management ability, which could directly impact yields.

In the model, cover crops are interacted with no-till, average slope, and farm size. These are all factors that could impact the effect of cover crops on yield in some way. No-till could impact the way cover crops help manage moisture and change the nutrient cycle. Slope could impact cover crop establishment and change the effect of cover crops on the nutrient cycle. Farm size as a proxy for farm management could influence the management of the cover crops. Including these interactions should help to reduce bias, and account for heterogeneity of the treatment effect on these factors. The econometric model is shown in equation 4.2.

Equation 4.2 Corn mean yield model

$$corn\ yield = \beta_0 + \beta_1 covercrop + \beta_2 N\ app + \beta_3 covercrop * N\ app + \beta_4 N\ app^2 + \beta_5 P\ app + \beta_6 covercrop * P\ app + \beta_7 K\ app + \beta_8 covercrop * K\ app + \beta_9 notill + \beta_{10} covercrop * notill + \beta_{11} seedrate + \beta_{12} treatment + \beta_{13} drain + \beta_{14} covercrop * drain + \beta_{15} moll + \beta_{16} mix + \beta_{17} slope + \beta_{18} covercrop * slope + \beta_{19} fsize + \beta_{20} covercrop * fsize + \sum_{i=1}^{8} \beta_{i+20} Year_i + \sum_{i=2}^{20} \beta_{i+28} County_i + U$$

The derivative of equation 4.2 with respect to cover crops is shown in equation 4.3. This is the marginal effect of cover crops on average yields. The derivative was analyzed at the means of the trimmed sample for all of the independent variables except nitrogen application. It was analyzed over a range of 50 to 250 lbs of applied nitrogen.

Equation 4.3 Derivative of corn yield model with respect to cover crop use

$$\frac{\partial(corn\ yield)}{\partial(covercrop)} = \beta_1 + \beta_3 N\ app + \beta_7 P\ app + \beta_9 K\ app + \beta_{13} slope + \beta_{15} notill + \beta_{18} drain + \beta_{24} fsize$$

The *a priori* assumption for this model is that cover crops will increase average yields at relatively low nitrogen levels, but this effect will decrease as nitrogen application increases. This assumption is based on the view that the main benefit of cover crops is the addition of fixed and scavenged nitrogen for use by the corn crop.

4.2.3 Soybean yield regression models

The model used for soybeans is similar to the model used for corn. The main difference is that the quadratic term for nitrogen application is not included in the soybean model, because soybeans do not respond to applied nitrogen the same way that corn does. The yield model for soybeans is shown in equation 4.4

Equation 4.4 Soybean mean yield model

$$soybean\ yield = \beta_0 + \beta_1 covercrop + \beta_2 N\ app + \beta_3 covercrop * N\ app + \beta_4 P\ app + \beta_5 covercrop * P\ app + \beta_6 K\ app + \beta_7 covercrop * K\ app + \beta_8 notill + \beta_9 covercrop * notill + \beta_{10} seedrate + \beta_{11} treatment + \beta_{12} drain + \beta_{13} covercrop * drain + \beta_{14} moll + \beta_{15} mix + \beta_{16} slope + \beta_{17} covercrop * slope + \beta_{18} fsize + \beta_{19} covercrop * fsize + \sum_{i=1}^{8} \beta_{i+19} Year_i + \sum_{i=2}^{20} \beta_{i+27} County_i + U$$

The derivative of this model with respect to cover crops is presented in equation 4.5. This derivative was analyzed at the means for the independent variables in the trimmed sample. Because nitrogen was not an important factor, the derivative was not calculated for different levels of applied nitrogen, as it was in corn.

Equation 4.5 Derivative of Soybean mean yield model 1 with respect to cover crop use

$$\frac{\partial(corn\ yield)}{\partial(covercrop)} = \beta_1 + \beta_3 N\ app + \beta_7 P\ app + \beta_9 K\ app + \beta_{13} slope + \beta_{15} notill + \beta_{18} drain + \beta_{24} fsize$$

The *a priori* assumption for this model is that cover crops will have a neutral to positive effect on soybean yield. This assumption is different from corn because soybeans would likely not have any yield response to additional nitrogen fixed or scavenged by the cover crop.

4.3 The impact of cover crops on yield variability

Yield variation may be another way in which cover crops can provide economic benefits. Temporal variation is an important measure of the uncertainty faced by farmers as they plan for the future (Anderson et al., forthcoming). Yield variation is the primary component of production risk, which is a significant source of risk to producers. It is possible that including cover crops in their cropping system could help farmers reduce yield risk. If cover cropped fields could maintain equal or higher average financial returns while reducing the variation of those returns, then cover cropping would be theoretically preferred by risk-averse farmers (Barry and Ellinger 2012). The effect of cover crops on yield variation could also be used in the analysis performed to determine crop insurance premiums. If cover crops could be shown to reduce production risk, then lower crop insurance premiums might be justified.

4.3.1 The impact of cover crops on yield variability in corn

To evaluate absolute yield variability in corn, temporal standard deviation ($yield_{sd}$) was used as the dependent variable. The only interactions in the model were between cover crops and the average and standard deviation of applied nitrogen. This was done in corn because corn yields are very sensitive to nitrogen application.

The control variables included in the regression were average nitrogen application ($N\ app_{av}$), standard deviation of nitrogen application ($N\ app_{sd}$), phosphorus application ($P\ app_{av}$), potassium application ($K\ app_{av}$), seed treatment ($treatment$), the field's average slope ($slope$), no-till ($notill$), tile drainage ($drain$), Mollisols soil type ($moll$), Alfisols/Molisols mix (mix), and location variable indicating whether the field was located in northeast Indiana (ne).

All of the control variables used in this model showed correlation with cover crop use. Each also was also theoretically linked to yield variation. Levels of fertilizer application might affect yield variability by improving the health of the plant and thus improving the plants' resiliency. Seed treatment could help improve yields in years when pests might otherwise damage the crop. Fields with higher slopes may have soil that is degraded from erosion. No-till could improve soil physical properties such as water holding capacity. Tile drainage could help farmers plant earlier and crops achieve better establishment by removing excessive spring moisture. Soil types would impact the water-holding capacity and drainage among a host of other factors that could impact yield variation. Finally, location could be important because of local climate, soil, or other factors. Including dummy variables for counties was considered. However, this would add 20 additional variables to the regression. Instead, a binary variable indicating whether the farm was in the northeast region of Indiana was used. This helped avoid reducing the degrees of freedom too much. The yield standard deviation model for corn is displayed in equation 4.6.

Equation 4.6 Absolute variability regression model for corn

$$yield_{sd} = \beta_0 + \beta_1 covercrop + \beta_2 N\ app_{av} + \beta_3 covercrop * N\ app_{av} + \beta_4 N\ app_{sd} + \beta_5 covercrop * N\ app_{sd} + \beta_6 N\ app_{av} * N\ app_{sd} + \beta_7 covercrop * N\ app_{av} * N\ app_{sd} + \beta_8 P\ app_{av} + \beta_9 K\ app_{av} + \beta_{10} treatment + \beta_{11} slope + \beta_{12} notill + \beta_{13} drain + \beta_{14} moll + \beta_{15} mix + \beta_{16} ne + U$$

The derivative of corn yield standard deviation with respect to cover crops will be the estimated effect of cover crops. This derivative is shown in equation 4.7. Cover crops are expected to decrease the standard deviation of corn yield.

Equation 4.7 Derivative of absolute variability model for corn with respect to cover crop use

$$\frac{\partial(yield_{sd})}{\partial(covercrop)} = \beta_1 + \beta_3 N\ app_{av} + \beta_5 N\ app_{sd} + \beta_7 N\ app_{av} * N\ app_{sd}$$

To evaluate relative yield variability in corn, temporal yield coefficient of variation ($yield_{cv}$) was used as the dependent variable. The functional form and the control variables are the same as were used in equation 4.6. The only difference is the output variable. This model is shown in equation 4.8.

Equation 4.8 Relative variability regression model for corn

$$yield_{cv} = \beta_0 + \beta_1 covercrop + \beta_2 N\ app_{av} + \beta_3 covercrop * N\ app_{av} + \beta_4 N\ app_{sd} + \beta_5 covercrop * N\ app_{sd} + \beta_6 N\ app_{av} * N\ app_{sd} + \beta_7 covercrop * N\ app_{av} * N\ app_{sd} + \beta_8 P\ app_{av} + \beta_9 K\ app\_av + \beta_{10} treatment + \beta_{11} slope + \beta_{12} notill + \beta_{13} drain + \beta_{14} moll + \beta_{15} mix + \beta_{16} ne + U$$

The derivative of yield coefficient of variation with respect to cover crops will be the estimated effect of cover crops. This derivative is given for corn in equation 4.9. Cover crops are expected to decrease the coefficient of variation for corn yield.

Equation 4.9 Derivative of relative variability model for corn with respect to cover crop use

$$\frac{\partial(yield_{cv})}{\partial(covercrop)} = \beta_1 + \beta_3 N\ app_{av} + \beta_5 N\ app_{sd} + \beta_7 N\ app_{av} * N\ app_{sd}$$

4.3.2 The impact of cover crops on yield variability in soybeans

The analysis of variation in soybeans follows nearly the same methodology as the models for corn. The one difference is the way nitrogen application is used. For soybeans, average nitrogen application was included in the regression model, but the standard deviation was not.

Cover crops were also not interacted with nitrogen or any other variable. Soybeans do not respond to applied nitrogen because they fix all the nitrogen they can use. The yield standard deviation model for soybeans is displayed in equation 4.10. The control variables are included for the same reasons they were included in the corn models.

Equation 4.10 Absolute variability regression model for soybeans

$$yield_{sd} = \beta_0 + \beta_1 covercrop + \beta_2 N\ app_{av} + \beta_3 P\ app_{av} + \beta_4 K\ app_{av} + \beta_5 treatment + \beta_6 slope + \beta_7 notill + \beta_8 drain + \beta_9 moll + \beta_{10} mix + \beta_{11} ne + U$$

The derivative of yield standard deviation with respect to cover crops is simply β_1. This coefficient is not expected to be significant based on prior research (Anderson et al., forthcoming).

To evaluate relative yield variability in soybeans, temporal yield coefficient of variation ($yield_{cv}$) was used as the dependent variable. The functional form and the control variables are the same as were used in equation 4.10. The only difference is the output variable. This model is shown in equation 4.11. The marginal effect of cover crops in this model is β_1, which was not expected to be significant.

Equation 4.11. Relative variability regression model for soybeans

$$yield_{cv} = \beta_0 + \beta_1 covercrop + \beta_2 N\ app_{av} + \beta_3 P\ app_{av} + \beta_4 K\ app_{av} + \beta_5 treatment + \beta_6 slope + \beta_7 notill + \beta_8 drain + \beta_9 moll + \beta_{10} mix + \beta_{11} ne + U$$

4.4 Stochastic farm budget analysis

The use of cover crops can have many agronomic benefits. However, these benefits may not all have a short-term, direct economic impact on the farm business. Excluding cost share programs, there are only a few ways that cover crops could directly provide economic benefit in the short run. These are (1) increased revenue through yield benefit, (2) increased revenue from harvesting and marketing or using the cover crop, (3) reduced input costs, and (4) reduced risk. In this study, we will not include any revenue from harvesting the cover crop.

The most relevant information for the decision maker is the direct benefits and costs. If the benefits to the farm business of using cover crops are greater than the costs, then adoption by farmers is an economically attractive choice. The measure of financial return used in this analysis was contribution margin (contribution margin = revenue – variable costs) per acre. Because we treat labor as fixed, contribution margin is the return to land and labor. Using contribution margin implicitly assumes that growing cover crops does not change labor or other fixed costs. Admittedly, it is possible that cover crops could add to equipment costs if the farm was required to purchase additional equipment, such as a specialized planter. However, most farmers already own the necessary equipment. By not including labor in variable costs, the assumption is that the number of workers is fixed for the farm size and that the addition of cover crops will not require supplementary laborers. This would also require that the workers are salaried, not hourly, workers. This assumption would likely be realistic for family labor but not necessarily for hired labor.

The farm budget model is calculated on a per acre basis. The revenue component was calculated by multiplying the estimated price and yield. The variable costs were then subtracted to obtain the contribution margin. These cost categories and cost estimates were obtained from Purdue Extension for 2018 (Langemeier, 2018). The cost categories were fertilizers, seed, pesticides, dryer fuel, machinery fuel, machinery repairs, hauling, interest, and insurance/miscellaneous. Additional cost categories were added for cover crops, including cover crop seed, cover crop termination, and variable costs for planting the cover crop. The bottom line on the budget was the contribution margin.

The corn budget compared three scenarios, the first was a baseline without cover crops, the second included cover crops but no cost adjustment for nitrogen, and the third was cover crops with a nitrogen credit. The nitrogen credit was the difference in nitrogen application in the 20% trimmed sample between fields with and without cover crops. The soybean budget contains two scenarios, the first without cover crops and the second with cover crops. Additionally, the outputs of corn and soybeans were combined to show the average financial impact for a field in a two-year corn-soybean rotation. The corn-soybean rotation contribution margins had three scenarios: baseline without cover crops, cover crops with no nitrogen adjustment in corn, and cover crops with a nitrogen adjustment in corn.

We simulated a farm budget based on the typical farm in the 20% trimmed sample. The budgets had stochastic inputs and output distributions and were modeled using Monte Carlo simulation with 5,000 iterations. The output distributions were analyzed with the intent of ranking the economic desirability of each. First, we compared the mean, standard deviation, minimum, maximum, 90% lower bound, and the probability of the contribution margin being negative. Then, we tested for first- and second-degree stochastic dominance to determine the best choice based on economic utility theory. Lastly, we calculated and plotted the certainty equivalent across the relative risk aversion coefficient. These analyses allowed us to draw conclusions concerning the relative economic desirability of each production system.

4.4.1 Budget input data

The yield inputs into the farm budget were modeled as stochastic distributions. Each yield distribution was assumed to be normal. The actual yield distributions in the data were close to normally distributed, although each had a slight left skew. The distributions were truncated at ± 3 standard deviations from their respective means. The distribution parameters came from the previous analyses of yield means and standard deviations using the regressions from the 20% trimmed sample. The yield distributions with and without cover crops were found to be correlated; the correlation was estimated by year from the data. @Risk allowed the correlations to be easily modeled by creating a correlation matrix with these numbers. The full correlation matrix used is included in the appendix.

All historical prices in this analysis were converted to real prices using the corn producer price index (PPI), soybean PPI, or an average of the two as appropriate (BLS, 2019a, 2019b). Corn and soybean crop prices were adjusted to their respective PPIs, while fertilizer prices were adjusted by the average of both. The original PPI data used a base year of 1982. The base year was changed to 2018 to match the other price and yield estimates.

The model included one price distribution for corn and one for soybeans. This was done so that only one draw was taken for each price in each iteration of the simulation. The prices distributions were fitted to historical data (NASS, 2019a, 2019b). The resulting best fits were Laplace distributions for both corn and soybean prices. The expected corn price was $3.55 per bushel and the expected soybean price was $8.88 per bushel.

Corn specific budget inputs included the fertilizer application rates in table 4.4. The first two nitrogen rates were the mean for fields without a cover crop while the last was the mean for fields with a cover crop, in the 20% trimmed sample. This reflected what farmers actually did when adapting their system to cover crops. This nitrogen credit does not necessarily reflect the economically optimal reduction in nitrogen for corn after a cover crop. However, it does represent what farmers believe is the optimal reduction. As noted previously, these farmers typically had several years of cover crop experience and were likely making a well-informed decision. The other fertilizer applications were based on the overall mean for the 20% trimmed sample. In the data, all nitrogen applications were reduced in fields with cover crops. This was true for both the full sample as well as the 20% trimmed sample. In this analysis, only nitrogen was reduced in the third scenario. This was done because there is a significant precedent in the literature for cover crops replacing nitrogen. The literature is not as definitive on the reduction of other fertilizers. However, future research could include this as a benefit as well.

Table 4.4 Fertilizer application in corn (lbs/acre of nutrient)

Nutrient	Baseline	Cover crop	Cover crop + N credit
Nitrogen	199.29	199.29	168.73
Phosphorus	65.03	65.03	65.03
Potassium	78.91	78.91	78.91

Fertilizer application in soybeans was modeled at the average application rates for all soybean fields in the 20% trimmed sample. These application rates are shown in table 4.5.

Table 4.5. Fertilizer application in soybeans (lbs/acre of nutrient)

	Baseline soybeans	Soybeans with a cover crop
Nitrogen	7.42	7.42
Phosphorus	17.47	17.47
Potassium	38.11	38.11

Fertilizer price distributions were fitted to 20 years of historic data converted to real prices (ERS, 2018). The adjustment from real to nominal was made using the average producer price index for corn and soybean farmers. Fertilizer cost was calculated by multiplying the price distribution by the fertilizer application rates. The cost of nitrogen application was calculated from the price of anhydrous ammonia. The expected price of anhydrous ammonia given the fitted distribution was $502.54 per ton based on historical real prices. This led to a cost of $0.31 per pound of nitrogen nutrient applied. The expected values for other fertilizer prices were also estimated by fitting distributions to historical prices adjusted for inflation. The cost of phosphorus application was calculated from the price of diammonium phosphate. The expected price of diammonium phosphate given the fitted distribution was $423.36 per ton based on historical real prices. This led to a cost of $0.47 per pound of phosphorus nutrient applied. The cost of potassium application was calculated from the price of potassium chloride. The expected price of potassium chloride given the fitted distribution was $340.86 per ton based on historical real prices. This led to a cost of $0.28 per pound of potassium nutrient applied.

Most of the variable production cost data for this budget model were Purdue Extension estimates (Langemeier, 2018). These included all of the costs in the baseline scenario. Cover crop seed costs of $17.79 per acre were taken as an average from the farmer data, from farmers who included seed costs separately in the survey. The variable costs of $1.30 per acre for planting was a University of Illinois estimate (Schnitkey & Lattz, 2017). The variable costs for planting only included fuel and lubricants for machinery. The total per acre variable establishment costs were estimated to be $19.09. These costs were deterministic inputs into the budget. Cover crop chemical termination is usually done in conjunction with the standard spring burn down. If this holds true, there should be no additional cost for herbicide when cover crops are grown. However, our farmers occasionally found that the cover crops required an additional herbicide application to be completely eradicated. To model this we used a binomial distribution with an outcome of zero or one to turn on or off this additional cost for each iteration of the simulation; the probability is based on the farmer data. Additional costs only applied in approximately 24.3% of the draws, reflecting frequency of the use of a second pass of herbicide for cover crop termination. The average cost of $15.43 per acre for an additional herbicide application was an average from the farmer data. The expected cost of termination is $3.76 per acre. The variable costs of production are shown in table 4.6 for corn and 4.7 for soybeans.

Table 4.6 Estimated variable cost of production for corn

		Baseline budget	Cover crops
Fertilizers	$ 114.83	$ 114.83	$ 105.35
Seed	$ 111.00	$ 111.00	$ 111.00
Cover Crop Seed	$ -	$ 17.79	$ 17.79
Pesticides	$ 61.00	$ 61.00	$ 61.00
Cover crop termination	$ -	$ 3.76	$ 3.76
Dryer fuel	$ 35.00	$ 35.00	$ 35.00
Machinery fuel (7.32 gal)	$ 18.00	$ 18.00	$ 18.00
Machinery repairs	$ 22.00	$ 22.00	$ 22.00
Cover Crop Drilling	$ -	$ 1.30	$ 1.30
Hauling	$ 17.00	$ 17.00	$ 17.00
Interest	$ 12.00	$ 12.00	$ 12.00
Insurance/misc.	$ 38.00	$ 38.00	$ 38.00
Total Variable Costs	**$ 428.83**	**$ 451.67**	**$ 442.19**

Table 4.7 Estimated variable cost of production for soybeans

	Baseline budget	Cover crops
Fertilizers	$ 21.35	$ 21.35
Seed	$ 67.00	$ 67.00
Cover Crop Seed	$ -	$ 17.79
Pesticides	$ 65.00	$ 65.00
Cover crop termination	$ -	$ 3.76
Machinery fuel (7.32 gal)	$ 11.00	$ 11.00
Machinery repairs	$ 18.00	$ 18.00
Cover Crop Drilling	$ -	$ 1.30
Hauling	$ 5.00	$ 5.00
Interest	$ 8.00	$ 8.00
Insurance/misc.	$ 34.00	$ 34.00
Total Variable Costs	**$ 229.35**	**$ 252.19**

4.4.2 Output distributions

There is an output distribution for the contribution margin in each cover crop scenario for both corn and soybeans. There are also output distributions for the average contribution margin for corn and soybeans in each cover crop scenario. The average contribution margins were used to show the average effect over two years. The reason the average was chosen was to model the per-acre situation for farmers with half their land in corn and half in soybeans.

Output distributions are represented by a probability density histogram and a cumulative probability distribution. Statistics describing the distribution such as the mean, standard deviation, minimum, and maximum were calculated. The estimated probability of a negative contribution margin for each scenario was also estimated.

4.4.3 Mean, standard deviation, and probability of loss

The first and most basic analysis that will be done is the comparison of the means for the output distributions of contribution margin from the simulated budget. This is the basic measure of economic attractiveness for cover crops. Additionally, the standard deviations of the distributions were compared. This provided a basic risk assessment for each option. The options were ranked based on the assumption that the farmer should choose the alternative which maximizes returns while minimizing risk (Markowitz, 1952), (Barry & Ellinger, 2012). This is true as long as the farmer is at least slightly risk-averse, which seems a very reasonable assumption in practice.

The probability of loss was also used for the basic risk analysis. This follows the theory of “safety first”; which says that agents are concerned with minimizing the probability of loss to an acceptable level before maximizing returns (Roy, 1952). In classical economic theory, a contribution margin of zero—the point where a firm cannot cover variable costs—is considered the “shutdown point” (Gunther, 1977). However, the decision-making process of farm management is dynamic, and the variable costs of production do not occur simultaneously. Thus, the variable costs that have already occurred should be treated as sunk costs and should not enter into the decision-making process. For example, if a farmer were about to harvest his crop and conditions were such that the contribution margin would be negative, so long as the revenue would be greater than the cost to harvest, harvesting is still the best choice. Even in situations where the cost of harvesting is greater than the expected revenue at the current price, if the commodity is storable, a farmer may still choose to harvest and market the crop at a later time. Consequently, a negative contribution margin in a single year would not likely cause a farm to cease operations.

4.4.4. First order stochastic dominance

In order to determine if any cover crop option always has a higher probability of higher returns, we tested for first order stochastic dominance as defined by Quirk and Saposnik (1962) and amended by Hadar and Russell (1969) as well as Hanoch and Levy (1969). In practical terms, first order stochastic dominance means that the dominating option is more likely to provide higher payoffs at every payoff level (Hadar & Russell, 1969). This method is useful for partial ordering of competing alternatives. First order stochastic dominance is a very strong condition with very limited assumptions regarding the utility function of the agent. The only assumption that is necessary for first order stochastic dominance is that the agent possesses monotonic preferences (Hadar & Russell, 1969). In other words, the agent prefers more to less.

To express the notion of stochastic dominance we begin by defining X to be the set of possible outcomes. Given two choices that are random variables, option A and option B, A is said to dominate B if and only if the conditions in equation 4.12 hold:

Equation 4.12 Definition of first order stochastic dominance

$$\forall\, x \epsilon X, P(A \geq x) \geq P(B \geq x)\ and\ \exists\ x_0 \epsilon X, such\ that{:}\ P(A \geq x) > P(B \geq x)$$

However, since $CDF_A(x) = P(A \leq x)$ and $CDF_B(x) = P(B \leq x)$, then it follows that $1 - CDF_A(x) = P(A \geq x)$ as well as $1 - CDF_B(x) = P(B \geq x)$. By substituting these equations into the above criterion and performing simple algebraic manipulation we can restate the above conditions in terms of $CDF_A(x)$ and $CDF_B(x)$. Therefore, we can say that A dominates B if and only if the conditions in equation 4.13 hold:

Equation 4.13 Definition of first order stochastic dominance using CDFs

$$\forall\ x \epsilon X, CDF_A(x) \leq CDF_B(x)\ and\ \exists\ x_0 \epsilon X, such\ that: CDF_A < CDF_B$$

The simulation outputs from @Risk were used to generate cumulative density data. This was done by ordering the outputs from smallest to largest and creating a new variable for the cumulative probability by dividing the row number by 5000. This new variable was the y value and the sorted outputs were the corresponding to the x values in each row which defined the CDFs for each distribution. The structure of the data had matching y values across distributions, but the x values were all unique for each distribution. Because of this structure, the definition in equation 4.12 is not straightforward to evaluate at all values of x. Instead of comparing the CDFs at all values of x, the equivalent definition in equation 4.14 was evaluated at all values of y.

Equation 4.14 Definition of first order stochastic dominance using inverse CDFs

$$\forall\ y \epsilon [0,1], CDF_A^{-1}(y) \geq CDF_B^{-1}(y) and\ \exists\ y_0 \epsilon [0,1], such\ that: CDF_A^{-1}(y) > CDF_B^{-1}(y)$$

This transformation can be made because the CDFs are monotonically increasing, bounded on y, and continuous. The difference in the x values $(x_{i,A} - x_{i,B})$ at every y value were calculated. First order stochastic dominance (A dominates B) was determined if and only if, the minimum value of the differences was greater than, or equal to 0; and at least one of the differences was strictly positive.

4.4.5 Second order stochastic dominance

In order to test determine which option was preferred under the assumption of risk aversion, we checked for second order stochastic dominance between each pair of output distributions (Saha, Shumway, & Talpaz, 1994). First order stochastic dominance implies second order stochastic dominance, yet it is not a necessary condition (Hadar & Russell, 1969). Second order stochastic dominance means that the dominant alternative is preferred by all agents with concave and monotone utility functions (Hadar & Russell, 1969). In other words, individuals who prefer more to less and are risk-averse. Second order stochastic dominance indicates desirability independent of the agent's level of risk aversion. In cases where first order stochastic dominance fails, impacts on risk may be observable through second order stochastic dominance.

Following Hanoch and Levy (1969), defining X as the set of all possible outcomes, option A is second-order stochastically dominant over B if and only if the conditions in equation 4.15 hold:

Equation 4.15 Definition of second order stochastic dominance

$$\forall\ x \epsilon X, \int_{-\infty}^{x} [CDF_B - CDF_A] dx \geq 0 \ and \ \exists\ x_0 \epsilon X, \int_{-\infty}^{x} [CDF_B - CDF_A] dx > 0$$

Because of the structure of the data defining the CDFs, estimating the integral used in the definition of second order stochastic dominance over x values was not straightforward. Instead of estimating the integral in equation 4.15 over x, an equivalent integral was estimated over y. The equivalent condition when integrating with respect to y for second order stochastic dominance is shown in equation 4.16:

Equation 4.16 Alternative definition of second order stochastic dominance

$$\forall\ y \epsilon [0,1], \int_{0}^{y} [CDF_A - CDF_B] dy \geq 0 \ and \ \exists\ y_0 \epsilon [0,1], \int_{0}^{y} [CDF_A - CDF_B] dy > 0$$

This transformation can be made because the CDFs are monotonically increasing, bounded on y, and continuous. Using the data for the (x, y) pairs which define the CDFs for the output distributions, the integral specified above was estimated by the formula in equation 4.17.

Equation 4.17 Calculation for determining second order stochastic dominance

$$\sum_{i=1}^{n} \frac{\left(x_{i-1,A} - x_{i-1,B}\right) + \left(x_{i,A} - x_{i,B}\right)}{2} * (y_i - y_{i-1})$$

This sum was calculated on a running basis for every *i* from 1 to 5000. The conditions for second order stochastic dominance (A dominating B) require the minimum of these sums greater than, or equal to 0, and at least one of the sums to be strictly greater than 0. This was the test used in this analysis for second order stochastic dominance.

4.4.6 Certainty equivalent

Under the assumption of risk aversion by the farmer, we further evaluated the options at different levels of relative risk aversion (Saha et al., 1994). The objective of this analysis was to determine if the relative attractiveness of the competing alternatives changed at varying levels of risk aversion. If any of the alternatives were first or second order stochastically dominant in the previous analyses, the order of preference should not change in this analysis either. However, if there was no evidence of first- or second-degree stochastic dominance, then the order of preference may change with changes in risk aversion levels.

This analysis was done using the SERF (Stochastic efficiency with respect to a function) method developed by Hardaker et al. (2004). This method consists of using an assumed utility function to calculate the certainty equivalence at various levels of the relative risk aversion coefficient. The certainty equivalent is then graphed over the domain of the risk aversion coefficient.

The utility function that was chosen was the isoelastic utility function also known as the power utility function. This utility function exhibits constant relative risk aversion, implying that decision making is not affected by scale (Wakker, 2008). This was very important for this particular analysis because an initial level of wealth was included to keep the input to the function from being negative. Working capital per acre was used as the initial wealth in the utility functions (Zwilling, 2018). Working capital seemed appropriate to include because it is a short-term measure and more liquid than land values. For these reasons, a negative contribution margin would cut into working capital before it affected equity in the farm land. The measure of initial wealth could be left out in theory, but it serves the purpose of keeping the inputs of the utility function positive. This is important for some of the iterations in the simulation that had a negative contribution margin. Equation 4.18 shows the general form of the isoelastic utility function, where w_0 is the initial level of wealth, x is the return to labor and capital, and r is the relative risk aversion coefficient.

Equation 4.18 Definition of isoelastic utility function

$$u(x) = \begin{cases} \dfrac{(w_0 + x)^{1-r} - 1}{1 - r} & r \neq 1 \\ \ln(w_0 + x) & r = 1 \end{cases}$$

This function was used to calculate utility for each iteration of the stochastic simulation. The expected utility and expected value were used to calculate the certainty equivalent, which was computed for levels of r from 1 to 5. This output was graphed with the relative risk aversion coefficient (r) on the horizontal axis and the dollar amount of certainty equivalence on the vertical axis. At a given level of relative risk aversion, the production practice with the highest certainty equivalence would be the preferred alternative. The domain selected for r was the closed interval [1,5]. When r=1, the agent would be only slightly risk-averse. When r=5 the agent would be strongly risk-averse (Friend & Blume, 1975; Meyer & Meyer, 2005).

4.5 Conclusion

The analysis in this study begins with the effect of cover crops on average yield and yield variability. These impacts were then quantified into financial impacts on contribution margin. The effect of cover crops on risk was then determined. Scenarios were ordered by economic attractiveness under different sets of assumptions about the decision maker's approach to risk. A variety of methods were used in this study to help capture the often-nuanced economic conditions surrounding cover crops.

CHAPTER 5 RESULTS AND DISCUSSION

5.1 Introduction

The majority of studies on the effect of cover crops on yield are done on test plots at universities and research stations. These analyses are valuable but may not be able to tell the whole story from an actual on-farm perspective. There are two main issues that may create a divide between results from test plots and observed on-farm outcomes. The first is that cover crops may have a very different effect based on the particular farming system into which they are introduced. In a university research setting the farming systems may not be adapted for the use of cover crops. Thus, there may be systems-based interaction effects that are not accounted for in this research. The farmers who use cover crops in our sample have nearly 10 years of experience growing cover crops. It seems likely that these farmers have made adjustments over time to adapt their system. Some of these adjustments are observed in our data. For example, cover crop farmers apply nitrogen fertilizer at a rate of 36 pounds per acre less than farmers who do not use cover crops. Cover crops are also frequently paired with no-till in our sample. There are likely many other additional adjustments that are not evident in the data that may help cover crops be more effective than they might be in a strip trial.

The second important difference between this observational research and much of the current research on cover crops is number of years cover crops have been used on the field or plot prior to the yield measurements. Many studies add cover crops and begin to estimate the yield effects the first year. This is likely too soon for the cover crops to have had a substantial impact on soil health. In the data for this research, the cover crop fields have been cultivated using this practice for an average of more than four continuous years. Even this average understates the true picture, because in the event a field missed even one year of cover cropping the count was reset. Additionally, many of the farmers had been using cover crops for years prior to the start of the study period. As a result, this research specifically addresses the impact of cover crops on fields that have been cover cropped for a number of years continuously.

These two differences combine to show that this research addresses a slightly different question using observational data than controlled plot-level studies seek to answer. The research results for this study are conditioned on the circumstances of the data. The cover crop observations came from farmers who were experienced in cover cropping and had likely adapted many details of their farming system. These data were also from fields that had likely had enough years of continuous cover cropping to improve some aspects of soil health. Consequently, these results are for mature systems in terms of cover crop adoption and adaption.

The results of the analyses described in chapter 4 are presented in this chapter in nearly the same order as the previous chapter. The regression results are discussed in terms of the estimated effects since the non-linear form for many of them makes interpretation of the coefficients somewhat difficult. In many cases, graphs are also included to ease interpretation and provide a more complete analysis of the data. For reference, the full tables of regression coefficients, R squared values, and observation counts are provided in appendix C.

Each section describes the results of an analysis that was performed using the data from this project. Subsections detail the results from different iterations of each analysis or the results of a subordinate analysis. Section 5.2 covers the propensity score that was estimated to trim the sample. Section 5.3 is concerned with the results of the analysis of average yields. Section 5.4 discusses the effect of cover crops on yield variation. Section 5.5 describes the results from the stochastic farm budget model. These results are analyzed extensively to assess the economic desirability of the competing alternatives based on different criteria.

5.2 Results from the analysis of the impact of cover crops on average yields

The analysis of average yields was accomplished by running the yield regression models on the appropriate data. Then, the interpretation and analysis of these results were validated using visualizations and hypothesis tests. The results from each of these steps are discussed in this section beginning with corn yields and then moving to soybean yields. The derivatives of interest are presented for each model. However, interpretation is not straightforward due to several interaction and non-linear terms. For this reason, the derivatives are plotted over nitrogen while holding other variables constant at their means in the trimmed sample.

5.2.1 Corn yield response to cover crops

The models used to estimate the impact of cover crops on mean corn yield were designed with the nitrogen cycle in mind. Specifically, the ability of cover crops to scavenge residual nitrogen and the ability of legume cover crops to fix nitrogen. Consequently, all of the corn results presented here are yield responses with nitrogen application on the horizontal axis. The nitrogen levels range from 50 to 250 pounds per acre. While nitrogen is sometimes applied at greater rates, this is the approximate range where cover crop farmers applied nitrogen. Tables with the full regression results are provided in appendix C for reference.

The derivative of the corn yield model with respect to cover crops is the impact of cover crops on yield, including the interaction effects. This derivative, with the estimated coefficients inserted, is displayed in equation 5.1. While equation 5.1 is difficult to directly interpret, it shows the relative size of each interaction effect. It helps put into perspective the pathways which cover crops impact yield, their direction of impact, and their relative importance.

The derivative, or marginal effect of cover crops, is graphed in figure 5.1. All of the variables except nitrogen application were held at their respective means from the trimmed sample. Nitrogen application is on the horizontal axis. Also included in the graph are 90% confidence bars to show the estimated margin of error. Where these confidence intervals do not include zero, the effect is statistically significant at the 90% level. The marginal effect decreases as nitrogen application increases. It is statistically significant (p<0.1) from about 60 lbs/acre to 170 lbs/acre of nitrogen application. The lowest p-value of 0.048 occurred at 140 and 145 lbs/acre of nitrogen with marginal effects of 16.92 and 16.18 lbs/acre, respectively. The marginal effect of cover crops on yield is 27.99 bu/acre at 60 lbs/acre of nitrogen and decreases linearly to 12.49 bu/acre at 170 lbs/acre of nitrogen. The rate of decline in the marginal effect is 0.141 bu/acre for every additional lb/acre of nitrogen applied.

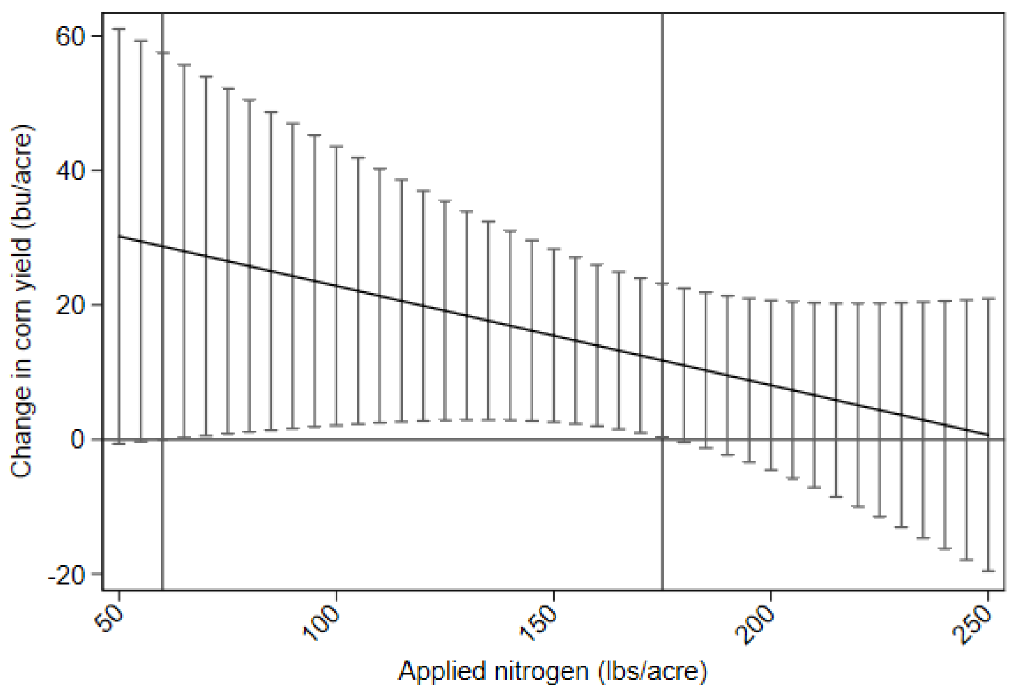

Figure 5.1 Marginal effect of cover crops on corn yield in 20% trimmed sample

The yield response curves for nitrogen with and without cover crops are shown in figure 5.2. Dashed vertical lines are included to show the range of nitrogen applications for which the difference is statistically significant. The curve showing the predicted yields for cover crops is higher than the curve showing the predicted yields for fields without cover crops. All other variables in the model were held constant, so the difference between the curves is the estimated effect of cover crops on corn yield.

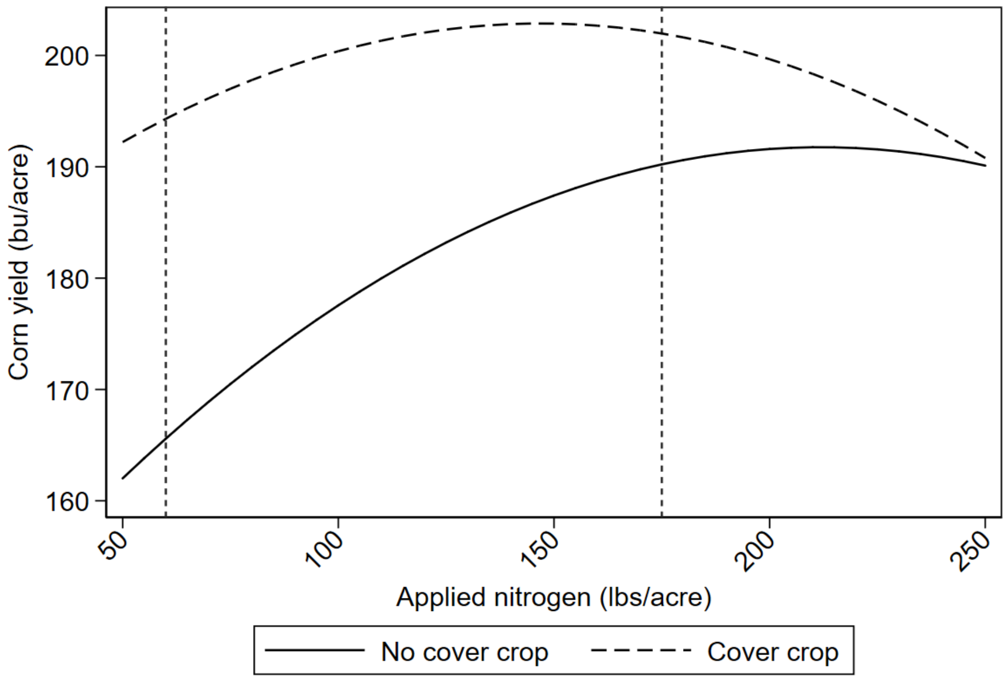

Figure 5.2 Predicted corn yield with and without cover crops

Both figures 5.1 and 5.2 demonstrate a strong relationship between the rate of nitrogen application and the results of cover cropping. One explanation for this might be that the benefit of cover cropping in corn likely comes from scavenging or fixing nitrogen in the soil, which would allow the corn to produce at the same level with lower nitrogen input. If this was the case, and there were no other benefits to cover crops, we would expect the curve for cover cropped fields in figure 5.2 shift to the left compared to the curve for yield without cover crops. The curve for fields with cover crops does appear to have a leftward shift. The peak yield of 191.76 bu/acre occurs at approximately 210 lbs/acre of nitrogen application for corn without cover crops. The peak yield of 202.87 bu/acre occurred at approximately 145 lbs/acre of nitrogen application for corn with cover crops. Notably, the peak corn yield for fields with cover crops is also higher than the peak yield for fields without cover crops. This would indicate that the effect of cover crops on yield must not be limited simply to nitrogen replacement. This additional yield impact may be the result of the long-term impact of cover crops on soil health. The fields with cover crops in this study, as previously noted, had typically been cover cropped for several years. Many of the fields had been cover cropped prior to the start of the study and continued throughout the study period. This condition makes these results specifically valid for long-term cover cropped fields. The ability of cover crops to impact soil health is known to be a relatively slow process. One key improvement in soil health that cover crops can help with is increasing soil organic matter. Increasing soil organic matter with cover crops may take years of continuous cover cropping but can increase the nutrient holding capacity of the soil. Consequently, the additional yield noted for corn in this study, beyond nitrogen replacement, is likely a long-term benefit of cover crops. The financial implications discussed in later sections are also applicable to mature cover cropping systems.

These results are unique among studies focused on the yield impact of cover crops because the many different levels of nitrogen application by farmers provided many observations at different nitrogen applications. Some past studies have shown the yield response at different nitrogen levels, but the intervals are large. This data had the advantage of a more continuous range of nitrogen applications. However, some other studies have shown similar nitrogen replacement advantages at different levels of fertilization (Andraski & Bundy, 2005; Ott & Hargrove, 1989).

The results were partially driven by the fact that crimson clover (the only legume widely used in this data) was included in about 21% of the cover crop mixes in corn in the 20% matched sample. When cover crop observations with crimson clover were removed the difference in the curves was no longer statistically significant. However, the curve for fields with a cover crop was still above the yield curve for non-cover cropped fields. The lack of statistical significance without crimson clover is probably due to the nitrogen replacement capacity of crimson clover. It may also be partly due to the much smaller sample size from dropping so many observations.

5.2.2 Soybean mean yield response to cover crops

The model used to determine the impact of cover crops on soybeans was slightly different than that used for corn. The difference was the absence of a quadratic term for nitrogen application and the interaction of nitrogen with cover crops. Soybeans do not have the same yield response to applied nitrogen because they are a legume and fix nitrogen for their own needs. For this reason, nitrogen application does not play nearly as important a role in the analysis of soybean yields. The charts showing the results of the model for soybeans were created holding all other variables constant, including nitrogen.

Figure 5.3 shows the predicted yields holding all of the variables at their respective means in the 20% trimmed sample. The difference in the yield levels is the estimated effect of cover crops. The difference shows that cover crops reduced soybean yields by 1.9 bu/acre, but the effect is not statistically significant ($p=0.521$).

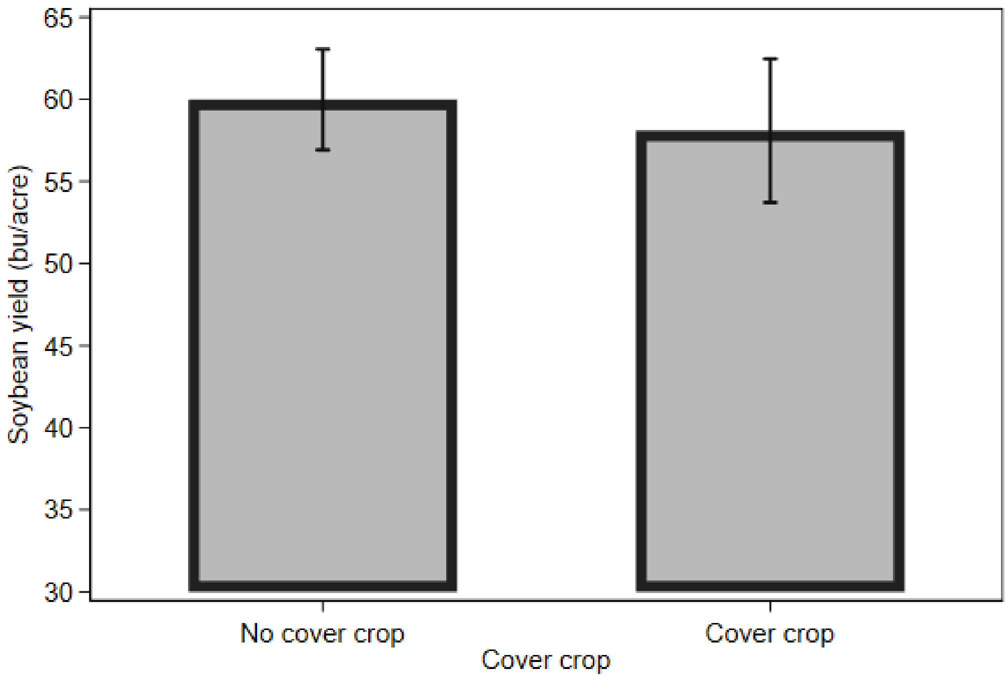

Figure 5.3 Predicted soybean yield with and without cover crops

The lack of an effect on soybean yields is different from the effect on corn yields. This was not totally unexpected, because the effect on corn was probably largely due to nitrogen-fixing and scavenging. Since additional nitrogen would not increase soybean yields, cover crops would not be expected to have as much of an impact. However, as noted earlier, with corn there seemed to be more than just the nitrogen effect present. The lack of this effect may be due to poor establishment of the cover crops the previous fall. Most of the data in this study were from a corn-soybean rotation; so, corn would have been the cash crop in the year before soybeans were grown. Corn is harvested much later than soybeans and gives cover crops much less time for fall establishment. This is particularly true in northern Indiana, where the first frost comes soon after corn harvest. Many farmers in the northern part of the state seed cover crops aerially before the corn is harvested to allow additional time for fall establishment. However, aerial seeding often does not provide good quality establishment in less than ideal conditions (Carlson, 2012). In summary, poor fall establishment in the cover crop prior to soybeans likely drives the insignificant result shown here. In Indiana—particularly the northern part of the state—cover crops after corn and before soybeans may not provide economic benefit through yield improvements.

If cover crops after corn and before soybeans struggle with fall establishment, what would happen if they were given extra time in the spring to grow? In our data, we did not have planting times, but a reasonable proxy for planting times could be represented by the presence of a tile drainage system. This may seem a strange proxy at first thought. However, fields with a tile drainage system are likely to be planted earlier on average than fields without drainage (Shekoofa, 2018). Farmers in Indiana often struggle with wet field conditions delaying planting. If fields were systematically planted later, perhaps cover crops would have time to grow in the spring and yield higher biomass for contributions to the soil. They may also scavenge nutrients that would have otherwise been lost in spring runoff. To confirm this hypothesis the analysis was run on only fields without tile drainage. These results are shown in figure 5.4 when the binary indicator for tile drainage is held at 0 for both groups. In this case, cover crop soybeans are predicted to outperform the baseline soybeans by 6.81 bu/acre ($p=0.006$). This result may indicate that the lack of statistical significance for soybeans overall is driven by poor cover crop establishment in the fall. An alternative explanation for this result could be that cover crops help manage spring moisture by improving water penetration and using up excess moisture.

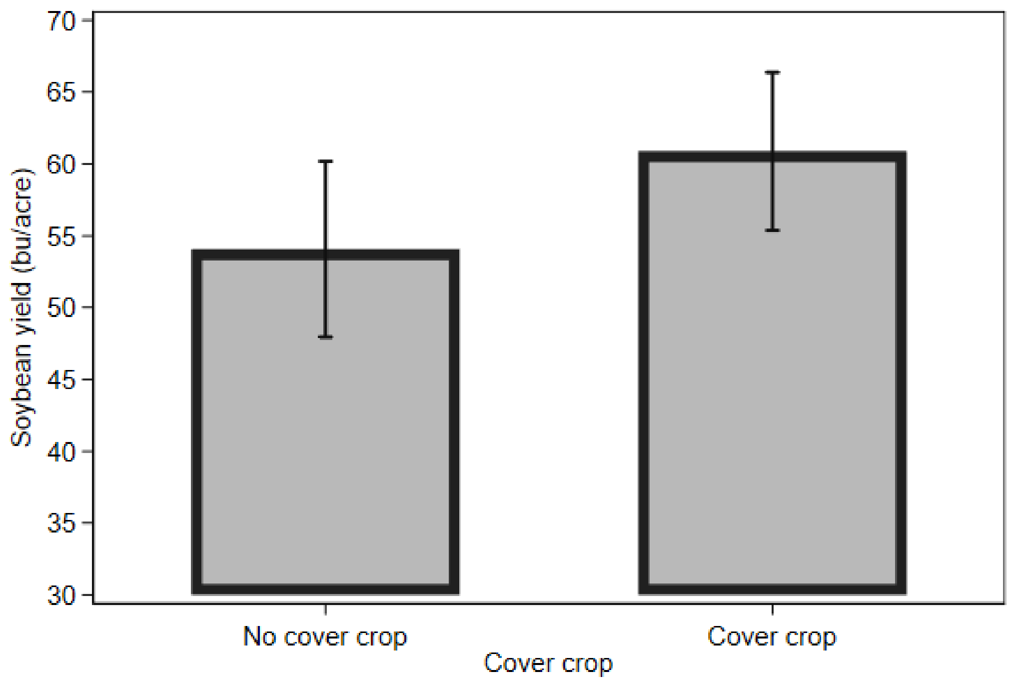

Figure 5.4 Predicted soybean yield by cover crop for fields without tile drainage

5.3 Effect of cover crops on cash crop yield variability

This section discusses the estimated effect of cover crops on temporal yield variability at the field level. Two measures of temporal yield variability were used in the analysis, these were standard deviation and coefficient of variation. The effect of cover crops in terms of standard deviation is the effect on the absolute variability. This is the effect that is used in the analysis of the farm budget. On the other hand, coefficient of variation is a measure of variability relative to the temporal mean yield at the field level.

Yield variability is interesting because it is a source of risk for farmers. Farmers are exposed to production risk because of uncertain future growing conditions. However, practices that could help crops to be more resilient and consistent reduce such risk. If cover crops could reduce risk, that would be an additional economic benefit. This benefit is tested in this section and later incorporated into the analysis of the farm budget.

5.3 Effect of cover crops on corn yield variability

The results of analysis of the effect of cover crops on the variability in corn yield are shown in table 5.1. The effect is negative and statistically significant. The marginal effect of cover crops was a reduction of 21.01 bu/acre in standard deviation (p=0.004). For coefficient of variation, cover crops showed a reduction of 15.42 percentage points (p=0.01).

Table 5.1 Marginal effect of cover crops on corn yield variability

	Standard deviation	Coefficient of variation
Cover crop	-21.01***	-15.42**
	(6.883)	(5.801)
Observations	69	69

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

These results are similar to those found in previous studies (Anderson et al., forthcoming). Cover crops not only help reduce excess moisture, but they also help soil retain adequate soil moisture as well by adding organic matter (Daigh et al., 2014). Additionally, cover crops help moderate soil temperature (Blanco-Canqui et al., 2015). Soil moisture and temperature, particularly during flowering, have been shown to account for a large portion of yield variation (Hammac, Maaz, Koenig, Burke, & Pan, 2017). There are perhaps other ways in which cover crops could reduce variability. However, more research is needed in this area.

These results show that cover crops reduced corn yield variance in fields with long-term cover cropping systems. Reduced risk will be quantified later in the farm budget. However, the reduction in corn yield variability shown here may also be informative for crop insurance analysis. Additionally, lower crop insurance premiums could act as an incentive for cover cropping.

5.3.2 Effect of cover crops on soybean yield variability

The effect of cover crops on soybean yield variability was very small and statistically insignificant. These results are shown in table 5.2. Column 1 is the effect on the temporal standard deviation, while column 2 is the effect on the temporal coefficient of variation. These results are different than the results from the analysis of corn yields. The reason for the difference is uncertain. However, it is similar to results from previous research. Anderson et al. (forthcoming) also failed to find a significant effect of soil conservation practices including cover cropping on soybean yield variation.

Table 5.2 Marginal effects of cover crops on soybean yield variability

	Standard deviation	Coefficient of variation
Cover crop	1.306 (1.402)	2.426 (2.622)
Observations	68	68

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

5.4 Results of stochastic farm budget models

The farm budget model was intended to quantify the direct financial impact of cover crops as well as ranking alternatives by economic desirability. This analysis considers both the expected economic effect as well as the impact on risk. The static farm budgets are presented in terms of expected value for each stochastic input and output distribution. Details about the estimated distribution are presented through visualizations as well as summarized by statistics.

The effect of cover crops on the expected outcome and the outcome distributions and practical drivers and implications are discussed.

5.4.1 Corn enterprise budget

The predicted means and standard deviations for each scenario are presented in table 5.3. These are predicted from the mean yield and yield variance regression models based on the nitrogen application and the presence of cover crops. Other variables were held at their means from the data. The year 2018 was used as the period for all of the yield and variability predictions. The predicted mean corn yields were 191.58 bu/acre for the baseline, 199.75 bu/acre for cover crops without a nitrogen adjustment, and 202.33 bu/acre for cover crops with a nitrogen adjustment.

Table 5.3 Corn yield distribution parameters

	Baseline budget	Cover crop	Cover crop + N credit
Predicted mean yield	191.58	199.75	202.33
Predicted standard deviation	42.96	36.02	24.48

The parameters in table 5.11 define the yield distributions in the first row of the enterprise budget, which is shown in table 5.4. Because the price of corn is the same for all corn scenarios within each iteration of the simulation, differences in revenue are exclusively based on yield levels. Revenue per acre was $680.93 for the baseline, $709.96 for cover crops without a nitrogen adjustment, and $719.13 for cover crops with a nitrogen adjustment. The total variable costs were $428.83 for the baseline, $451.76 for cover crops, and $442.19 for cover crops with a nitrogen adjustment. The bottom line of the budget was the contribution margin, representing the returns to capital and labor. The expected value of the contribution margin was $252.10 for the baseline, $258.29 for cover crops, and $276.94 for cover crops with a nitrogen adjustment.

Table 5.4 Corn enterprise budget

Corn Budget	Baseline budget	Cover crop	Cover crop + N credit
Yield Per Acre	191.58	199.75	202.33
Price Per Bushel	$ 3.55	$ 3.55	$ 3.55
Gross Revenue	**$ 680.93**	**$ 709.96**	**$ 719.13**
Fertilizers	$ 114.83	$ 114.83	$ 105.35
Seed	$ 111.00	$ 111.00	$ 111.00
Cover Crop Seed	$ -	$ 17.79	$ 17.79
Pesticides	$ 61.00	$ 61.00	$ 61.00
Cover crop termination		$ 3.76	$ 3.76
Dryer fuel	$ 35.00	$ 35.00	$ 35.00
Machinery fuel (7.32 gal)	$ 18.00	$ 18.00	$ 18.00
Machinery repairs	$ 22.00	$ 22.00	$ 22.00
Cover Crop Drilling	$ -	$ 1.30	$ 1.30
Hauling	$ 17.00	$ 17.00	$ 17.00
Interest	$ 12.00	$ 12.00	$ 12.00
Insurance/misc.	$ 38.00	$ 38.00	$ 38.00
Total Variable Costs	**$ 428.83**	**$ 451.67**	**$ 442.19**
Corn contribution margin	**$ 252.10**	**$ 258.29**	**$ 276.94**

The results of the enterprise budget for in table 5.12 show the ability of cover crops to pay for their own costs with or without a nitrogen credit in corn. However, cover crops raised the variable cost of production in both cases over the baseline. This means that the economic attractiveness shown by the larger contribution margins is the result of the estimated increase in yields. As was noted at the beginning of this chapter, the estimated increase in yields in this analysis is likely valid for mature and adapted cover cropping systems. The increases in contribution margin showed here may not be evident in the first few years of cover cropping. As such, it may take several years of increased contribution margin to recover the additional costs of the beginning years.

5.4.2 Output distributions from corn enterprise budget

The output distributions of contribution margins from the 5000-iteration stochastic simulation are summarized in table 5.5. The means of the distributions were similar to the original expected values. Both the means for the cover crop groups are statistically different from the baseline ($p<0.01$). The standard deviation, a basic measure of risk was lower for both cover crop scenarios when compared with the baseline. The standard deviations were $154.26 for the baseline, $136.75 with cover crops, and $108.74 with cover crops and a nitrogen adjustment. The probability of loss stood at 4.41% for the baseline, 2.2% with cover crops, and 0.17% with cover crops and a nitrogen adjustment.

Table 5.5 Summary for output distributions from corn enterprise budget

Simulation results	Baseline budget		Cover crop		Cover crop + N credit	
Mean	$	249.74	$	256.47	$	275.71
Standard Deviation	$	154.26	$	136.75	$	108.74
Min	$	(169.40)	$	(146.10)	$	(64.15)
Max	$	813.44	$	796.87	$	742.14
Probability CM<0		4.405%		2.200%		0.174%

The results in table 5.5 are interesting for several reasons. First, they confirm that cover crops can increase the contribution margin even under conditions with price fluctuations and other random events. Second, these results show a reduction in risk in both scenarios where cover crops are used. The reduction in variability shown by the lower standard deviations is driven by reduced yield variability. This shows cover crops can reduce the uncertainty of the contribution margin. The lower probability of loss when cover crops are used is driven by both the increased yield and reduced variability. This shows cover crops can reduce the likelihood of severe economic adversity. Figure 5.5 displays the histograms of the simulated contribution margin distributions in corn for each of the scenarios under consideration. The differences in variability are evident in the visual examination of the histograms. The histograms in figure 5.10 are the data representation of the probability density function (PDF).

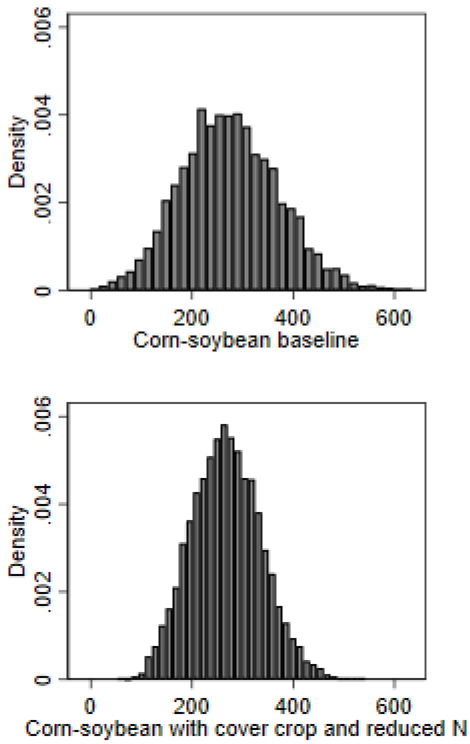

Figure 5.5 Output distribution histograms for corn enterprise budget

The comparison of baseline corn and corn with cover crops CDFs in figure 5.6 was evaluated visually for first degree stochastic dominance. The curves clearly cross each other which would indicate that neither curve is first degree stochastically dominant. This was indeed the case when the data was analyzed. However, the analysis did determine that corn with cover crops showed second degree stochastic dominance over the baseline. This result means that risk-averse farmers should prefer using cover crops in corn compared with convention methods. This result is driven by both the increased mean yield with cover crops as well as decreased variability.

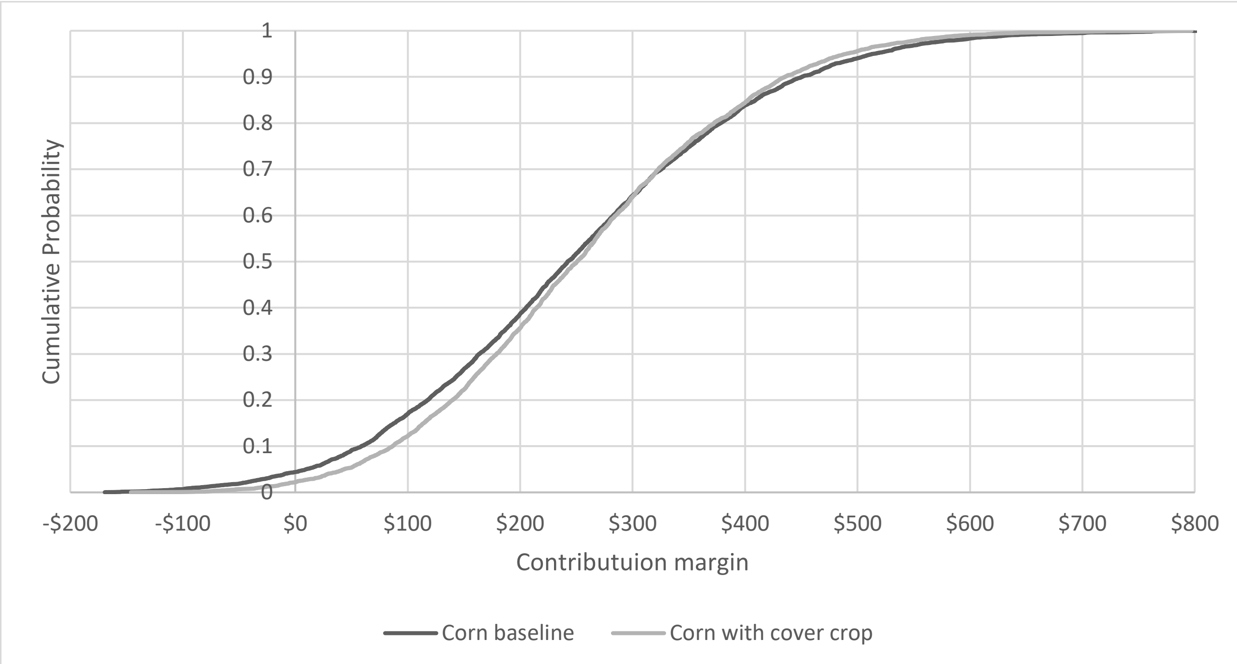

Figure 5.6 CDFs for baseline and cover crop corn

When the CDF of the baseline distribution is compared to corn with a cover crop and reduced nitrogen, no first degree stochastic dominance is observed. However, corn with a cover crop and reduced nitrogen is second degree stochastically dominant over the corn baseline. These CDFs are displayed in figure 5.7. Corn with cover crops and reduced nitrogen shows reduced risk when compared with the baseline. The reduction of nitrogen in cover crops also has a risk-reducing effect over keeping nitrogen at conventional levels. The comparison of cover crops at the typical nitrogen application and the reduced level showed that corn with reduced nitrogen was second order stochastically dominant over the baseline. This reduction is interesting because it demonstrates the interaction between the nitrogen level and risk. There is likely an optimal reduction in nitrogen application that could minimize risk. This may be an interesting topic for future research.

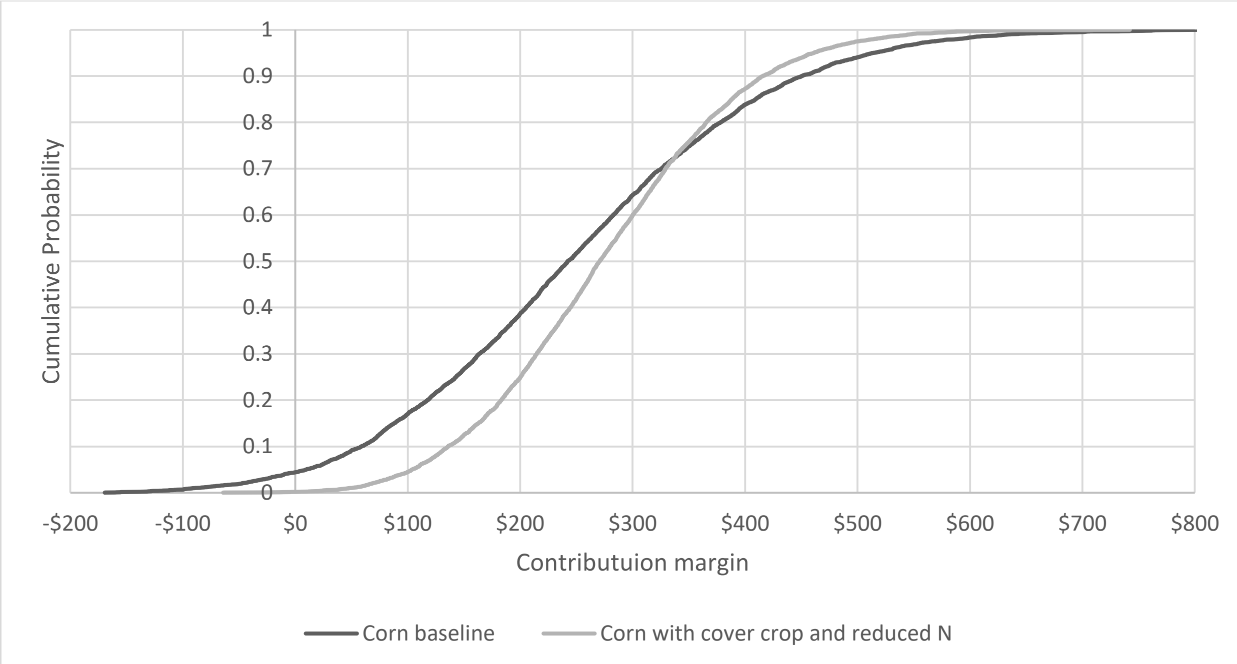

Figure 5.7 CDFs for baseline and cover crop corn with reduced nitrogen

The information in figure 5.8 shows the relative desirability of each scenario in corn by graphing certainty equivalence over various levels of the relative risk aversion coefficient. The values on the y axis are higher than the contribution margin because $281 in working capital was added to the contribution margin before being used as an input into the utility functions. The most important information in this figure is the position of the curves relative to each other. Corn with optimal nitrogen has the highest certainty equivalence over all levels of relative risk aversion. Certainty equivalence for corn with cover crops remains between the other scenarios, higher than the baseline and lower than corn with a nitrogen credit. Certainty equivalence for the baseline is lower than the other scenarios for all levels of relative risk aversion. Interestingly, for higher levels of relative risk aversion the three scenarios begin to diverge. This indicates that the more risk-averse the decision maker is, the more strongly they would prefer either of the cover crop choices over the baseline. The risk premiums ranged from $24.00 to $155.37 for the corn baseline, $18.03 to $102.67 for corn with cover crops, and $10.77 to $56.71 for corn with a cover crop at reduced nitrogen.

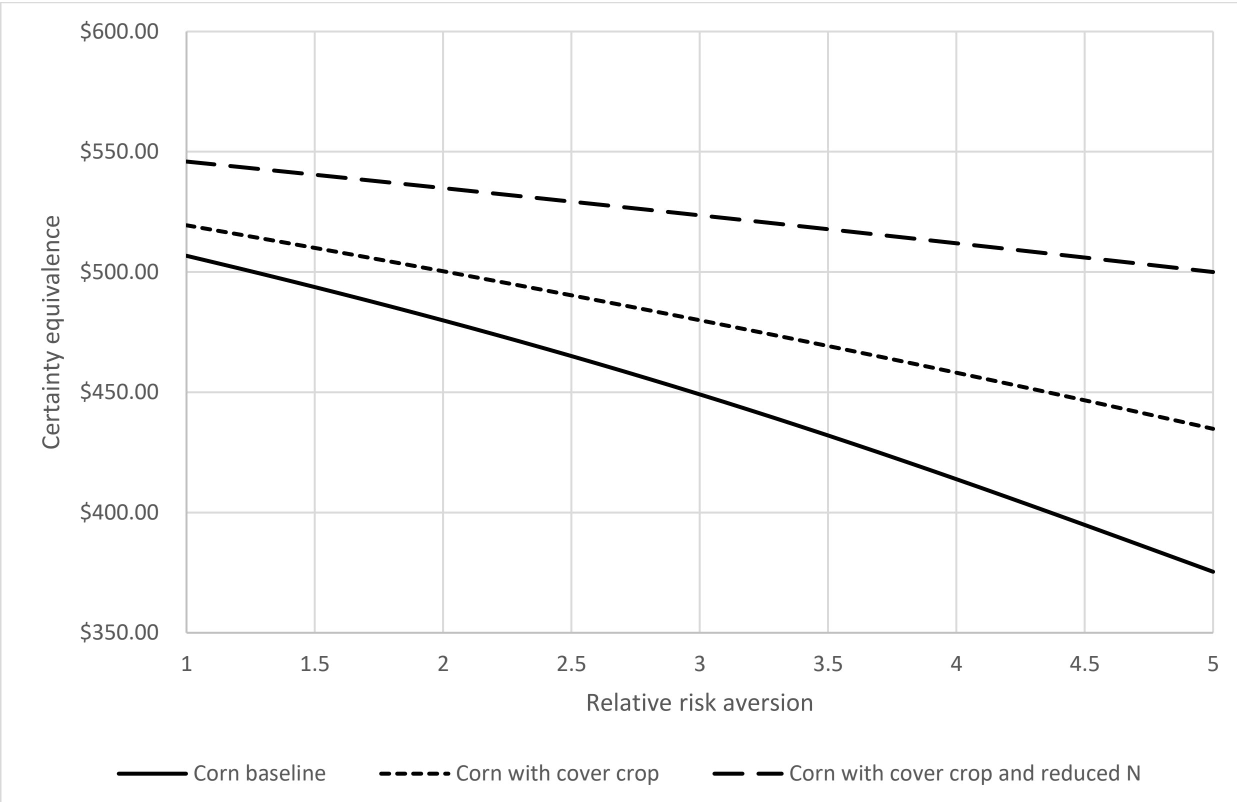

Figure 5.8 Certainty equivalence for corn contribution margin over risk aversion coefficient

5.4.3 Soybean enterprise budget

The baseline predicted mean soybean yield was 59.8 bu/acre with a standard deviation of 6.34. The predicted mean soybean yield with cover crops was 57.9 bu/acre with a standard deviation of 7.64. The soybean yield distribution parameters are shown in table 5.6. It is immediately noted that cover crops have a lower predicted yield and higher standard deviation. This is opposite from the effect in corn, which is benefited by cover crops both by increased yields and decreased standard deviation. This result is sensitive to the inclusion of a tile drainage system, as was shown in the analysis of yields. In the absence of tile drainage, soybeans would yield more with cover crops. However, this analysis was conducted using the means of the 20% trimmed sample, in which almost three-quarters of fields had a tile drainage system.

Table 5.6 Soybean yield distribution parameters

	Baseline budget	Cover crop
Predicted mean yield	59.80	57.90
Predicted standard deviation	6.34	7.64

The soybean static enterprise budget is shown in table 5.7. The revenue for the baseline budget without cover crops is higher at $530.86 than soybeans with a cover crop at $514.00. The bottom line of the budget is the contribution margin, which was $301.51 for the baseline budget and $261.81 for the cover crop scenario. This difference is due to the slightly lower yield with cover crops as well as the added costs. As previously discussed, the lack of a yield benefit in soybeans may be driven by the difficulty of establishing a cover crop after corn. This challenge is particularly serious in the northern counties in Indiana where most of the cover crops in this study were located.

Table 5.7 Soybean enterprise budget

Soybean Budget	Baseline budget		Cover crops	
Yield Per Acre		59.80		57.90
Price Per Bushel	$	8.88	$	8.88
Gross Revenue	**$**	**530.86**	**$**	**514.00**
Fertilizers	$	21.35	$	21.35
Seed	$	67.00	$	67.00
Cover Crop Seed	$	-	$	17.79
Pesticides	$	65.00	$	65.00
Cover crop termination			$	3.76
Dryer fuel	$	-	$	-
Machinery fuel (7.32 gal)	$	11.00	$	11.00
Machinery repairs	$	18.00	$	18.00
Cover Crop Drilling	$	-	$	1.30
Hauling	$	5.00	$	5.00
Interest	$	8.00	$	8.00
Insurance/misc.	$	34.00	$	34.00
Total Variable Costs	**$**	**229.35**	**$**	**252.19**
Soybean contribution Margin	**$**	**301.51**	**$**	**261.81**

5.4.4 Output distributions from soybean enterprise budget

The output distributions for the soybean enterprise budget are summarized in table 5.8. The mean contribution margins were very similar to the expected values. The standard deviations were $62.99 and $71.26 for the baseline and the cover crop scenarios, respectively. The probability of the contribution margin being less than zero was 0% for both scenarios. The relatively small impact of cover crops on mean yield and yields variability are amplified in the financial analysis, because soybeans have a higher price per bushel than corn. Another important thing to remember is that the small yield difference that is driving the larger financial difference was not statistically significant in the analysis of yields. However, even calculating the budget with no difference in yields shows cover cropped soybeans at a disadvantage because of added costs.

Table 5.8 Summary for output distributions from soybean enterprise budget

Simulation results	Baseline budget		Cover crops	
Mean	**$**	**299.83**	**$**	**259.98**
Standard Deviation	**$**	**62.99**	**$**	**71.26**
Min	**$**	**115.19**	**$**	**38.56**
Max	**$**	**550.48**	**$**	**543.06**
Probability CM<0		**0.000%**		**0.000%**

The output distributions for soybeans which are summarized above are shown in figure 5.9. These histograms show a similar story to the one told by the statistics in table 5.27. The distribution for soybeans with a cover crop is wider and shifted slightly to the left when compared to the baseline distribution.

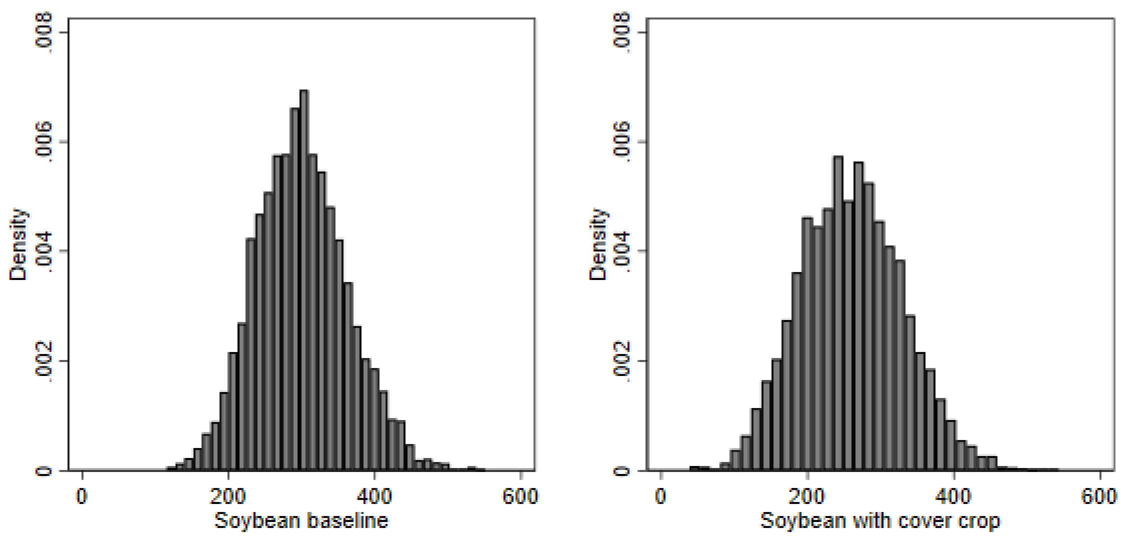

Figure 5.9 Output distribution histograms for soybean enterprise budget

The CDFs for the contribution margin for soybeans with and without a cover crop are compared in figure 5.10. The distribution for the baseline scenario was both first and second degree stochastically dominant to the cover crop scenario.

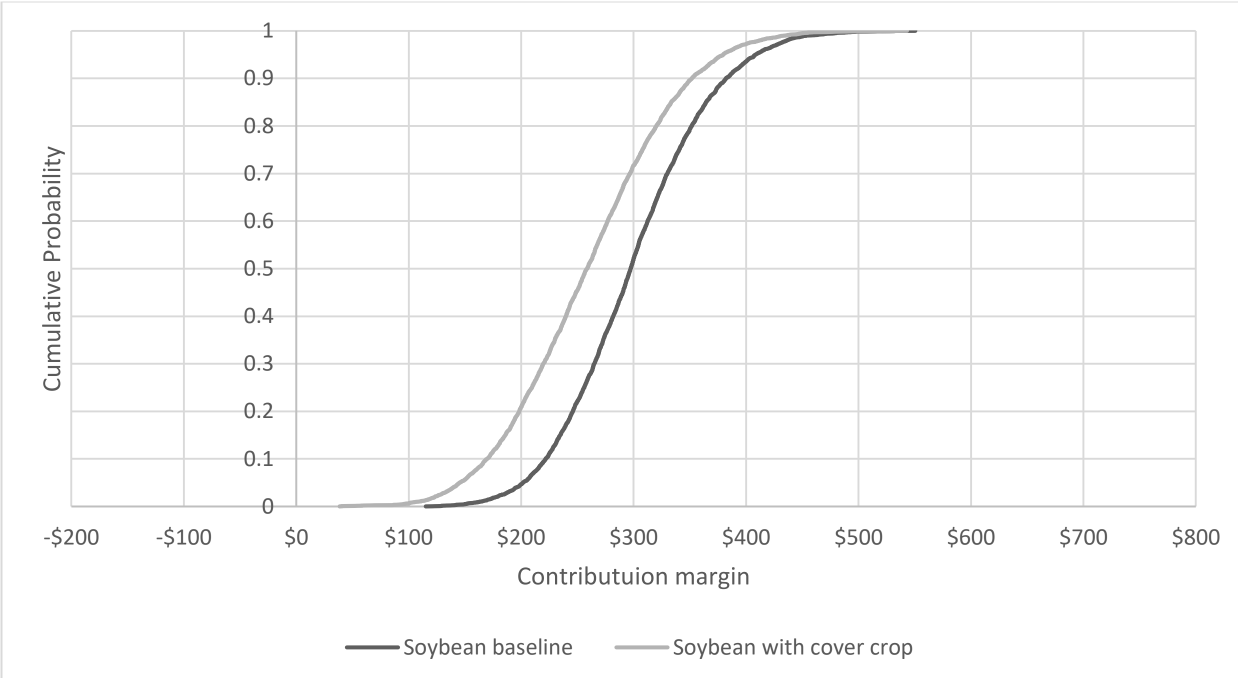

Figure 5.10 Cumulative density curves for baseline and cover crop soybeans

Certainty equivalence for soybeans is graphed with the relative risk aversion coefficient on the horizontal axis in figure 5.11. The values on the y axis are higher than the contribution margin because $281 in working capital was added to the contribution margin before being used as an input into the utility functions. The certainty equivalent for the baseline was always greater than it was for cover cropped soybeans. The difference between the curves remains about the same over the portion of the domain that was graphed. This indicates that the main driver of the difference is the mean of the underlying distribution rather than the variance. The risk premiums ranged from $3.40 to $16.97 for the soybean baseline and $4.72 to $24.07 for soybeans with cover crops.

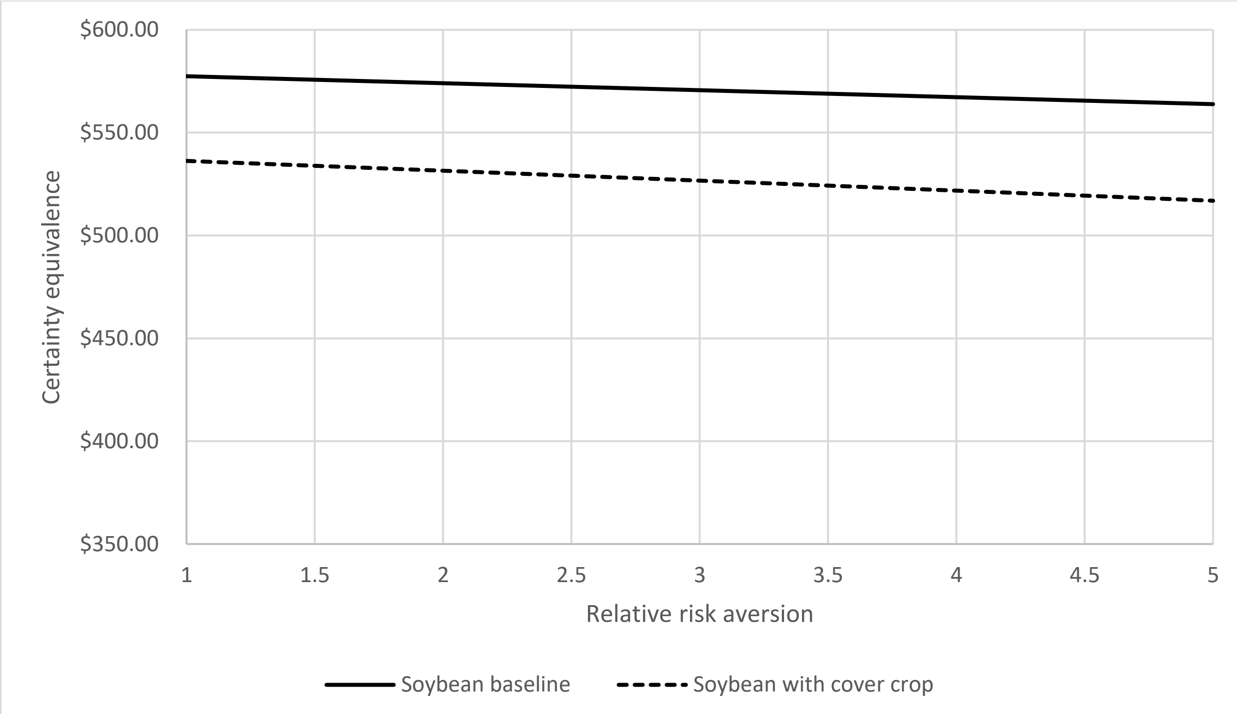

Figure 5.11 Certainty equivalence for soybean contribution margin

5.4.5 Corn-soybean rotation average contribution margin

To determine the best choice under a corn-soybean rotation, the average contribution margin was computed. The expected values for the contribution margins for corn and soybeans along with the average of the two are displayed by scenario in table 5.9. The scenarios are the same as the corn budget, with the soybean contribution margin not changing between cover crop columns. The average contribution margins were $276.81 for the baseline, $260.05 for cover crops without a nitrogen adjustment in corn, and $269.38 for cover crops with a nitrogen adjustment in corn. The expected values of the contribution margin are lower in both of the cover crop scenarios, although the differences are relatively small. The financial advantage with cover crops in corn and the disadvantage in soybeans come close to canceling each other out, on average over two years. The stochastic analysis may help to provide a clearer ranking of the options.

Table 5.9 Contribution margin with corn-soybean rotation

	Baseline budget	Cover crop	Cover crops + N credit
Contribution margin corn	$ 252.10	$ 258.29	$ 276.94
Contribution margin soybeans	$ 301.51	$ 261.81	$ 261.81
Average contribution margin	$ 276.81	$ 260.05	$ 269.38

5.4.5 Output distributions for corn-soybean rotation average contribution margin

The output distributions for the corn-soybean average of distributions are summarized in table 5.10. The means of the distributions are similar to the expected values above. The standard deviations are reduced for both cover crops scenarios when compared to the baseline. The scenario with cover crops and reduced nitrogen has the lowest standard deviation as well as the lowest probability of loss. This indicates lower risk although the mean contribution margin is lower than the baseline. Depending on how the decision maker views the trade-off between risk and return, the cover crop with reduced nitrogen may be the most attractive alternative. This trade-off will be discussed later as part of the analysis of certainty equivalence.

Table 5.10 Summary for output distributions of corn-soybean average

	Baseline budget	Cover crop	Cover crops + N credit
Mean	$ 274.79	$ 258.22	$ 267.84
Standard Deviation	$ 97.72	$ 86.85	$ 69.65
Min	$ (1.71)	$ (8.68)	$ 52.86
Max	$ 634.10	$ 619.30	$ 541.64
Probability CM<0	0.030%	0.028%	0.000%

The distributions are displayed in figure 5.12, with a histogram for each scenarios output distribution. Although the histograms of the distributions are centered over approximately the same value, the baseline distribution is wider than both of the cover crop distributions. Another interesting observation is that the baseline distribution has slightly longer tails than the other two distributions, although this difference is really quite minor. In general, the histograms of theses distributions are similar.

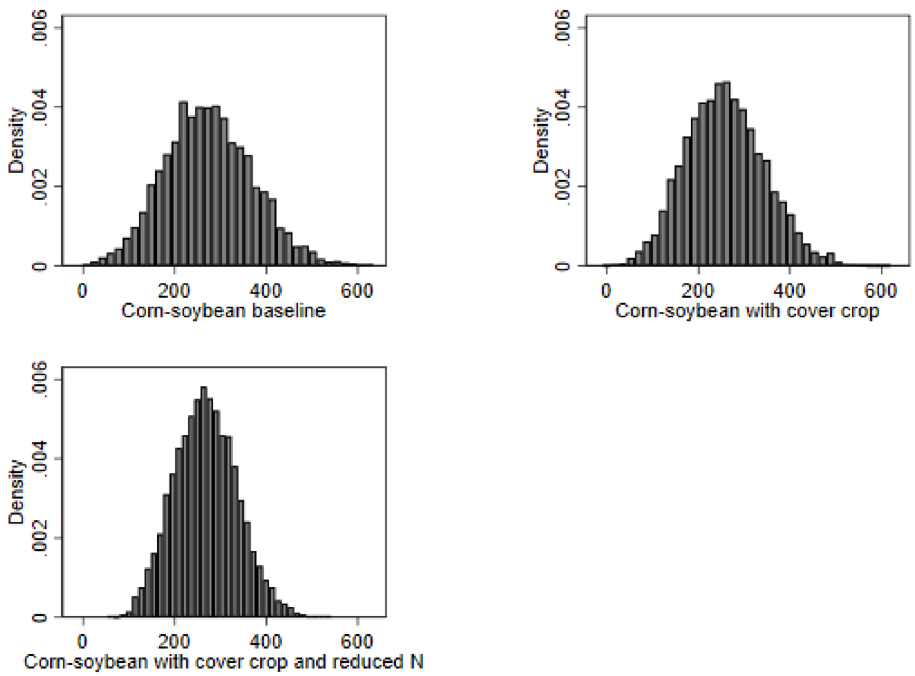

Figure 5.12 Output distribution histograms for corn-soybean average

A pairwise comparison of cumulative probability density functions between the baseline and the cover crop scenario is shown in figure 5.13. Neither curve stochastically dominated the other in the first or second degree. However, the graph does show that the baseline CDF is below the cover crop CDF for most of the range (0, 1) of the function. When $CDF_A(x_0) < CDF_B(x_0)$ for any $x_0 \in X,$ then $P(A \leq x_0) < P(B \leq x_0)$. In other words, when one CDF is lower than another at any level of contribution margin, the probability of a contribution margin smaller than the given level is highest in the second CDF. Given this, cover crops would be less preferred than the baseline for most of the domains in figure 5.20. However, without any degree of stochastic dominance, there are no strong statements that can be made regarding one option always being preferred to the other.

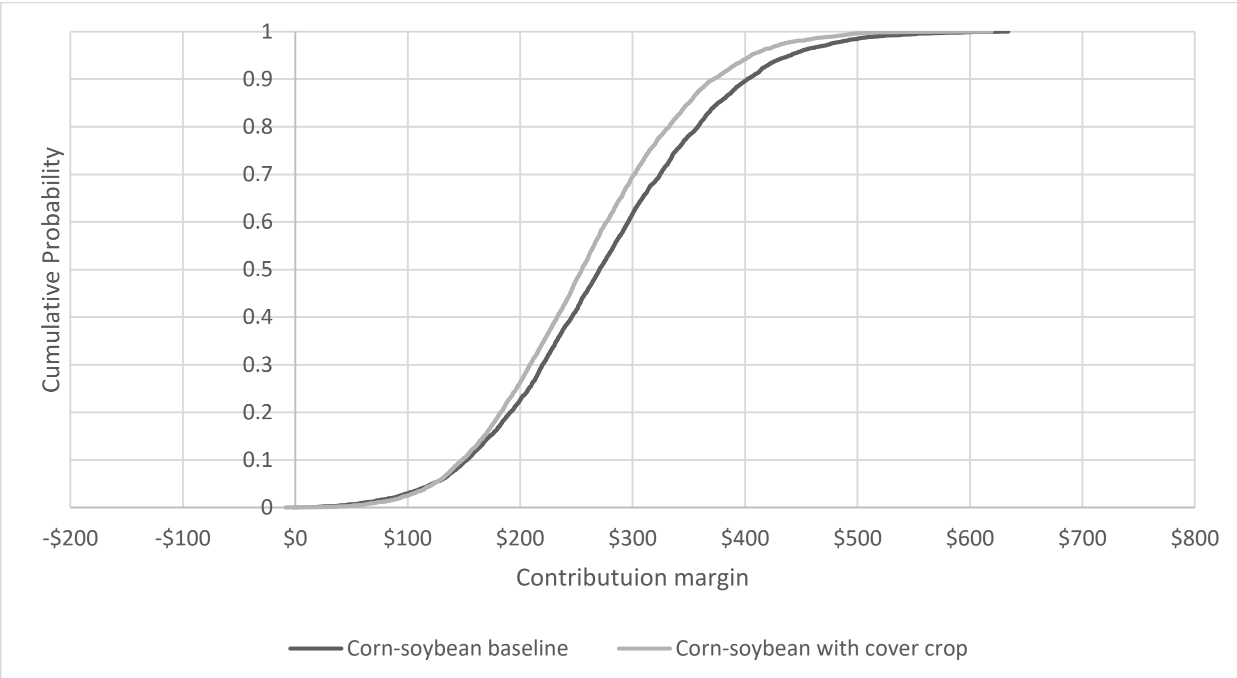

Figure 5.13 Cumulative density curves for baseline and cover crop corn-soybean average

An additional pairwise comparison was plotted in figure 5.14 comparing the baseline to corn-soybeans with cover crops and adjusted nitrogen in the corn year. This graph shows the two cumulative distribution functions together. Neither curve stochastically dominated the other in the first or the second degree. Additionally, neither curve was lower than the other for the majority of the domain of the functions. Although cover crops do not provide a strong incentive on average over the two-year rotation, even a small cost share payment could make it worthwhile. Additionally, since this analysis did not include any explicit value for reduced soil erosion, soil compaction, or reduced inputs, any additional benefits the farmer may recognize could make the difference in the decision to cover crop over the two years of the rotation.

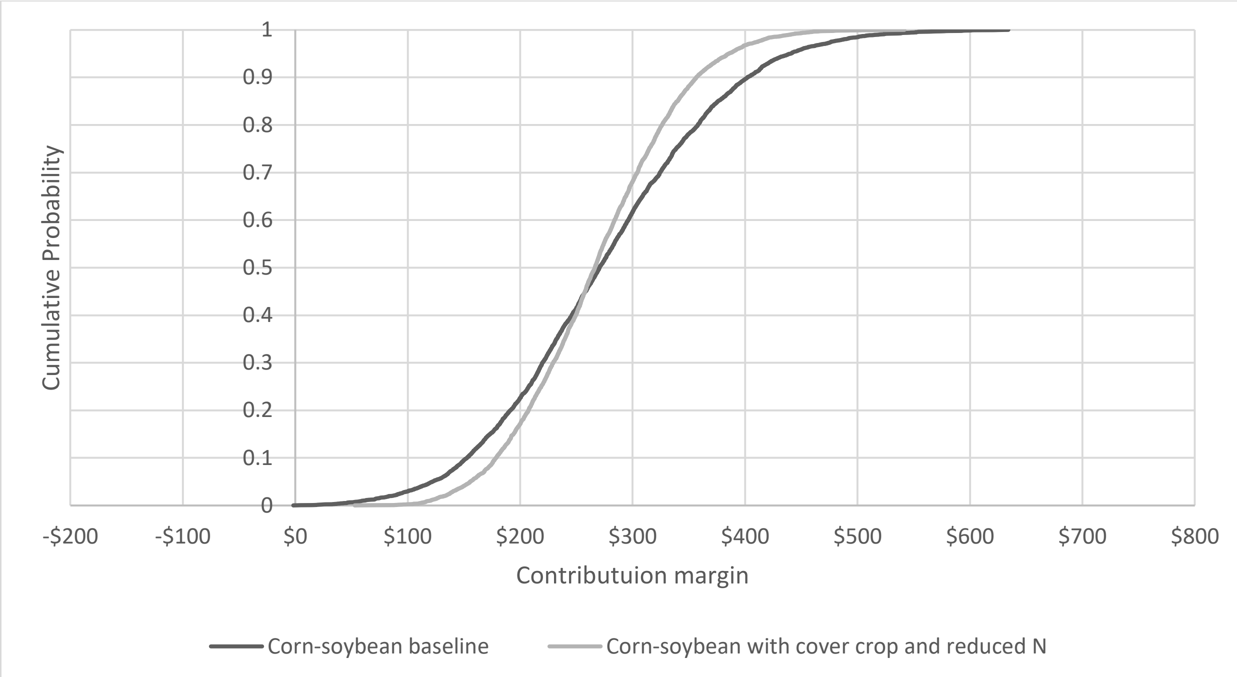

Figure 5.14 Cumulative density curves for baseline and cover crop with optimized nitrogen corn-soybean average

Certainty equivalence for the three options under a corn-soybean rotation is shown in figure 5.15. The values on the y axis are higher than the contribution margin because $281 in working capital was added to the contribution margin before being used as an input into the utility functions. The horizontal axis is the risk aversion coefficient. Beginning at a relative risk aversion coefficient of 1 the baseline scenario is the preferred option. However, as relative risk aversion increases the value of the lower risk under the scenario with a cover crop and adjusted nitrogen becomes relatively more valuable. At a relative risk aversion coefficient value of about 1.7, the cover crops with reduced nitrogen become the best scenario. Research has shown that farmers have an estimated relative risk aversion coefficient between 1.6 and 4.4 (Myers, 1989). Thus, most farmers should prefer cover crops in a corn-soybean rotation. The risk premiums ranged from $8.68 to $45.03 for the corn-soybean baseline, $7.03 to $35.87 for the corn-soybean rotation with cover crops, and $4.43 to $22.38 for the corn-soybean rotation with a cover crop at reduced nitrogen.

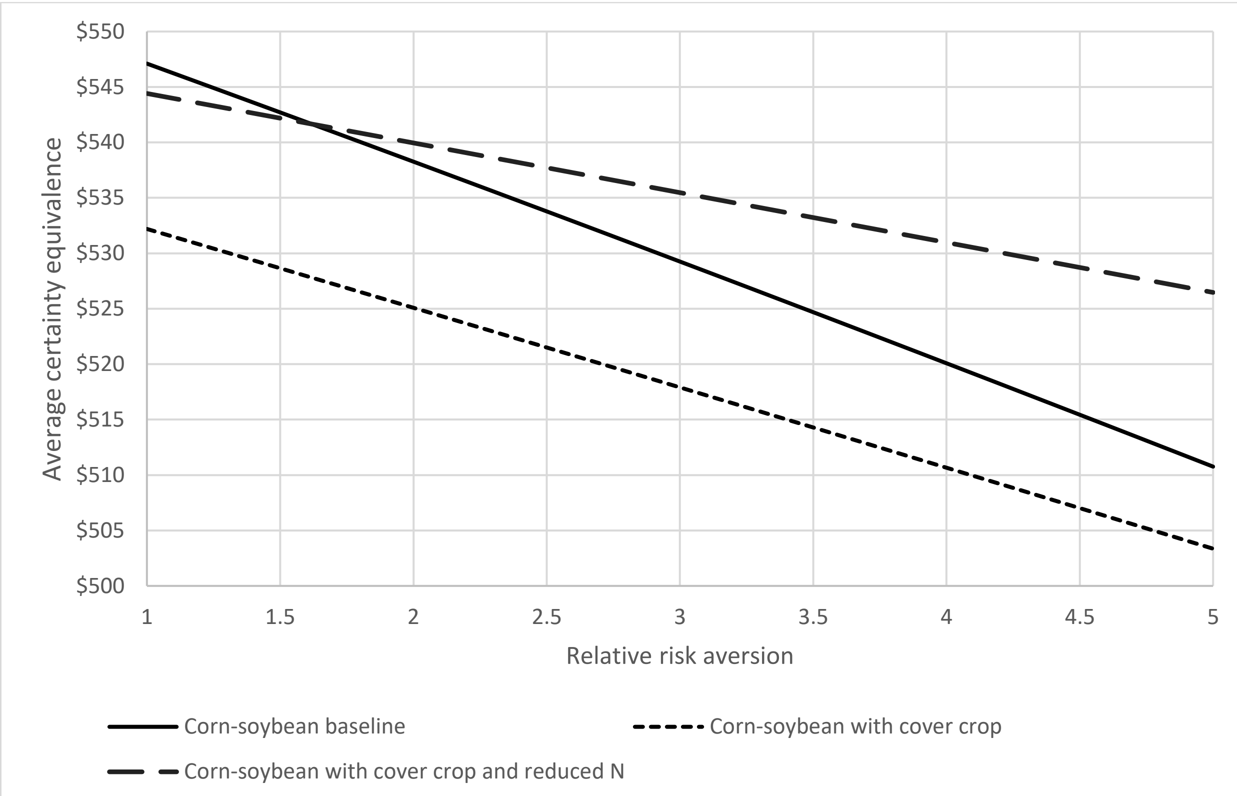

Figure 5.15 Certainty equivalence for corn-soybean average contribution margin

5.5 Conclusion

The results of this analysis show the ability of cover crops to provide economic benefit to farmers when grown prior to a corn cash crop. The benefits are shown in increased yield, reduced need for nitrogen fertilizer, and increased temporal yield stability. These impacts of cover crops translate into higher revenue from the sale of the grain, lower input costs, and lower risk and uncertainty. However, the results for soybeans were not as favorable. The results from soybeans were universally statistically insignificant and typically showed a negative effect on desirable measures. This led to lower projected revenue and higher projected costs. Cover crops also had an unfavorable, though statistically insignificant, impact on soybean yield variability.

This lead to increased expected risk. Even with soybeans at a disadvantage, the average corn-soybean contribution margin with cover crops was nearly the same as the baseline scenario. Furthermore, the analysis of risk showed that the corn-soybean average would be preferred by risk-averse farmers.

The difference between the effect of cover crops in corn and soybeans merits further discussion and research. At least part of the difference in the effects is likely due to the fact that cover crops impact corn yield by supplying additional nitrogen to the crop through nitrogen-fixing and scavenging. However, this does not appear to be the sole source of benefit in corn. The corn yield curve with cover crops is shifted up and to the left of the baseline, suggesting more than just nitrogen replacement. An additional explanation that may help account for the difference between the effect of cover crops on corn and soybeans is late planting dates for cover crops after corn. Corn is harvested late in the fall and establishing a cover crop after harvest in central and northern Indiana is difficult at best. Seeding the cover crop into standing corn aerially or otherwise is often plagued by poor establishment as well. With poor establishment the impact of the cover crop on the subsequent cash crop—usually soybeans after corn—is most likely minimal. If farmers could overcome this particular management challenge, cover crops may be able to provide benefits for soybean crops as well.

CHAPTER 6 SUMMARY AND CONCLUSIONS

6.1 Summary

The world relies heavily on agriculture for food and fiber. Agriculture relies heavily on the soil as a main resource. While the soil has been able to sustain an ever-growing population, care must be exercised to avoid depleting this essential resource. Currently, soil erosion and degradation rates are at unsustainable levels even in the United States (Nearing et al., 2017; Scherr, 1999). The private incentive to reduce soil erosion remains minimal in terms of present value, yet the long-term consequences for society remain significant (Ervin & Washburn, 1981). An ideal solution would need to be able to provide short-term value to farmers as well as long-term soil erosion control while enhancing soil health. Cover crops have the potential to accomplish all three of these objectives as part of a conservation-focused farming system.

Water is another resource vital to continued success as a society. Currently, agriculture contributes a great deal to the pollution of waterways in the United States. This pollution threatens water quality and aquatic life in rivers, streams, lakes, and even the Gulf of Mexico (Burkart & James, 1999). This pollution is mostly from excess fertilizer which is washed away in runoff or leaches through the soil. This lost fertilizer is an added cost to farmers as well as a societal cost. Cover crops help to scavenge residual nitrogen and keep it from being lost from the farming system and polluting waterways.

Private adoption of cover crops remains low. Farmers have been slow to adopt the practice of cover cropping despite cost share programs and much encouragement from advocates of the practice. Many express concerns over the economic returns or the risk associated with cover crops (S. M. Lira & Tyner, 2018; Singer et al., 2007). This study uses a large dataset and innovative methods of analysis to measure the effect of cover crops on farm finances and production risk. This information will assist farmers in making better cover crop adoption decisions. This information may also help policy makers structure incentive programs for conservation. The analysis of cash crop yield variability and impacts on risk may be of interest to crop insurance providers.

This study used a large set of observational data from 23 farms across Indiana with multiple fields and 8 years of historical data. This provided production level information in real-world farming conditions. The data also provided a range on farming practices, such as the level of fertilizer application, which is not possible in small university-run trials. Cover cropped fields had typically been farmed using cover crops for a significant period of time by farmers with considerable experience using cover crops. This is important because the effect of cover crops in this case was the effect of a mature cover cropping system. Therefore, the results may have some limitations in application to new cover crop systems and inexperienced managers. The main drawback to this data was the lack of random selection for both participation in the study as well as assignment of the cover crop treatment. The issue of the non-random assignment was considered in the analysis and rigorous measures were taken to remove the resulting bias. Any possible bias from this source was not obvious and steps were not taken to correct for it.

The analysis used regression analysis to determine the effect of cover crops on the temporal variability and average yield of the subsequent cash crop. The treatment effect of cover crops was discussed in terms of bushels per acre for these analyses. The outcomes from these models were used as inputs into stochastic farm budget models. Cover crops increased yield in corn at all nitrogen levels. The leftward shift in the yield nitrogen response curve suggested a nitrogen replacement effect. The higher peak of the yield nitrogen response curve indicated an additional effect of cover crops on yield. Cover crops were also shown to reduce temporal yield variation in corn. Soybeans did not respond as favorably to cover crops with no statistically significant benefits under the standard set of assumptions. However, when modeled on fields without tile drainage, yield benefit was evident.

The observed yield benefits of cover crops in corn translated into financial benefit in the stochastic budget. The per acre contribution margin was higher for cover crop corn and showed second order stochastic dominance. This was true for cover crops at both levels of nitrogen considered. Cover crops should always be preferred in corn by risk-averse farmers. The additional cost of cover cropping severely reduced the attractiveness of cover cropping in soybeans, since there was no yield increase or nitrogen credit to compensate. Over two years of cover cropping in a corn-soybean rotation, the benefits of cover cropping in corn essentially cover the additional costs of the practice in soybeans. However, in a corn-soybean rotation, cover crops with adjusted nitrogen had a higher certainty equivalence when the relative risk aversion coefficient was greater than 1.7.

6.2 Conclusions

This research produced several important and unique findings about the effects of cover crops on farm finance and risk. The information provides farmers and others valuable insights into the economics of cover crops. Listed below are key findings that came out of the analyses for this thesis.

- Cover crops increased corn yield, at nitrogen levels up to 250 lbs/acre. This yield improvement appeared to be due to an N replacement effect as well as an additional effect. The additional effect could be the result of improved soil health or greater rotational diversity. With a nitrogen reduction, cover crops provided an additional $24.65 in contribution margin over the baseline for corn.

- Temporal yield stability in corn was improved with the addition of cover crops. The reduction in variability attributed to cover crops was estimated to be 15.42 percentage points in coefficient of variation. As a result of this reduction in variability, cover crops reduced risk in corn. The contribution margin for both of the cover crops scenarios were second degree stochastically dominant over the corn baseline.
- Under the standard assumptions, cover crops did not have a statistically significant effect on soybean yields or yield variation, likely due to poor fall establishment after late corn harvest. This result suggests the potential for a system of "rotational" cover crops. This could be an area of future research.
- When yields were modeled in soybeans for fields without tile drainage, cover crops showed a statistically significant and positive effect on yields. This may happen because fields without good drainage are planted later in the season, giving cover crops time to mature and provide agronomic benefits. Alternatively, cover crops might help reduce soil moisture by increasing porosity and reducing compaction. This could be an area of future research.
- Modeling a corn-soybean rotation showed that the baseline scenario had a slightly larger contribution margin. However, the SERF analysis using certainty equivalence showed that the cover crops with reduced nitrogen became the preferred choice for risk averse farmers.

6.3 Suggestions for future research

Future research could investigate the reasons why cover crops improve yield for soybeans in fields without tile drains. This study used a nitrogen reduction in corn from observing actual application levels. Perhaps future research might seek to find the economically optimal nitrogen reduction for corn when cover crops are grown previously. More research is also needed to understand the impact of cover crops on risk. This may be a previously overlooked private benefit of cover crops which could encourage adoption. Finally, more research should investigate the benefits of rotational cover crops before corn, but not before soybeans.

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APPENDIX A: ADDITIONAL SUMMARY TABLES AND FIGURES FOR FULL SAMPLE

Figure A.1 Total acre-years by county

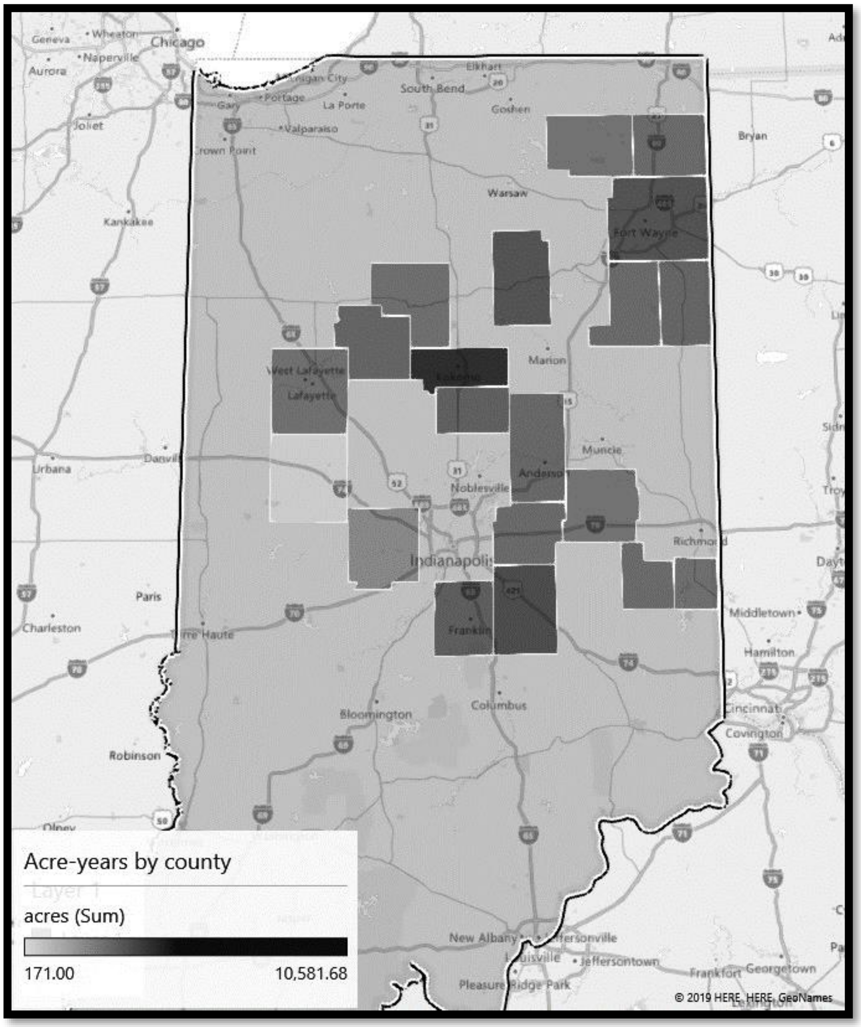


Table A.1 Soybean yield by year

Year	Obs	Acres	Mean	SD	Min	Max
2009	22	1320	56.48	5.54	40	63
2010	19	1016	55.58	6.45	39	66.1
2011	55	3419	51.73	8.11	28	69.1
2012	46	2522	53.88	11.69	18.72	76
2013	59	4344	56.32	7.81	38	67
2014	49	2627	57.81	10.76	42.44	77
2015	64	4494	52.67	7.64	22	70.3
2016	50	2800	57.24	12.78	37	77.81
2017	65	4830	56.19	8.90	35	76.96
2018	38	1807	60.66	10	36.8	86.65

Table A.2 Corn yield by year

Year	Obs	Acres	Mean	SD	Min	Max
2009	18	967	189.72	22.68	101	219
2010	23	1309	178.92	32.14	53	262
2011	43	2415	159.59	24.49	73.4	214.5
2012	56	3522	125.31	44.97	20	204.5
2013	50	2693	177.06	33.83	71	234
2014	60	4327	206.87	25.01	108	257
2015	46	2568	159.42	30.37	97.6	254
2016	55	3996	199.81	26.62	138	263
2017	44	2086	188.26	27.76	95.1	242.5
2018	48	3398	214.30	33.59	148.9	270

Table A.3 Tillage practices

	Proportion
Conventional Tillage	34.74%
Minimum tillage	6%
No-till	59.26%
Continuous no-till	46.17%
Every other no-till	25.11%

Table A.4 Tillage practices in soybeans

	Proportion
Conventional Tillage	21.6%
Minimum tillage	6.9%
No-till	71.5%
Continuous no-till	47.06%
Every other no-till	23.10%

Table A.5 Tillage practices in corn

	Proportion
Conventional Tillage	48.79%
Minimum tillage	5.04%
No-till	46.17%
Continuous no-till	45.21%
Every other no-till	27.26%

Table A.6 Fertilizer application and other farming practices by cash crop

Soybeans	Mean	SD	Min	Max
Applied nitrogen (lbs/acre)	6.59	16.95	0	160.68
Applied phosphorus (lbs/acre)	16.41	31.58	0	138
Applied potassium (lbs/acre)	40.45	72.26	0	504.42
Seed Rate (thousands/acre)	172.31	24.47	120	225
Seed treatment	57.75%	.	.	.
Cover crop	24.22%	.	.	.
Cover crop establishment rank (1-5)	3.43	1	1	5
Previous crop-corn	91.21%	.	.	.
Previous crop-soybeans	8.79%	.	.	.
Years of continuous cover crop	4.58	2.47	1	10
Corn	**Mean**	**SD**	**Min**	**Max**
Applied nitrogen (lbs/acre)	198.03	43.76	11.18	334.37
Applied phosphorus (lbs/acre)	61.69	48.83	0	208
Applied potassium (lbs/acre)	80	74.15	0	330
Seed Rate (thousands/acre)	33.67	2.29	26	63.05
Seed treatment	55.28%	49.78%	0	1
Cover crop	24.85%	43.27%	0	1
Cover crop establishment rank (1-5)	3.2	0.81	1	5
Previous crop-corn	3.97%	19.55%	0	1
Previous crop-soybeans	96.03%	19.55%	0	1
Years of continuous cover crop	4.13	2.44	1	10

Table A.7 Field attributes

	Mean	SD	Min	Max
Field size (acres)	62.04546	50.91109	6.6	271
Average slope (% grade)	2.16	2.04	0	13
Drainage system	69.32%	46.14%	0	1
Northeast Indiana	31.63%	46.5%	0	1

Table A.8 Overall soil profile

	Mean	SD	Min	Max
Alfisols	41.02%		0	1
Mollisols	31.73%	46.57%	0	1
Inceptisols	0.41%	6.40%	0	1
Mollisols/Alfisols mix	25.6%	43.64%	0	1
Histisols	0.88%	9.32%	0	1
Soil organic matter (%)	3.07	2.94	1.3	36.13
Soil organic matter (excluding 2 outliers, %)	2.77	0.66	1.3	5.23
Soil PH	6.55	0.35	5.83	7.53
Soil phosphorus (ppm)	45.53	31.46	8.33	169
Soil potassium (ppm)	151.45	54.99	48	310.33
Soil magnesium (ppm)	262.07	83.62	111.33	722.67
Soil Calcium (ppm)	1801.56	628.72	1000	4619
Cation exchange capacity	12.78	3.6	6.5	28.9
Potassium saturation (%)	3.18	0.96	1.47	5.93
Magnesium saturation (%)	17.10	3.98	8.07	25.24
Calcium saturation (%)	69.88	7.57	57	86.4

Table A.9 Operator characteristics in 2017

	Mean	SD	Min	Max
Operator farming experience	30.26	15.96	6	54
Operator cover crops experience	5.57	9.39	0	42
High school	0.35	.	.	.
Bachelor's degree	0.39	.	.	.
Graduate degree	0.26	.	.	.
Operator's age	51.57	15.64	24	74
Total acres managed	1672.61	2095.75	60	7500
Total acres of cover crops	202.43	354.44	0	1500
Farm laborers	3.46	2.86	1	10

APPENDIX B: SUMMARY STATISTICS FOR 20% TRIMMED SAMPLE

Table B.1 Summary statistics for crop specific variables in soybeans by cover crop (20% trimmed sample)

Without cover crops	Mean	SD	Min	Max
Cash crop yield (bu/acre)	52.49	8.25	29	72.7
Minimum tillage	.03	.18	0	1
No-till	.92	.27	0	1
Continuous no-till	.47***	.5	0	1
Every other no-till	.44***	.5	0	1
Previous crop-corn	.9	.29	0	1
Previous crop-soybeans	.1	.29	0	1
Applied nitrogen (lbs/acre)	3.52***	7.67	0	31.58
Applied phosphorus (lbs/acre)	10.46***	21.91	0	93.41
Applied potassium (lbs/acre)	18.85***	39.74	0	220.5
Seed rate (thousands/acre)	169.98**	26.75	120	225
Seed treatment	.39	.49	0	1
Cover crop	0	0	0	0
With cover crop				
Cash crop yield (bu/acre)	51.69	8.7	25	69
Minimum tillage	.02	.15	0	1
No-till	.96	.21	0	1
Continuous no-till	.95***	.23	0	1
Every other no-till	.01***	.1	0	1
Previous crop-corn	.87	.34	0	1
Previous crop-soybeans	.13	.34	0	1
Applied nitrogen (lbs/acre)	12.82***	23.71	0	92
Applied phosphorus (lbs/acre)	27.18***	38.78	0	138
Applied potassium (lbs/acre)	64.78***	64.25	0	209.89
Seed rate (thousands/acre)	164.05**	20.31	120	225
Seed treatment	.32	.47	0	1
Cover crop	1	0	1	1

Without cover crop group included 126 observations
With cover crop group included 91 observations
Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

Table B.2 Summary statistics for crop specific variables in corn by cover crop (20% trimmed sample)

Without cover crop	Mean	SD	Min	Max
Cash crop yield (bu/acre)	168.95	38.84	53	243.3
Minimum tillage	.02	.13	0	1
No-till	.43***	.5	0	1
Continuous no-till	.43***	.5	0	1
Every other no-till	.48***	.5	0	1
Previous crop-corn	.04	.21	0	1
Previous crop-soybeans	.96	.21	0	1
Applied nitrogen (lbs/acre)	199.29***	43.12	27	271.3
Applied phosphorus (lbs/acre)	82.41***	43.9	0	208
Applied potassium (lbs/acre)	102.71***	55.95	0	300
Seed rate (thousands/acre)	33.03*	1.93	26	37
Seed treatment	.48	.5	0	1
With cover crop				
Cash crop yield (bu/acre)	162.5	38.38	47	246
Minimum tillage	.02	.15	0	1
No-till	.89***	.31	0	1
Continuous no-till	.88***	.33	0	1
Every other no-till	.08***	.28	0	1
Previous crop-corn	.01	.11	0	1
Previous crop-soybeans	.99	.11	0	1
Applied nitrogen (lbs/acre)	168.73***	51.07	20.09	242.4
Applied phosphorus (lbs/acre)	41.16***	36.29	0	123.2
Applied potassium (lbs/acre)	46.23***	46.76	0	216
Seed rate (thousands/acre)	32.61*	1.58	29	36
Seed treatment	.28	.45	0	1

Without cover crop group included 114 observations

With cover crop group included 83 observations

Difference of means test (with vs without cover crops)

*** p<0.01, ** p<0.05, * p<0.1

Table B.3 Summary statistics for field attributes by cover crop (20% trimmed sample)

Without cover crops	Mean	SD	Min	Max
Field size (acres)	53.41***	32.03	15	230
Average slope (% grade)	2.36***	1.85	.5	9
Drainage system	.63	.48	0	1
Northeast Indiana	.43*	.5	0	1
Mollisols	.32	.47	0	1
Mollisols/Alfisols mix	.08	.28	0	1
With cover crops				
Field size (acres)	55.14***	46.48	15	230
Average slope (% grade)	3.3***	1.62	.5	9
Drainage system	.61	.49	0	1
Northeast Indiana	.42*	.49	0	1
Mollisols	.3	.46	0	1
Mollisols/Alfisols mix	.05	.22	0	1

Without cover crop group included 240 observations
With cover crop group included 174 observations
Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

Table B.4 Summary statistics for farmer characteristics in 2017 by cover crop (20% trimmed sample)

Farmers not using cover crops	Mean	SD	Min	Max
Operator farming experience	32.6	13.15	9	45
Bachelor's degree	.3	.48	0	1
Graduate degree	.7***	.48	0	1
Operator's age	65.7	12.12	35	74
Total acres managed	386	463.13	190	1700
Farm laborers	1.3	.95	1	4
Farmers who use cover crops				
Operator farming experience	35.67	15.94	6	54
Operator cover crops experience	9.46	11.03	0	43
Bachelor's degree	.26	.44	0	1
Graduate degree	.15***	.37	0	1
Operator's age	58.18	12.67	24	72
Total acres managed	754.41	651.58	200	2500
Total acres of cover crops	309.56	307.76	0	1500
Farm laborers	2.97	1.94	1	7

Without cover crop group included 10 observations
With cover crop group included 39 observations
Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

Table B.5 Summary statistics for soil attributes by cover crop (20% trimmed sample)

Without cover crops	Obs	Mean	SD	Min	Max
Soil organic matter (%)	176	2.85***	.79	1.3	5.23
Soil PH	150	6.41**	.24	5.83	6.8
Soil phosphorus (ppm)	150	27.75***	18.39	10	94.33
Soil potassium (ppm)	150	136.31	43.48	65.33	270.33
Soil magnesium (ppm)	150	293.05***	92.73	111.33	464.5
Soil Calcium (ppm)	150	1608.09**	323.69	1028.5	2166.57
Cation exchange capacity	150	12.34***	2.34	7.8	15.7
With cover crops					
Soil organic matter (%)	165	2.93***	.8	1.75	5.23
Soil PH	116	6.46**	.34	5.83	7.1
Soil phosphorus (ppm)	116	33.21***	21.13	10	94.33
Soil potassium (ppm)	116	121.52	60.36	48	270.33
Soil magnesium (ppm)	116	198.97***	65.51	111.33	292.33
Soil Calcium (ppm)	116	1405.71**	283.29	1000	1929.33
Cation exchange capacity	116	10.21***	2.26	6.5	15

Difference of means test (with vs without cover crops)
*** p<0.01, ** p<0.05, * p<0.1

Table B.6 Summary statistics for crop specific variables in soybeans (20% trimmed sample)

	Obs	Mean	SD	Min	Max
Cash crop yield (bu/acre)	217	52.15	8.43	25	72.7
Minimum tillage	217	.03	.16	0	1
No-till	217	.94	.25	0	1
Continuous no-till	217	.67	.47	0	1
Every other no-till	217	.26	.44	0	1
Previous crop-corn	217	.89	.31	0	1
Previous crop-soybeans	217	.11	.31	0	1
Applied nitrogen (lbs/acre)	217	7.42	17.01	0	92
Applied phosphorus (lbs/acre)	217	17.47	31.19	0	138
Applied potassium (lbs/acre)	217	38.11	56.12	0	220.5
Seed rate (thousands/acre)	217	167.49	24.38	120	225
Seed treatment	217	.36	.48	0	1
Cover crop	217	.42	.49	0	1

Table B.7 Summary statistics for crop specific variables in corn (20% trimmed sample)

	Obs	Mean	SD	Min	Max
Cash crop yield (bu/acre)	197	166.23	38.68	47	246
Minimum tillage	197	.02	.14	0	1
No-till	197	.62	.49	0	1
Continuous no-till	197	.62	.49	0	1
Every other no-till	197	.31	.47	0	1
Previous crop-corn	197	.03	.17	0	1
Previous crop-soybeans	197	.97	.17	0	1
Applied nitrogen (lbs/acre)	197	186.42	48.91	20.09	271.3
Applied phosphorus (lbs/acre)	197	65.03	45.6	0	208
Applied potassium (lbs/acre)	197	78.91	59.17	0	300
Seed rate (thousands/acre)	197	32.85	1.8	26	37
Seed treatment	197	.4	.49	0	1
Cover crop	197	.42	.5	0	1

Table B.8 Summary statistics for field attributes (20% trimmed sample)

	Obs	Mean	SD	Min	Max
Field size (acres)	414	54.14	38.72	15	230
Average slope (% grade)	414	2.76	1.82	.5	9
Drainage system	414	.63	.48	0	1
Northeast Indiana	414	.43	.49	0	1
Mollisols	414	.31	.46	0	1
Mollisols/Alfisols mix	414	.07	.26	0	1

Table B.9 Summary statistics for operator characteristics in 2017 (20% trimmed sample)

	Obs	Mean	SD	Min	Max
Operator farming experience	49	35.04	15.34	6	54
Operator cover crops experience	49	7.71	10.44	0	43
Bachelor's degree	49	.27	.45	0	1
Graduate degree	49	.27	.45	0	1
Operator's age	49	59.71	12.81	24	74
Total acres managed	49	679.22	631.53	190	2500
Total acres of cover crops	49	246.39	301.45	0	1500
Farm laborers	49	2.63	1.9	1	7

Table B.10 Summary statistics for soil profile (20% trimmed sample)

	Obs	Mean	SD	Min	Max
Soil organic matter (%)	341	2.89	.8	1.3	5.23
Soil PH	266	6.43	.29	5.83	7.1
Soil phosphorus (ppm)	266	30.13	19.78	10	94.33
Soil potassium (ppm)	266	129.86	51.94	48	270.33
Soil magnesium (ppm)	266	252.02	94.25	111.33	464.5
Soil Calcium (ppm)	266	1519.83	322.26	1000	2166.57
Cation exchange capacity	266	11.41	2.54	6.5	15.7
Potassium saturation (%)	254	3.04	.93	1.6	5.3
Magnesium saturation (%)	254	18.03	4.5	8.07	25.24
Calcium saturation (%)	254	67.08	7.07	57	80.37

APPENDIX C: INPUT DISTRIBUTIONS

Table C.1 Input levels into the yield models for the budget analysis.

	Corn			Soybeans	
	No cover crop	Cover crop	Cover crop with reduced N	No cover crop	Cover crop
Cover crop	0	1	1	0	1
Applied nitrogen (lbs/acre)	212.15	212.15	108.42	7.42	7.42
Applied phosphorus (lbs/acre)	65.03	65.03	65.03	17.47	17.47
Applied potassium (lbs/acre)	78.91	78.91	78.91	38.11	38.11
No-till	0.62	0.62	0.62	0.94	0.94
Seed rate (thousands/acre)	32.85	32.85	32.85	167.49	167.49
Seed treatment	0.40	0.40	0.40	0.36	0.36
Drainage system	0.63	0.63	0.63	0.63	0.63
Mollisols	0.31	0.31	0.31	0.31	0.31
Mollisols/Alfisols mix	0.07	0.07	0.07	0.07	0.07
Average slope (% grade)	2.76	2.76	2.76	2.76	2.76
Total acres managed	681.5	681.5	681.5	681.5	681.5

Table C.2 Input levels into the corn yield variability model corn

	No cover crop	Cover crop	Cover crop with reduced N
Cover crop	0	1	1
Average N application	212.15	212.15	108.42
Standard deviation of N application	25.54	25.54	25.54
Average P application	65.03	65.03	65.03
Average K application	78.91	78.91	78.91
Seed treatment	0.40	0.40	0.40
Average slope	2.76	2.76	2.76
No-till	0.62	0.62	0.62
Tile drainage	0.63	0.63	0.63
Mollisols	0.31	0.31	0.31
Alfisols/Mollisols	0.07	0.07	0.07
Northeast Indiana	0.43	0.43	0.43

Table C.3 Input levels into the corn yield variability model for soybeans

	No cover crop	Cover crop
Cover crop	0	1
Average N application	7.42	7.42
Average P application	17.47	17.47
Average K application	38.11	38.11
Seed treatment	0.36	0.36
Average slope	2.76	2.76
No-till	0.94	0.94
Tile drainage	0.63	0.63
Mollisols	0.31	0.31
Alfisols/Mollisols	0.07	0.07
Northeast Indiana	0.43	0.43

Figure C.1 Baseline corn yield input distribution (bu/acre)

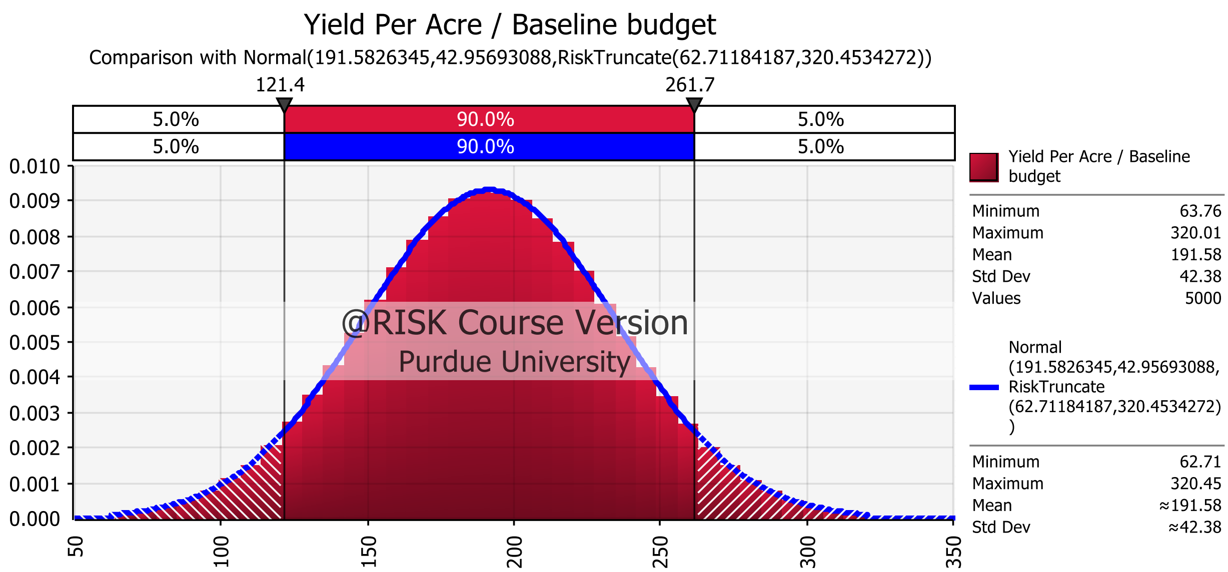


Figure C.2 Cover cropped corn yield input distribution (bu/acre)

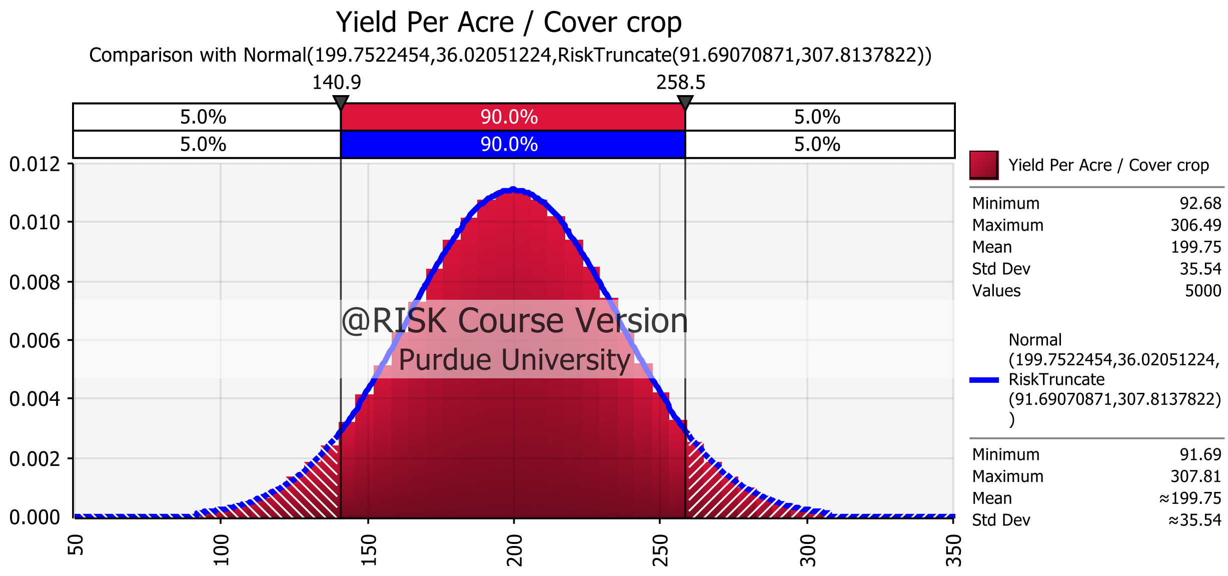


Figure C.3 Cover crops with reduced nitrogen corn yield input distribution (bu/acre)

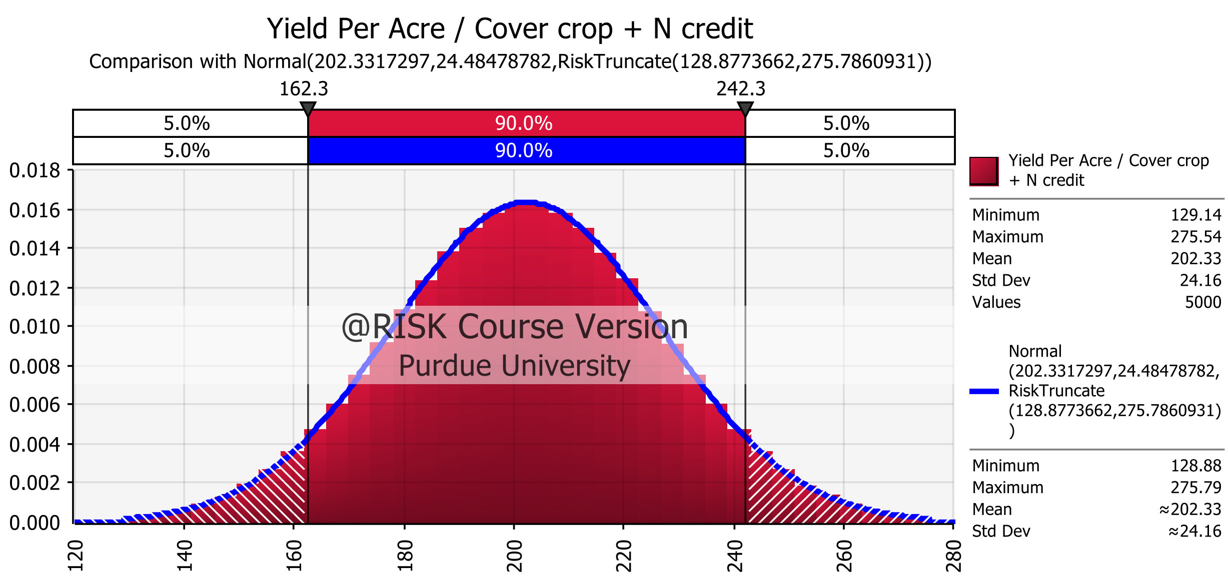


Figure C.4 Baseline soybean yield input distribution (bu/acre)

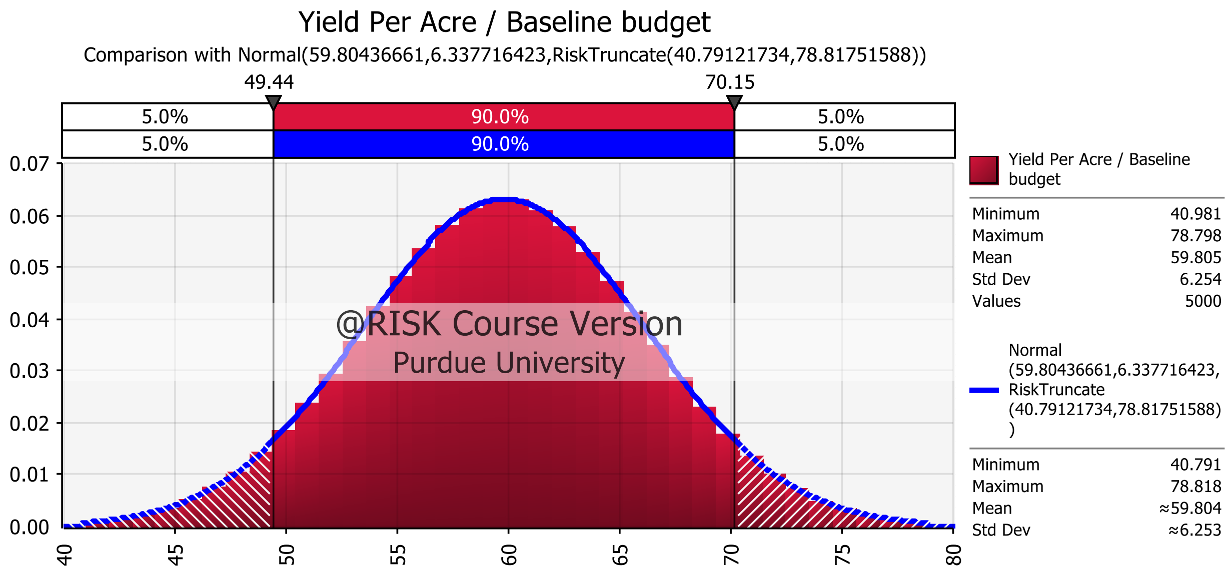


Figure C.5 Cover cropped soybean yield input distribution (bu/acre)

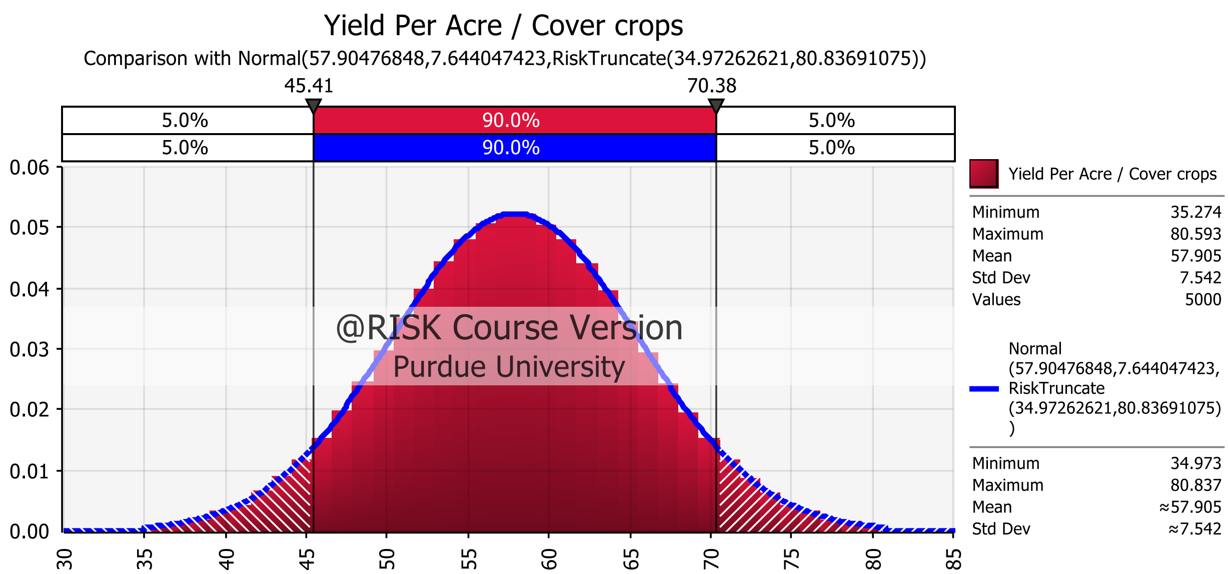


Figure C.6 Fitted distribution for the real corn price ($/bu)

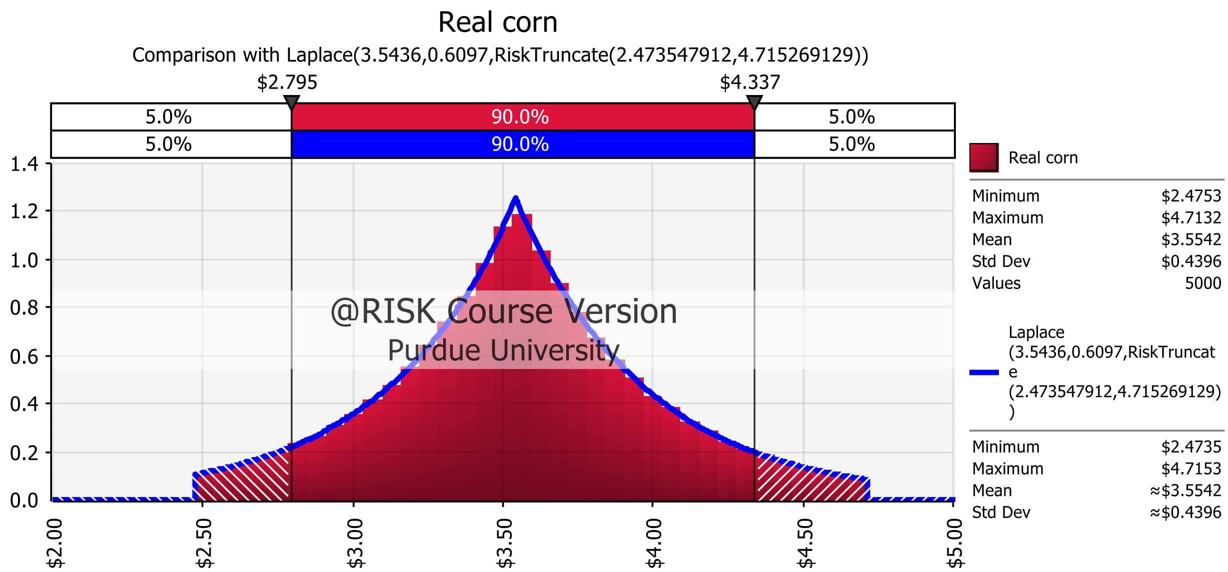


Figure C.7 Fitted distribution for the real soybean price ($/bu)

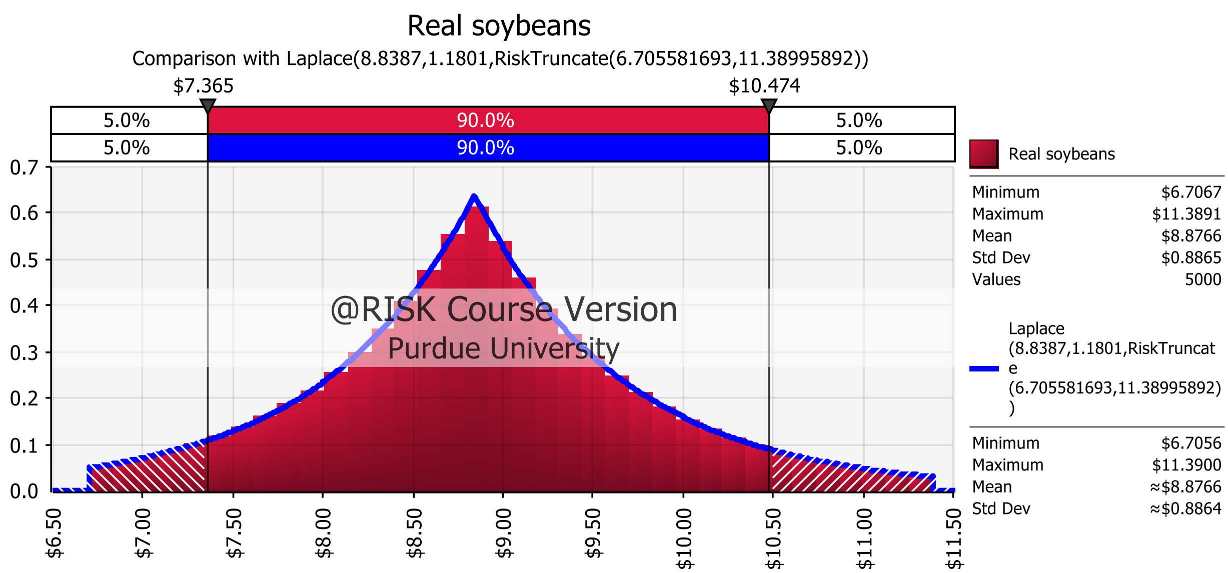


Figure C.8 Fitted distribution for the real anhydrous ammonia price ($/ton)

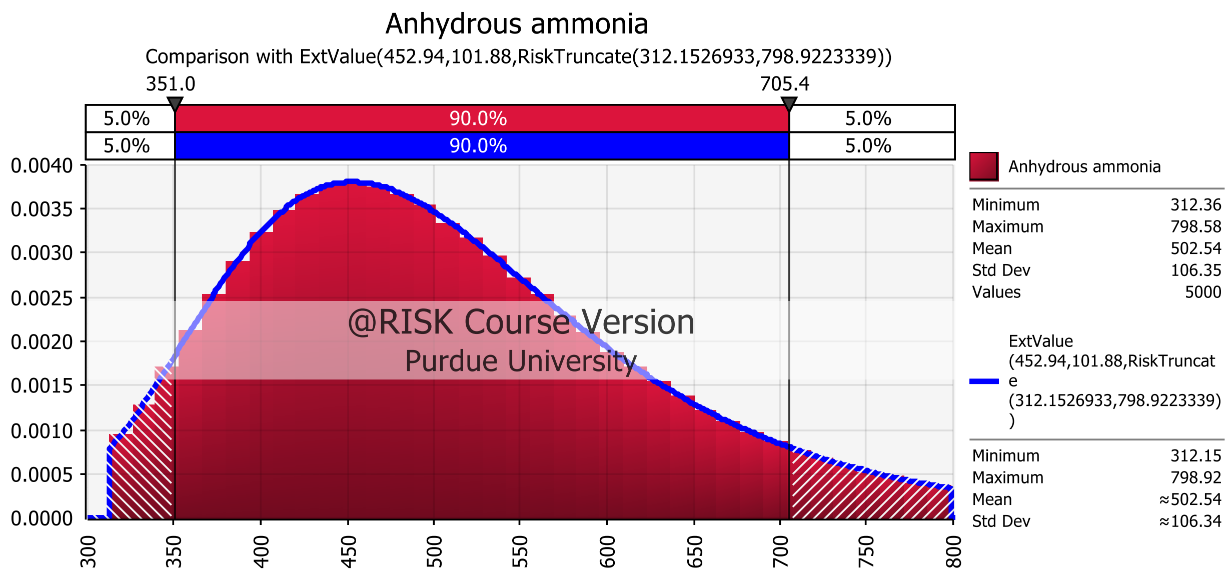


Figure C.9 Fitted distribution for the real diammonium phosphate price ($/ton)

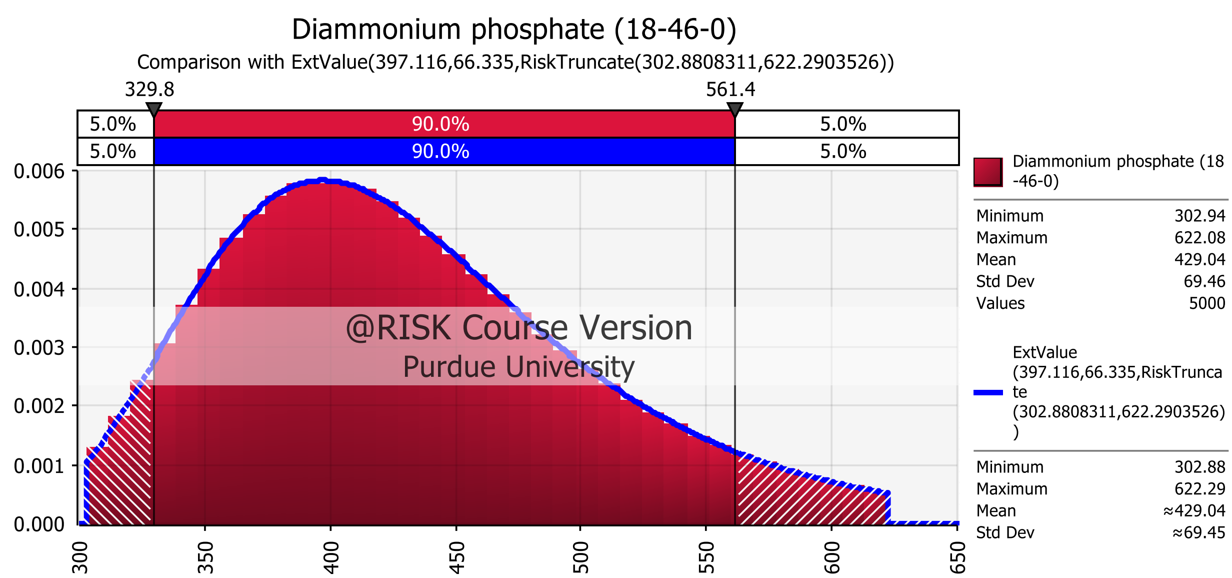


Figure C.10 Fitted distribution for the potassium chloride real price ($/ton)

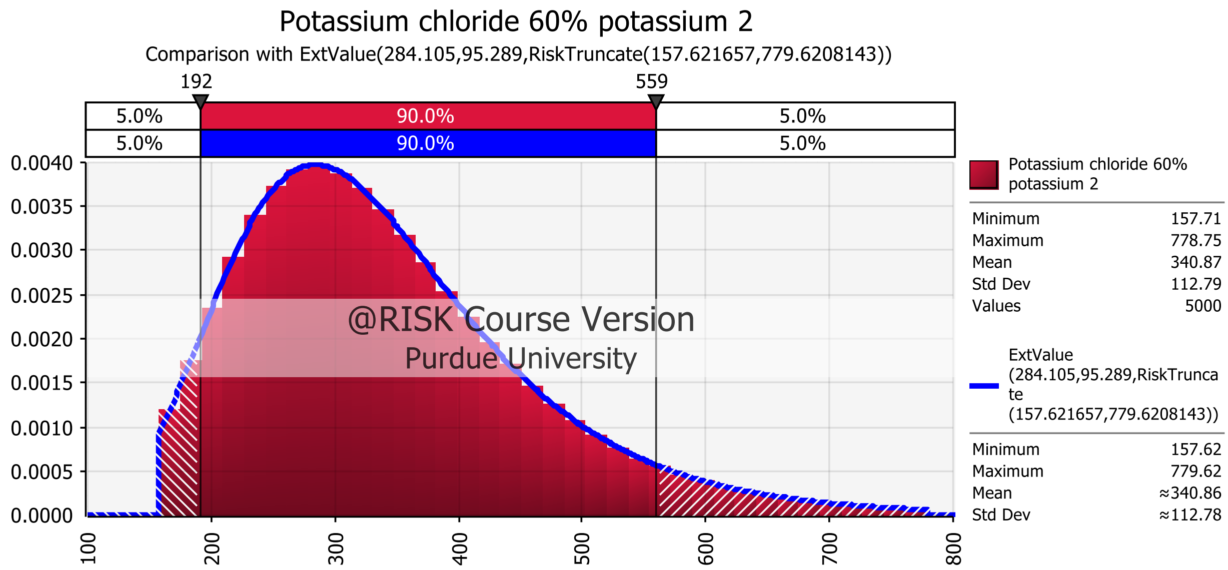


Figure C.11 Binomial distribution defining the probability of a second herbicide application

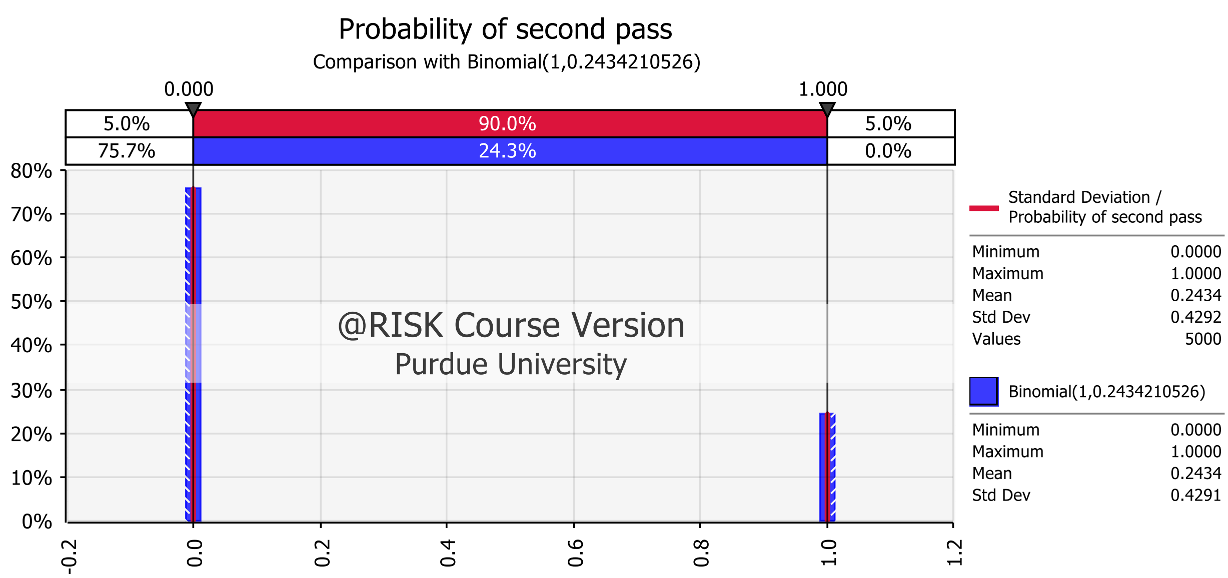
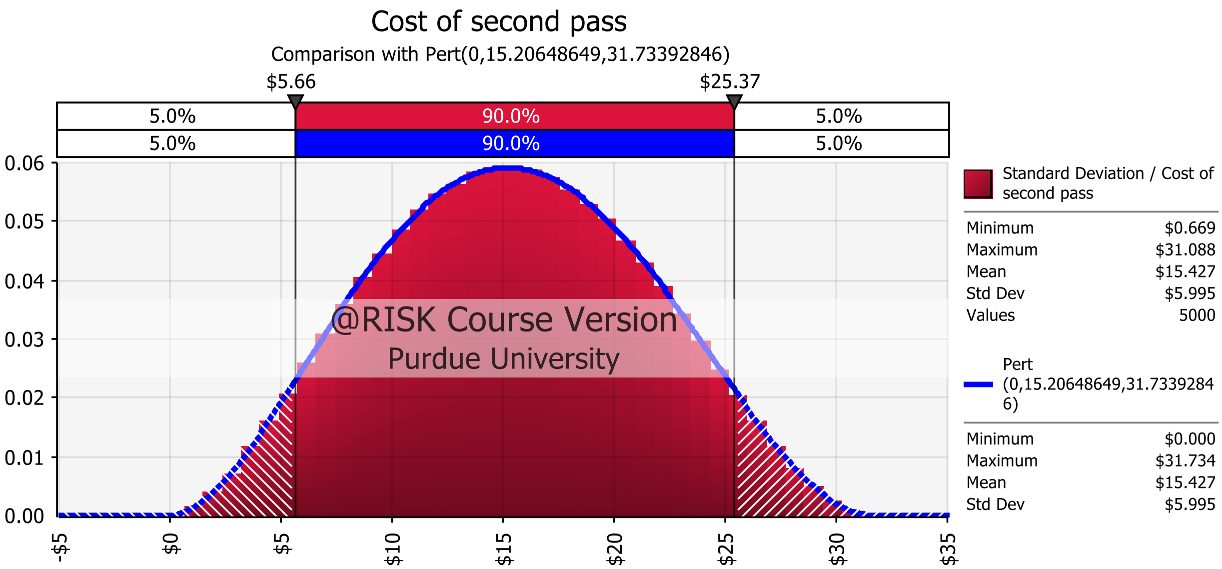


Figure C.12 PERT distribution defining the cost of a second herbicide application



APPENDIX D: ADDIDIONAL TABLES AND FIGURES OF RESULTS

Table D.1 Regression coefficients for corn yield model

VARIABLES	(Full sample) Cash crop yield (bu/acre)	(20% Trimmed sample) Cash crop yield (bu/acre)
Cover crop = 1	23.48	-4.451
	(19.78)	(38.18)
Applied nitrogen (lbs/acre)	0.00767	0.481*
	(0.147)	(0.270)
1.covercrop#c.n_app	-0.159*	-0.148
	(0.0847)	(0.137)
c.n_app#c.n_app	0.000271	-0.00114
	(0.000404)	(0.000919)
Applied phosphorus (lbs/acre)	-0.0530	-0.179
	(0.0584)	(0.109)
1.covercrop#c.p_app	0.0436	0.175
	(0.121)	(0.176)
Applied potassium (lbs/acre)	-0.0372	0.0189
	(0.0320)	(0.0767)
1.covercrop#c.k_app	0.0616	0.0780
	(0.0856)	(0.117)
No-till	-0.723	31.09**
	(5.890)	(14.52)
1.covercrop#c.notill	-2.645	9.271
	(10.23)	(14.14)
Seed rate (thousands/acre)	0.824	6.007**
	(0.574)	(2.586)
Seed treatment	15.07***	12.11
	(5.246)	(8.781)
Drainage system	5.559	-18.08
	(5.539)	(19.23)
1.covercrop#c.drain	1.096	17.28
	(7.882)	(13.82)
Mollisols	5.286	7.904
	(3.547)	(7.714)
Mollisols/Alfisols mix	14.65**	43.83***
	(5.885)	(11.68)
Average slope (% grade)	-0.770	0.910
	(0.746)	(2.532)
1.covercrop#c.slope	-3.642**	-1.905
	(1.721)	(3.410)
Total acres managed	-0.00236	0.0127
	(0.00218)	(0.0116)

1.covercrop#c.fsize	0.00906**	0.0193
	(0.00422)	(0.0118)
Year = 2010	-4.487	-31.62**
	(9.746)	(14.18)
Year = 2011	-16.51*	-22.75**
	(8.654)	(10.45)
Year = 2012	-48.50***	-66.27***
	(9.459)	(10.97)
Year = 2013	5.821	-0.497
	(9.038)	(10.77)
Year = 2014	20.37**	6.026
	(8.576)	(10.09)
Year = 2015	-18.42**	-30.79***
	(9.098)	(11.71)
Year = 2016	12.03	-10.35
	(8.727)	(10.73)
Year = 2017	6.993	5.405
	(9.254)	(9.948)
Year = 2018	32.05***	12.68
	(8.917)	(10.47)
County = 2, Allen	-16.10	-54.35**
	(13.02)	(25.70)
County = 3, Carroll	44.58***	28.63
	(12.33)	(36.76)
County = 4, Cass	35.74***	18.31
	(12.45)	(35.52)
County = 5, DeKalb	-9.357	-9.463
	(8.721)	(23.23)
County = 6, Fayette	-5.146	-38.76**
	(14.14)	(17.04)
County = 7, Hancock	5.511	34.75*
	(10.09)	(19.01)
County = 8, Hendricks	-8.235	-36.02*
	(13.68)	(19.24)
County = 9, Henry	-6.827	-4.727
	(12.73)	(24.63)
County = 10, Howard	33.16***	
	(11.42)	
County = 11, Johnson	7.240	-46.13**
	(11.42)	(22.84)
County = 12, Madison	10.20	
	(11.47)	
County = 13, Montgomery	-33.61	-58.35**
	(20.57)	(25.63)
County = 14, Noble	15.21	-8.551
	(14.42)	(23.35)

County = 15, Shelby	-10.58	15.78
	(11.81)	(25.01)
County = 16, Tippecanoe	14.00	-30.31
	(12.67)	(20.13)
County = 17, Tipton	27.19***	
	(8.842)	
County = 18, Union	19.75*	-17.60
	(11.97)	(24.28)
County = 19, Wabash	11.47	
	(16.68)	
County = 20, Wells	13.22	-12.82
	(9.413)	(18.59)
Constant	126.4***	-74.97
	(25.10)	(89.83)
Observations	432	197
R-squared	0.706	0.676

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table D.2 Regression coefficients for soybean yield model

VARIABLES	(Full sample) Cash crop yield (bu/acre)	(20% Trimmed sample) Cash crop yield (bu/acre)
Cover crop = 1	8.127***	10.81*
	(2.853)	(5.553)
Applied nitrogen (lbs/acre)	-0.161	0.0497
	(0.168)	(0.323)
1.covercrop#c.n_app	0.209	0.00572
	(0.176)	(0.341)
Applied phosphorus (lbs/acre)	0.0611	0.00900
	(0.0586)	(0.122)
1.covercrop#c.p_app	-0.0269	0.0117
	(0.0645)	(0.124)
Applied potassium (lbs/acre)	-0.000244	-0.00109
	(0.0127)	(0.0324)
1.covercrop#c.k_app	-0.00326	-0.00268
	(0.0185)	(0.0376)
No-till	0.0354	1.487
	(1.491)	(2.966)
1.covercrop#c.notill	-2.824	-3.230
	(2.786)	(5.805)
Seed rate (thousands/acre)	0.0350	0.142**
	(0.0278)	(0.0574)
Seed treatment	1.110	5.267**
	(1.543)	(2.166)
Drainage system	1.407	9.472
	(1.746)	(6.341)
1.covercrop#c.drain	-7.945***	-13.92***
	(2.453)	(4.960)
Mollisols	0.0718	2.878*
	(1.000)	(1.727)
Mollisols/Alfisols mix	-1.116	-5.811*
	(1.315)	(3.090)
Average slope (% grade)	-0.0830	1.133*
	(0.302)	(0.584)
1.covercrop#c.slope	-0.506	-0.407
	(0.521)	(0.808)
Total acres managed	0.00148**	0.00306
	(0.000712)	(0.00196)
Year = 2010	0.459	2.119
	(2.044)	(3.506)
Year = 2011	-2.768*	-4.468
	(1.569)	(2.912)
Year = 2012	-0.00238	-2.411
	(2.078)	(3.417)

Year = 2013	0.317	-2.441
	(1.575)	(3.126)
Year = 2014	5.730***	5.217*
	(1.691)	(3.075)
Year = 2015	-2.603	-0.925
	(2.003)	(3.300)
Year = 2016	7.121***	5.984*
	(1.902)	(3.372)
Year = 2017	3.200*	3.579
	(1.793)	(3.237)
Year = 2018	7.187***	8.143**
	(1.932)	(3.231)
County = 2, Allen	-9.828***	-14.54***
	(3.571)	(4.800)
County = 3, Carroll	5.037	-2.621
	(4.208)	(8.195)
County = 4, Cass	-0.850	-14.49*
	(4.280)	(8.157)
County = 5, DeKalb	-1.568	-1.295
	(2.181)	(6.673)
County = 6, Fayette	-5.183*	-4.202
	(2.962)	(4.392)
County = 7, Hancock	-1.131	0.175
	(2.754)	(6.270)
County = 8, Hendricks	-7.782*	5.269
	(4.226)	(5.099)
County = 9, Henry	-2.317	-10.04
	(3.890)	(7.339)
County = 10, Howard	3.601	
	(3.810)	
County = 11, Johnson	3.789	8.307
	(3.040)	(5.513)
County = 12, Madison	1.775	5.596
	(3.209)	(5.893)
County = 13, Montgomery	-1.871	10.61**
	(2.693)	(4.281)
County = 14, Noble	1.808	4.919
	(3.303)	(5.895)
County = 15, Shelby	0.863	-5.533
	(2.696)	(8.275)
County = 16, Tippecanoe	-2.936	7.640*
	(2.663)	(4.231)
County = 17, Tipton	8.286***	
	(2.225)	
County = 18, Union	-0.459	-4.527
	(3.446)	(5.913)

County = 19, Wabash	-14.23**	
	(5.560)	
County = 20, Wells	-3.989	-10.44*
	(2.648)	(5.824)
Constant	43.87***	13.98
	(5.224)	(11.73)
Observations	454	217
R-squared	0.504	0.504

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure D.1 Yield response to nitrogen in corn (full sample)

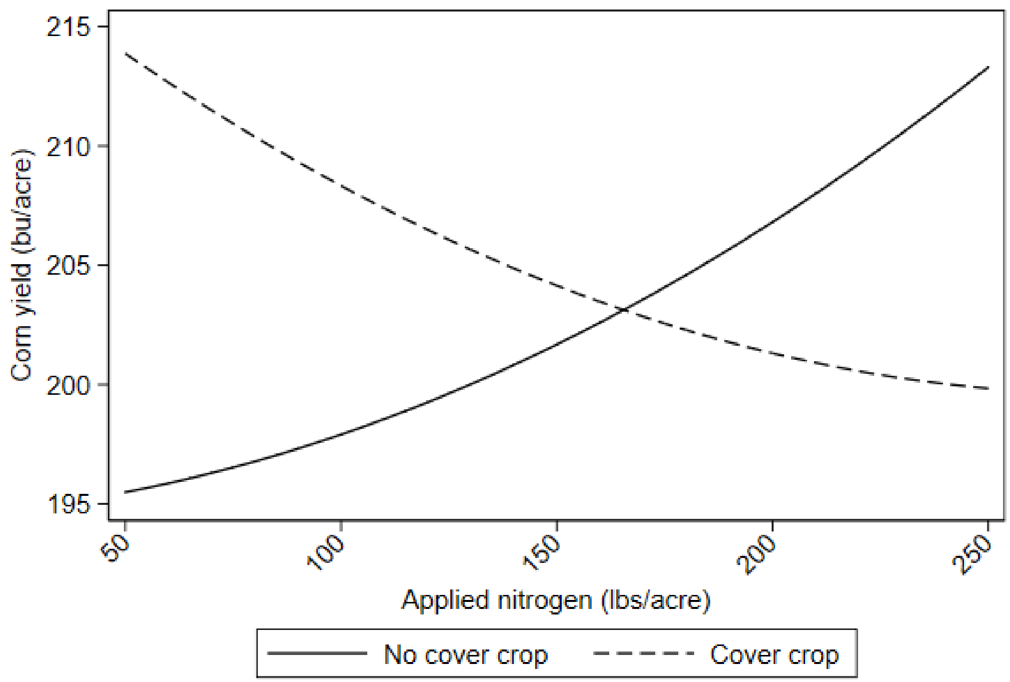


Figure D.2 Marginal effect of cover crops on corn yield (full sample)

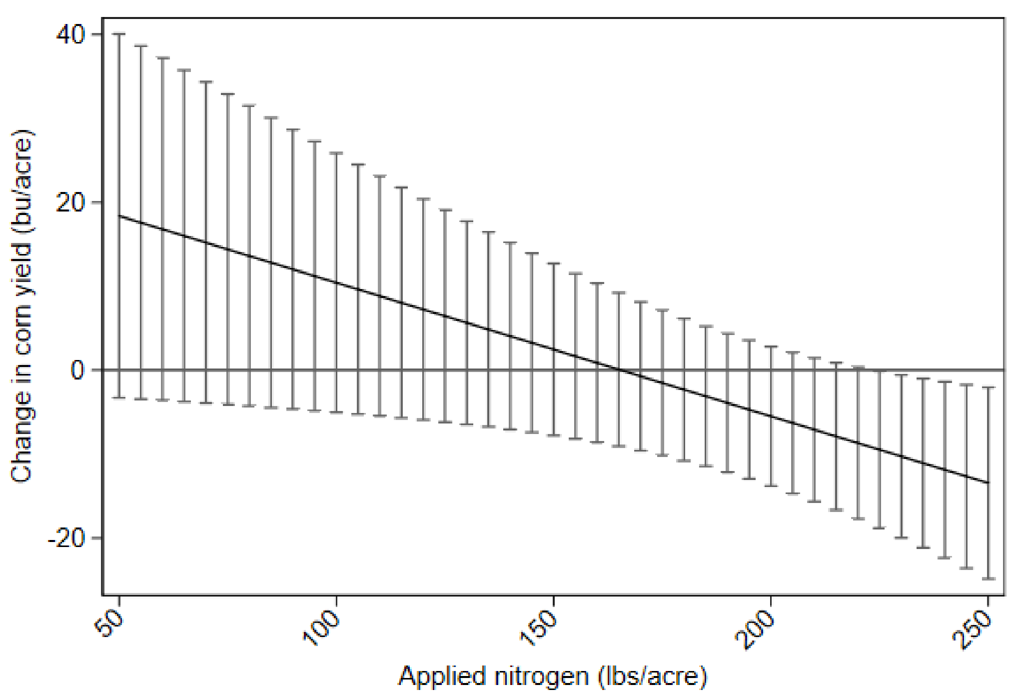


Figure D.3 Predicted soybean yields (full sample)

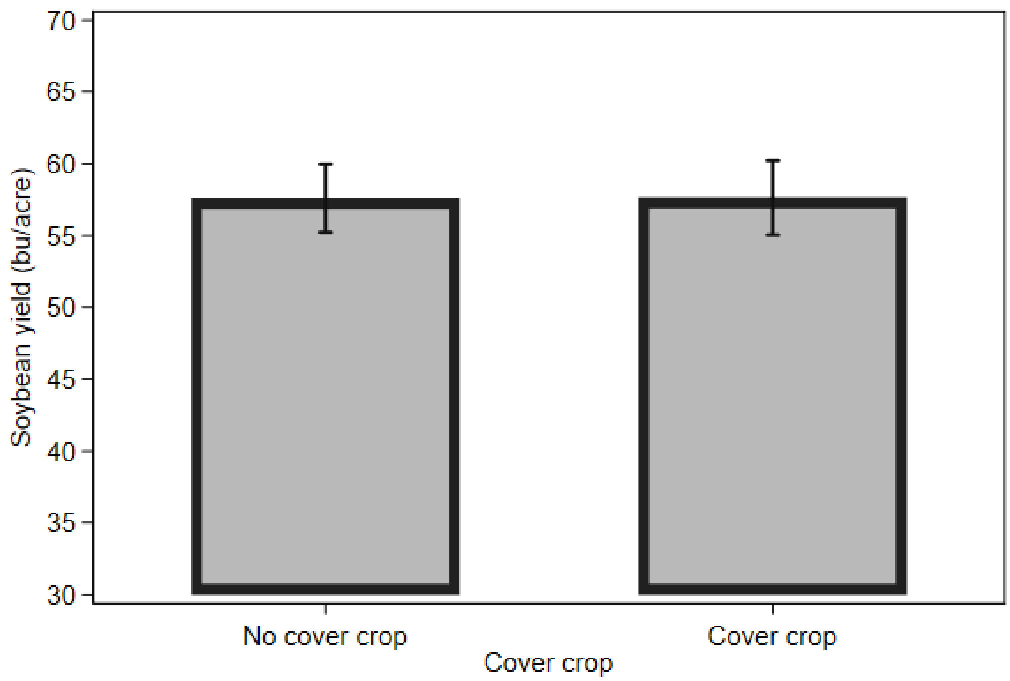


Figure D.4 Predicted soybean yields without tile drainage (full sample)

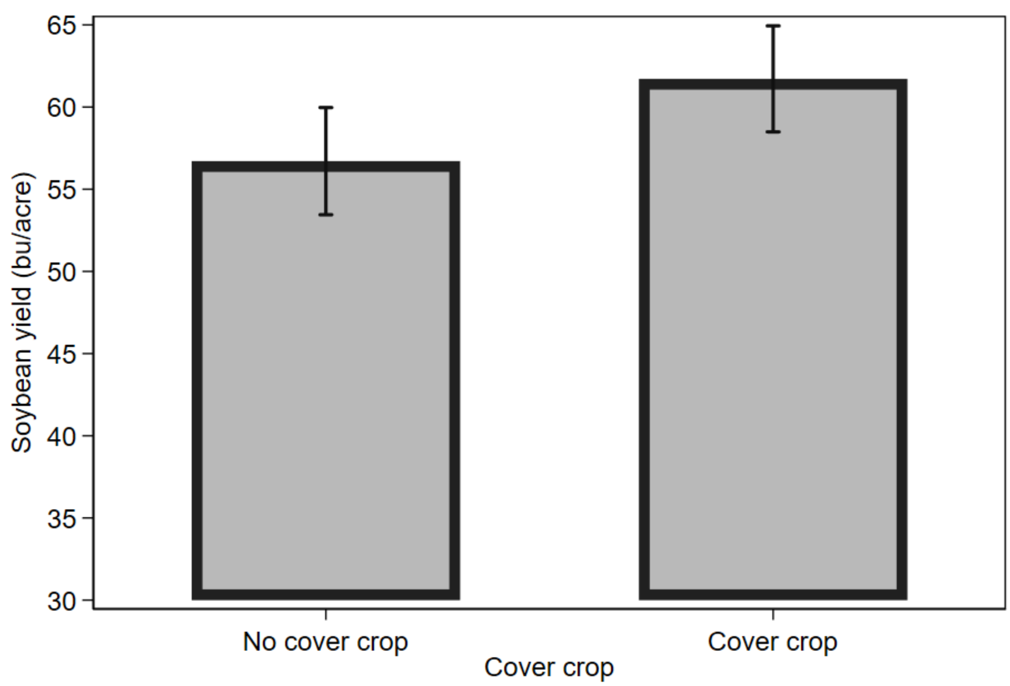


Table D.3 Regression coefficients for corn yield variability model

VARIABLES	(1) sd_yield	(2) sd_yield	(3) coefvar	(4) coefvar
covercrop	-169.2***	-171.4**	-100.9***	-107.7*
	(44.44)	(71.19)	(29.58)	(55.53)
av_n_app	-0.561***	-0.582**	-0.314***	-0.355
	(0.156)	(0.275)	(0.108)	(0.224)
c.covercrop#c.av_n_app	0.801***	0.789*	0.466***	0.482
	(0.248)	(0.404)	(0.167)	(0.315)
sd_n_app	-2.252***	-3.087**	-1.210**	-1.723
	(0.775)	(1.503)	(0.526)	(1.273)
c.covercrop#c.sd_n_app	2.260*	2.254	1.406*	1.439
	(1.306)	(2.015)	(0.806)	(1.591)
c.av_n_app#c.sd_n_app	0.0109**	0.0166*	0.00558*	0.00874
	(0.00420)	(0.00898)	(0.00291)	(0.00781)
c.covercrop#c.av_n_app#c.sd_n_app	-0.0107	-0.00987	-0.00669	-0.00630
	(0.00805)	(0.0122)	(0.00492)	(0.00974)
av_p_app	-0.0522	-0.122	-0.00667	-0.0432
	(0.0828)	(0.125)	(0.0579)	(0.0857)
av_k_app	0.0989*	0.111	0.0671*	0.0834
	(0.0540)	(0.0911)	(0.0365)	(0.0680)
treatment	9.306	10.05	3.219	2.423
	(6.406)	(9.389)	(4.858)	(6.986)
slope	1.592*	0.489	1.087*	0.352
	(0.860)	(0.753)	(0.595)	(0.626)
notill	3.454	4.853	6.460	8.828
	(6.275)	(8.159)	(5.594)	(7.671)
drain	-11.04***	-9.941**	-10.85***	-9.288***
	(4.061)	(4.407)	(3.416)	(3.331)
moll	-8.499**	-8.476**	-8.024***	-8.003**
	(3.845)	(4.141)	(2.911)	(3.262)
mix	-13.69**	-20.03***	-8.478**	-12.57**
	(5.974)	(7.158)	(3.969)	(4.762)
ne	-3.226	-8.312	-0.618	-3.449
	(5.044)	(7.080)	(3.317)	(4.572)
Constant	150.2***	158.1***	87.09***	96.77**
	(30.55)	(52.05)	(20.75)	(40.61)
Observations	107	69	107	69
R-squared	0.389	0.433	0.418	0.425

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.4 Marginal effects of cover crops on corn yield variability (full sample)

	Standard deviation	Coefficient of variation
Cover crop	-20.85***	-14.22***
	(5.619)	(4.196)
Observations	107	107

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.5 Regression coefficients for soybean yield variability model

VARIABLES	(1) sd_yield	(2) sd_yield	(3) coefvar	(4) coefvar
Cover crop	0.846	1.306	1.641	2.426
	(1.391)	(1.402)	(2.598)	(2.622)
av_n_app	0.0747	0.0633	0.193	0.189
	(0.0750)	(0.0762)	(0.139)	(0.144)
av_p_app	0.0583	0.0410	0.117	0.0835
	(0.0531)	(0.0565)	(0.0931)	(0.103)
av_k_app	-0.0328*	-0.0255	-0.0728**	-0.0588
	(0.0180)	(0.0195)	(0.0318)	(0.0356)
Treatment	-0.936	0.914	-2.312	0.676
	(0.845)	(1.307)	(1.506)	(2.408)
Slope	0.142	0.0800	0.458	0.347
	(0.253)	(0.263)	(0.480)	(0.499)
notill	-0.357	2.258	0.212	5.080*
	(1.034)	(1.556)	(1.781)	(2.657)
drain	-0.827	0.507	-2.222	-0.146
	(0.836)	(0.944)	(1.564)	(1.779)
moll	1.156	1.951*	1.846	3.117*
	(0.926)	(1.025)	(1.636)	(1.800)
mix	1.477*	3.177***	2.707**	5.442***
	(0.756)	(0.912)	(1.265)	(1.405)
ne	-1.864**	-3.569***	-2.491*	-5.590***
	(0.736)	(1.119)	(1.334)	(2.006)
Constant	7.246***	3.832**	12.75***	6.790**
	(1.417)	(1.795)	(2.601)	(3.108)
Observations	106	68	106	68
R-squared	0.173	0.339	0.216	0.365

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table D.6 Marginal effects of cover crops on corn yield variability (full sample)

	(1)	(3)
	herearemargins1	herearemargins1
VARIABLES	y1	y1
Cover crop	0.846	1.641
	(1.391)	(2.598)
Observations	106	106

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1