THREE ESSAYS ON THE ECONOMICS OF PRECISION AGRICULTURE

by

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DEDICATION

I would like to dedicate this thesis to my beautiful wife and my beloved parents.

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ABSTRACT

Precision agriculture is rapidly emerging as a cornerstone of transformation in modern farming as farmers adjust to changing needs in their management and dissemination of technology. While technological innovations associated with precision agriculture—such as remote sensing, GIS mapping, and drone usage—are widely recognized, there remains a substantial gap in understanding the economic implications and behavioral responses that accompany its adoption. This research addresses that gap by exploring three key questions related to the economics of precision agriculture, each examined through a distinct empirical lens. Chapter two investigates the current state of PA adoption in the United States and GIS mapping use in Canada, drawing on data from the Census of Agriculture. The analysis explores the relationship between farm size and adoption behavior, revealing that larger farms are significantly more likely to implement precision technologies. Capital availability and investment capacity also appear to be key drivers of adoption. Chapter three evaluates the impact of a pro-precision agriculture policy on farmers' risk behavior, proxied by crop insurance coverage rates. Using county-level data from the Summary of Business and Risk Management Agency (RMA) for corn producers and applying a two-way fixed effects difference-in-differences framework, the study finds that farmers in Virginia—following the implementation of the tax credit policy—reduced their insurance coverage rates relative to North Carolina. This suggests that PA adoption may influence farmers' perceived need for insurance and their attitudes toward risk. Chapter four shifts the focus to Australia, analyzing how farmers planned adoption of drones relates to their technical efficiency. Using survey-level data and a two-stage approach with truncated regression and subsample bootstrapping, the study finds a positive association between drone adoption plans and technical efficiency. This chapter contributes to the growing literature on how emerging technologies may support productivity improvements in agriculture. Collectively, these three chapters offer new empirical evidence on the adoption, policy impacts, and efficiency outcomes associated with precision agriculture, providing insights that are vital for researchers, policymakers, and practitioners alike.

CHAPTER ONE

INTRODUCTION

Precision agriculture (PA) is a modern farm management strategy that uses information technologies to collect and analyze data from multiple sources in order to make site-specific decisions about crop production. It aims to optimize inputs like water, fertilizer, and pesticides—applying them only where and when needed—to increase productivity, enhance sustainability, and reduce environmental impact. The term PA was first used in a workshop sponsored by Montana State University in Great Falls, Montana, in 1990. The notion of PA emerged in the 1980s in the US, and in the 1990s it was termed PA (Oliver et al., 2013).

The urgency to enhance agricultural productivity with limited use of resources has never been greater. With the growing impacts of rising input costs and labor constraints, PA could potentially offer a promising path forward for sustainable intensification. However, its full potential can only be realized if economic feasibility and adoption barriers are better understood. In order to have successful dissemination of PA, target potential laggard farmers, and realize its economic gains, broad-scale economic studies need to be undertaken. This study is part of this attempt to address some of the economics of PA. Although there has been a plethora of studies regarding the agronomy and environmental benefits of PA, very few studies have been dedicated to understanding the economics side of PA for the USA. Besides, little is known about the current adoption and economics of PA in the US. While the primary focus is the U.S., this thesis draws on international cases to enrich the analysis. This thesis contributes to the literature by providing one of the first multi-country comparative analyses of the economics of PA, combining insights from the U.S., Canada, and Australia. It explores both adoption behavior and downstream effects on efficiency and risk management—dimensions that are rarely studied together.

To address these questions, this thesis adopts a “Three Essays” structure to provide a focused yet comprehensive exploration of the economics of PA. Each essay addresses a distinct research question, using different datasets, methods, and geographic contexts to illuminate different dimensions of PA. This modular approach is particularly well-suited for examining a topic as complex and multifaceted as PA, which spans technology adoption, policy incentives, and production efficiency. The first essay (Chapter 2) investigates the primary drivers and spatial patterns of PA adoption across different agricultural systems in the United States and Canada. It uses a comparative descriptive and econometric framework to understand where PA adoption is concentrated and which farm- or region-level characteristics are associated with uptake. The second essay (Chapter 3) examines how Virginia’s tax credit policy—designed to encourage PA and conservation tillage—affects farmers’ risk management behaviors, particularly crop insurance coverage, using a difference-in-differences approach. The third essay (Chapter 4) focuses on Australian farmers and explores the link between farm-level technical efficiency and the intention to adopt emerging PA technologies, such as drones, using a two-stage DEA model combined with bootstrapped regression.

A key motivation running through these chapters is the question: What databases currently exist that allow us to analyze Precision Agriculture adoption, and what can we learn from them? In leveraging available datasets from the U.S., Canada, and Australia, this thesis contributes not only empirical insights but also a roadmap for how diverse sources of data can be used to study the economics of PA. While each chapter stands alone analytically, together they build a broader narrative about how PA is being adopted, how policy may influence its diffusion, and how it relates to farm-level economic performance. This structure provides the flexibility to use empirical strategies best suited to each question, while contributing cumulatively to a deeper, more nuanced understanding of PA's economic landscape.

The findings from this research have important implications for agricultural policy, technology dissemination strategies, and farm-level decision-making in the context of an increasingly data-driven agricultural economy. By examining adoption behavior, policy impacts, and efficiency outcomes across diverse contexts, this thesis aims to inform not only academic discourse but also the practical decisions of policymakers, researchers, and agricultural stakeholders engaged in promoting effective and equitable integration of Precision Agriculture technologies.

CHAPTER TWO

PRECISION AGRICULTURE IN THE US and CANADA

Introduction

PA can potentially lead to a significant shift in farming, harnessing technological advancements to optimize agricultural practices. This approach can potentially reduce the environmental impact of agriculture and enhance efficiency and productivity (Balafoutis et al., 2017; Bongiovanni & Lowenberg-DeBoer, 2004). For countries like the US and Canada, where most farms are large in terms of area, PA can be particularly useful in optimizing farming practices, despite the substantial investment required, owing to the possible benefit of economics of scale. While PA demands a significant financial investment, there is a growing amount of research finding promising financial returns. Schimmelpfennig (2018) suggests that using variable rate input applications, automated guidance systems, and soil and yield maps can lead to a potential 2% increase in net returns. Moreover, there is evidence that PA can sustain long-term profits and cover the large initial investment. Yost et al. (2019), in their on-field trial study in Central Missouri, found that PA paid off 97% of the field with profit, and the cost of the initial investment was recovered in 11 years, with the profit remaining sustainable thereafter. In a previous study, Yost et al. (2017) noted that while soil and yield mapping increased wheat yield, corn yield remained unchanged. However, PA contributes to increased yield stability for both corn and wheat. These findings may help boost farmers' confidence, especially those reluctant to adopt PA due to its high upfront cost.

Despite the increasing volume of research and investment for PA and promotion by private and government agencies, its widespread adoption in North America remains barely explored, particularly at national and sub-national levels in countries like Canada and the USA. Understanding the factors that influence PA adoption is essential for devising effective policies, guiding public and private investments, and supporting farmers in transitioning to data-driven farming practices. Targeted interventions are required to achieve the goal of technology dissemination, and studying adoption patterns is a great approach. Literature suggests that adoption of PA is influenced by a range of socioeconomic and institutional factors. Farm size, farmer education, access to technical training, risk preferences, and availability of credit all play critical roles in determining the likelihood of adoption (Pathak et al., 2019; Yatribi, 2020). Larger, commercially oriented farms are generally better equipped to absorb the financial risks associated with PA investments, while smaller farms may lack the capital or confidence to experiment with new technologies (Daberkow and McBride, 2003). In addition, capital or income is positively related to adoption of PA (Yatribi, 2020). Without attention to these needs, the full potential of PA to transform agriculture may remain unrealized, particularly among under-resourced or risk-averse farming populations.

In both the US and Canada, there has been a concerted effort to promote PA adoption (Ken Research, 2025). Also, research on creating new forms of PA technology has been actively pursued. However, a key question remains: to what extent have North American farmers embraced these technologies? This knowledge gap is inadequately addressed, as there is limited scholarly work studying the national-level scenario of PA adoption. The use of yield maps, yield monitors, soil maps, variable rate technology (VRT), drones, and guidance systems at the state level in the United States was recently examined by McFadden et al. (2023). However, no other comprehensive research has examined adoption at a more detailed level, such as the county for the US. In addition, no studies for the US have attempted to explore factors relating to adoption at the county level. Previous studies using survey data were only limited to a particular state or region of the US (see Kolady et al., 2021; Castle et al., 2016). Besides, an extensive literature review failed to produce published results of studies on the adoption and factors affecting PA in Canada. This study fills the gap by examining granular-level adoption patterns and exploring the relationships between various factors and PA adoption at the county level in the United States, as well as at the Census Consolidated Subdivision (CCS) level in Canada. While studies on factors related to the adoption of PA at a small scale can be traced, no such research has been conducted for Canada. This study advances literature by offering the first cross-national, fine-scale analysis of PA adoption in North America. By leveraging county-level data for the US and CCS-level data for Canada, it moves beyond the limitations of prior regional or state-level surveys. The study also uniquely investigates the underlying drivers of adoption across both countries, allowing for comparative insights that can inform more geographically targeted policies and extension services.

This study uses three different datasets. First, county-level data from the National Agricultural Statistics Service's (NASS) Census of Agriculture that offers data on PA adoption and the Bureau of Economic Analysis (BEA), which provides data on agricultural gross domestic product (GDP), were employed for all the descriptive analysis for the US. Additionally, data on the location of PA businesses in Montana was collected and presented for further investigation. Second, the Canadian Census of Agriculture data offers data at the CCS level, which allowed us to delve deeper into studying the effect of farm size on the adoption of GIS mapping while controlling for meaningful variables potentially related to adoption. We reported the current adoption rate and relationship dynamics of adoption with key economic indicators. While limited data prevents comprehensive econometric analysis spanning time for the US, our findings provide a valuable snapshot and lay the groundwork for future research. Further, the findings from Canada helped us strengthen our results for the US, as we found interesting relationship among the variables studied for Canada, which are consistent with the findings for the US. The potential impact of this study on future research and policy formulation is significant, as it can bridge the knowledge gap surrounding adoption patterns, inform investment decisions, and underscore the factors associated with adoption. Looking ahead, longitudinal analysis, robust econometric modeling, and targeted regional and farm-specific studies are essential for fully realizing the transformative potential of PA in the US, ushering in a more sustainable and efficient future for American agriculture, and bringing about an exhilarating and anticipated changeover in the domain.

Literature Review

The main goal of this chapter is to study the factors related to the adoption of PA. A plethora of studies have aimed to explore the factors related to the adoption of PA in the US and beyond, at the state level or region level. In most cases, farm size was found to be a significant driver of PA adoption. Castle et al. (2016) conducted a farmer-level survey in Nebraska with 135 row crop farmers on factors affecting adoption of PA. Their results from Poisson regression suggest that farmers with larger crop areas are more likely to adopt PA. They also found that non-smartphone users are reluctant to use PA. Their results suggest the relevance of large farm areas and the use of technology to PA. The positive relationship between farm size and PA adoption was also evinced in Lambert et al. (2015) and Larson et al. (2008). In line with this, Schimmelpfennig and Lowenberg-DeBoer (2020), using ARMS phase 2 data at US national level provided evidence that with the increase in wheat farm acres from 250 acres to 3000 acres, adoption of guidance systems can increase from 18% to 80%, VRT seeding from 2% to 7%, VRT fertilizer from 4% to 10%, and VRT and VRT pesticides from 1% to 5%. Substantial increases were also found in yield mapping, with an increase from 8% to 15%; soil mapping, with an increase from 2% to 4%; and remote sensing, with an increase from 0.1% to 1%. Adoption of these technologies was even more pronounced in the case of corn farms, with up to a 69%, 41%, 34%, 9%, 47%, 26%, and 10% increase in adoption of guidance systems, VRT seeding, VRT fertilizer, VRT pesticides, yield mapping, soil mapping, and remote sensing, respectively, with the increase of farm acres from 250 acres to over 3000 acres. Similar types of results can also be found in the context of other countries. For instance, Vecchio et al. (2020) conducted a survey on 200 farmers in Italy. Results from their logit model suggest that larger farm-size farmers are more likely to adopt PA. Further, some research from Germany also supports the positive relation between farm size and adoption of PA. For example, Paustian and Theuvsen (2016), with their survey data of 227 German farmers, showed that with one unit increase in the arable land, a farmer is 6.7 times more likely to adopt PA. The highest level of adoption is observed on farmland with more than 500 ha. Also, they noted that farm size less than 100 ha is negatively associated with adoption. This finding is also reflected in the study of Tamirat et al. (2018) on Germany and Denmark, where they showed that farm size is a significant driver of adoption. In addition, Yarashynskaya and Prus (2022), in their review study of 16 papers on Poland, noted that larger farmers are more likely to adopt PA.

Further, another strong driver of the adoption of PA reported in the literature is farm capital. The farm capital may enable farmers to invest in PA technologies like GPS systems and drones. With more financial resources, farmers might be better positioned to afford these tools, making adoption less risky and more profitable. Swinton and Lowenberg-Deboer (2001) argued that due to the reliance on expensive capital to automate information processing, PA will be particularly appealing in regions where capital is more abundant than management labor. Next, Tey and Brindal (2012) noted that a farm with higher capital has a greater financial capacity to make large investments. In addition, Bentivoglio et al. (2022) presented a theoretical framework of PA adoption in Brazil, where they acknowledged that lack of financial capital is a major constraint for agricultural innovation in small and medium-sized farms. Meanwhile, some studies have argued that human capital is a significant driver of adoption (see Paxton et al., 2011; Tey and Brindal, 2012).

More studies emphasize certain demographic characteristics of the farm operators related to the adoption of PA. Age primarily has been widely explored with its connection to PA use. Daberkow and McBride (2003) analyzed the 1998 ARMS survey data for the USA at the national level to study the factors affecting awareness and adoption of PA. They found that age is negatively related to both awareness and adoption. Possible reasons are that old farmers are less aware and more conservative and may have less knowledge of advanced technology. Also, older farmers have a short time frame to have such a large investment for which money recovery takes a lot of time (Kolady et al. 2021). A similar outcome was reported in a study by Castle et al.

(2016) in Nebraska. They collected survey data on row crop farmers in 2014-15, and their regression results indicated that as age increases, farmers become more reluctant to adopt PA. Further, Torrez et al. (2016) in Kansas, with data from 453 farmers, found that 83% of them adopt PA, which is very high compared to the national level. They also found a negative association between the operator's age and adoption of PA. Moreover, the negative relation was more pronounced in yield monitors with GPS and less pronounced in variable rate technology. In contrast to the findings, some papers found a positive relation between operator age and adoption. Isgin et al. (2008) used the Ohio Farmland Lease and Precision Agriculture Survey of 816 respondents from to study the factors related to PA adoption. Their results showed that age is positively correlated with adoption. Similar results were reported in Torbett et al. (2007), where they studied the factors for cotton farmers in the USA states of Alabama, Florida, Georgia, Mississippi, North Carolina, and Tennessee. Meanwhile, some studies showed that age has no effect or an insignificant relationship with adoption. Paustian and Theuvsen (2017) claimed that age has nothing to do with adoption in a study of German farmers. Kolady et al. (2021), in their study of South Dakota farmers, evinced that age has a null effect on the adoption of PA.

Some other adoption drivers discussed in the literature include, but are not limited to, operator's education, land tenure, and operator's experience. Education is mostly positively related to adoption of PA (see Walton et al. 2008; Larson et al. 2008; Pierpaoli et al. 2013). Whereas there is also evidence by Martin et al. (2008) that education has no effect on adoption. Moreover, land ownership has been found to be a significant positive driver of adoption (Isgin et al., 2008, and Roberts et al., 2002). A farmer is more inclined to manage land they own in a better way compared to land they rent (Roberts et al., 2004). In addition, the role of farming experience has been claimed to be largely insignificant in the literature (Tey and Brindal, 2012). However, Khanna (2001) evinced that experience leads to higher adoption of variable rate applicators. Next, soil quality was cited as a significant driver of adoption in Pierpaoli et al. (2013), as they mentioned that farmland with fertile soil that pays off more production is where PA is mostly adopted.

Data

The study was made possible with two different groups of datasets from the US and Canada, respectively. First, the data on county-level adoption of PA in the US is sourced from the National Agricultural Statistics Service (NASS) Census of Agriculture (COA) dataset. This dataset is cross-sectional and only covers the year 2022. Moreover, it also contains data on farm size, sales revenue, ownership and crop type. Second, Gross Domestic Product (GDP) and Agricultural GDP data were collected from the Bureau of Economic Analysis (BEA). The final dataset was obtained by merging the two sources by county. Our dataset includes most of the counties in the continental USA. Additionally, the paper conducted a more in-depth examination of PA in Montana using data on the presence of PA businesses and service providers obtained through a thorough online search.

The second group of data set for Canada came from the Canadian Census of Agriculture. We used the Canadian census data from the years 2011, 2016, and 2021. The data was employed at the CCS level. The data spanned all the provinces with 2035 CCSs. Information on farm size, lag farm size, operator’s age, land tenure, farm capital, sex, crop acreage, and adoption of GIS mapping was retrieved for analysis. Data on the adoption of GIS mapping was only available for the years 2016 and 2021. Lag farm size data was retrieved from the years 2011 and 2016. We merged the data for three different years by CCS and year. While comprehensive data on the adoption of PA in Canada are not currently available, we proxied it with the use of GIS mapping—a core component of modern PA technologies.

Variables

For the US dataset, the adoption rate of PA is calculated as the number of farms adopting any of the PA equipment divided by the total number of farms times 100 reported in a county. As for Canada, GIS adoption rate was calculated by dividing the number of farms with GIS mapping by the total number of farms in a CCS times 100. Farm size was determined by dividing total crop acreage by the number of farms in a CCS. Farm average capital was calculated by dividing the total farm capital (in monetary value) by the number of farms in a CCS. Further, Average age denotes the mean age of farm operators in a CCS, and Female represents the number of female operators. Partnership refers to the number of farm entities operating as partnerships. Additionally, Lag farm size is calculated as the total crop acreage divided by the number of farms in the same CCS five years prior. The main motivation behind averaging most variables by the number of farms is to standardize the data across CCSs, allowing for meaningful comparisons and reducing the influence of scale differences. Furthermore, we standardized all variables by subtracting the mean from each value and dividing by the standard deviation, in order to compare the effects of all coefficients.

Methodology

The first part of the research, which uses U.S. data, is purely descriptive in nature due to data limitations and is intended to highlight key patterns and relationships in PA adoption.

Notably, the U.S. dataset lacks variation at the county level, which restricts the use of any causal inference modelling. It is worth noting that COA labels any farm adopting PA if it uses any PA equipment. Descriptive summaries of the dataset are visualized with graphs and maps. No econometric method was applied due to several reasons. First, although the dataset is cross-sectional, it does not vary by county. Instead, it varies by domain categories (e.g., farm sales level, farm size, farm type), making it infeasible to merge all the key variables simultaneously. Second, due to its cross-sectional nature, the dataset does not allow us to capture any causal relationship. Finally, the scope of this chapter is to offer a broad overview of PA rather than study any policy effect.

The second part of the research with the Canadian dataset uses an Instrumental Variable (IV) method to account for potential endogeneity of farm size. Farm size in much research has been considered endogenous (Noack and Larsen, 2019; Chamberlin and Jayne, 2020). While larger farms may facilitate greater technology adoption, it is also possible that farms adopt technologies that enhance productivity and enable expansion, leading to larger farm sizes. Additionally, unobserved factors such as managerial ability, access to credit, or risk tolerance could simultaneously influence both farm size and the adoption of PA, biasing regression estimates. Measurement errors in reporting land area can further compound the issue. In order to account for this endogeneity, many include fixed effects, but this can only handle unobserved fixed factors. Hence, our target is to overcome time-varying omitted variables using an IV. Following the methodology of Weiss (1999) and Dolev and Kimhi (2008), we use lagged farm size—specifically, the average farm size in the same CCS five years prior—as an instrument for current farm size. The rationale is that past farm size is likely correlated with current farm size due to the persistence in farm structure, but it is less likely to be directly influenced by current unobserved shocks affecting GIS adoption, thus satisfying the relevance and exclusion criteria for a valid instrument. Farm size is likely to be related to future farm size due to factors like access to resources and economies of scale. Larger farms today tend to have more resources to expand in the future. However, past farm size doesn't significantly influence current technology adoption, as adoption is driven by more immediate factors like access to information, financial capacity, and current market conditions, rather than historical farm size. Thus, while farm size today can predict future size, it doesn't directly determine the adoption of new technologies. We employed a two-stage least squares model with fixed effects to account for as much endogeneity as possible. Combining fixed effects with the IV approach can be traced in the work of Milner et al. (2018) and Hahn et al. (2007). While looking at the pairwise relationship among our variables we found a clustered relationship between adoption of GIS mapping and Farm size which we further discovered to be potentially coming from type of crops grown (see appendix). We created a new dummy variable to categorize CCSs based on crop dominance. Specifically, each CCS was labeled as either Corn-Soybean, Wheat, or Canola dominant, depending on which of these crops had the highest acreage within that unit. The decision to group corn and soybeans into a single category reflects a common agricultural practice in Canada: these two crops are typically grown in rotation on the same fields due to their complementary agronomic characteristics. Rotating corn and soybeans helps manage pests, reduce disease pressure, and improve soil fertility, making this combination a distinct and functionally integrated cropping system. As such, treating corn and soybeans as a unified group better captures the underlying farming systems and land-use decisions that influence crop allocation patterns in these regions. In addition, it enables us to retain a larger number of observations, thereby potentially enhancing the robustness and stability of our regression estimates. While crop type may influence GIS adoption, we did not include crop type or its interaction with farm size in our instrumental variable (IV) model due to identification constraints. In our setup, farm size is the endogenous variable, which we instrument using lagged farm size and other exogenous controls in the first stage. Although it is theoretically possible to include an interaction between farm size and crop type in the second stage, doing so would require us to also treat the interaction term as endogenous. This would necessitate an additional instrument—specifically, an interaction between lagged farm size and crop type—to satisfy the exclusion restriction and maintain proper identification. However, we do not have such an instrument available. As a result, including the interaction would render the model under identified and invalidate our IV estimation. To preserve the validity of our identification strategy, we excluded both crop type and its interaction with farm size from the model. Finally, we ran our regression in three different groups: corn-soybean-dominant, wheat-dominant, and canola-dominant.

Two Stage Least Squares (2SLS) Model

In a 2SLS model, a reduced form equation is employed to obtain the fitted values of the endogenous variable, in our case farm size. At first, we regressed our instrumental variable, which is lagged farm size and other exogenous control variables, and fixed effects on current farm size, which provides fitted values for farm size, which is used in the second stage. The first stage reduced form model is described below in eq. 2.1:

$$FarmSize_{ct} = \alpha + \beta_1 \cdot LagFarmSize_{ct} + \beta_2 \cdot Age_{ct} + \beta_3 \cdot Age_{ct}^2 + \beta_4 \cdot Female_{ct} + \beta_5 \cdot Partnership_{ct} + \gamma_t + \delta_r + \varepsilon_{ct} \tag{2.1}$$

Here, all the variables are standardized. Controls include mean age of operators, number of female operators, and number of farms with partnerships. All the variables except the fixed effects vary by CCS and year. γ_t and δ_r denote CAR (county agricultural region) and year fixed effect, respectively. Our results from the first-stage regressions showed that the relevance condition holds, as the coefficient on lag farm size was statistically significant and the regression F-stat was greater than 10 for all three groups. We also argue that lagged farm size satisfies the exogeneity condition, as it is plausibly uncorrelated with the contemporaneous error term. Unobserved shocks affecting the adoption of GIS mapping in the current period are unlikely to have an impact on farm size in the previous period because it was decided before the adoption decision in the current period. It is a valid tool in our model since this temporal ordering lowers the possibility of reverse causality and validates the idea that lagged farm size is exogenous to current adoption behavior.

In our 2SLS model, we include year and CAR fixed effects to control unobserved heterogeneity. Year fixed effects account for time-specific shocks that affect all regions equally, such as policy changes, economic conditions, or weather events. CAR fixed effects control for time-invariant regional characteristics like soil quality, historical farming practices, and infrastructure differences. Although our data is at the CCS level, we include fixed effects at the CAR level rather than the province level. CARs provide a more granular and agriculturally relevant unit than provinces, capturing regional differences in factors like soil quality, infrastructure, and historical practices. With around 82 CARs—compared to over 2,000 CCSs and only 10 provinces—this approach balances statistical efficiency and regional specificity, helping control for unobserved heterogeneity without overfitting the model. Together, these fixed effects help isolate the causal effect of farm size on GIS adoption by removing bias from unobserved factors that vary across time or regions.

In the second stage, we take the farm size fitted values and other exogenous control variables and fixed effects and regress them on GIS adoption, which is our outcome variable (Eq. 2.2). The instrumental variable approach helps us isolate the exogenous portion of farm size.

$$GISAdoption_{ct} = \alpha + \theta_1 \cdot \widehat{FarmSize}_{ct} + \theta_2 \cdot Age_{ct} + \theta_3 \cdot Age_{ct}^2 + \theta_4 \cdot Female_{ct} + \theta_5 \cdot Partnership_{ct} + \gamma_t + \delta_r + \varepsilon_{ct} \tag{2.2}$$

By using the fitted values of farm size in the second stage, we ensure that our estimate of the effect of farm size on GIS adoption reflects the causal relationship, isolating the exogenous variation in farm size that comes from the instrument (lagged farm size). This IV approach helps eliminate bias from any potential reverse causality or unobserved confounders that could distort the relationship between farm size and GIS adoption while still accounting for other meaningful control variables and showcasing their relationship with GIS adoption.

Results from the U.S. Data

Firstly, we start with the descriptive findings from the US data. It depicts the key findings of adoption and relationship of adoption and key economic indicators. Figure 2.1 shows the adoption rate of PA in the USA by county.

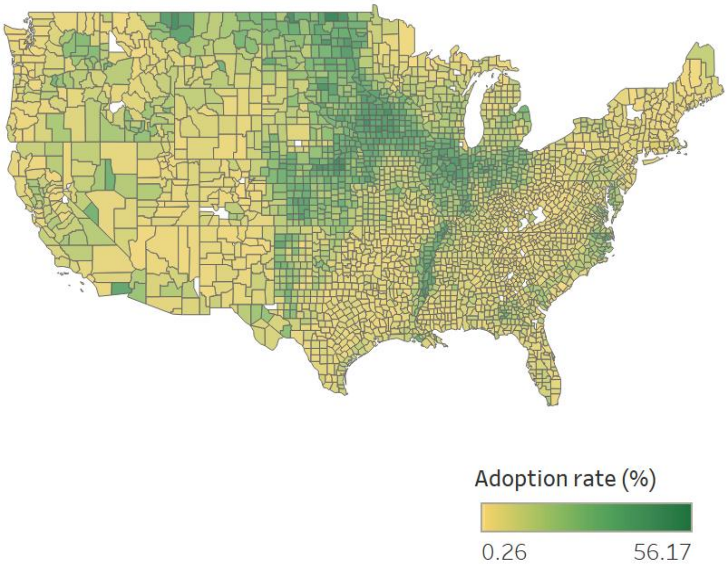


Figure 2.1 Adoption of PA in the continental USA. Note: The adoption of PA is showcased in the map of continental USA by county. The counties in white have missing data on the adoption rate.

The adoption rate of PA demonstrates notable regional clustering, with higher rates in the Midwest and surrounding vicinities, while other parts show much lower adoption. This observation prompts a vital question: Is there a spatial relationship in adopting PA? We categorized states into corn-belt and non-corn-belt regions and analyzed their respective adoption rates to explore this. Corn-belt regions include the state of Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin. Moreover, non-corn belt regions involve the rest of the other states. Our findings indicated that the mean adoption rate in corn-belt states is 17%, compared to just 11% in non-corn-belt states.

Additionally, we conducted a t-test to assess the significance of the mean difference, which yielded a t-value of -11 and a p-value close to 0, confirming that the difference in means is statistically significant. This significant difference suggests a potential association between the type of cropping system and the adoption of PA technologies. The higher adoption rate among corn belt farmers indicates that they may be more inclined to utilize advanced agricultural practices, possibly due to the intensive nature of corn production and the availability of advanced technology in the region. Additionally, the prevalence of agronomic research and extension services in these regions may facilitate the dissemination of PA techniques, further contributing to their adoption. However, it is important to note that while these findings point to a correlation, we cannot establish a causal relationship due to data constraints. Factors such as regional agricultural policies, farmer education levels, and access to technology could also influence adoption rates, complicating our ability to draw definitive conclusions. Future research should address these limitations by incorporating a more comprehensive dataset and exploring the underlying factors driving adoption in different agricultural contexts. It is also worthwhile examining the underpinning motivations and causes of adoption differences across different crop types. Suppose we can identify the need for PA relative to different types of crops. In that case, concerted efforts can be put forward to emphasize certain crops that mandate more PA equipment, thus concocting a pragmatic policy for disseminating such technologies.

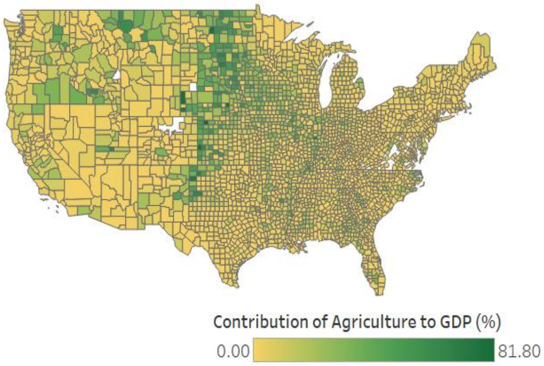


Figure 2.2 Agriculture's Contribution to GDP

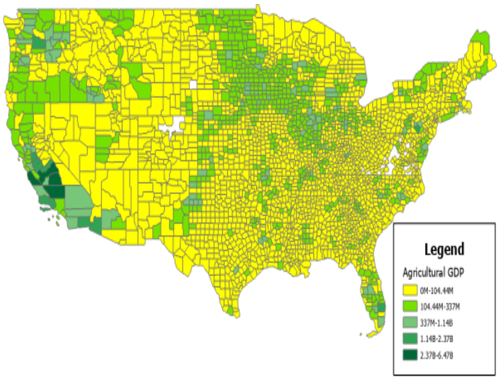


Figure 2.3 Agricultural GDP

Further, to obtain an in-depth insight into key economic factors tied to adoption, we first start by plotting the Agricultural GDP map. The value added by agriculture to the economy could be a significant driver behind adoption as counties with more agricultural production are supposed to have more capital for farming and thus better farming practices due to the concentration of more agri-tech businesses and dealerships, which make the PA tools reasonably available. When comparing the maps of PA adoption, agriculture's contribution to GDP, and agricultural GDP, intriguing correlations and potential causal relationships emerge. Both maps show an intense concentration of high values in the Midwest region, indicating that areas with greater agricultural productivity and higher agricultural GDP are more likely to adopt PA technologies. Additionally, the maps highlight regional disparities, with the Western and Southern regions generally exhibiting lower levels of agricultural GDP and PA adoption. This suggests that regions with higher agricultural GDP may have the resources and incentives to invest in PA technologies, further boosting productivity and economic output. To capture a clearer picture of this phenomenon, we plot the relationship between adoption rate and mean contribution of agriculture to GDP. By breaking down the contribution of agriculture to GDP across different adoption rate percentiles, we observe a clear positive linear relationship between the adoption rate and the agricultural sector's contribution to GDP. While a direct one-to-one correlation may not be apparent, the patterns observed point to a plausible relationship between the adoption of PA and agricultural GDP (Figure 2.2, Figure 2.3, and Figure 2.4).

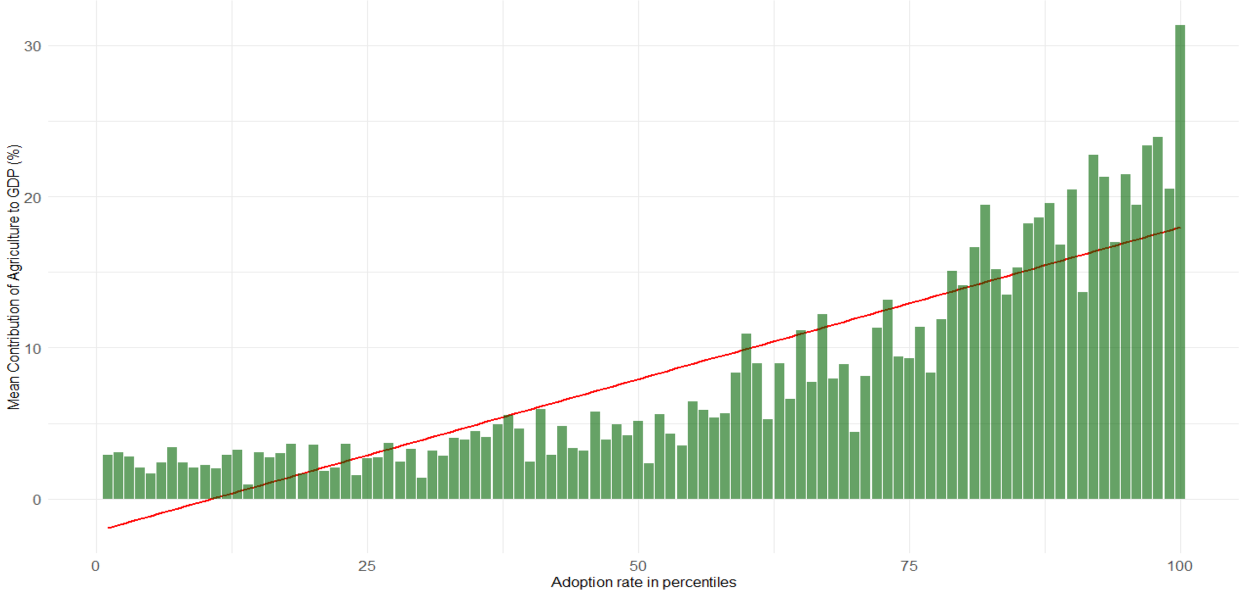


Figure 2.4 Relationship between Adoption and Contribution of Agriculture to GDP. Note: The relationship between PA's adoption rate and agriculture's contribution to GDP is plotted. The red linear line is the linear regression line that goes through the data points.

Next, to identify the direction of the relationship between the adoption of PA and the area of operation, we broke down the adoption level by different land area categories. It is apparent from Figure 2.5 that farms with higher land areas have higher adoption rates on average despite some occasional dips in the higher-level categories. The decrease in adoption rate for farms in the highest area category can be attributed to several factors. Larger farms may have already adopted many of the available technologies, leading to a saturation effect where fewer new innovations are left to be adopted. Additionally, the complexity and cost of integrating new practices on a large scale can make these firms more cautious or selective in their adoption decisions. Highly specialized operations in the highest area category might find that certain new technologies are not well-suited to their specific needs, further contributing to the lower adoption rates. Finally, these farms might prioritize optimizing existing practices over adopting new ones, affecting their overall adoption rates. Thus, while larger farms generally show higher adoption rates, these factors can lead to slightly lower adoption in very large farms.

Further, our analysis shows a general positive relationship between adoption rate and sales (Figure 2.5); however, we cannot conclusively determine causality for several reasons. First, our study is primarily cross-sectional, meaning it provides a snapshot of the data at a single point in time rather than tracking changes over time. Inferring causality requires observing how changes in one variable led to changes in another over a period. Second, there might be other factors influencing the adoption rate and sales volume that have not been accounted for. These omitted variables could affect the relationship between adoption rate and sales, making it difficult to isolate the effect of one on the other. Simply put, without longitudinal data tracking changes over time and without controlling for other influencing factors, we cannot definitively establish that changes in sales volume cause changes in adoption rate or vice versa. Even if any causality persists between farm sales and adoption rates, the direction of it could be either way. For instance, larger farms and farms with higher sales can have more financial means and capacity to employ PA. Farmers who use PA can expand their farm area to achieve economies of scale and might generate more revenues through sales as they might produce more output with smart technology.

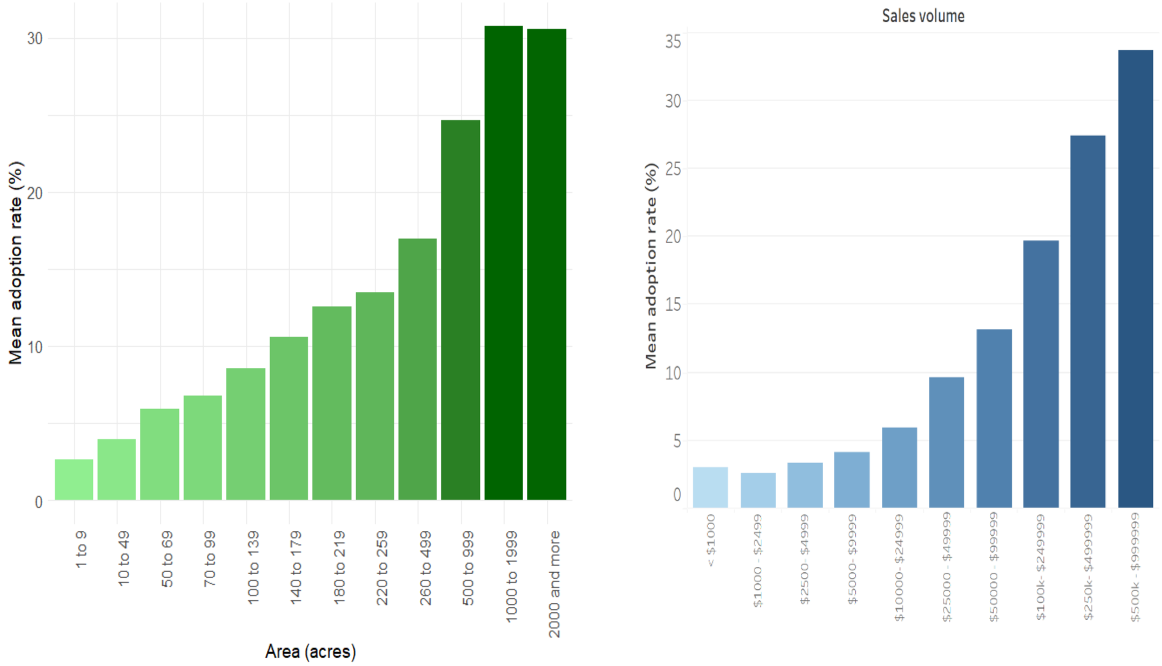


Figure 2.5 Relationship between Adoption and Area of Operation and Sales Volume.

After that, we depict a breakdown of the adoption rate by different farm categories. Note that these categories are, by default, present in the COA by NAICS classification. We cannot extend this further since there is no information on certain crop categories. Cotton farms are the largest adopters of PA, followed by oilseed and grain. Cattle feedlots rank third with more than a 20% adoption rate. Most livestock categories seem to be the least adopted, with sheep and goats having the lowest adoption rate, followed by poultry and eggs. However, hog and pig farms were found to have about a 10% adoption rate. Other crop types, including tobacco, greenhouse nursery and floriculture, vegetables and melon, sugarcane, and hay, had 17%, 12%, 7%, and 6% adoption rates, respectively (Figure 2.6). One thing clear from this result is that PA is very unpopular among livestock farmers and vegetable and fruit growers. Besides, adoption is higher in grain crops like corn, wheat, and barley. We are unsure of how the adoption varies by different grain crops; we can predict based on our findings from figure 1 that corn farmers are the ones who employ PA the most.

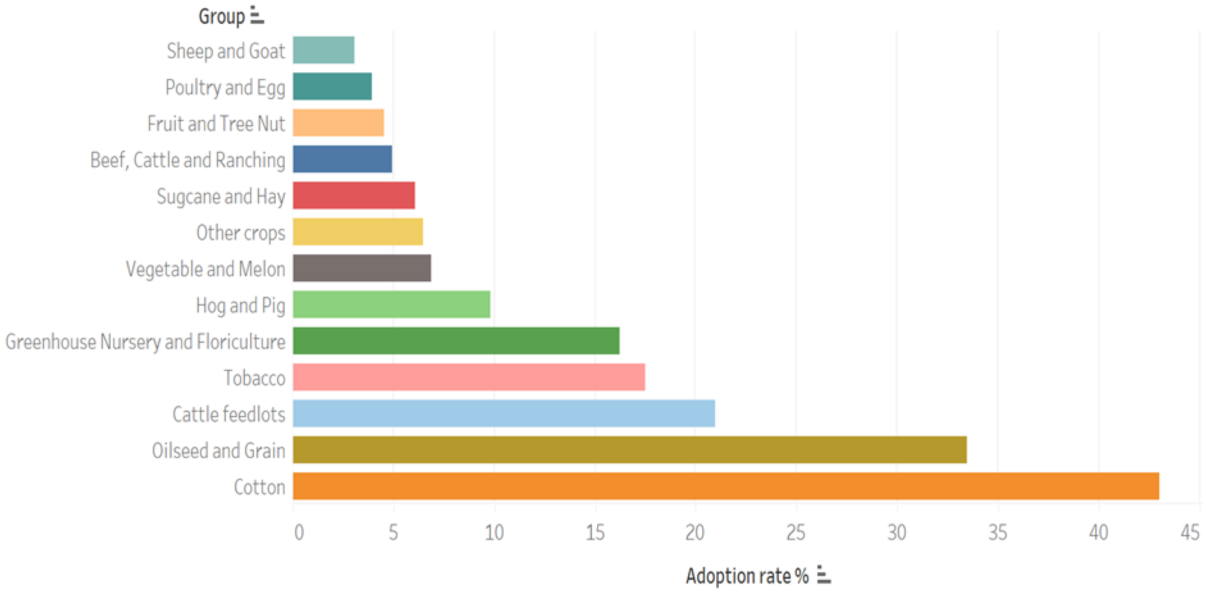
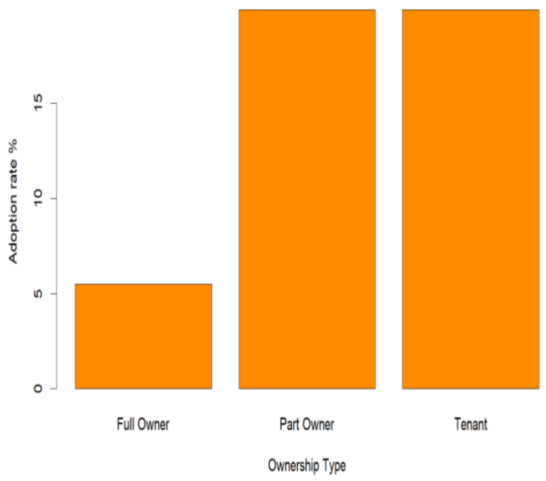


Figure 2.6 Breakdown of Adoption by Farm

Further, we analyzed the mean adoption rate by ownership type and found an intriguing pattern: full owners tend to have a lower adoption rate compared to part owners and tenants (Figure 2.7). This suggests a potential relationship between ownership status and the adoption of new technologies. One possible explanation is that jointly owned farms often have access to more financing resources than solely owned farms. PA technologies can be quite expensive, and farms with shared ownership might be better positioned financially to invest in these costly innovations. Additionally, during a field visit in Havre, Montana, we learned that full owners are often older farmers. Existing literature supports the notion that older farmers may be more hesitant to adopt new technologies (Ruzzante et al., 2021; Fikire et al., 2022), possibly due to a preference for traditional practices or skepticism about the benefits of novel approaches. This combination of financial capacity and potential generational attitudes towards technology may explain why full owners, despite having substantial resources, show lower adoption rates compared to part owners and tenants who might be more inclined or financially able to embrace new technologies.



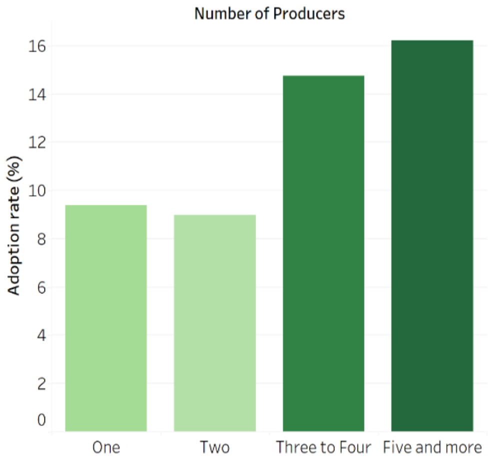


Figure 2.7 Relationship between Adoption and Type of Ownership

Figure 2.8 Relationship between Adoption and Number of Producers

Moreover, we attempted to extrapolate the relationship between the number of producers on a farm and the adoption rate. Although the relationship is not obvious, we can argue that there is some positive relation between the number of producers in an operation and the inclination to adoption (Figure 2.8). This is ascribed to the fact that a farm operation that has a greater number of producers can accumulate and invest a greater amount of physical and monetary capital. Since introducing PA is costly, it can be challenging for a single-owner farmer, while having more investors can be advantageous.

Then, we stepped forward to discover the special case of Montana's adoption rate and the relationship between the presence of PA business and the adoption rate by country. Figure 2.9 highlights the adoption rate of PA by county in 2022. It is discernible that the golden triangle regions (northwestern counties) are the most adopting; we observe minuscule adoption in the western and central reaches of the state. It should be noted that the areas of higher adoption are where most agricultural operations occur. In addition, we have also presented the location of PA businesses that sell products or offer farming services, including consulting (Figure 2.10 and 2.11). The data has been gathered through an online search, which might not be completely enlisting all such businesses. However, the spatial relationship between the location of the businesses and the adoption rate should still be considered imperative. Apparently, counties with higher adoption rates seem to have a significant presence of PA businesses, despite some exceptions. This is also an implication that there is the coexistence of a higher adoption rate and the presence of PA business. It would be interesting to have an econometric study showcasing correlation and the direction of causality.

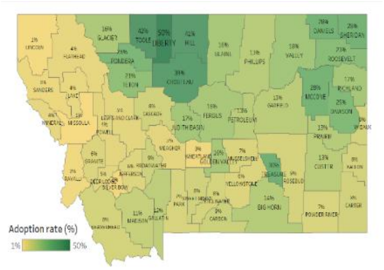


Figure 2.9 Adoption of PA in Montana

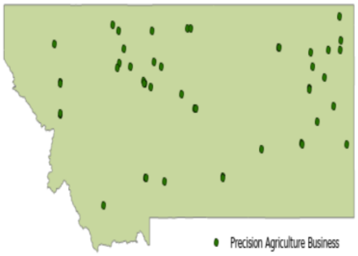


Figure 2.10 Location of PA Businesses in Montana

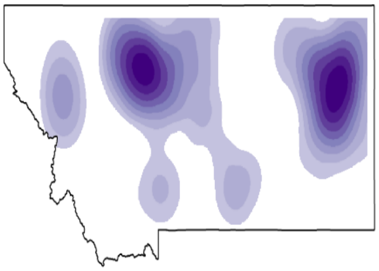


Figure 2.11 Heatmap of PA Businesses in Montana

Now, to delve deeper into the causal analysis with the adoption of PA, and in order to strengthen our findings related to the US, we move forward with the Canadian data. First, we discuss data summary statistics in the following section.

Descriptive Statistics from the Canadian Data

Before going into the econometric findings for the Canadian data, we discuss the data summary statistics. First, figure 2.12 shows the change in adoption of GIS mapping in Canada by CCS units from 2016 to 2021. We can argue that the change in adoption is uneven across geography. We can see a notable increase in the usage of GIS mapping in prairie provinces and parts of British Columbia. Some positive change is also observed in parts of Quebec and Ontario provinces. Parts of Quebec and the Maritime provinces show a decline in adoption over the 5 years. No data was reported for mostly northern Canada, which can be attributed to no agricultural activity around that area due to hostile geography. It is important to note that higher increase areas are mostly dominant with wheat. Further analysis will be drawn up in our econometric analysis to identify the factors related to changes in adoption.

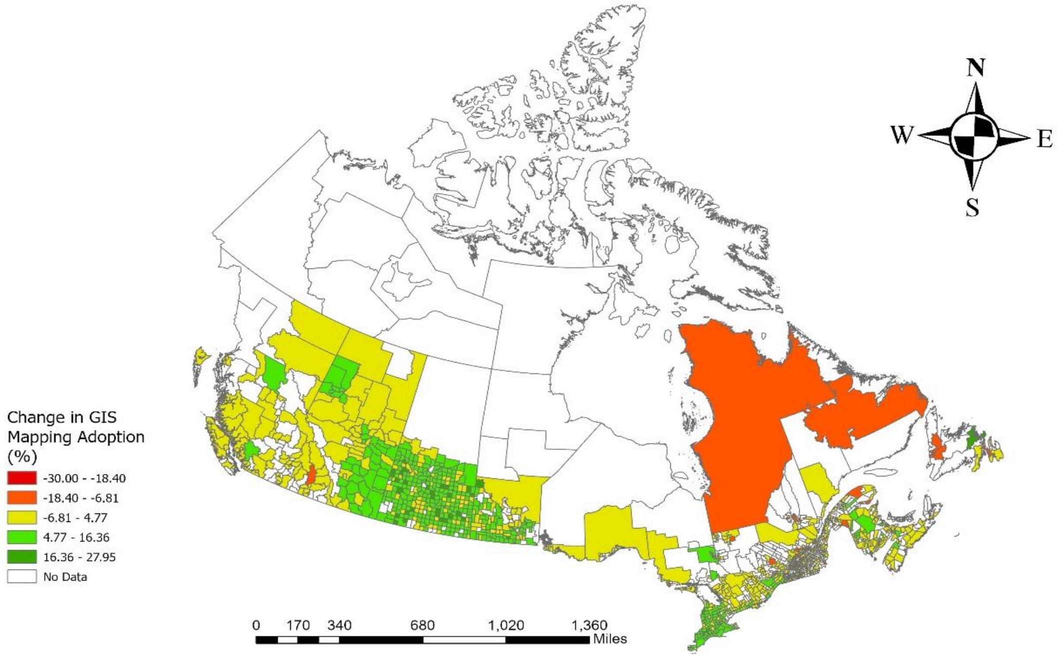


Figure 2.12 Change in Adoption of GIS Mapping from Year 2016 to 2021. Note: The adoption of PA is showcased in the map of Canada by CCS. The CCSs in white have missing data on the adoption rate.

Table 2.1 displays the summary statistics for the main study data with all the study variables. Farm size is expressed in acres. There is a substantial deviation between the mean and median of the farm size. Farm size is averaging at 644 acres, with a minimum of 13 acres and a maximum of 2804 acres. Lag 5-year farm size also follows the same deviation between mean and median. It should be noted that the mean and median of current farm size are greater than the 5-year lag farm size, which indicates that over the years Canada's per-head farm area is on the rise. The mean and median of the capital are pretty close, with an average of 3,037,470 CAD. It should be noted that although capital is reported in the summary statistics, it was not included in the baseline regressions due to its high correlation with farm size. However, it was included in the robustness checks. Regarding age, we only see older people reported in the data, as the age range is between 45 and 67.7, with a mean of 55. Further, the number of farms operated under a partnership structure and the number of female operators reveal substantial variation across CCSU. On average, there are about 36 partnership farms per unit, but the median is only 17, indicating a right-skewed distribution where a few regions have a large number of such farms (up to 377). Similarly, the number of female operators shows significant variation, with an average of 112 and a median of 60, suggesting that most areas have relatively few female-operated farms, while a few have very high numbers, reaching up to 2,100. GIS mapping adoption is low in Canada, with a mean of 12% adoption and a maximum of 46% in a particular CCS. Also, the adoption seems to vary a lot across different areas, as the standard deviation is also high.

Table 2.1 Descriptive Statistics of Study Variables for Canada

	Mean	Median	SD	Min	Max	N
Farm size	644.559	332.909	581.528	13.183	2804.698	
Lag Farm size	592.931	310.181	521.411	12.418	2490.988	
Capital	3037470	2823172	1598012	466938.8	12757697	2035
Age	54.79	55	2.61	45	67.7	
Partnership	35.809	17	54.559	1	577	
Female	112.105	60	161.672	5	2100	
GIS Adoption	12.088	10.638	7.535	0.478	46.153	

Further summary statistics are broken down by different crop-dominant CCS areas. Table 2.2, Table 2.3 and Table 2.4 represent the summary statistics for Corn-soybean dominant group, Wheat dominant group and Canola dominant group, respectively. There is a significant disparity in farm size and lag farm size between corn-soybeans, wheat, and canola. While the average farm size of corn-soybean-dominant CCSU (259 acres) is significantly lower than that of wheat

(1003 acres) and canola (1100 acres). In terms of capital, canola and wheat farms tend to have higher mean capital than corn-soybean farms, suggesting potentially greater investment capacity. Interestingly, the average age of operators remains relatively consistent across crops, hovering around 54–55 years, although canola areas show slightly older operators on average. Institutional structure and gender dynamics also differ. Farms growing wheat and canola have higher average numbers of female operators (143 and 121, respectively) than those growing corn and soybeans (96), potentially reflecting broader participation or different farm labor structures. Partnership numbers are also highest in wheat areas, with greater variation, suggesting more collaborative or corporate farming arrangements. Regarding technology adoption, GIS mapping use is slightly higher in canola (mean of 12.8%) and wheat (12.3%) areas than in corn-soybean regions (11.6%), indicating a modest technological edge that may correlate with larger scale or greater capital access. These differences underline the importance of tailoring policy and technology dissemination strategies to the unique structural and socioeconomic characteristics of each cropping region.

Table 2.2 Descriptive Statistics of Study Variables for Corn and Soybean Group in Canada

	Mean	Median	SD	Min	Max	N
Farm size	259.171	224.861	198.038	18.963	2301.862	1061
Lag Farm size	244.058	216.4	172.653	18.792	1720.049	
Capital	2825261	2526489	1656853	499453.7	12757697	
Age	54.64	54.6	2.869	45	67.7	
Partnership	32.619	15	48.826	1	577	
Female	96.088	55	141.594	5	2100	
GIS Adoption	11.622	9.756	7.678	0.552	45.153	

Table 2.3 Descriptive Statistics of Study Variables for Wheat Group in Canada

	Mean	Median	SD	Min	Max	N
Farm size	1003.684	980.05	675.122	13.183	2804.698	
Lag Farm size	923.374	924.465	606.578	12.418	2490.988	
Capital	3408485	3188184	1859328	466938.8	10433778	
Age	54.63	54.9	2.558	46.3	61.7	
Partnership	39.705	14	68.258	1	486	363
Female	143.3058	65	219.976	5	1445	
GIS Adoption	12.256	11.564	7.411	0.478	45.555	

Table 2.4 Descriptive Statistics of Study Variables for Canola Group in Canada

	Mean	Median	SD	Min	Max	N
Farm size	1100.428	1098.107	495.726	45.422	2792.744	
Lag Farm size	1002.428	1022.3	437.882	39.602	2490.988	
Capital	3185546	3005229	1229168	713061.2	9916965	611
Age	55.146	55.3	2.114	46.8	61.7	
Partnership	39.036	21	54.598	1	405	
Female	121.383	80	149.959	5	1250	
GIS Adoption	12.797	11.881	7.306	0.649	40	

Econometric Results for Canada

Table 2.5 reports the baseline 2nd stage regression results from the 2SLS model for corn-soybean-dominant, wheat-dominant, and canola-dominant groups. Model 1 includes corn-soybeans dominant group, model 2 embodies wheat dominant group and model 3 accounts for canola dominant CCSUs. CAR and year fixed effects were employed for all the regressions.

Table 2.5 Baseline 2SLS Regression Results for Canada

Dependent variable: Adoption of GIS Mapping			
	(1)	(2)	(3)
Farm Size	1.731***	0.702***	0.789***
	(0.180)	(0.083)	(0.054)
Age	-0.226	-1.322	-0.678
	(0.562)	(1.513)	(1.126)
Age^2	0.176	1.175	0.678
	(0.563)	(1.523)	(1.126)
Partnership	0.124*	-0.074	-0.159**
	(0.068)	(0.090)	(0.067)
Female	-0.163***	0.064	0.194***
	(0.057)	(0.072)	(0.0067)
CAR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1061	363	611

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance.

In all three cases, farm size seems to have a significant positive effect on the adoption of GIS mapping. For corn-soybean and canola dominant groups, one standard deviation increase in the farm size can lead to a 1.731 standard deviation unit increase in the adoption of GIS mapping. And for the wheat-dominant group, we expect that increase to be 0.702 standard deviation unit. This suggests that larger farms are more likely to adopt GIS mapping, potentially due to greater economies of scale. Larger operations may also face more complex management challenges, making the benefits of spatially explicit data more pronounced. This finding aligns with prior literature emphasizing that scale is a key driver in the adoption of PA technologies. Then, the coefficients on age and age^2 turned out to be statistically insignificant; however, they still offer valuable insights. The coefficient on age is negative, while that on age^2 is positive. This suggests that younger farmers are less likely to adopt GIS mapping, whereas older farmers are more likely to adopt it. This finding is contrary to conventional expectations, as younger farmers are typically assumed to be more open to adopting new technologies. One possible explanation for this result could be the omission of capital from the regression. In the robustness checks, we will include capital to examine whether this result changes. Further, the effects of partnership status, and gender on the adoption of GIS mapping vary across crop-specific farm groups. Partnership status shows a positive and significant effect for corn-soybean farmers, suggesting that collaborative business structures may facilitate technology adoption in this group. However, the effect becomes negative and significant among canola farmers, potentially reflecting different management or decision-making processes in canola-focused operations. Regarding gender, the effect of being a female operator is negative and significant for corn-soybeans, turns positive but insignificant for wheat, and becomes positive and significant for canola, suggesting that female canola producers are more likely to adopt GIS mapping. These variations highlight how the influence of demographic and structural factors on technology adoption is shaped by the dominant crop type.

While our other control variables showcase a varied degree of relationship with the adoption of GIS mapping, the direction and significance of our target coefficient, farm size, remain the same across three different groups. This also serves as a robustness for our regression. Regardless of the type of crop grown, it can be argued that farm size is a major propeller of the adoption of PA. Larger farm size consistently increases the likelihood of adopting precision agriculture technologies such as GIS mapping. This reinforces the argument that farm size plays a pivotal role in enabling or encouraging the adoption of precision agriculture practices, likely due to economies of scale, better resource availability, and a stronger incentive to invest in cost-saving technologies. Further regressions were run as part of robustness checks to solidify our baseline finding.

As part of our robustness checks and to better account for regional heterogeneity, we performed additional regressions by dividing the sample into three crop-dominant groups—Corn-Soybeans, Wheat, and Canola. For these regressions, first we applied the robust linear model (RLM) in the second stage using the same baseline specification (Table 2.6). The rationale for using RLM is its ability to handle extreme observations by assigning them less weight in the regression, thereby reducing their influence on the estimated coefficients.

Table 2.6 Robust Linear 2SLS Regression Results for Canada

Dependent variable: Adoption of GIS Mapping			
	(1)	(2)	(3)
Farm Size	1.666***	0.672***	0.796***
	(0.161)	(0.078)	(0.053)
Age	-0.034	-1.99	-0.297
	(0.501)	(1.425)	(1.099)
Age^2	0.026	1.897	0.292
	(0.502)	(1.434)	(1.092)
Partnership	0.169	-0.037	-0.143**
	(0.060)	(0.089)	(0.066)
Female	-0.169***	0.044	0.180***
	(0.051)	(0.068)	(0.065)
CAR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
N	1061	363	611

Note: ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels of significance.

Although we observe a little change in the magnitude of the coefficients, there was no change in the direction and significance of the coefficients with the RLM model. This adds strength to our base findings.

Further, we introduced province fixed effects to control unobserved time-invariant differences across provinces (see appendix A.2 and A.3). We ran separate regressions with OLS and RLM with province fixed effects. These differences could include variations in provincial agricultural policies, subsidy programs, land tenure systems, or infrastructure investments that may influence farm-level outcomes but are not directly observable or measurable in our dataset. This approach complements our earlier use of CAR fixed effects, which primarily control agro-climatic and geographical heterogeneity—such as differences in temperature, precipitation, soil types, and cropping patterns. While CAR fixed effects are well-suited for capturing biophysical and agronomic variability, province fixed effects enable us to isolate the influence of broader institutional and policy-related factors that operate at the provincial level. By using both strategies, we aim to ensure that our estimated effects are not confounded by either climate-induced or policy-driven heterogeneity.

Furthermore, we conducted an additional robustness check by controlling capital and including County Agricultural Region (CAR) fixed effects (see appendix A.4). After adding capital, the magnitude of the coefficient on farm size changed, which is expected due to collinearity. Interestingly, the coefficients on age and age^2 both changed direction, although they remained statistically insignificant. In the baseline results, we found that younger farmers were less likely to adopt. However, after controlling capital, younger farmers appeared more likely to adopt. This suggests that the lower adoption rate among younger farmers may be driven by limited access to capital. Importantly, our main coefficient of interest—farm size—remained consistent, thereby reinforcing the strength of our baseline findings.

In the first-stage regression, we used lagged farm size as an instrumental variable (IV) to address potential endogeneity concerns. The results confirm that the IV satisfies the relevance condition; that is, lagged farm size is strongly correlated with current farm size, making it a valid instrument for our analysis. This is important because farm size may be endogenous due to reverse causality or omitted variable bias—factors such as productivity shocks or unobserved farmer characteristics could simultaneously influence both farm size and the outcome variable.

In the second-stage regression, we found that the coefficient on farm size remained both statistically significant and consistent in sign and magnitude with our main specification that used CAR fixed effects. This stability suggests that our core findings are robust to different model specifications and are not sensitive to the choice of regional fixed effects. In other words, whether we control agro-climatic variation (via CAR) or institutional-political differences (via province), the relationship between farm size and the outcome variable remains intact. This adds confidence to the credibility and generalizability of our empirical results. Overall, these robustness checks support the internal validity of our identification strategy and reinforce the main conclusion: that farm size plays a consistent role in shaping the outcome of interest, regardless of regional or institutional context.

Conclusion

PA could potentially be a pivotal tool for revolutionizing American agriculture, potentially fostering sustainability and efficiency. This study provides a valuable initial exploration of its current adoption landscape across the continental US and Canada. Key findings from the US data reveal clustering of adoption rates in specific regions, with the Midwest leading the pack. Additionally, a positive correlation exists between adoption, farm size, sales revenue, and certain crop types like corn, wheat and cotton. Interestingly, livestock operations show lower adoption rates, with cattle feedlots being a notable exception. Ownership structure also seems to play a role, with part-owner and tenant farms exhibiting higher adoption compared to sole proprietorships. While this initial descriptive analysis offers valuable insights, limitations in data prevent causal inferences.

However, our analysis with Census of Agriculture—Canada data allowed us to delve deep into econometric analysis where we explored the effect of farm size on adoption of GIS mapping, controlling potentially crucial drivers like capital, partnership, and some demographic variables. Our findings from Canada suggest that farm size can possibly lead to higher adoption of PA, strengthening our initial results for the US. Moreover, the Canadian data analysis also revealed that farm capital has a statistically significant and positive effect on GIS adoption, underscoring the role of financial capacity in enabling farms to invest in advanced technologies. This complements our previous U.S. findings, where we observed that regions with higher agricultural GDP tend to exhibit higher rates of precision agriculture adoption, pointing toward the broader economic environment as another key enabling factor.

This chapter sets a stage for future research on the economics of PA in the US, given more data becomes available. However, we are able to come up with some potentially significant econometric findings for Canada, which also support some of the correlations that we found for the US. However, future research utilizing longitudinal analysis, robust econometric modeling, and targeted regional studies is crucial to fully grasp the dynamics of adoption and unlock the transformative potential of PA in the US. Given what is presented, we suggest some future research avenues as follows:

First, research on causal drivers of PA adoption in the US should be conducted as more data become available. This study used the county-level COA data for 2022 that has information on PA adoption. Another year of adoption data should be good enough to study any causal inference. The proposed study can be helpful to identify the gap and barriers in technology dissemination. The findings should be helpful in shaping policy towards promoting PA by targeted intervention.

Second, a study on the effects of PA business on crop productivity, labor force participation in agriculture, value added by agriculture, and the local economy can be designed using the PA business location data of Montana that we gathered for this study. In the future, we will collect information on the date of establishment for each business so that we can replicate a natural experiment study and examine the causal effects of these PA businesses on the local economic development of Montana.

Third, it would be interesting to study the effects of PA programs in the state universities on the productivity of major crops, especially corn and wheat. This study opens the door to exploring all these avenues. The knowledge could well be instrumental in crafting effective policy and investment strategies, potentially ushering in a new era of sustainable and efficient American agriculture.

CHAPTER THREE

RISK MANAGEMENT AND THE PRECISION AGRICULTURE AND CONSERVATION TILLAGE TAX CREDIT: EVIDENCE FROM VIRGINIA

Introduction

In the ever-evolving landscape of modern technology, PA could bring about a revolution, offering a transition to production systems as some evince that they are not only economically viable but also environmentally sustainable (Papadopoulos et al., 2024). It harnesses sensor technologies, data analytics, and decision-making tools to potentially optimize crop production, improve resource management, and boost productivity (Mulla, 2023). These technologies, such as GPS-guided systems, variable rate technology (VRT), and satellite-based remote sensing, have the potential to enable more precise application of inputs like fertilizers, pesticides and irrigation, thereby reducing waste and potentially reducing costs. The focus of PA on cost reduction and waste minimization is a promising indicator of its potential economic benefits, with the aim of enhancing efficiency and ensuring the sustainable use of natural resources while maximizing crop yields. This makes it a potentially transformative innovation in modern agriculture (Tayari et al., 2015; Friedl, 2018). While PA use is increasing around the world, the United States has the potential to play a leading role in the global transition in farming, given its strong economy and extensive agricultural lands.

The benefits of PA are multifaceted and presented in scholarly research. Schimmelpfennig and Ebel (2016), with their analysis of USDA Agricultural Resource

Management Survey (ARMS) data, claimed that the blend of PA technologies—particularly VRT alongside soil and yield mapping—could lead to significant cost savings, with estimates ranging from \$13.45 to \$25.01 per acre in the USA. They also suggested that adopting PA earlier could lead to greater benefits. Early adopters, particularly larger farms, may play a key role in realizing the most significant payoffs, though the efficiency gains might diminish over time. This implies that the early economic advantages of PA might become less pronounced as the technology matures, potentially exacerbating farm consolidation trends as larger farms are better positioned to absorb the initial costs and apprehend the longer-term benefits of PA systems (DeLay et al., 2022). However, the costs involved in adopting PA could be a significant barrier to adoption (GAO, 2024).

Moreover, there is some evidence that PA technologies could offer substantial energy savings and a positive return on investment for the agricultural sector. Especially in a heavy energy-dependent nation like the US, it has the potential to appease the burden of energy use, leading to cost reduction and eventually lower emissions. In North Dakota, a study by Bora et al. (2012) found that 34% of farms reported using GPS guidance systems, and among those, machine time and fuel consumption were reduced by approximately 6% on average. Additionally, 27% of farms had adopted auto steering, which was associated with average reductions of 5.75% in machine time and 5.33% in fuel use. On average, GPS guidance saved 1,647 liters of fuel per farm, translating to about \$733.85 in 2012, or approximately \$970.88 in 2025 dollars. Auto steering saved 1,866 liters, equating to roughly \$851.27 in 2012, or \$1,126.23 today.

Moreover, the concept of precision could be a key advantage of PA, as it has the potential to ensure the application of the right amount of inputs in the right place at the right time (Shafi et al., 2019). By utilizing site-specific knowledge, PA aids in reducing nutrient imbalances and losses from applications, such as nitrogen (N) and other chemicals, improving resource efficiency. The approach could also help mitigate the development of pesticide resistance and enhance the overall health of ecosystems. While many studies infer environmental benefits through reduced chemical loading, there is evidence that effective spatial management of inputs can maintain profitability while promoting environmentally friendly agricultural practices (Bongiovanni & Lowenberg-DeBoer, 2004). PA also has potential to bring intangible benefits such as improved knowledge of field variability and more effective weed control (Robertson et al., 2007). Another potential advantage of PA is its ability to identify the lessor and more productive parts of a field and can guide cropping decisions across low-productive regions by either substituting it for another non-crop activity or using it at low cost.

PA and conservation agriculture (CA) have the potential to complement each other, as they share a common goal of conserving resources, reducing costs, and enhancing productivity. Recently, precision techniques, including data on surface and underground flow, have shown promise in supporting farmland and natural area conservation (Delgado & Berry, 2008). CA refers to a series of production activities ranging from minimizing soil disturbance, cover crops, crop rotation, retention of crop residue, and soil and water conservation (Basso, 2003). Conservation tillage was introduced in the USA in the 1930s. After seeding, it involves leaving at least 30% of the plant residue on the soil surface. When soil erosion is a threat, conservation tillage maintains at least 1100 kg/ha of slight grain residue on the surface throughout the critical wind period (Derpsch et al., 2001). No-till, mulch-till, and ridge-till are the most common forms of conservation tillage practiced in the USA (CTIC, 2000). It was found that farmers who use PA also use no-tillers (Schimmelpfennig & Ebel, 2016). While the benefits of PA and CA are evident, many have claimed that PA and CA can help farmers manage risk better (see Liu et al., 2017; Kane et al., 2021; Won et al., 2024).

When newly advanced sustainable agricultural techniques aid in risk mitigation, crop insurance is a direct measure for US farmers managing crop risk failure. Crop insurance is mainly rolled out at the federal level. Congress first authorized federal insurance by the Federal Crop Insurance Corporation in 1938. Currently, the Risk Management Agency (RMA) regulates the insurance schemes and sets the premium rates, although private insurance companies sell the insurance products (Yu et al., 2021). Farmers choose the insurance coverage level and pay a portion of the premium or none if they choose a catastrophic coverage policy. The federal government pays the rest of the premium, which is, on average, 60% of the total premiums. The government subsidy on premiums can range from 38% to 80%. Premium rates increase as farmers choose higher coverage levels (Shields, 2010). Given the significance of crop insurance, understanding farmers risk management is crucial at the state level, like Virginia, where 7300000 acres of land are under agricultural production with 39000 operations (NASS-USDA, 2023). Livestock accounts for 63% of annual cash receipts to Virginia farmers. Corn and soybeans are the major crops grown in the state, with corn adding USD 325,076,000 in 2022 (ERS-USDA, 2025). Corn was planted on 495,000 acres of land, and corn grain production was at 58,090,000 BU (NASS-USDA, 2023). In 2021 the state of Virginia enacted a conservation tillage and precision agricultural-equipment tax credit policy, which mainly targets PA tools and fosters the use of PA. With the introduction of the policy, a farmer who purchases eligible PA or conservation tillage equipment qualifies for a tax rebate of 25% of the cost of the equipment up to $17,500 USD. Recently, the sunset date was extended from 2026 to 2030 (Virginia SB298, 2024). More information on this policy is later discussed in the background section. The main goal of this policy is to promote the adoption of PA among farmers to achieve economic gains while maintaining environmental sustainability.

There is a considerable volume of research that addresses the use of PA and risk management (Liu et al., 2018, 2017; Gardezi and Bronson, 2019; Oriade and Popp, 2000). PA has the prospect to reduce yield variability and help manage crop failures caused by disease or infestation. While this could be significant if farmers opt to lower their insurance coverage or participation after adopting PA, the influencing factors may be complex and varied. This could be related to improved production systems that minimize crop risk and financial constraints following costly PA adoption. Whatever the potential factors are, it is worth studying the effect of PA adoption on insurance choice. However, ideal data is not always available, and the same applies to this study. This chapter examines such a policy that can identify some sort of relationship with the insurance coverage selection. This chapter thus aims to examine the effects of conservation tillage and precision agricultural equipment tax credit policies on corn farmers' insurance premiums in Virginia. This area has not been explored in existing literature. While considering soybeans and cotton could help our result be more generalized, we only opted to study corn due to data availability. Nonetheless, corn is one of the primary crops in the state, and the majority of corn production in Virginia is non-irrigated. While previous studies have established connections between soil conservation, precision agriculture, and crop insurance, few have specifically examined these interactions within Virginia's unique agricultural context. This study fills a critical gap in understanding localized dynamics by focusing on how state-specific policies and practices influence farmers' financial decisions regarding insurance costs.

Additionally, integrating conservation tillage and precision agriculture within the framework of insurance premium adjustments offers a fresh perspective on the interplay between environmental sustainability and economic viability. This research contributes to the discourse on effective policy interventions that can support farmers in managing financial risks while addressing environmental challenges, ultimately expanding knowledge on the economic implications of agricultural practices and providing practical recommendations for policymakers in Virginia and beyond. Besides, Virginia is home to more than 20,000 new beginning farmers. Understanding how financial incentives, such as tax credits for conservation tillage and precision agriculture equipment, impact the decision-making of these new farmers. Given that beginning farmers often face higher financial constraints and risks, evaluating the effectiveness of such policies in reducing insurance premiums can provide valuable insights into their long-term sustainability and success. The tax credit policy specifically promotes the state-wide adoption of precision agricultural techniques. Although this chapter does not directly estimate the effect of precision agriculture use on farmers' risk attitudes as proxied by their insurance coverage decisions, it paves the way for understanding the effect of a pro-precision agriculture policy, which can be invaluable in comprehending how farmers' risks are shaped through the introduction of such modern technology.

This chapter attempted to replicate a natural experiment using county-level data from the Summary of Business (SoB) and Risk Management Agency (RMA) to identify the tax credit policy's effects on farmers' effective coverage rate. I employed a two-way fixed-effect model to estimate the policy effect in a difference-in-difference setting. My results suggest that the policy led to a 0.019-unit reduction in the coverage rate while controlling for area under cultivation, and lag yield. The results were robust across different models and were not sensitive to state-specific time trends.

Background

Precision Agriculture and Soil Conservation Policies in the USA

Recent legislative initiatives by U.S. Senators Deb Fischer (R-Neb.) and Amy Klobuchar (D-Minn.), both members of the Senate Agriculture Committee, focus on expanding farmers' access to precision agriculture equipment. These technologies are designed to help producers cut costs and potentially optimize productivity and minimize their environmental impact. One significant proposal, the Precision Agriculture Loan (PAL) Act, aims to establish a program within the U.S. Department of Agriculture (USDA) that would provide financing options for farmers and ranchers interested in adopting precision agriculture tools (Fischer, 2023).

In alignment with these efforts, the American Farmland Trust (AFT) is advocating for the inclusion of a $5 per acre crop insurance premium rebate for planting cover crops in the upcoming Farm Bill. This initiative is part of the COVER Act (S. 1690 / H.R. 3478), introduced by Representatives Casten (D-IL), Bost (R-IL), Slotkin (D-MI), and Senator Brown (D-OH) (AFT, 2023). By incentivizing cover crop adoption, this proposal promotes soil health and integrates financial support mechanisms that could enhance the overall resilience of farming systems.

The historical context of these initiatives is rooted in the 1985 Food Security Act, which introduced Conservation Compliance, mandating soil and wetland conservation as a condition for eligibility in most federal farm programs. Farmers must implement conservation systems on highly erodible land and avoid draining wetlands; violations can result in losing federal agricultural benefits, including crucial crop insurance premium subsidies added under the Agricultural Act of 2014 (Claassen and Bowman, 2017). This framework highlights the longstanding connection between conservation practices and federal support, emphasizing the importance of sustainable land management.

The 2018 Farm Bill further builds on this foundation by promoting the establishment of a secure data warehouse, enhancing access to agricultural data. This initiative is designed to enable researchers to analyze the links between farming practices, yields, and associated risks, aiming to boost productivity, sustainability, and the efficiency of insurance programs (Stubbs, 2019). By fostering data-driven approaches, this bill supports the integration of precision agriculture and conservation practices, paving the way for more informed decision-making.

Wisconsin is one of four pilot states where producers can purchase lower-cost crop insurance against yield losses, contingent on adhering to recommended rates in a nutrient management plan (NMP) or following best management practices (BMPs) without a formal plan (Fyksen, 2003). This approach has the potential to demonstrate how aligning financial incentives with conservation efforts could enhance sustainability while providing farmers with necessary risk management tools. In summary, the interconnected efforts of legislation, financial incentives, and data integration illustrate a comprehensive strategy to promote precision agriculture and soil conservation.

Tax Credit Policy in Virginia

The Conservation Tillage and Precision Agriculture Equipment Tax Credit is a new refundable state income tax credit in Virginia that offers farmers a credit equal to 25% of the cost of qualifying equipment, capped at $17,500. The tax credit equals 25% of all expenditures made by the taxpayer for the purchase of equipment certified by the Virginia Soil and Water Conservation Board to reduce soil compaction, such as a "no-till" planter, drill, or other equipment that provides more precise pesticide and fertilizer application or injection. For this credit, equipment that reduces soil compacts includes planters, drills, or other equipment that may be attached to the taxpayer's existing equipment. The credit cannot exceed $17,500 in the year of purchase. Recently the sunset date of this policy was extended from January 01, 2026, to January 01, 2031. The legislation expanding this tax credit, SB 1163, was enacted on March 18, 2021, and effective on July 01, 2021. (FIC, 2024). If a taxpayer's allowed credit exceeds their responsibility for the taxable year, the excess will be returned at 100% of face value within 90 days after submitting the income tax return. The credit applies to the following equipment categories: soil compaction equipment, sprayers for pesticides and liquid fertilizers, pneumatic fertilizer applicators, monitors, computer regulators, height-adjustable booms, manure applicators, tramline adapters, and starter fertilizer banding attachments for planters (Virginia Tax, 2024). To qualify, applicants must be engaged in agricultural production for the market, have an approved soil conservation plan from their local Soil & Water Conservation District, and possess a Nutrient Management Plan developed by a certified planner (Virginia Law, 2024). This policy aims at leveraging significant financial incentives for the farmers to invest in precision agriculture due to a considerable amount of refundable credit and a long time frame of a 10-year phase.

Literature Review

Soil Conservation and Risk Management

The relationship between soil conservation and crop insurance has been a significant area of inquiry for several decades. Early research by Christensen and Norris (1983) established that these two elements are intricately linked, suggesting a foundational relationship without detailing the specific mechanisms. This early exploration laid the groundwork for more comprehensive studies that would later illustrate the complexities of this connection. More recently, Das et al. (2022) conducted a study in Nebraska that shed light on the motivations for farmers adopting soil health management practices. One compelling reason was the potential to reduce crop insurance premium rates. This underscores the role of financial considerations in farmers' decisions regarding soil conservation, highlighting that economic incentives can be powerful motivators for adopting sustainable agricultural practices. This finding aligns with the broader trend in agricultural policy that encourages practices to enhance environmental sustainability while also addressing farmers' financial concerns.

Building upon these insights, Canales et al. (2018) emphasized the anticipation of greater yields as a significant motivating factor for adopting no-till practices. This connection reinforces the notion that farmers view soil conservation as an environmental necessity and a pathway to increased productivity and profitability. However, the discourse becomes more nuanced when considering earlier findings by Ding et al. (2009), which indicated a negative correlation between the extent of land under conservation tillage and the percentage of farmers participating in crop insurance programs. This suggests that while some farmers may prioritize conservation practices for long-term sustainability, others may hesitate to engage with insurance options, fearing that conservation measures might not align with their immediate financial interests.

Contrasting these findings, Fleckenstein et al. (2020) presented evidence that crop insurance and conservation tillage can work synergistically. They proposed that crop insurance could enhance the viability of conservation practices, suggesting a more complex and interdependent relationship between these factors. This idea was further expanded by Gong et al. (2021), who found that farmers with crop insurance are more likely to adopt no-tillage methods. Their research underscores the potential for financial instruments, like crop insurance, to encourage environmentally sustainable farming practices, thus creating a feedback loop where sustainable practices are financially reinforced.

Further contributing to this dialogue, Dixit et al. (2022) conducted experiments in India highlighting the benefits of improving soil conservation and utilizing cover crops. They argued that such practices enhance the resilience of dryland production systems, which can significantly reduce the risk of crop failures. Lower crop failure risks, in turn, can lead to lower crop insurance premiums, allowing farmers to redirect those savings into additional resilience-building initiatives. This creates a compelling case for integrating soil conservation efforts into broader financial planning and risk management strategies.

Kane et al. (2021) added another layer to this discourse by examining the impact of soil organic matter on maize yields and crop insurance payouts in the U.S. during drought conditions. Their research revealed that a 1% increase in soil organic matter correlates with a 2.2 Mg ha^{-1} (about 32.7 bu ac^{-1}) yield increase and a 36% reduction in insurance payouts under severe drought conditions. This improvement can be attributed to enhanced soil water retention and cation exchange capacity, emphasizing the critical role of soil health in mitigating financial risks associated with climate variability

Won et al. (2024) further explored this relationship by analyzing a dataset that combines satellite-derived cover crop data with county-level crop insurance information. They found that counties with higher cover crop adoption rates tend to experience lower crop insurance losses related to prevented planting. However, it's unclear whether this relationship reflects a true causal effect or simply that cover crops are more prevalent in regions with inherently lower drought risk—an important distinction that could be better addressed through a difference-in-differences analysis over time. This risk reduction is more significant with long-term cover crop use, which enhances soil conditions by improving water absorption and infiltration. They advocate the importance of long-term investment in soil health practices for environmental and economic stability.

On the other hand, some studies have examined the potential disincentives associated with crop insurance participation regarding cover crop use. Connor et al. (2022) suggested that crop insurance coverage may exert a statistically significant disincentive effect on county-level decisions to adopt cover crops after corn and soybean harvests in Indiana. However, the effect is relatively small and likely not economically meaningful. This nuance indicates that farmers may weigh immediate financial benefits against long-term environmental considerations when deciding cover crops.

Similarly, Lee and McCann (2019) found no statistically significant relationship between crop insurance use and cover crop adoption for soybeans in their probit regression model. Their findings point to the complexities of the interaction between these factors, suggesting that multiple variables beyond just insurance participation influence the decision-making process. Hence, the relationship between soil conservation and crop insurance iscomplex, likely driven by economic incentives and farmer priorities. A cooperative approach can enhance resilience and financial outcomes, promoting sustainability in agriculture.

Precision Agriculture and Risk Management

PA has the potential to be a valuable tool for managing agricultural risks, particularly in addressing crop diseases, which can impact farmers' productivity and profitability. For instance, Liu et al. (2017) demonstrated the effectiveness of precision farming technology in mitigating risks associated with potato late blight. They also mentioned that by facilitating precise and timely fungicide applications, it not only controls the disease but also enhances profitability and reduces financial uncertainty for potato growers. Such advancements could significantly improve resilience against biotic stresses, which are increasingly critical due to changing climate conditions.

Building on this foundation, Liu et al. (2018) explored the application of precision agriculture in managing tomato late blight. Their research, involving extensive data from field trials and computer simulations, revealed that the BlightPro Decision Support System (DSS) offers a more effective fungicide scheduling method than traditional calendar-based approaches. This case illustrates a broader potential for precision agriculture technologies in disease management, indicating that systems like BlightPro could be adapted for various crops, further enhancing agricultural sustainability. This continuity in research highlights how technological innovations can translate across different crops, reinforcing the value of precision agriculture in mitigating risks.

Gardezi and Bronson (2019) emphasized how PA technologies might empower farmers to manage environmental risks more effectively. By granting more significant control over farming operations, these technologies may enable proactive responses to potential threats such as fluctuating weather patterns and pest infestations. This idea resonates with Gawande et al. (2023), who underscore that precision farming facilitates close crop health monitoring, allowing for timely interventions. By linking these insights, we see a clear trajectory. As farmers utilize precision technologies, they may be able to more effectively adapt to and mitigate risks, enhancing their financial stability and long-term viability in a rapidly changing agricultural landscape.

Moreover, Oriade and Popp (2000) noted that precision farming mainly benefits producers facing significant variability in their production environments. By customizing inputs to specific areas of their fields, farmers can increase yields and profitability, adapting to the unique conditions in different parts of their farms. This customization aligns with the findings of Lowenberg-DeBoer and Aghib (1999), who pointed out that insurance companies were more likely to offer lower premiums to farmers using variable-rate technology (VRT) for input applications. The rationale was that tailored input use could reduce yield variability and lower the risk of crop losses and insurance claims, highlighting a potential financial benefit of precision agriculture. It would be interesting to investigate whether this relationship has persisted in the decades since, especially given changes in insurance structures and technology adoption.

Benami et al. (2021) further suggested that remote sensing and satellite data could be crucial in reducing insurance premiums by enabling more accurate and cost-effective assessments of agricultural losses. Improved yield estimation and risk assessment techniques can significantly enhance the value of index insurance, potentially leading to lower premiums for farmers. This approach creates a positive feedback loop: as insurance becomes more accessible and affordable, farmers are incentivized to invest in precision technologies, reinforcing the interconnectedness of risk management and agricultural innovation.

While precision farming technologies may significantly reduce agricultural risks by creating more homogeneous growing environments and allowing for tailored input applications, some studies indicate limited benefits regarding weather-related risks. Nevertheless, VRT has been shown to decrease variability in net returns, particularly concerning phosphorus and potassium applications. Furthermore, Larson et al. (2002) highlight that these technologies assist farmers in managing risks related to environmental quality, food safety, and product differentiation, thereby expanding the scope of precision agriculture's impact across multiple dimensions of agricultural management.

Finally, Woodard et al. (2019) explored how big data and precision agriculture can enhance crop insurance and risk management. They emphasized that integrating high-resolution satellite data with conservation practices can lead to improved risk assessments and more accurate insurance pricing. This connection underscores the transformative potential of these technologies in modern agriculture, as they not only aid in risk management but also contribute to the sustainability and resilience of agricultural systems in an era marked by environmental uncertainty. By harnessing the power of data and precision farming, the agricultural sector can better navigate the complexities of risk, ensuring both profitability and environmental stewardship.

Determinants of Crop Insurance Coverage Choice

The literature examined the drivers of crop insurance participation, insurance demand elasticities, moral hazard and determinants of insurance coverage choice. Earlier, Babcock and Hart (2005) studied the effect of premium subsidy on coverage rate selection using county-level data for corn, soybeans, and wheat. They examined the effect of coupling premium subsidies on coverage rate choices and found that, following the implementation of the premium subsidy policy, farmers' selection of higher coverage rates increased by up to 400%. This result demonstrates that subsidies can lead to the selection of higher coverage rates. Ginder et al. (2010) conducted a farmer-level survey in northern Illinois to unveil the factors of coverage choice by farmers. Their findings from the sample of 315 respondents indicate that the price of insurance was the most crucial factor they considered before making a coverage choice, with higher costs leading to lower coverage. 87% of the farmers reported that federal subsidies are critical for retaining higher coverage. Further, it was noted that coverage choices are sensitive to farmers' risk attitudes.

Further, Bradley et al. (2016) studied the effects of the 2014 farm bill on the farmers' coverage level choice using RMA data ranging from 2008 to 2015 for corn, soybeans, and wheat in Oklahoma, Illinois, and Ohio. They argued that the policy had an impact, and after its introduction, farmers' coverage level was boosted. They were unclear about the grounds for such a finding; one potential cause was the omission of direct payments, which lowered the farmer's guaranteed income. Recently, Boyd and Belasco (2022) modeled the determinants of insurance coverage rates employing the Agricultural Resource Management Survey (ARMS). Their findings from the fixed effect model suggest that farmers with higher revenues opt for higher coverage levels. Higher premium costs hinder coverage rate decisions. They also established evidence of credit constraints to decrease coverage levels. Similarly, DelCurto (2020) studied the determinants of insurance participation and coverage level choice for livestock. She implemented linear fixed effect regressions to examine the effect of factors relating to premium payments on the coverage level and participation in Pasture, Rangeland, and Forage (PRF) insurance program. She also studied the impacts of projected prices, previous year's income, and the Livestock Forage Disaster Program (LFP) on coverage level choices and participation. Her result underscored that the more costly the premium payments, the lower participation in insurance program. It was also noted that previous year's loss ratio had varying effects in different cases while county base value found to be negatively impacting participation.

Data and Variables

Data

The study data comes from three sources. First, it leverages county level Summary of Business (SOB) data that spans from 1999 to 2023. The SOB data provides information on insurance coverage rate, premium, liability and premium rate. Second, data on yield comes from Risk Management Agency (RMA) dataset spanning from 1999 to 2023. Ideally, in a difference-in-differences study setting, having more data could lead to more reliable estimates. Both datasets offered us 22 years of pre-policy data and only 3 years of post-policy data. In an ideal case we would have more than 3 years of post-data to isolate the policy's long-term impact. However, the natural experiment design helps us capture the causal effects even with the 3 years of post-policy data. The two datasets were joined by county and year. To omit potential confounding issues, only counties that were common across all the years were considered. Although this approach penalizes us with a lower number of observations, it helps with the consistency of our analysis. Since our study focuses on corn, we opted to subset this category, and later, we only kept the counties that have over 5000 acres of corn land for our initial regressions. Besides, we narrowed down the dataset to include only "Grain" to keep our analysis directly relevant. This approach ensures that we focus on areas with substantial production, making our results more reliable and meaningful while excluding counties with minimal production that might not add much value to the study. Further, to ensure data integrity, we omitted any counties where the premium is greater than 30% of the liability. From the SoB dataset, out of observations 16892, 910 had premium greater than 30% of the liability. After omitting these observations, we retained 15982 observations. Later, we calculated the weighted coverage only specific to corn (grain) which eventually decreased the observations to 1050.

High premium-to-liability ratios may suggest unusual cases, such as data entry mistakes, extreme outliers, or counties with unique circumstances like unusually high weather risks or uncommon insurance practices. Including these outliers could distort the results and lead to conclusions that don't reflect the broader patterns we're interested in. Observations with premiums exceeding 30% of the liability were excluded from the analysis. By removing these counties, we help ensure that our dataset is clean and representative, which strengthens the credibility and reliability of our findings. The details of the policy was derived from Virginia Tax (2024).

Variables

In order to capture the true policy effect, we tried to minimize the omitted variable bias issues by adding meaningful covariates to the model. Most of the variables had to be processed before inclusion. Following the variables and the way of construction are discussed.

Dependent variable: Effective coverage rate or acres weighted coverage rate is the sole outcome variable for this research. We calculated the effective coverage rate by the follow equation:

$$Acres\ weighted\ cvg = \frac{\sum_{i=1}^{n} acres_i \cdot cvg_i}{\sum_{i=1}^{n} acres_i} \tag{3.1}$$

This equation calculates the acres-weighted average coverage by adjusting the coverage values based on the size of each observation, measured in acres for each county. The numerator sums the coverage values of each county, each multiplied by the corresponding number of acres, giving more weight to areas with larger acreage. The denominator sums the total acres across all observations to normalize the result.

Control variables: We included the yield at one lag year as a covariate. Farmers' insurance coverage rate decisions are often influenced by historical yield data, as past performance could serve as a critical indicator of future risks and productivity (Sherrick et al., 2004). Including yield at one lag year as a covariate captures this relationship, recognizing that farmers assess their coverage needs based on recent outcomes. The direction of the relationship between lag yield and coverage selection could be either positive or negative. For instance, a low yield in the previous year due to adverse weather or pest issues may prompt farmers to opt for higher coverage rates to mitigate potential financial risks. On the flip side, a farmer who experiences consistently higher yields from a particular crop may discard farming on high-risk lands and put more emphasis on productive areas. He might want to keep hedging his risk by either maintaining the same coverage or increasing it. Moreover, we also took an area of land that is under corn cultivation. Large farmers might be financially more solvent, which can lead them to purchase higher levels of coverage. Controlling this is crucial, as this omission could bias our estimate and overlook the economics of scale effect.

Summary Statistics

Table 3.1: Descriptive Statistics of Study Variables

	Mean	Median	SD	Min	Max	N
Acres weighted coverage	0.678	0.683	0.052	0.529	0.778	
Premium rate	0.127	0.131	0.041	0.027	0.235	
Acres	16077.3	12252	9775.04	5062	55796	1050
Yield_{t-1}	121.159	123	35.31	17.5	198.2	

Table 3.1 reports the summary statistics for the total dataset employed. The average effective coverage is 0.678 with a minimum of 0.529 and a maximum of 0.778. Second, the premium rate mean and median were calculated at 0.127 and 0.131, respectively. Premium rate values range from 0.027 to 0.235. The minimum area of corn was 5062, and the maximum was 55796, with the mean of 16077.3 and the median of 12252. . Lastly, yield lag average was 121 with a standard deviation of 35. Its value spans from 17.5 to 198.2. One notable thing here is that yield lags have a substantial deviation year to year, which is not abnormal since yield can be varied due to weather events and other factors.

Table 3.2: Descriptive Statistics of Study Variables by State

		Mean	Median	SD	Min	Max
Effective coverage rate	Virginia	0.696	0.693	0.048	0.56	0.778
	North Carolina	0.668	0.675	0.051	0.529	0.763
Premium rate	Virginia	0.142	0.141	0.029	0.071	0.234
	North Carolina	0.118	0.12	0.044	0.027	0.235
Yield lag	Virginia	125.5	132.9	38.633	17.5	198.2
	North Carolina	118.663	143.8	33.735	33.4	195.2
Area	Virginia	10814.2	10548	3265	5249	23110
	North Carolina	19001.8	15529	10901	5062	55796

Further, summary statistics are broken down by state and depicted in Table 3.2. It highlights some interesting differences between Virginia and North Carolina. Virginia stands out with the higher average effective coverage (0.696) and premium rate (0.142), with effective coverage ranging from 0.56 to 0.778 and premium rates from 0.071 to 0.234. North Carolina has a slightly lower average effective coverage (0.668) and an average premium rate of 0.118, but the state shows more variability in premium rates, which range from 0.027 to 0.235. Regarding the previous year's yield, Virginia has the highest average yield (125.5 bu/acres), with a more consistent range between 17.5 and 198.2. North Carolina has the lower average yield of the previous year (118.663), ranging from 33.4 to 195.2 bu/acres. Moreover, we observed a significant difference in the land size under the corn between Virginia and North Carolina. Per county, Virginia has less land under cultivation (10814 acres) than North Carolina (19001 acres) on average. Virginia's largest county for corn is 23110, while North Carolina has 55796 acres. These differences across states could be attributed to the unique regional factors, such as weather conditions and crop characteristics, that influence coverage, premium rates, yields, and loss ratios.

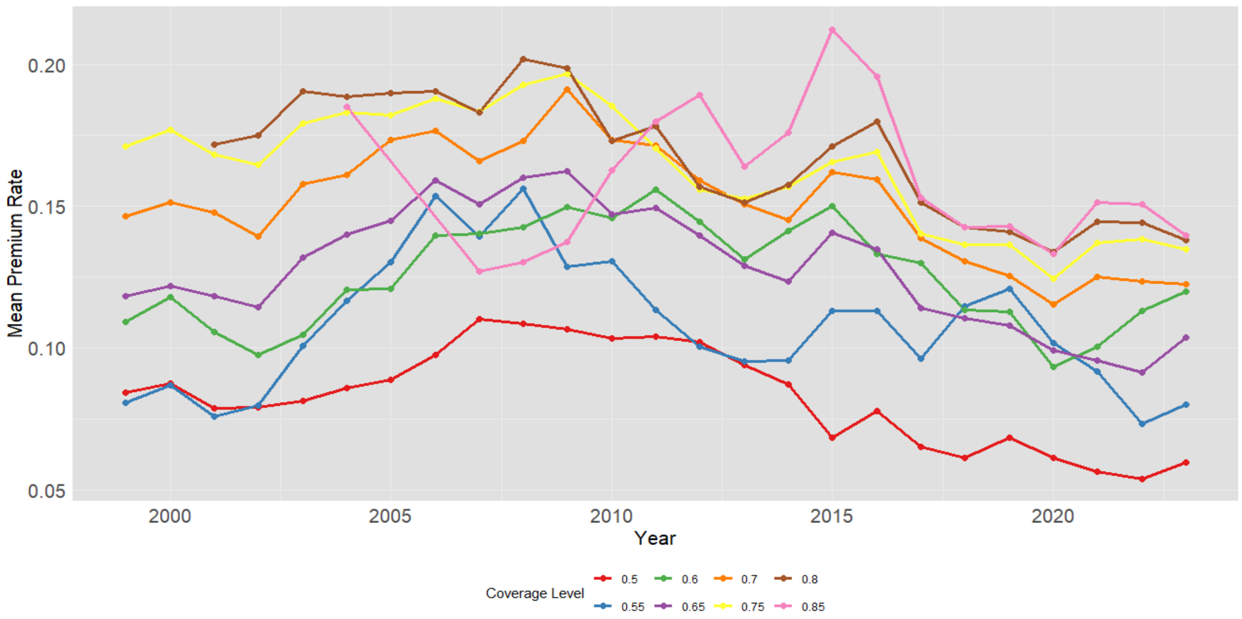


Figure 3.1 Trend in Premium Rates by Coverage Level in Virginia

Further, Figure 3.1 plots the mean premium rate by different coverage levels across 1999 to 2023 for Virginia. This helps us with a clear view of how premium rates vary by different coverage rates. On average, it can be inferred that, over the years, premium rates have gone down at all respective coverage rates. Simply put, either the level of the premium went down or the amount of liability increased. This could be attributed to a variety of factors, including an increase in total liability, changes in insurance subsidy policies, improvements in farm risk management, or shifts in coverage choices. It is also possible that farmers of Virginia are shifting away from riskier land and emphasizing more on fertile fields, which might have reduced the premium rate over the year, as less risky lands are supposed to have lower costs of insurance. I also compared this to North Carolina. I observed a similar trend in North Carolina with some periodic deviations (Appendix B.1.)

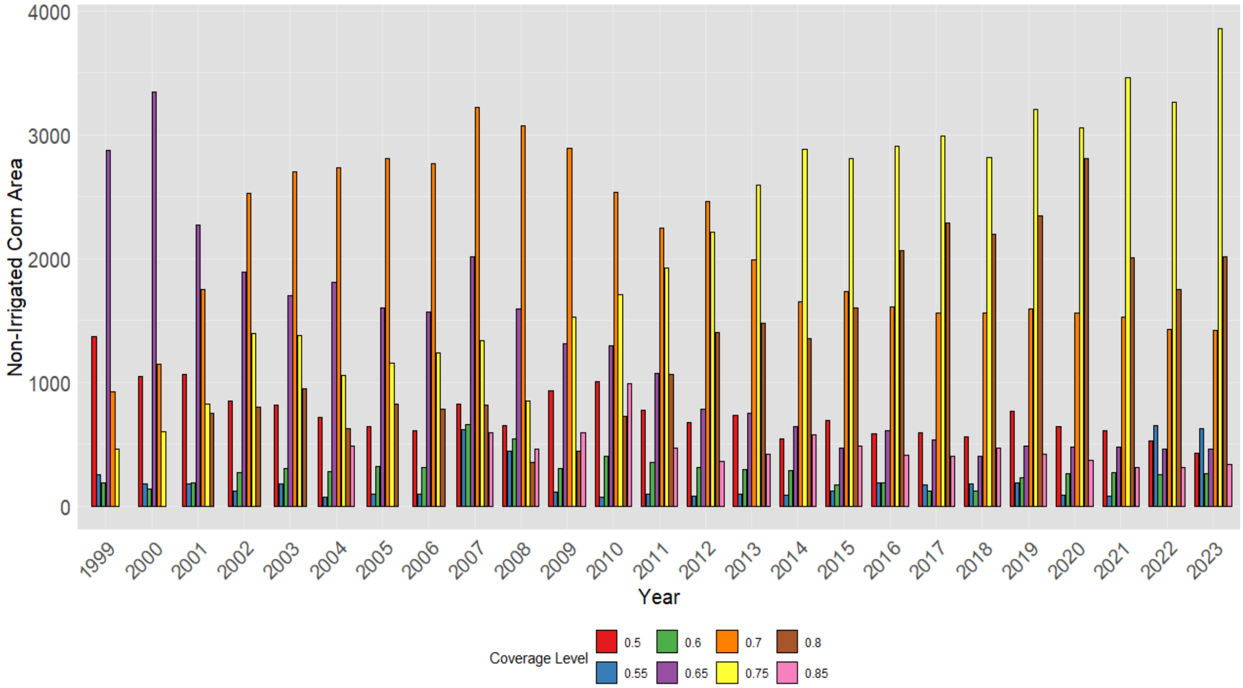


Figure 3.2 Trend in Land Under Different Coverage Levels in Virginia

We further depicted the trend in areas of corn under different coverage rates. Farmers, on average, select higher coverage rates (0.7 and higher). The size of land rates of 0.75 and 0.8 have increased over the years while the land under the higher coverage rate of 0.85 has decreased (Figure 3.2). A significant variability can be observed in the trend in land area under other lower coverage rates. From this figure, it can be inferred that farmers have gradually moved away from the highest coverage rates. This change can be attributed to the farmers' risk management strategies while they find a balance between premium costs and expected benefits. Potential factors could involve better risk management practices, relative benefits in mid-high level coverages, and changes in subsidies. This is where this study will help explore the reasons behind this shift while studying the effect of the tax credit policy that encourages the adoption of precision agriculture. Our findings will also showcase whether this policy that supports precision agriculture can be viable for mitigating risk through improved management practices.

Moreover, figure 3.3 portrays the trend in effective coverage rates by counties in Virginia included in the study. Although the trend varies over the years across different counties, an increasing trajectory can be observed. Similar types of trends across most of the counties also suggest potential county-level correlations that require to be addressed. Besides, the variability across some counties could indicate that local factors—such as climate risks, farm composition, and policy differences— might continue to influence insurance decisions.

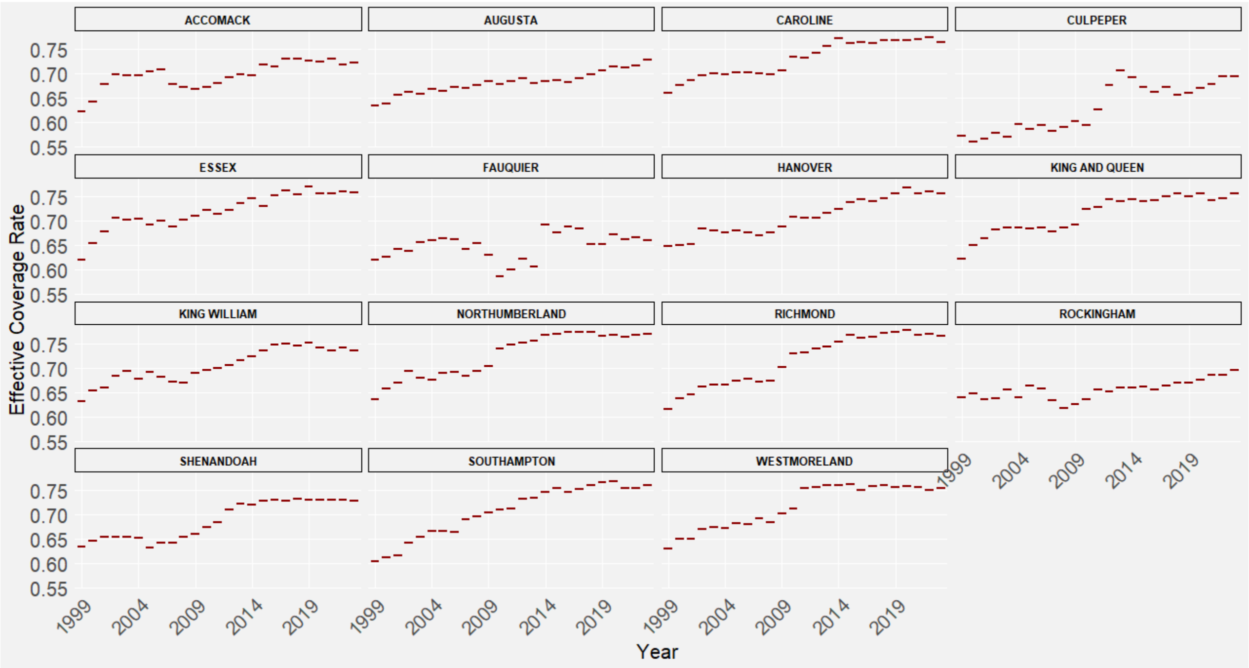


Figure 3.3 Trend in Effective Coverage Rate by County in Virginia. Notes: The red-colored box plots across 1999 to 2023 denote the measure of effective coverage rate for a particular year. The plots are segmented by individual counties considered in the study.

Next, to capture the causal effect, it is essential to ensure parallel trends hold for the control and treatment groups. The parallel trend assumption implies that in the absence of treatment, the trend of the outcome variable in the treatment and control groups would follow the same trajectory. Since, after the advent of treatment, we cannot know the counterfactual trend in that group if no treatment took place, we make comparisons with a closely related group as a counterfactual. For this study, Virginia is the treatment group, and North Carolina was chosen as the control state. The rationale behind the inclusion of North Carolina as a control is that its agricultural production system, along with the climatic and geographical characteristics, is quite like that of Virginia. Additionally, North Carolina likely has comparable farming practices, crop types, and risk exposure, which potentially helps ensure that any differences in insurance coverage rates can be attributed more confidently to the policy rather than other external factors. It is worth noting that it did not include other surrounding states (e.g., West Virginia and Maryland); adding more groups could introduce variation that may compromise the consistency of the comparison. The effectiveness of a control group hinges on its ability to closely mirror the treated group in terms of key characteristics, such as agricultural practices, economic conditions, and climatic factors. By limiting the control group to one specific state, we try to ensure a more precise and reliable comparison, which allows us to isolate the effect of the policy on insurance coverage rates without introducing unnecessary noise from states with potentially different characteristics or policies. Next, we plot the trends of effective coverage rate for treatment and control groups as depicted in Figure 3.4.

Figure 3.4 Trend in Effective Coverage Rate for Treatment and Control Groups. Note: Here, the green line denotes the trend of effective coverage rates for Virginia, and the red line signifies the trend of that for West Virginia and North Carolina. The blue line indicates the policy effect year 2021. Here, Virginia is the treatment state and North Carolina serves as the control group.

The trends of effective coverage rate for Virginia and North Carolina follow a parallel line on average. Although in some years there is a slight deviation in the trend lines, before the policy year, the trajectory can be argued parallel and useful for identifying our model. The fact that the trends for Virginia and North Carolina are mostly parallel helps strengthen the case for using a difference-in-differences approach. It suggests that the control states offer a good comparison for Virginia before the policy was introduced. Even though there are small deviations in some years, the overall parallel movement between the two groups provides a solid foundation for identifying the policy's effects in our model. However, in order to control pre-trend violations, state-specific time trends are included in robustness test.

Empirical Method

Ideal Experiment

The main goal of this study is to examine the effect of the Conservation Tillage and Precision Agriculture Tax Credit policy on Virginia farmers' effective insurance coverage rate. First, I will discuss the ideal experiment to capture the causal effect of the policy. In an ideal situation, we would have data on representative samples of individual farmers from Virginia who purchase PA or CA tools for farming. We would have multiple data periods before and after the policy effect year. We would have controlled farmers of similar characteristics from Virginia or similar agricultural production regions and have representative data of the control group. The policy treatment should be rolled out randomly, and study farmers cannot decide on their insurance coverage anticipating the introduction of the policy. Next, no spillover effect should be observed. Further, study data should be free of measurement error. The most important aspect of this study is establishing a parallel trend assumption. Simply put, in the absence of treatment, the outcome variable of the control and treatment groups should follow a similar pattern.

However, achieving ideal data in an actual situation is complex, and this study is no different. This study replicates a natural experiment design using county-level data from Virginia and control states. Of the significant challenges in identifying the actual effect is the violation of the parallel trend assumption. Later, I plot the trends of effective coverage rate for treatment and control for establishing parallel trends. Moreover, unobserved heterogeneity in the model can lead to wrong estimates, and in order to address this issue, we will incorporate state-fixed and year-fixed effects. Further, suppose any violation of the parallel-trend assumption is suspected. In that case, we incorporate the state-specific time trend, which relaxes the assumption of a parallel trend and shifts to parallel growth, which is less stringent. Another challenge is measurement error in covariates, as it can lead to attenuation bias. Reverse causality could be another issue. But for this study, the issue is unlikely as any trend in farmers' insurance coverage selection should not trigger the state government to promote a sustainable agriculture policy like this. Another identification threat is a spillover effect, which is unlikely to occur in this scenario. Because the policy is explicitly limited to the state of Virginia. The policy is unlikely to affect any farmers in the control group (North Carolina). However, in certain situations, farmers in nearby counties along the Virginia-North Carolina border may have farms in both states as well as homes in Virginia. As a result, even if a farmer lives in Virginia and owns a farm in North Carolina, they may benefit from it. In reality, the effect should be negligible because few farmers own farms in both states. To identify our model, we replicate a natural experiment with a difference-in-difference approach to minimize the issues, which will be discussed later.

Two Way Fixed Effect Model

To achieve the study objective, a two-way fixed effect model containing difference-in-difference estimates for the policy is employed. This model helps us to replicate a natural experiment to isolate the causal effect of the policy on the outcome. Since covariates, as well as state and year fixed effects, are included, this follows the TWFE approach. We first employed the following base model:

$$Cov_{c,s,t} = \beta_0 + \beta_1 \cdot Policy_{s,t} + \sum_{i=1}^{n} \beta_i \cdot Controls_{c,s,t} + \gamma_s + \lambda_t + \epsilon_{c,s,t} \tag{3.2}$$

As per eq. 3.2, Effective coverage rate is our dependent variable that varies by county, state and year. Our target variable is the tax credit policy which varies by state and time. β_1 is our coefficient of interest that captures the change in the effective coverage rate in Virginia in the post policy period, compared to North Carolina. We further controlled area of corn under cultivation, Yield_{t-1} which vary by county, state and year. γ_s and λ_t denote state and year fixed effects. State fixed effects help us control for unobserved time-invariant characteristics for each state, and year fixed effects control for shocks or trends that are common for all states each year. State fixed effect absorbs differences between states that do not change over time but could influence the outcome variable. Examples include geographical characteristics (e.g., climate, soil type), cultural factors, or long-standing policies unique to each state. Year fixed effect absorbs the influence of factors that vary over time but are the same for all states in a given year. Examples include nationwide economic recessions, changes in federal policies, or technological advancements.

I extended this model to include the state-specific time trend as shown in eq. 3.3. $\theta_{s,t}$ captures the state-specific time trend. The state-specific trend helps us account for differential pre-trends in the outcome variables, in this case, the effective coverage rate. It allows each of Virginia and North Carolina to have its own coverage rate trend. Besides, it controls unobserved factors unique to a particular state and varies over time (e.g., economic shocks, climatic shocks). This approach helps us make the identification of the policy more robust.

$$Cov_{c,s,t} = \beta_0 + \beta_1 \cdot Policy_{s,t} + \sum_{i=1}^{n} \beta_i \cdot Controls_{c,s,t} + \gamma_s + \lambda_t + \theta_{s,t} + \epsilon_{c,s,t} \tag{3.3}$$

Also, the state-specific trends allow us to relax the parallel trend assumption, which moves the underlying assumption from parallel trends to parallel growth. Now, the trend lines need not have the same slope. The two groups must have linearly increasing or similar nonlinear trends, a less stringent assumption than the parallel trend assumption (Mora & Reggio, 2012). Moreover, we reported clustered standard errors to overcome the spatial correlation among counties. Importantly, robust checks were also conducted. These checks, which compare Virginia to its adjacent North Carolina counties within 100 miles of the state border, play a crucial role in enhancing the validity of our comparisons regarding climate and geography and with different combinations of corn-grown land areas. Additional checks were conducted, with subsets of counties with more than 10000 acres of corn land, dropping year 2021 from the regression, considering it as a transition period and including 2021 as a post policy period., including other controls, state-fixed and year-fixed effects, and state-specific time trends.

Results

To examine the causal effect of the tax credit policy I applied the TWFE model in the difference- in-difference setting. Table 3.3 reports the findings from the base regressions. Four different models are initially reported with varying numbers of covariates. The effective coverage rate is the dependent variable for all four models reported in the table. Model (1) is primary regression, where only the policy was modeled against the effective coverage rate. Model (1) is likely to be biased due to omitted variables and the direction and magnitude of the coefficient of interest may not be accurate. Model (2) extends the base model by including Yield_{t-1} as another covariate. Further, model (3) adds another covariate, Area of corn, alongside Yield_{t-1} . Finally, model (4) considers all the study covariates while controlling state-specific time trends. State-fixed and Year-fixed effects were considered across all the models. The reason behind showing results from different combinations of covariates and fixed effects is to evaluate model stability and where our coefficient of interest remains robust across different model specifications, which helps us argue about the robustness of our findings. Standard errors were clustered at the county level across all six models.

Table 3.3 Base Regression Results on the Effect of the Policy on Insurance Coverage

Dependent variable: Effective coverage rate

	(1)	(2)	(3)	(4)
Policy	-0.015***	-0.012***	-0.012***	-0.019**
	(0.004)	(0.004)	(0.004)	(0.009)
$Yield_{t-1}$		-0.001***	-1.4e-04***	-1.5e-04***
		(4.7e-05)	(4.5e-05)	(5.8e-05)
Area			4.6e-07	4.2335e-07
			(2.9e-07)	(2.9e-07)
State FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
State-time trend	No	No	No	Yes
N	1050	1050	1050	1050

Note: Model (1) is the base regression with only the policy variable as a covariate. Model (2) adds $Yield_{t-1}$ as a control. Model (3) controls $Yield_{t-1}$ and Area. Model (4) additionally accounts for state-specific time trends alongside fixed effects. ***, **, and * denote statistically significant at 1%, 5%, and 10% levels of significance.

Across models (1) to (3), the value of the coefficient on the policy does not vary substantially, meaning that even after accounting for the potential threat of omitted variable bias, our results remain stable. The policy coefficient is statistically significant in all three cases at a 1% significance level. Further, when we included state-specific time trends, the value of the magnitude of the coefficient underwent a slight change, although the direction remained unchanged. In addition, the direction of the coefficient on Area and $Yield_{t-1}$ remained stable across the different models employed. However, the magnitude of the coefficient on Area is positive, close to zero, and statistically insignificant, implying a very minimal effect of Area on the effective coverage rate.

As per model (3), the value of the policy coefficient is –0.0127 (significant at a 1% significance level). This implies that in the post-policy periods in Virginia, the tax credit policy caused a 0.0127-unit reduction in the effective coverage rate relative to the pre-policy period, compared to the change observed in North Carolina. Further, when considering state-specific time trends, we observe a slight change in the magnitude of the coefficient. In model (4), the coefficient of policy is -0.019 and is statistically significant at a 5% level of significance. Simply put, the policy led to a 0.019-unit fall in the effective coverage rate following the policy year compared to the pre-policy era when compared to the trend in North Carolina.

The policy effect is negative across all the models, and we will explain its mechanism in the discussion section. Although the policy coefficient is statistically significant, it must be assessed for its economic significance. The absolute value of the coefficient is 0.019, which is less than the Standard deviation of the adequate coverage rate of the primary dataset, which is 0.052. Besides, effective coverage rates vary from 0.52 to 0.77. Thus, the effect can be considered moderate and cannot be overlooked. However, this policy did not drastically change the coverage rates.

Robustness Check

In order to scrutinize the validity of our results, we performed multiple robustness checks. First, we confine our dataset to equal to or more than 10000 acres of corn land counties. The results with two different models are reported in Table 3.4. Model (1) from table 2 replicates model (3) from Table 1, including all the covariates of the base model, state, and year-fixed effects, but disregards the state-specific time trends. Next, model (2) reproduces model (4) from Table 1 and applies all the covariates, including the state-specific time trends and state and year-fixed effects. Model (1) results are consistent with the base results in Table 3.3. The coefficient on the policy variable was –0.0127 and statistically significant at a 1% significance level. Here, the policy coefficient is -0.0103 and statistically significant at a 5% significance level. The magnitude and sign of another coefficient in model (1) did not change much compared to model (3) in Table 3.3. Further, I compare model (2) results where I included state-specific time trends. The coefficient on policy is –0.024 and significant at a 5% level, whereas the model in Table 3.3 (4) generates a coefficient on the policy of -0.019 with the same significance level. The signs of other coefficients in this model remain stable when compared to the base model in Table 3.3. Therefore, it can be argued that that our findings are robust across these models, and the results from Table 3.4 add strengths to our base findings.

Table 3.4 Regression Results on the Effect of the Policy on Insurance Coverage for Counties with at Least 10,000 Acres of Corn Land

Dependent variable: Effective coverage rate

	(1)	(2)
Policy	-1.03e-02** (0.004)	-2.4e-02** (0.009)
Yield_{t-1}	-1.1e-04* (4.5e-05)	-1.2e-04** (5.6e-05)
Area	2.6e-07 (2.5e-07)	2.3e-07 (2.5e-07)
State FE	Yes	Yes
Year FE	Yes	Yes
State-time trend	No	Yes
N	742	742

***, **, and * denote statistically significant at 1%, 5%, and 10% levels of significance.

More robustness checks were conducted, and the results are depicted in Table 3.5. For the control group, instead of considering all the counties of North Carolina, we took a sample of counties in North Carolina that are within 100 miles of the border of Virginia. Our methodology involved identifying the precise centroid of each county of North Carolina and then calculating the exact distance between the centroids of each county to the closest point on the border of Virginia. Later, we subset the counties whose centroids fall within 100 miles of the border of Virginia. This approach helps us to achieve a closer comparison. Adjacent counties of North Carolina are more similar in geography, climate, and production system, minimizing the risk of bad control for the difference-in-difference in setting. Model (1) in table 3.5 represents the base model without the state-specific time trends and model (2) further expands the base model to allow for state-specific time trends. Although the magnitude of the coefficients changed a bit compared to the base model, the sign and significance remain the same when considering no state-specific time trend. However, the coefficient of policy becomes statistically insignificant when considering state-specific time trends. But the direction of the coefficient remains negative. This loss of significance likely results from a reduction in the number of observations, which weakens statistical power, and a loss of variation in the data, as state-specific trends absorb part of the variation that previously contributed to identifying the policy effect.

Table 3.5 Regression Results on the Effect of the Policy on Insurance Coverage (Control Counties within 100 Miles of VA Border)

Dependent variable: Effective coverage rate

	(1)	(2)
Policy	-9.8e-03** (0.004)	-1.4e-02 (0.01)
Yield$_{t-1}$	-1.9e-04*** (5.3e-05)	-2.2e-04*** (6.6e-05)
Area	6.7e-07*** (2.4e-07)	6.5e-07*** (2.4e-07)
State FE	Yes	Yes
Year FE	Yes	Yes
State-time trend	No	Yes
N	800	800

***, **, and * denote statistically significant at 1%, 5%, and 10% levels of significance.

Additionally, as a final robustness check, we experimented with dropping the year 2021 from our original regression (Table 3.6 model (1)). This was in recognition of 2021 as a transition period, with the policy coming into effect in March 2021. The results of this check show no deviation in our coefficients' sign. Furthermore, the magnitude and significance of the coefficients remain largely consistent. We then included 2021 as a post-year to observe any change in the main findings. Our results in model (2) are consistent with the base results, reinforcing the robustness of our findings. This robustness check once again supports the validity and consistency of our findings, demonstrating that they are not likely sensitive to model specifications and thereby instilling confidence in the robustness of our research.

Table 3.6 Regression Results on the Effect of the Policy on Insurance Coverage (With different timeframes)

Dependent variable: Effective coverage rate

	Dropping 2021	2021 post
Policy	-2.03e-02** (0.009)	-1.9e-02** (9.8e-03)
Yield_{t-1}	-1.4e-04** (5.8e-05)	-1.5e-04*** (5.8e-05)
Area	4.3e-07 (2.9e-07)	4.2e-07 (2.9e-07)
State FE	Yes	Yes
Year FE	Yes	Yes
State-time trend	Yes	Yes
N	1008	1050

***, **, and * denote statistically significant at 1%, 5%, and 10% levels of significance.

Discussion

Our results provide evidence that following the introduction of conservation tillage and precision agriculture tax credit policy, the effective coverage rate of Virginia corn farmers has gone down. It is possible that this policy had a greater impact on yield-based insurance than on revenue-based insurance. Since the policy aims to promote precision agriculture, which can potentially help stabilize yields, farmers may perceive a lower need for yield-based coverage. Yet, revenue-based insurance accounts for both yield and price risks, making it less likely that farmers would adjust their coverage solely in response to this policy, as it does not directly influence market prices. However, due to the minimal number of post-policy years, we can argue that our findings pertain to the short-run dynamics of the policy. Our results could be explained a variety of mechanism. First, the strongest argument could be a change in farmers' risk perception shaped by the policy. Since the policy targets the promotion of PA, many farmers might adopt

PA. PA could give farmers more confidence in farming. PA technologies could be associated with a reduction in farmers' perceived risk. Many might consider themselves less risky due to modern farming equipment, such as precision soil management, automated planting, or pest detection systems. This shift in perception could lead to a reduced reliance on insurance coverage, as farmers might feel that their operations are more resilient or productive thanks to the adoption of PA tools. Gardezi and Bronson (2019) demonstrated that precision farming can aid in hedging environmental risks, including fluctuations in weather patterns, using advanced farming techniques, which in turn reduces crop failure. Liu et al. (2017, 2018) evinced that PA tools can facilitate disease management, including alleviating potato late blight and tomato late blight. Additionally, farmers might think that PA adoption improve their efficiency and profitability, which is also evident in some research (see Lencsés et al., 2014; Schimmelpfennig, 2016; Thompson et al., 2019). This assumption could lead to reduced needs for coverage as producers might believe that increased profit from PA can offset any uncertainty they face.

Second, the tax credit policy is especially targeted to promote PA technology among the state farmers. The policy might have encouraged farmers to invest in PA tools gradually as farmers have more incentives to buy a PA tool. For instance, the price of soil mapping tools can range between $10,000 and $30,000. With the tax credit policy, the actual price will be $7500 to $22500. Hence, the policy can reduce a farmer's costs by $2500 to $7500. However, this still costs a farmer a lot. With a huge investment cost, a producer might opt for a relatively lower amount of insurance coverage to compensate for their extra spending over time. If the effect of the policy works through this mechanism, the policy effect may fade gradually in the long run as the farmers adjust their long-term finance. Since our data is limited to only two post-policy years, the true effect might not be captured. It could be possible that due to huge spending, farmers chose to drop their coverage in the short run while they manage their funds and gain stability as time goes on and increase their coverage in the long run. Had we had more years of data, we could have explored this avenue.

Third, this policy can instigate farmers' expectations of future policies promoting more sustainable agriculture and subsidies, which can give them a feeling of a better management situation. Modern technologies in farming have the potential to stabilize crop production against climatic and geological threats by using intensive data management and forecasting, which is a great innovation by PA (Oliver et al., 2013; Prajapati and Pandya, 2025). For instance, a farmer who uses data management platforms like John Deere Opscenter and ClimateView can gain insight about the potentially low productive parts of the field as well as the possibility of crop risk due to varying levels of humidity, precipitation, sunshine, or other climatic events. The more data someone has, the better he can hedge against pre-evaluated risk. This can lead them to choose lower coverage for mitigating yield risk.

Fourth, another potential factor influencing the observed decline in the effective coverage rate could be the increasing presence of younger farmers and their risk behavior in farming. Historically, a significant share of the total farming population in Virginia is younger newcomers. It is possible that the policy can attract some young individuals as they are more familiar with technology. Young people may be more risk-takering. Additionally, younger farmers are more aware of modern trends in farming; they have access to more data related to crop health and yield. They might be cognizant of the fact that modern farming can reduce crop yield failure risk and thus could be triggered to take a lower level of insurance coverage. Furthermore, younger farmers may prioritize investment in technology over traditional risk management strategies like insurance, especially in the short run. The financial incentives provided by the tax credit could encourage them to allocate more resources toward PA equipments rather than maintaining high insurance coverage. While these explanations shed light on the observed trend, we suggest that future research look into the policy's long-term implications to examine whether the coverage rate reduction persists as more farmers adopt PA technologies and adjust their risk management strategies.

Lastly, our coefficients on control variables also seem to be logically reasonable. First, the coefficient on yield lag was negative and statistically significant across different models. This implies that a bad last-year yield will lead to a higher coverage selection this year and vice versa. This is reasonable and makes farmers, in many cases, take farming decisions based on previous year results. For instance, a farmer who experienced huge loss in yield last year will perceive himself as risky and thus will hedge more against potential threats through insurance. At the same time, farmers with high yields last year may become confident about the current year's crop and may perceive themselves as less risky, which could lead to selecting lower coverage. Second, the coefficient on the area of corn cultivation is positive, meaning that an increase in non-irrigated farmland is associated with a higher insurance coverage level. This finding is intuitive, as non-irrigated farmland is more susceptible to weather variability and drought risk, making farmers more likely to seek greater insurance protection. However, the statistical significance of this coefficient varies across different models, suggesting that while the relationship generally holds, it may be sensitive to model specification or other interacting factors. Moreover, the results are indicative of the importance of these control variables to isolate the actual effect of the policy. After controlling these variables, our policy coefficient remained stable and robust.

Conclusion

There is an increasing volume of research on the potential economic viability of PA, farming efficiency gains by PA tools, and factors affecting PA adoption. However, there has been very little data in the context of the U.S. While the avenues require attention in future research, this chapter delved into a new arena of the economics of PA. To the best of my knowledge, this is the very first study that examines the effects of a pro-precision agriculture policy on the farmers risk perceptions, proxied by insurance coverage levels. This study scrutinized the role of the conservation tillage and precision agriculture tax credit policy in shaping farmers' insurance coverage rates in Virginia. We replicated a natural experiment in a difference-in-difference setting to identify the policy effect. This identification strategy leverages the variation in policy exposure between Virginia and North Carolina, making it possible to estimate the causal effect of the policy on farmers' insurance decisions. The reason behind selecting North Carolina as a control was that it is the most adjacent state to Virginia and very similar in geography, farming practices, and climate. Our graphical visualization of the trend in coverage rates in Virginia and North Carolina suggested that the parallel trend assumption is likely to hold, which helps in robust inferences.

The study data were sourced from SoB and RMA spanning 1999-2023. Effective coverage rates were calculated as acres-weighted insurance coverage. To address the threat of omitted variables bias, after careful review of existing literature, we controlled for the premium rate, yield lag, loss ratio lag, and area of corn cultivation. The base regression results suggested that, the tax credit policy leads to 0.023 units decrease in coverage rates in Virginia in the post-policy period compared to that of North Carolina. The coefficient on policy was also statistically significant. Although the size of the effect is not substantial, it can be considered economically meaningful. Our results including the coefficients on the control variables were mostly robust across different combinations of alternative models. Although this is a novel attempt into the study of this policy, the study entails some limitations and thus needs future research.

First, although the data spanned over a long period of time, the post-policy period only covers two years. This restricts us inferring our results to short-term effects. In the future, another study should be conducted using a more number of post-policy periods to observe the long-term trend. This study anticipates the long-term effect to be stable over time and might be different than the short-term findings. Second, a more ideal experiment would have encompassed farmers' level granular data instead of county-level data. Our study data limit us from knowing the actual farmer-level response to the policy; rather, our findings imply the aggregate response of farmers at a particular county, which could be often misleading if there is a substantial amount of intra-county variation. Third, due to data limitation, we could not exploit this study framework for other major crops in Virginia, soybeans, and cotton. Hence, we cannot argue about a broader generalizability of our research. Future research can examine the effect of the policy and observe whether different crop producers respond differently to this type of pro-PA policy.

Lastly, future research should look into the direct casual effect of adoption of PA on insurance coverage rate given more years of data available. The findings presented here serve as a starting point for future studies that could explore the broader implications of PA adoption on farm sustainability, profitability, and resilience to climate and market variability. The expansion of the scope of analysis and the use of more granular data could help policymakers, researchers, and farmers themselves make more informed decisions in an increasingly complex agricultural landscape.

CHAPTER FOUR

DRONE ADOPTION PLANS AND TECHNICAL EFFICIENCY OF FARMERS IN AUSTRALIA

Introduction

PA has the potential to transform agriculture into a more economically viable and cost-effective module (Bhakta et al., 2019). PA can potentially transform how farmers approach their work, giving them the tools to make smarter, data-driven decisions that may increase crop yields, reduce input use, and increase production efficiency. Technologies like drones, GPS, and data analytics are at the heart of this change. Drones, for example, offer farmers a bird's-eye view of their fields, making it easier to spot issues like pests, disease, or uneven soil conditions, all in real-time. GPS technology helps map fields with greater accuracy, with the ability to ensure that fertilizers and pesticides are applied only where needed, reducing cost and potentially resulting in environment benefits. With the help of data analytics, farmers can process PA generated information to make timely decisions, potentially improving efficiency and productivity. These innovations can help farmers produce more while using fewer resources and staying competitive in a rapidly evolving agricultural landscape.

While various digital equipment is in use, unmanned aerial vehicles (UAVs), commonly known as drones, have been one of the most recent additions. Drone use in agriculture is relatively new compared to other popular PA equipment like Variable Rate Technology (VRT), soil mapping, yield monitors, etc. However, the recent trend for drone adoption in farming is very promising. The worldwide agricultural drone market is expected to develop at a compound annual growth rate (CAGR) of more than 30% by 2027, parallel to the rising use of other precision farming methods (Uncrewedaviation, 2024). The use of drones could bring multifaceted benefits for the farmers. First, farmers can potentially better monitor their crop health and disease situation with high-quality spectral images through drones. The images collected by drones are able to help farmers in determining which part of the field they need to give more attention to achieving a higher yield (Rejeb et al., 2022). Second, drones can be utilized to assess soil health, nutrient conditions, and field mapping. Drone images are capable of offering precise data on soil nutrient deficiency and signaling the need for nutrient application in the proper place of a field (Inoue, 2020). Previously, with manual equipment, judging the proper application of nutrients would be difficult. Drones hereby have the potential to reduce farmers' costs and time by offering more details about proper soil health management. Third, drones are becoming increasingly popular for precise fertilizer and pesticide applications. It can be helpful to ensure even nutrient and pesticide application, thereby reducing cost (Velusamy et al., 2021). Fourth, some advanced drones are used to plant seeds nowadays, particularly in challenging parts of the fields. While improving to handle uneven terrains, it has also contributed to less use of labor and thus potentially minimize the cost associated with it (Wan et al., 2022). Moreover, in recent days, drones have been helping farmers with irrigation management decisions. Drone cameras can potentially identify soil moisture status and areas of over- and under-irrigation (Ihuoma et al., 2021). In turn, this can help farmers to irrigate appropriately without wasting water. Further, some tech platforms offer yield protection services using drone data, which can help farmers make prudent farming decisions and hedge against potential future risks.

Drone application in agriculture has been largely adopted in major developed countries, and Australia is among the major leaders (Nazarov et al., 2023). The country has diverse agricultural, fisheries, and forestry sectors, producing various crops and livestock products. The gross value of agricultural production has increased by 51% in the past 20 years in real terms (adjusted for consumer price inflation), from \$62.2 billion in 2003–04 to \$94.3 billion in 2022–23. When including fisheries and forestry, the total value of agricultural, fisheries, and forestry production has increased by 46% in real terms in the same 20-year period from approximately \$68.5 billion in 2003–04 to \$100.1 billion in 2022–23 (ABARSS, 2024). However, there has been a slight decline in the labor force in Australian agriculture, down 0.7% from a decade earlier (ABS, 2024). Despite the decline in the use of labor, Australian agriculture production is robust, and part of that can be attributed to digital agriculture. To maintain its rapid growth, feed its growing population, and maintain sustained exports, automation could be essential for the country. Drones could be a pivotal propeller for transforming its farming system in this milieu. This study lays a foundation for assessing the association of farmers' attitudes towards drone adoption and technical efficiency and aims to help Australian policymakers by providing proper guidelines.

The concept of technical efficiency is a firm's capacity to create as much output as feasible with a specific level of input given the available technology. It can also refer to a scenario in which it is difficult, with present technological knowledge, to increase output from given inputs or achieve a given output using less of one input without using more of another (Farrell, 1957). This study aims to examine the relationship between drone adoption plan and technical efficiency. In order to achieve the study goal, we first adopted a two-stage DEA model where DEA scores were extracted using the output-oriented DEA in the first stage. In the second stage, DEA scores were converted to proportional output scaling factor and regressed on drone use plan and other covariates. Our findings from the two-stage DEA indicate that farmers who plan to use drones in the next five years are more technically efficient than those who do not. Later, we employed a sub-sample bootstrapping approach to check the stability and robustness of our model. Our bootstrapping results imply that our original regression results are robust, and the truncated regression estimates converge quickly toward the true value.

While numerous research studies have attempted to unveil the role of PA in cost reduction and technical efficiency (Koutsos & Menexes, 2017; McFadden, 2017; Delay et al., 2021), there is a dearth of research that examines the relationship of future drone use and technical efficiency of the farmers, especially in Australia. As drones become increasingly significant in Australian agriculture, a case study like this is essential to understand the characteristics and efficiency patterns of potential future adopters. In this regard, this study attempts to fill this gap by examining the relationship between the adoption of future drone use and technical efficiency. Although this study is limited by a small sample size and cross-sectional data, it can still provide useful insights into how the prospect of future drone adoption is associated with farmers' current technical efficiency.

Background

Precision Agriculture in Australia

The use of modern PA in Australia can be traced back to 1934, with Smith (1938) describing yield variability using a yield map. Reflectance-activated sport spraying was first made available in Tamworth in the 1980s (Felton & McCloy, 1992). The country's GPS era began with civilian access in 1993, followed by major developments such as the advent of Fugro Starfix/OmniStar WADGPS in 1994-1995, the Beeline Navigator for agricultural machinery in the late 1990s, and the availability of high-accuracy CORS networks for agriculture by 2009. With the introduction of grid soil sampling and yield mapping, inspired by practices from the U.S., farmers quickly embraced technologies like variable-rate input applications. Key milestones included the launch of the first all-in-one hardware and software solution for yield mapping and variable-rate control in 1996, the first national PA conference in 1997, and the early 2000s adoption of high-accuracy elevation and yield maps. By the mid-2000s, variable-rate nutrient applications became popular, and by 2006, controlled traffic and swathing technology gained momentum. From 2007 onward, technologies such as plant reflectance sensors and automated implement control further transformed and advanced PA practices in Australia (Whelan, 2011).

The country's PA market is expected to grow at a rate of 11.6% over 2024 to 2030. The major leaders involve AGCO Corporation, John Deere, Farmers Edge, Trimble Inc, TeeJet Technologies, Raven Industries, Topcon Positioning Systems etc. (6Wresearch, 2024). The Grains Research and Development Corporation (GRDC) has committed 3 million AUD to support dissemination of PA. In viticulture, precision methods are thriving, with evidence showing that high-value vineyards benefiting from site-specific management (Lowenberg-DeBoer, 2003). The Australian agriculture, fisheries, and forestry sector aims to reach AUD100 billion in annual farm gate output by 2030, with digital agriculture potentially contributing around AUD 20.3 billion annually. Various state governments have been funding initiatives to promote the adoption of Internet of Things. These include New South Wales' Farms of the Future program, Victoria's On-farm IoT trial, Western Australia's eConnected Grainbelt program and IoT DecisionAg grants, and South Australia's AgTech demonstration farms (Hansen et al., 2022).

Use of Drones in Australian Agriculture

Drone integration in Australian agriculture is on the rise, supported by Civil Aviation Safety Authority (CASA) regulations. The first agricultural use drones in Australia were manufactured in the early 2000s, alongside GPS systems for precision agriculture and drones deployed for crop mapping and field analysis (Wilson and Robinson, 2023). The country ranks eight in terms of most productive countries and universities/organizations that contribute to agricultural drone-related research (Rejeb et al., 2022). Drones are capable of aiding in precision farming, monitoring, and water management in remote areas. However, high costs, training needs, and connectivity issues hinder wider use, despite their potential to enhance productivity and promote sustainability (Nazarov et al., 2023).

In Australia, farms are hiring drones to check crop health utilizing infrared mapping, such as normalized difference vegetation index (NDVI), to detect crop stress and health concerns on farming holdings (Logan, 2017). Additionally, drones are becoming increasingly popular for crop spot-spraying, soil and field analysis, seed distribution, and irrigation. Major products in the current market include DJI Agras T20 Spraying Drone and DJI Agras T30 Spraying Drone (DFH, 2025). Drones are presently used to assist operational activities by around 10% of Australian agricultural businesses. By 2040, agricultural drone usage is expected to reach 8,300 units under the low uptake model and 23,900 units under the high uptake model. Cost reductions for the agriculture, forestry, and fisheries industries are projected to total \$3.5 to \$10.4 billion from 2020 to 2040 under low, medium, and high adoption scenarios (Deloitte Access Economics, 2020). One thing worth noting is that Australia is depending largely on Chinese-manufactured drones instead of producing their own, due to the low cost, ease of use, and high performance of Chinese drones.

Data Envelopment Analysis

The efficiency analysis can be broadly categorized into parametric, which uses stochastic frontier regression, and non-parametric methods, such as data envelopment analysis (DEA) (Badunenko and Tauchmann, 2019). One advantage of a parametric approach is that while analyzing inefficiency, it can also showcase the factors affecting it. Meanwhile, DEA endogenously estimates a production frontier and does not explicitly identify the factors affecting efficiency. So, the use of two-stage DEA has gained popularity, where the first stage involves estimating the efficiency scores and the second stage runs a regression of the efficiency scores on a set of environmental variables. This study applies the output oriented (DEA). DEA assumes that a Decision-Making Unit (DMU) is an entity that transforms input into outputs. DMUs can denote individuals, firms, and banks; in this study, farmers represent DMUs. Input and output can be regarded as goods in DEA, where DEA estimates the degree to which inputs can be reduced with the same level of output or output levels can be increased without any increase in inputs. Due to data limitations, input or output information could be missing (e.g., price). DEA uses observable data to construct a feasible combination of inputs and outputs rather than establishing a cost or profit function. Output and input data can be in revenue/expenditure or physical quantity. A major advantage of using DEA is that it does not require any functional relationship between inputs and outputs. Another merit is that this method can be applied to panels, cross-sectional, or time series data. Our study is entirely cross-sectional and uses information on two inputs and one output to run the DEA model. DEA can impose increasing, decreasing, or variable returns to scale. To implement DEA, one must provide a possible movement "direction" and be able to build a hull that includes observed input-output observations from the DMU "reference set." The performance of other DMUs is evaluated compared to the reference set (Refsland, 2018). Over the years, DEA has become widely popular for estimating technical efficiencies.

"Output" oriented technical efficiency is the entity's capacity to maximize production using its limited resources. One business is more technically efficient if it generates more output than another with the same inputs and technologies (Skold and Popov, 1990). In assessing a firm's technical efficiency, it is assumed that 100% efficiency is the ideal, which is determined by the frontier production function. This concept, introduced by Farrell (1957), suggests that the best possible production level is the "frontier," and any deviation from it indicates inefficiency. Efficiency is compared to other firms facing similar challenges, making it a relative measure. For example, while Soviet agricultural industries might seem efficient compared to local peers, their efficiency could still fall below global standards. Farrell's original framework has been continuously updated to measure efficiency at the firm level. While there are basically, two major approaches for measuring technical efficiency (parametric and non-parametric), we choose to opt a non-parametric DEA approach because it is flexible, does not require assumptions about the functional relationship between inputs and outputs, and can handle multiple inputs and outputs with different units. For example, one input might measure lives saved, while another might measure dollars spent, without needing a predefined tradeoff. DEA compares each firm directly against its peers, making it a useful tool for assessing efficiency (Seiford and Thrall, 1990).

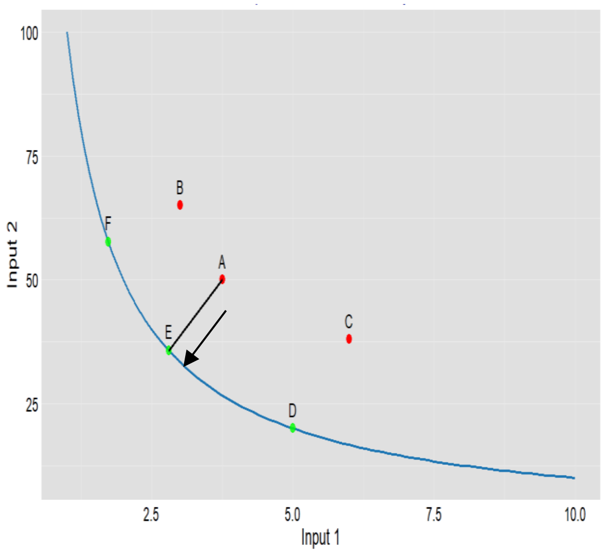


Figure 4.1 Input-Contraction Technical Efficiency

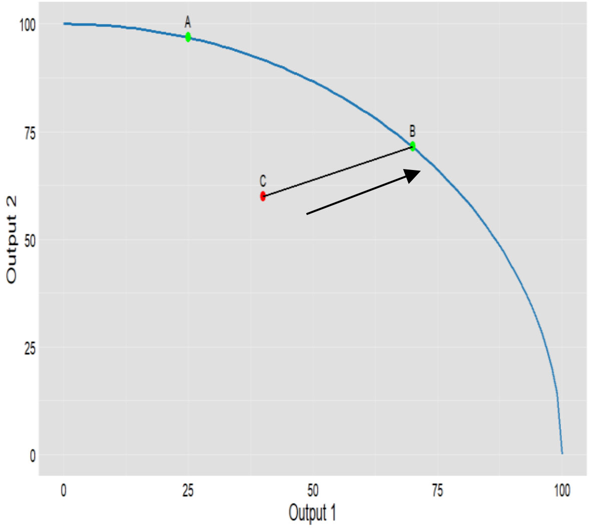


Figure 4.2 Output-Expansion Technical Efficiency

The concept of technical efficiency is graphically illustrated in Figures 4.1 and 4.2. While the left-side figure depicts the notion of potential input contraction, the right side symbolizes the idea of potential output expansion. In input contraction, firms A, B, C, D, E, and F output depends on input 1 and input 2. The convex blue line represents an isoquant curve defined by farms D, E, and F where each point on this curve corresponds to the same amount of output given two inputs. Farms D, E, and F are located on the curve and are fully technically efficient. This means they produce the maximum output using both inputs 1 and 2.

In contrast, farms A, B, and C lie above the isoquant curve. Simply put, in comparison with firms D, E, and F, farms A, B, and C are using more input to generate a specific output. For instance, farm A is technically inefficient and ideally wants to move as close to the isoquant as possible. As such, point E on the isoquant would become the target for farm A. Although farms D and F are also efficient, they are more distant from A. Hence, firm A will try to achieve full technical efficiency by reducing the input level of AE, keeping its output constant. Here, distance AE can be treated as its technical inefficiency.

Further, figure 4.2 shows output-expansion technical efficiency through the production possibility curve (PPC). PPC demonstrates the maximum attainable output combinations that can be produced with the efficient use of resources. Here, firms A, B, and C produce two distinct outputs, say output 1 and output 2, using a given level of input. Firms A and B lie on the PPC, which means they are fully technically efficient. Simply put, firms A and B produce the optimal combination of output 1 and 2 given scarce resources. Any point below the PPC implies inefficient use of resources, in other words, technical inefficiency. Firm C sits below the PPC and has room to increase its output combination from C to B. Thus, CB denotes the inefficiency of firm C. It is possible for firm C to increase its output to B without using any additional input, thereby achieving complete efficiency. It should be noted that firms cannot go beyond the PPC without further improvement in technology.

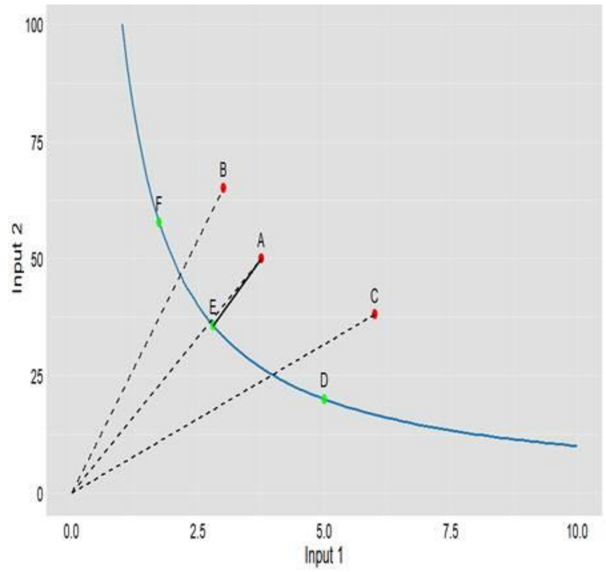


Figure 4.3 Input-Contraction DEA

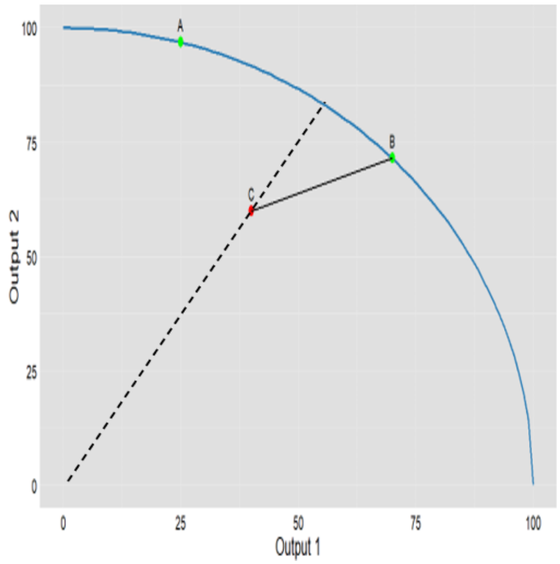


Figure 4.4 Output-Expansion DEA

The DEA framework operates differently from the mechanisms illustrated in Figures 4.1 and 4.2. Figures 4.3 and 4.4 depict the working principles of DEA. Specifically, Figure 4.3 demonstrates the concept of input-contraction DEA.

In this framework, instead of attempting to replicate Firm E to achieve efficiency, Firm A will adjust its inputs to reach the intersection of the isoquant curve and the straight line extending from the origin through Firm A. The same principle applies to Firms B and C. Rather than emulating their closest peers, Firm B will aim for a point on the isoquant curve between Firms E and F, while Firm C will move toward a point between Firms E and D on the isoquant curve. Further, figure 4.4 depicts the notion of output-expansion DEA. Here firm C, instead of trying to reach its closest peer B, will reach a point between B and C on the PPC where the straight line from the origin hits the PPC. This distinction highlights how DEA identifies efficiency targets based on input contraction or output expansion, guiding firms toward optimal production points rather than simply emulating their closest peers.

Literature Review

PA and Technical Efficiency

PA, IoT, and smart farming have the potential to bring tremendous changes to the sustainable methods of agriculture by making it more resource-efficient, productive, and cost-effective. Technologies are believed to help the farmer in soil, water, climate, pests, and crop health monitoring for informed decisions on better crop management, hence possibly assuring higher yields, lowering costs, and better usages of water and fertilizers in the face of climatic change and increasing demand for food. (Ali et al., 2023).

A review study of 128 research articles for Sub-Saharan countries found that precision technologies like soil and plant sensors, satellite imagery, GIS, and crop-soil simulation models can enhance resource use efficiency and support sustainable agriculture. While these technologies have proven effective, most are still in the experimental stage, with only South Africa applying them on large-scale commercial farms. The adoption of PA could significantly boost productivity for smallholders without requiring additional input (Onyango et al. 2021).

Further, McFadden (2017) analyzed USDA ARMS data to evaluate the effect of yield and soil mapping on technical efficiency. The study finds that yield mapping improves efficiency, while soil mapping reduces it. However, the combined effect of both technologies is slightly positive. The negative impact of soil mapping may be ascribed to the exclusion of other relevant precision agriculture technologies.

Delay et al. (2021) based on McFadden (2017) examines the relationship between PA adoption and technical efficiency using the 2016 USDA Agricultural and Resource Management

Survey (ARMS) data. Through cluster analysis, four distinct producer groups based on PA adoption were identified, corresponding to the technology adoption curve. Using stochastic frontier analysis (SFA) and stochastic meta-frontier analysis (SMFA), the study presented evidence that farms with advanced PA technology bundles were significantly more technically efficient than non-adopters. Specifically, early majority farms were 14% more efficient than laggards, and innovators were 16% more efficient.

Moreover, McFadden et al. 2022 using USDA survey data and stochastic frontier analysis examined the relationship between Midwest corn production and mapping technologies. Their findings reveal both direct and indirect productivity effects of map adoption, with field output increasing by 5.6% to 11.9%. They also evinced that yield maps enhance efficiency by 8.5%, and soil maps by 7.2%. The effects varied depending on operator experience and field characteristics, suggesting that there are untapped opportunities to improve productivity through field-level data usage. Meanwhile, Carrer et al. (2022) examined the adoption of PA Technologies in São Paulo's sugarcane farms in Brazil and their impact on technical efficiency and technology gap ratio (TGR). Their analysis based on Interviews with 131 farmers revealed that farm size, farmer education, and technical assistance positively influence PA adoption. The results further showed that adopters have higher technical efficiency and TGR scores than non-adopters, with greater efficiency in input use.

Čechura et al. (2021) analyzed the competitiveness of Czech cereal production. Precision farming technology is used employing micro-level data from 2005–2018. The results show significant technological progress, contributing to higher technical efficiency and cost savings. The average overall technical efficiency was 83%, with precision farming farms achieving 84%

technical efficiency. Their findings also claimed that Precision farming led to 17–18% reduction in cost, while overall cost reductions ranged from 5% to 47% based on efficiency estimates. The study also found that precision farming improved productivity and efficiency, particularly in land- and labor-saving technologies. Total factor productivity (TFP) grew by 3.4% annually from 2004 to 2012, but declined by 2.4% in the following years.

Further, Mwalupaso et al. (2019) examined the impact of mobile phone usage on agricultural productivity and technical efficiency (TE) in Zambia, focusing on actual usage rather than ownership. Using two models—stochastic production frontier (SPF) and propensity score matching-SPF (PSM-SPF)—it was found that mobile phone use significantly increase efficiency. The SPF model overestimates efficiency by 5.3% due to unaccounted biases. The study also claimed that increasing mobile phone adoption could reduce poverty severity by 5.13% and extreme poverty by 8.21%. Further research is needed to confirm these findings and explore causal mechanisms.

Moreover, a myriad number of studies evinced that precision agriculture leads to cost reduction (Schimmelpfennig and Ebel, 2016; Robertson et al., 2007). Besides, a large group of literature focuses on the factors affecting adoption of PA (Tey and Brindal, 2012; Castle et al. 2016). While research related to other PA equipment and farm efficiency, adoption and cost savings through precision agriculture is widely conducted, any study on relationship between drone adoption in farming and efficiency is primarily lacking. Despite McCarthy et al. (2023) highlighting that farmers in Malawi perceive drones as a means to reduce input costs, empirical studies investigating the direct relationship between drone adoption and farm efficiency are scarce. It would be ideal to study the effect of drone adoption on technical efficiency of the farmers. However, we do not have data to address this question. Rather, we are using a survey data from Australia to proxy this question with the relationship of drone use planning and technical efficiency. This planning variable serves as a useful proxy for drone adoption intentions and can be indicative of farmers who are more technologically inclined or are beginning to integrate drone-related practices into their operations. By linking this proxy to technical efficiency estimates derived using a two-stage DEA framework, we can explore whether a relationship exists between drone use planning and farm efficiency. While this does not allow us to claim a causal impact of drone use on efficiency, it provides valuable initial evidence and highlights an important direction for future research when more comprehensive data become available.

Two Stage DEA

Two-Stage DEA is based upon efficiency analysis using either DEA or Free Disposal Hull (FDH). In the first stage, DEA scores are calculated using the distance function, and in the second stage, the DEA scores are regressed on environmental variables (Simar and Wilson, 2011). One condition of using two-stage DEA is that the separability condition needs to be held. This assumption simply implies that environmental variables, such as a drone use in this case, cannot affect the production process but can only be related to the distribution of the efficiency frontier. Any violations of this assumption could lead to biased estimates in the second stage regression (Simar and Wilson, 2007). In order to avoid this issue, we will not include any environmental variables that are deemed to be potential inputs in the second stage regressions. Published demonstrations of the two-stage DEA method can be found in McCarty and Yaisawarng (1993), Charnes et al. (1994), Kooreman (1994), Kirjavainen and Loikkanen (1998), McMillan and Datta (1998), Dollery and Worthington (2000), Mukherjee et al. (2001), Wanke and Barros (2014), Chen et al. (2009), and Henriques et al. (2020).

The second stage involves a regression where efficiency scores are modeled on a set of environmental variables. We can find mainly three types of regression used in this approach. Johnson and Kuosmanen (2012), Chowdhury and Zelenyuk (2016), Gulati and Kumar (2017) and some other papers used truncated regression in the second stage. Meanwhile, Some of the studies adopted the Tobit model (see McDonald, 2009; Romagnoli et al., 2021; Liang et al., 2021). Further, some employed the OLS model to estimate the regression coefficients (see Yen et al. 2023; Ervural et al. 2018). Simar and Wilson (2007) made assumptions on the second stage where truncated regression can be estimated using the maximum likelihood approach. On the other hand, Banker and Nataranjan (2008) made assumptions that the second stage regression is an OLS approach, and the regression format is log-linear. However, they did not make any valid inference from their model. Hoff (2007) and Ramalho et al. (2010) argued that OLS, Tobit, or truncated regression models should be used in the second stage, but these papers do not specify a well-defined statistical model in which such structures would follow from the first stage, where initial DEA estimates are obtained.

Sub-sample Bootstrapping

Bootstrapping is a potentially powerful approach for statistical inference, offering a resampling-based approach to estimate the properties of complex estimators. Efron (1979) first introduced the idea of bootstrapping. He explained both parametric and non-parametric bootstrapping. His nonparametric bootstrapping involves resampling with replacement from the original sample size at the same size. This method is not reliable for making consistent inferences about the boundaries of the data's support. As a result, it is unsuitable for use with non-parametric estimators like Data Envelopment Analysis (DEA) and Free Disposal Hull (FDH) (Simar and Wilson, 1999a). This process remained quite popular for quite a bit of time until Politis et al. (1999) described a new sub-sample bootstrapping technique. This approach resamples without replacement a subsample size of m from an original sample size of n, where m is much less than n. Such samples are themselves samples of size m from true unknown distribution F of the original sample. Sub-sample bootstrapping can hold asymptotic consistency property even when classical bootstrapping fails (Chernick, 2011). In DEA literature, bootstrapping has been mainly used to estimate the bias-corrected DEA efficiency scores. The first study to apply a bootstrap technique for approximating the distribution of the DEA estimator under the Variable Returns to Scale (VRS) assumption was by Simar and Wilson (1998). However, DEA estimates obtained using a naïve bootstrap are inconsistent, especially near the boundary. In other words, as the sample size increases, the estimator does not converge to the true parameter. This occurs because the naïve bootstrap estimate has a non-zero probability of matching the sample estimate, but the probability of it matching the true parameter is zero (Kneip et al., 2008). To address the inconsistency issue, Simar and Wilson (1999b) introduced a homogeneous smooth bootstrap, which assumes that inefficiencies follow the same distribution for all DMUs. While this assumption is restrictive, the method still provides reliable estimates, even with a relatively small dataset. Further, Simar & Wilson (1999b) estimated Malmquist indices and proposed a procedure for confidence interval construction that does not explicitly use the bias-corrected estimates. Later, Simar and Wilson (2000) expanded their work by developing a heterogeneous smooth bootstrap, where inefficiency distributions can differ across DMUs.

In the bootstrap method, the convergence rate is of great importance and crucial for statistical inference. The convergence rate in the context of bootstrapping refers to how quickly the bootstrap estimates approach the true population parameters with the increase in sample size (Geyer, 2006). Faster convergence indicates higher accuracy and efficiency of the bootstrap method. The convergence rate of bootstrapped DEA estimates hinges upon the smoothing technique and the properties of efficiency distribution. The smoothed bootstrap adjusts bootstrap samples with a kernel density approach to achieve consistency, in order to minimize the bias and variance (Simar & Wilson, 2000). It was also illustrated that the convergence rate of the DEA estimators is on the slower side for finite samples, especially in small sample size and when DEA scores are influenced by outliers. However, the notion of finite sample properties in DEA has been in continued investigation. Kneip et al. (2008) stated that the convergence rate not only depends on the finite sample property but also on the data dimension. They noted that the convergence rate deteriorates as the number of input and output increases relative to the sample size.

Novelty and Contribution to Literature

To my knowledge, this is the first research of its niche from two standpoints. First of all, the efficiency analysis relating to the drone use plan cannot be traced in the literature. It would be great to study the effect of drone use on the technical efficiency of farmers; however, we have virtually no data on it. By treating technical efficiency as the outcome, the analysis examines whether farmers who intend to adopt drones in the future tend to be more technically efficient today. This could reflect a forward-thinking mindset or better resource management capabilities — traits that could both improve efficiency and encourage early interest in new technologies like drones. Early adopters of drone technology, for example, are often those who actively seek out tools that optimize inputs, reduce waste, and improve yields. Their willingness to experiment with or invest in such technology signals not just an interest in drones, but a broader tendency toward embracing modern, data-driven farming practices. In this context, the observed efficiency gains might not be solely due to drone usage itself, but rather a reflection of a broader technological orientation. These farmers may already be using or are more likely to adopt complementary tools—such as precision irrigation systems, satellite-guided tractors, or farm management software—which collectively enhance farm performance. Although this relationship is not causal, it provides meaningful insights into the characteristics of potential drone adopters and how efficiency aligns with openness to technological innovation. This is a pioneering study to investigate the technical efficiency of farmers in relation to drone adoption plans. At the same time, this is a novel endeavor to take Australia as a case. The findings may offer valuable insights into how farmers' plans for future drone adoption relate to their current technical efficiency, potentially informing investment decisions in drone technologies for improved farm management. Second, I made a novel methodological contribution through the use of sub-sample bootstrapping and estimated convergence rates of the truncated regression coefficients. All the previous studies employed subsample bootstrapping to estimate bias-corrected DEA and then convergence rates to learn the stability of DEA estimates. To the best of my knowledge, this is the very first paper to use sub-sample bootstrapping to estimate truncated regression coefficients, followed by estimating convergence rates and eventually building the confidence intervals. Additionally, this paper uses a real dataset to do such analysis. Most of the research generates artificial data and then applies bootstrapping for estimating convergence rates.

Hence, it may enable us to perceive the nature of model stability for the truncated regression coefficients that exploit the DEA scores with a real-world dataset. This novel approach could provide invaluable insights into the robustness and accuracy of the estimates, further potentially advancing our understanding of such model performance in efficiency analysis.

Data

The study leverages data from Zuo et al. (2021) encompassing farmers from three states in Australia- New South Wales, Victoria, and South Australia. This data is basically derived from a survey executed in 2015-2016. The original dataset had 1000 observations. The authors acknowledged their data quality limitations, and thus I had a critical review of the data to ensure sufficient data quality for analysis. To refine the dataset, I performed an initial exploratory analysis that involved visualizing summary statistics and identifying patterns and potential inconsistencies in the data. This entailed creating histograms, boxplots, and scatterplots to investigate the distribution of key variables, identify outliers, and evaluate the relationships between various factors influencing farm efficiency. Throughout this process, I discovered significant variation in income levels, with a high proportion of extreme values that could potentially skew the results. I limited the data to farmers with annual incomes between 50,000 and 150,000 AUD, resulting in a total of 364 observations. This decision was based on ensuring a more homogeneous sample that represents mid-sized commercial farms while excluding extremely low-income and high-income farmers, who may operate under different constraints. Table 4.1 represents the summary statistics of the data used for this research.

Table 4.1: Summary statistics of the study data

	Mean	Median	SD	Max	Min	N
Net Income (‘0000 AUD)	84.28	87.50	24.81	138	50	364
Water Use (ML)	834	495	1228	12500	0	
Land (Ha)	815	243	1978	20194	2.02	
Age	59.1	59	11.5	89	25	
Drone Use Plan	0.344	0	0.476	1	0	

Net income is expressed in ('0000 AUD) and has a mean of 84.24 and a median of 87.50. With a standard deviation of 24.81, net income ranges from 50k AUD to 138k AUD. Next, water use is measured with a mean of 834 Mega Litre (ML) and a median of 495 ML. Its value ranges from 0 to 12,500 ML, with a standard deviation of 1,228. Further, land is expressed in hectares, with an average of 815 and a median of 243. The maximum land for a farmer was found to be 20,194 ha, and the minimum is 2.02 ha. The standard deviation for land is 1,978. Moreover, farmers in the study represent a diverse age range, with an average of 59.1 years, a median of 59 years, and a standard deviation of 11.5. Their ages range from 25 to 89 years. Lastly, drone use plan is a categorical variable. In addition, drone use plan is marked as one if a farmer plans to use drones in the next five years and zero otherwise. 34% of the farmers are found to have drone use plan in the next 5 years, with a standard deviation of 0.476.

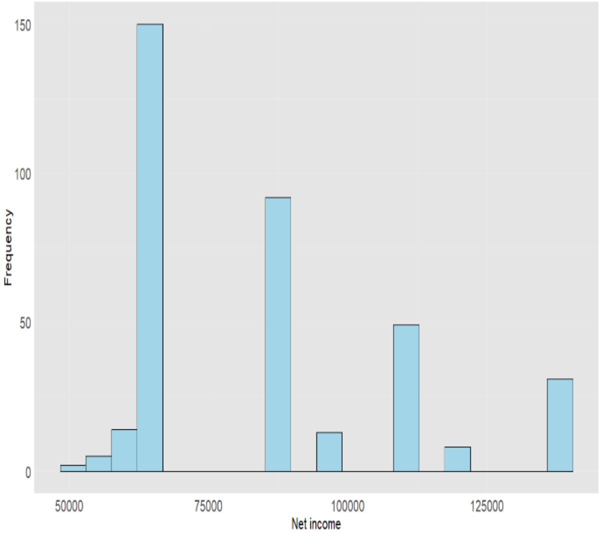


Figure 4.5 Histogram of Net Income

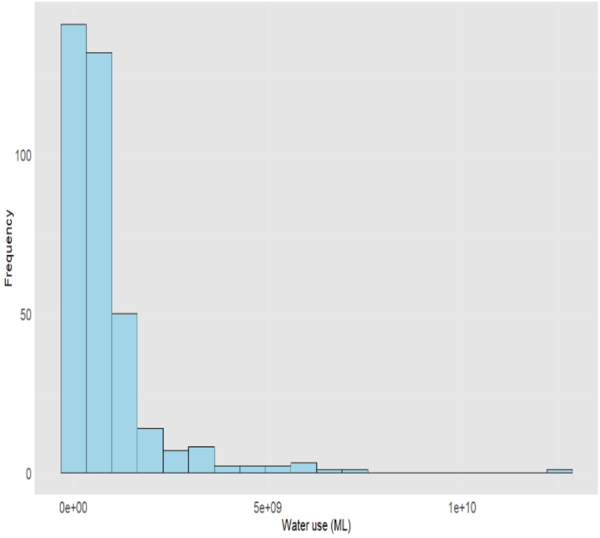


Figure 4.6 Histogram of Water Use

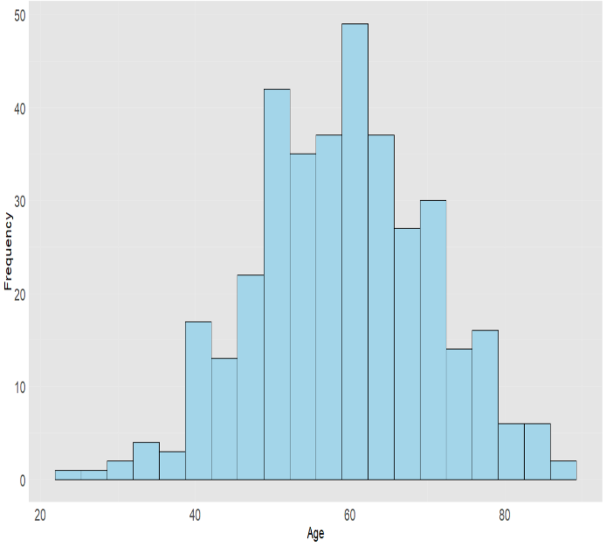


Figure 4.7 Histogram of Age

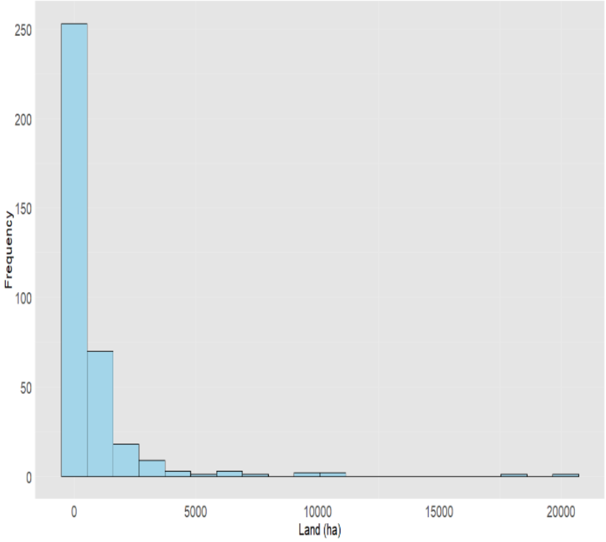


Figure 4.8 Histogram of Land

Further, the distribution of the study variables are shown in the figures 4.5 to 4.8 above. The distribution of net income is right-skewed, which suggests that there is income inequality within the group. Also, income seems to be stacked in some points. Water use is rightly skewed, with a few of the farmers having very high water use. Next, age seems to have a very close to normal distribution. The right-skewed nature of the distribution of land suggests that its distribution is uneven, with a few entities holding significantly larger amounts of land compared to the majority.

Methodology

This study employs a two-stage Data Envelopment Analysis (DEA) framework. In the first stage, efficiency scores are calculated and truncated between 0 and 1. To represent the proportional output scaling factor, we take the inverse of these efficiency scores. This scaling factor reflects the extent to which a production unit can proportionally expand its output given fixed input resources. The scores are further truncated at 1 on the lower end. In the second stage, these output scaling factors are regressed on one or more environmental variables.
Similar approach has been widely used in literature, including studies by Chakraborty et al. (2001), Mukherjee et al. (2001), and Ralston et al. (2001), among others. While many of these studies utilize the Tobit model, we apply a truncated regression model because our data is explicitly truncated, and values beyond a defined range are not observed. As Greene (2008) notes, applying a Tobit model to truncated data can bias coefficient estimates toward zero, underestimate the true effects, and produce incorrect standard errors. The truncated regression model, by contrast, is more appropriate in this context and helps avoid these biases.

The advantage of DEA is that it does not require any functional form of relationship between the output and inputs. It can also handle measuring efficiency for multiple outputs and inputs. DEA emphasizes revealed best practice frontier practices rather than the central tendency property of frontiers (Theodoridis and Psychoudakis, 2008). The distance function was first introduced by Chambers et al. (1996) into efficiency analysis. The inefficient DMUs can be projected to the frontier using direction $g=(-g_x, g_y) \neq 0_{m+s}$, where $g_x \in R^m$ and $g_y \in R^S$. In the first stage, we estimated the DEA with a distance function that showcases how far the observed input-output combination is from the efficient frontier. This estimates the efficiency score of DMUs relative to the distance of the fully efficient DMUs in the frontier. We used one output of net income, and inputs were the water use and land. The output-oriented DEA model aims to maximize the net income without increasing water use and land area. The formulation is as follows:

$$\max_{\theta,\lambda} \quad \theta \qquad \text{subject to,}$$

$$\sum_{j=1}^{n} \lambda_j \cdot \ln(\text{Land}_j) \leq \ln(\text{Land}_0) - \theta g_{\text{Land}} \tag{4.1}$$

$$\sum_{j=1}^{n} \lambda_j \cdot \text{WaterUse}_j \leq \text{WaterUse}_0 - \theta \cdot g_{\text{WaterUse}} \tag{4.2}$$

$$\sum_{j=1}^{n} \lambda_j \cdot \text{NetIncome}_j \geq \text{NetIncome}_0 + \theta \cdot g_{\text{NetIncome}} \tag{4.3}$$

$$\textstyle\sum_{j=1}^{n} \lambda_j = 1 \tag{4.4}$$

$$\lambda_j \geq 0, \quad \forall j \tag{4.5}$$

The main goal is to scale up θ, which is a proportional increase in net income considering the input constraints (eq. 4.1 and eq. 4.2), output constraints (eq. 4.3), convexity constraint for VRS (eq. 4.4), and non-negative constraint (eq. 4.5). Eq. 4.1 and eq. 4.2 ensure that inputs for land and water use cannot exceed their observed level in actual data, meaning that inputs are unchanged. Eq. 4.3 denotes that net income, which is our output, can scale up to θ. Eq. 4.4

ensures that VRS holds, and efficiency is evaluated compared to firms of similar scale. Eq. 4.5 aids in assigning weights to each DMU while calculating the efficiency scores. It ensures that all the DMUs contribute positively to the efficiency estimation. We took the inverse of the estimated DEA scores to represent a measure of inefficiency for all the DMUs. Hence, DMUs with a score of 1 are denoted as efficient, and those with scores greater than 1 are referred to as inefficient. The closer the efficiency score of DMU is to 1, the more efficient the DMU is.

Truncated Regression

After obtaining efficiency scores for each DMU, we then regress them on the sets of environmental variables for our model. The main model used in our study is as follows:

$$E_i = Z_i\beta + D_i\gamma + \epsilon_i, \qquad i= 1,2,\ldots J \tag{4.6}$$

E_i is a vector (J X 1) of technical efficiency for J DMUs, Z is a (J X R) matrix of environmental variables, D is the vector of the dummy variable for Drone use plan (0,1) and ϵ_i is a (J X 1) vector of residuals. The technical efficiency scores were truncated at 1, and the DMUs with a value of 1 were excluded from the regression. By truncating technical efficiency scores at 1 and excluding DMUs with an efficiency score of 1, the model focuses on the inefficient units, which allows for a meaningful analysis of how environmental variables are related to inefficiency. This approach can help prevent bias, potentially allows more variability in the dependent variable, and improves the accuracy of the regression analysis. γ is our coefficient of interest. All our variables only vary by individual DMU unit. It is worth noting that, due to the cross-sectional structure of the data and the inability to replicate a natural experiment design, the coefficient of interest only captures the correlation between drone use plan and efficiency score, and we will be very careful interpreting our results later.

Sub-sample Bootstrapping

To estimate the relationship between efficiency and drone adoption planning while accounting for variability in data, we applied the sub-sample bootstrapping in the original truncated regression model. While sub-sample bootstrapping has been extensively applied to DEA estimates, to the best of our knowledge, this is the first study to employ such a method in the second stage of DEA, where we regress the DEA scores on a set of environmental variables. For each bootstrap iteration, we draw a random subsample from dataset $\mathcal{D}^{(b)}$ of size n, with the subsample size of m (m << n). Each subsample represents an independent sample without replacement drawn from the population. S_b denotes the randomly selected indices for b iterations.

$$\mathcal{D}^{(b)} = \{\,(X_i, Y_i) \mid i \in S_b\,\}, \quad S_b \sim \text{Sample}(\{1, \dots, n\}, m)$$

We estimated the original DEA, then regressed the DEA scores on our covariates and bootstrapped the truncated regressions with 2500 bootstrap iterations. Next, we estimated the mean and median of the bootstrap estimates across different subsamples. Besides, standard deviations of the estimates were also calculated to estimate the rate of convergences to learn the model's stability.

We estimated the convergence rate following Politis et al. (1999). The convergence rate can be expressed in n^{β}, where β is some constant. In the usual case, it follows the square root law ($n^{0.5}$), where beta is 0.5. We need to estimate β to know the convergence rate under this supposition (Geyer, 2006). Further, we built the confidence intervals of the bootstrap estimates across different lists of samples. The ${}_{n}C_{m}$_mpick function (Atwood, 2023) was used to determine the optimal sub-sample size from the list of bootstrap samples. This function follows the procedure suggested by Simar and Wilson (2011). A confidence interval for the optimal sub-sample size for each estimate was reported. This process entails that confidence intervals meet a predefined significance level of 0.05 with confidence with a confidence interval lag (1 in this case).

Results

Before presenting the main regression results, the distribution of the proportional output scaling factor scores from the DEA model is depicted in Figure 4.9. The scores are slightly skewed, and many DMUs are far from the fully efficient point at 1. Only 37 DMUs are found to stand right on the efficient frontier. DEA uses these fully efficient farmers as a reference set and compares them with the other DMUs. Values close to 1 indicate that farmers are more efficient. The values are clustered at specific points and are not normally distributed. There are a few farmers who are highly inefficient, sitting very far away from the frontier. This figure also suggests that there is room for many farmers to improve their efficiency. The output proportional scores had a mean of 1.719 and a median of 1.571, with a standard deviation of 0.44. The scores ranged from 1.00 to 2.75. (Figure 4.10). Besides, I identified the number of DMUs with a score of 1 by drone use plan. It was found that 13 of the farmers planning to use drones have the perfect score, whereas the rest of the 24 farmers with a score of 1 do not intend to use drone. This is also a representation of our actual data, where 33% of the farmers planning to use drones.

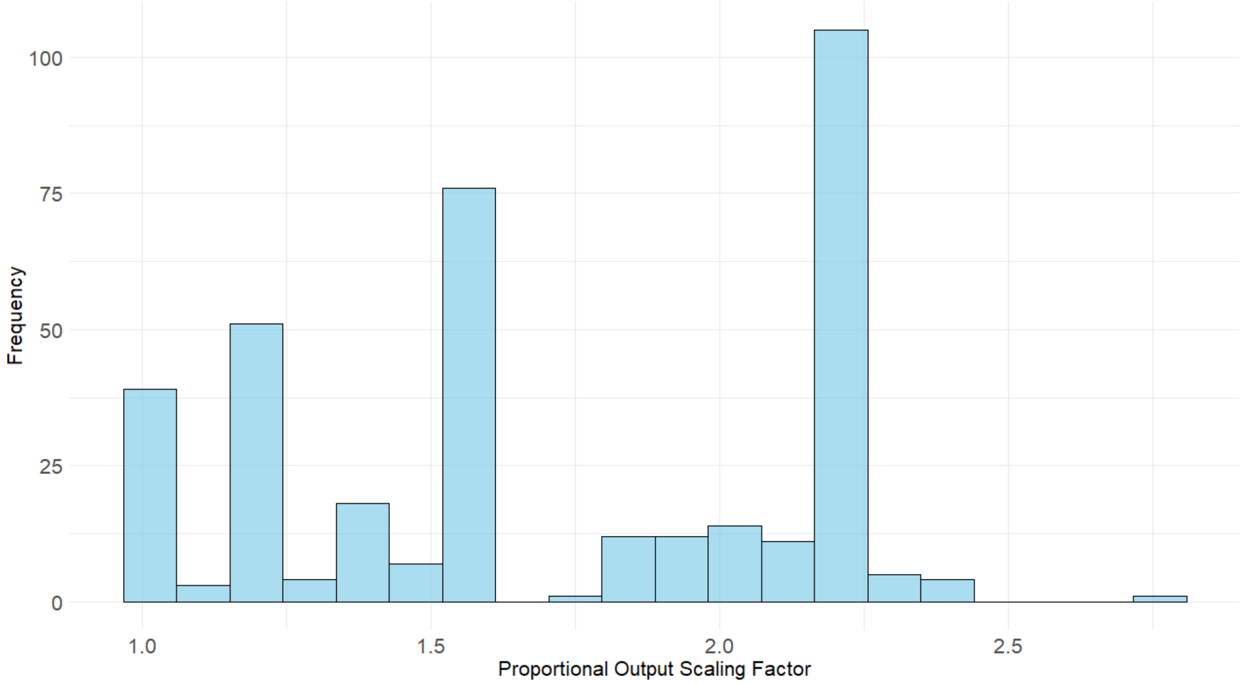


Figure 4.9 Histogram of Proportional Output Scaling Factor

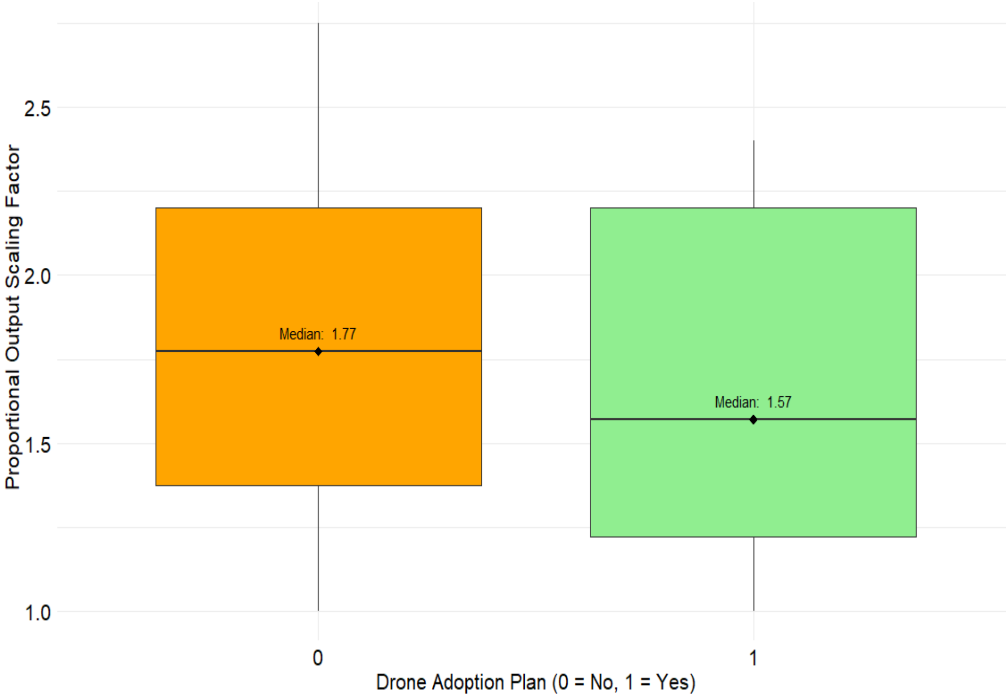


Figure 4.10 Break-down of Proportional Output Scaling Factors by Drone Use Plan

Later, I break down the Proportional Output Scaling Factor by drone use plan. The median score for farmers who plan to use drones is 1.57, while the median score for farmers who do not have such plan is 1.77. Since we took the inverse values of the DEA efficiency scores to truncate them at 1, a lower proportional output scaling factor for drones indicates that farmers who plan to use drones are, on average, more efficient than those who do not. This implies that farmers who do not intend to use drones could increase their output by up to 176%, given the same level of resources, while those who plan to use drones could expand their output by up to 157% under similar conditions. It is also worth noting that the scaling factor scores for future drone users are more widespread than those of non-users, suggesting a wide range of possibilities for improvement and inspiring further research and development in this area.

I then present the truncated regression results in table 4.2. Three regression models are presented here, with estimated proportional output scaling factor scores as the dependent variable. Model (1) is the basic regression, using Drone use plan as the only explanatory variable. I extended this basic model to Model (2) to control for age. In Model (3), I included a polynomial degree of 2 for age. The reason for adding Age^2 is to examine whether the relationship between age and proportional output scaling factor scores is non-linear.

Table 4.2: Truncated Regression Results on the Relationship of Drone Adoption Plan and Efficiency

	Dependent variable: Estimated proportional output scaling factor scores		
	(1)	(2)	(3)
Drone Use Plan	-0.168*** (0.056)	-0.155*** (0.055)	-0.161*** (0.055)
Age		0.005** (0.002)	0.041** (0.018)
Age^2			-0.001*** (0.001)
Intercept	1.819*** (0.032)	1.500*** (0.145)	0.466 (0.555)
N	326	326	326

Notes: The sample includes survey-level data from 2015 in Australia, with the dependent variable being the estimated DEA scores. Models (1), (2), and (3) use a truncated regression approach to analyze the relationship between the set of independent variables and Efficiency. Only the coefficients of interest are reported. Standard errors are shown in parenthesis.
* Statistically significant at the 10% level, ** at the 5% level, and *** at the 1% level.

In all three models, I found a significant positive association between drone use plan and proportional output scaling factor scores. The magnitude and significance of the drone use plan coefficient do not change much when extending the base model to Model (2) and Model (3). This also indicates the stability of our results. Previously, the summary statistics showed that farmers who do not plan to use drones could increase their output by 177% compared to their current levels, given the same resources. In contrast, farmers who plan to use drones could increase their output by up to 157% under the same conditions. The regression coefficient for the drone use plan suggests that if farmers without such a plan were to adopt it, their proportional output factor would decrease by 0.16 units, leading to an estimated 10% gain in efficiency. We also found a non-linear relationship between age and proportional output scaling factor scores. While the coefficients of age and age squared indicate that a younger farmer is comparatively inefficient, in the long run, as they mature, they become more efficient. Again, our main coefficient of interest is drone use plan, and we cannot infer causality from these models for the following reasons. This study uses a cross-sectional dataset for a single year. First, having multiple years of data on the same set of observations would have allowed us to observe changes over time and capture the effect. Drone use plan and proportional output scaling factor may be influenced by omitted variables that are not included in the models, such as farm size, location, or technology adoption culture, which could confound the observed association. These unaccounted variables could influence the relationship we observe between drone use plan and proportional output scaling factor. Third, the direction of causality between current technical proportional output scaling factor and plans for future drone use may be bidirectional. While intentions to adopt drone technology in the future could reflect a commitment to enhancing efficiency, it is also possible that farmers who are already technically efficient are more likely to plan for drone adoption. In this sense, current technical efficiency may signal a forward-thinking approach and strong resource management skills, which make these farmers more open to embracing innovative tools like drones. Therefore, the observed relationship between current technical efficiency and future drone use plans might not only indicate the potential effect of forward-thinking attitude but also reflect that efficient farmers are more predisposed to adopting new technologies. This suggests a reinforcing cycle where existing efficiency encourages future technology adoption, which could, in turn, further improve efficiency. Given these points, although we cannot infer causality, we establish a correlation that is also significant. This gives us an idea that there is a potential relationship between efficient farmers and attitude to drones.

While our study failed to establish causality, I checked the stability and robustness of our results with the sub-sample bootstrap approach. This method helps us evaluate the consistency of our findings across different sub-samples, providing a more reliable basis for inference even in the absence of definitive causality. Boxplots of regression coefficients on drone use plan, age, age^2 and intercept are presented in figures 4.11 to 4.14 below. Each boxplot for different estimates corresponds to different subsample groups of 1 to 10. Where subsample groups have observations 35, 42, 49, 57, 67, 79, 93, 109, 128 and 150, respectively. We performed 2,500 bootstrap replications, meaning that we repeated the estimation process 2,500 times, each time drawing a new sample from the original dataset. It is important to note that the samples are drawn randomly from the full dataset, without adhering to any specific rules or constraints regarding their composition. This randomness helps to ensure the generalizability of the results, reducing the potential bias in our bootstrap samples.

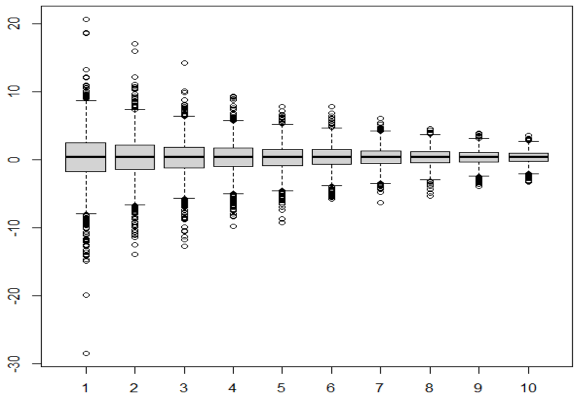


Figure 4.11 Boxplot of Bootstrapped Intercept

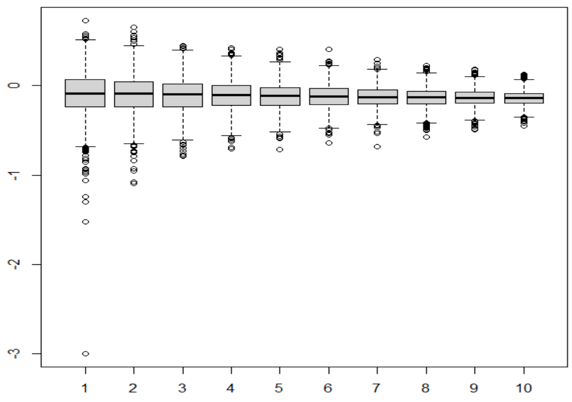


Figure 4.12 Boxplot of Bootstrapped Drone Use Plan Estimates

The distribution of the intercept estimates across sub-sample groups becomes gradually tight with the increase of the sample size. The estimates converge and remain unbiased across all the groups. On average, the coefficient stays positive for different groups, and this goes in line with the actual regression results, where our intercept estimate was 0.466 in the final model. Further, I plot the boxplots of the drone use plan estimates for our bootstrap sample groups. A gradual convergence is observed as we increase the sample size, and the spread of the estimates also tightens; however, it remains unbiased. Our base model yielded a coefficient of drone use of -0.16. Similarly, the estimate for each subsample group revolves around that value. This also suggests that our estimate is potentially consistent.

Further, figures 4.13 and 4.14 show the distribution of coefficients for age and age^2 across sub-sample groups. Both coefficients are converging with the gradual increase in sample size. Besides, both seem to be unbiased as they converge. When making comparisons with the estimates of the base truncated model, we see parallels. The regression coefficients on Age and Age^2 were 0.041 and -0.001, respectively. The estimates boxplot for these two revolves around the value of the regression results. One thing common for all of our estimates is that they converge to the true value. However, the boxplot results of the bootstrapped estimates are not enough to communicate the rate of convergence or how fast the estimate converges. Hence, we calculated the convergence rates for each case and graphically presented them.

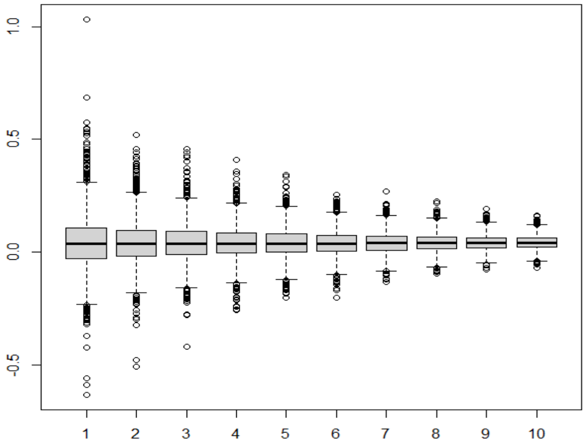


Figure 4.13 Boxplot of Bootstrapped Age Estimates

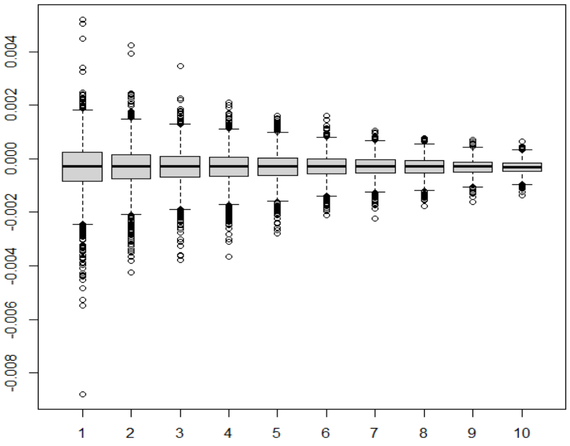


Figure 4.14 Boxplot of Bootstrapped Age^2 Estimates

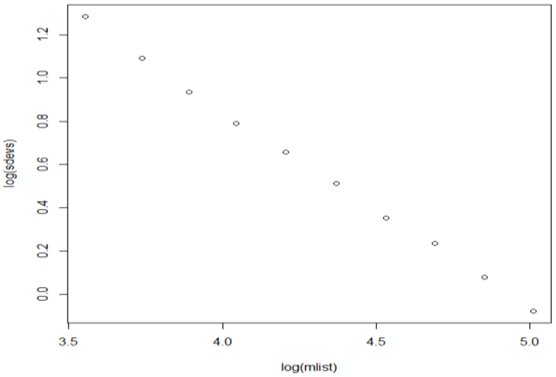


Figure 4.15 Convergence of Intercept

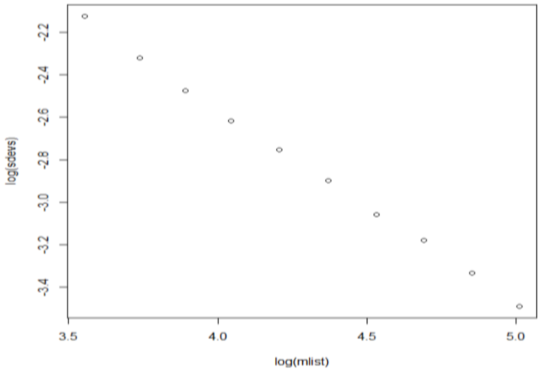


Figure 4.16 Convergence of Drone Use Plan

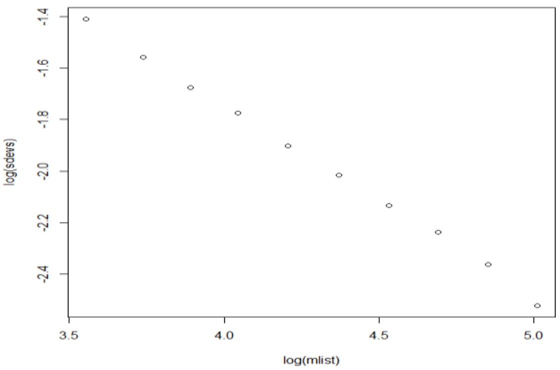


Figure 4.17 Convergence of Age

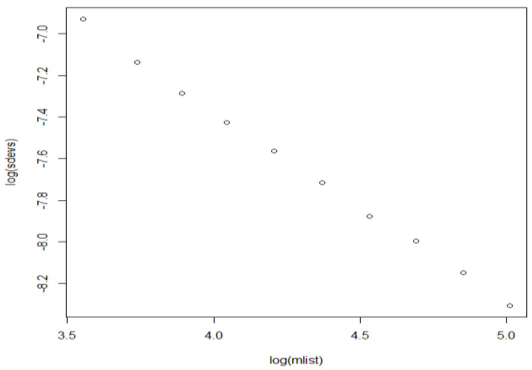


Figure 4.18 Convergence of Age^2

Figures 4.15 to 4.18 depict the rate of convergences, in other words, how quickly the bootstrap estimates become stable as we increase the sub-sample size. For each coefficient, we plotted the standard deviations against the sub-sample size. It captures the change in estimation variability, showing how the dispersion of bootstrap estimates decreases as the sample size increases. As the sub-sample size grows, the standard deviations tend to decrease and stabilize, indicating that the estimates become more reliable with larger sample sizes. Initially, with smaller sub-samples, the variability is higher due to increased sampling noise. However, as more data points are included in the estimation process, the bootstrap estimates converge toward their true values, and their standard errors shrink.

Bootstrap estimates for Intercept, Drone use plan, Age and Age^2 seem to be linearly converging to without any fluctuation. These figures indicate the nature of convergence; however, it is also imperative to know the actual rate. The estimated convergence rate for Intercept, Drone use, Age and Age^2 are 0.89, 0.75, 0.89 and 0.85 respectively. The rates are higher than theoretical rate of 0.5. However, indicating that our estimates stabilize much faster than expected. This suggests that fewer bootstrap resamples are needed to achieve precise estimates, reducing computational burden while maintaining accuracy. The rapid convergence implies that our data contains strong identifying information for the parameters, with well-defined relationships between proportional output scaling factor scores and explanatory variables. Initially, small sub-samples exhibit high variability due to sampling noise, but as the sample size grows, randomness diminishes, leading to stable estimates. The faster-than-expected convergence may be attributed to factors such as the structured nature of Data Envelopment Analysis (DEA), the truncated regression model, and the strong explanatory power of the selected variables.

Further, we calculated the mean value of the bootstrap estimates for respective subsample groups, presented in table 4.3. This provides us with an indication of how close our estimates are to the actual regression results. The mean of the intercept ranges from 0.424 to 0.366. Intercept seems to go down as the sub-sample size increases. Our original regression estimated the intercept at 0.466, and the bootstrap means remain relatively close to this value, suggesting that the estimates are stabilizing as the sample size grows.

Table 4.3: Mean of Bootstrap Estimates

	Sample size (2500 NB)									
	35	42	49	57	67	79	93	109	128	150
Intercept	0.424	0.397	0.397	0.402	0.422	0.412	0.422	0.389	0.381	0.366
Drone	-0.097	-0.105	-0.106	-0.113	-0.117	-0.124	-0.130	-0.134	-0.139	-0.143
Age	0.038	0.039	0.039	0.039	0.039	0.040	0.039	0.041	0.041	0.042
Age^2	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001

Table 4.4: Median of Bootstrap Estimates

	Table 3: Median of the bootstrap estimates Sample size (2500 NB)									
	35	42	49	57	67	79	93	109	128	150
Intercept	0.442	0.444	0.415	0.456	0.400	0.436	0.464	0.402	0.421	0.410
Drone	-0.097	-0.104	-0.108	-0.114	-0.115	-0.121	-0.123	-0.131	-0.137	-0.142
Age	0.036	0.037	0.038	0.037	0.040	0.039	0.038	0.041	0.040	0.041
Age^2	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001

Table 4.5: 95% Confidence Intervals of the Bootstrap Estimates

	Sample size (2500 NB)									
	35	42	49	57	67	79	93	109	128	150
Intercept	-0.50, 1.67	0.42, 1.59	-0.49, 1.61	-0.42, 1.53	-0.48, 1.53	-0.44. 1.50	-0.44, 1.50	-0.42, 1.49	-0.38, 1.46	-0.37, 1.46
Drone	-0.24, -0.10	-0.24, -0.10	-0.24, -0.10	-0.24, -0.09	-0.24. -0.09	-0.25, -0.09	-0.25 -0.09	-0.24 -0.09	-0.25 -0.09	-0.24 -0.09
Age	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.07	0.01 0.06
Age^2	-0.001 0.001	-0.001 -0.001	-0.001 0.001	-0.001 -0.001	-0.001 -0.001	-0.001 -0.001	-0.001 -0.001	-0.001 -0.001	-0.001 -0.001	-0.001 -0.001

Next, on average, the coefficient on drone use was consistently negative across all 10 subsample groups and gradually approached the coefficient value of the actual regression estimates. The range of the mean of the bootstrap estimates for drone use is -0.097 to -0.143, while regression yielded a coefficient of -0.16. Hence, our bootstrap results are very close to the regression estimates, and this further strengthens our findings. The consistent negative coefficient on drone use suggests that drone use is associated with lower technical inefficiencies, implying that farms planning to use drones tend to operate more efficiently. The gradual decline in the bootstrap estimates as the sample size increases indicates that larger samples provide more precise estimates of the true effect of drone use plan.

Additionally, I reported the median of the bootstrapped estimates in table 4.4. The median for the drone use plan coefficient spans from -0.097 to -0.143, which are very similar to the mean bootstrap estimates. Meanwhile, our actual regression yielded -0.16 for the drone use plan coefficient. Indeed, both the median and mean bootstrap estimates are close to the regression. This further strengthens the robustness of our results. The stability of these estimates across different sub-sample sizes indicates that our findings on the relationship between drone use plan and proportional output scaling factor are not driven by random variation but potentially reflect a systematic trend. The median of estimates for other variables, including the intercept, remains close to the original regression results. These bootstrap estimates enable us to evaluate the robustness of our regression, and since the results are close to the truncated regression, it is highly likely that the regression results capture the actual relationship between the variables studied.

Later we built the confidence intervals for each of the coefficients from the bootstrap output, which is reflected in table 4.5. It depicts the results of confidence intervals for bootstrap estimates. Confidence intervals define a range within which coefficient values are likely to fall, providing a more nuanced understanding of the estimations than point estimates. Confidence intervals are very important in statistical analysis because they let us determine the statistical significance of our coefficients. A confidence interval that excludes zero indicates that the related coefficient is likely to be statistically different from zero, implying a meaningful association between the predictor and the dependent variable. If the confidence interval includes 0, it indicates that the effect is not statistically significant, implying that the predictor does not have a meaningful effect on the outcome variable.

It is worth noting that the 95% confidence interval values for our coefficient of interest on drone use plan fall in the negative range for all 10 sample groups. This hints that the coefficient is different than zero and is statistically significant. More to add here is that since the coefficient value and the 95% confidence intervals are negative, it can be communicated that drone use plan is positively associated with technical proportional output scaling factor. Moreover, following the procedure suggested by Simar and Wilson (2011), we used the nCm_mpick function (Atwood, 2023) to determine the optimal sub-sample size from the list of bootstrap samples. For drone use plan, we found sub-sample number 8 with a confidence interval of [-0.24, 0.09]. Our mean bootstrap estimate and original regression coefficient for drone use also fall within this range, further strengthening the significance of the coefficient. Next, the confidence intervals for the intercept across all 10 subsample groups include positive, negative, and zero values. This indicates that the true value of the intercept could be either positive, negative, or zero, meaning there is no strong evidence to suggest that the intercept is significantly different from zero. In our original regression results, the intercept was already found to be statistically insignificant, meaning that we did not have enough evidence to conclude that it differs from zero. The bootstrap confidence intervals further reinforce and validate this finding by demonstrating that, even when using a resampling approach, the range of possible intercept values remains inconsistent in sign and includes zero. Besides, the confidence interval for age in all the sub-sample groups is positive and different than zero. The optimal sub-sample group was 7 for age, where their confidence intervals range from 0.01 to 0.07. Our original regression coefficient on age and mean bootstrap estimates for all the sub-sample sizes fall within this range. The fact that the confidence intervals never cross zero suggests that, across different sub-sample groups, the effect of age remains robust and consistently different from zero. Moreover, confidence intervals associated with Age^2 consistently fall in negative values across 10 different subsamples, while the best one was found to be number 7. This is also different than zero and similar to the value of the regression coefficient on Age2 and bootstrap estimates. This also implies that the coefficient on Age^2 is statistically significant, identical to the main regression finding.

Finally, we estimated the one-tailed p-value associated with the bootstrap estimates for different optimal sub-sample groups for each variable and intercept. One-tailed p-value for intercept for sub-sample groups for intercept, drone use plan, Age and Age^2 were found to be 0.151, 0.00, 0.011, and 0.0184, respectively. The intercept is statistically insignificant while drone use plan, age, and age^2 are statistically significant. These results add value and strength to the confidence intervals obtained for the bootstrap estimates and the actual truncated regression results. In all different cases, our estimates and their significance are consistent. Overall, the alignment between our bootstrap confidence intervals, p-values, and original regression results strengthens our conclusions, providing further confidence in the validity and reliability of our findings.

In line with our preliminary regression results and bootstrap estimation, the farmers who are currently planning on using drones are technically more efficient. While we cannot establish causality and direction of the casual effect. Rather, this finding captures the correlation. It could be possible that farmers who plan to use drones might well be producing in a cost-effective, efficient manner; thus, their technical inefficiency might be a lot lower than those who do not. On the flip side, it is also possible that farmers who are already more efficient favor adopting drone. To exemplify, farmers who are already more efficient—meaning they operate closer to optimal efficiency—may be more inclined to adopt drones as part of their continued efforts to refine and enhance their production processes. These farmers likely recognize the marginal gains that drone technology can provide in terms of precision monitoring, input optimization, and labor savings. Since they are already operating at a relatively high efficiency level, their motivation to adopt drones could stem from a desire to further fine-tune their operations, reduce costs, and maintain a competitive edge. Besides, with respect to our results for age, we observed a non-linear relationship with proportional output scaling factor, as the coefficient on Age is positive and Age^2 is negative. Simply put, younger farmers are relatively technically inefficient, however, as farmers become mature they attain higher efficiency. This pattern can be explained by a variety of ways. Younger farmers may be relatively technically inefficient due to a lack of experience, limited financial resources, and poor decision-making skills, whereas older farmers benefit from accumulated knowledge, stronger networks, and better access to financial capital, allowing them to make more efficient production decisions. Furthermore, older farmers are likely to have a better understanding of their land, improved risk management strategies, and a track record of experimenting with best farming practices, all of which contribute to increased efficiency over time. As they gain experience, they are more likely to invest in PA technologies and implement resource-optimizing practices. Overall, our findings suggest that technical efficiency is closely linked to both attitudes towards drones, and the experience accumulated over time, highlighting the importance of both technological progress and farmer expertise in enhancing production efficiency.

Conclusion

A growing trend of research is showcasing evidence that advanced agricultural technologies are likely to be related to cost-effective and efficient production. However, hardly any study examined the relationship of farmers' drone adoption in farming and technical efficiency. Due to a lack of ideal data, this study replicated an alternative approach of studying the relationship between farmers' drone adoption plan and technical efficiency. Technical efficiency is the measure of maximizing output without wasting any additional input or minimizing output without producing any extra output. This study examined the association of drone use plan and technical efficiency, taking Australia as a case. A two-stage DEA model was developed where the DEA scores were estimated taking water use and land use as inputs and net income as output. Then, the efficiency scores obtained from the first stage were converted into proportional output scaling factors and regressed on environmental variables, including drone use plans, age, and age^2. Later, for robust inference, we applied the sub-sample bootstrapping technique on the truncated regression for 2500 iterations. The mean and median of the bootstrap estimates were presented, as well as the convergence rate estimated for each coefficient and intercept. The statistical significance of our findings provided a potentially more reliable inference on the regression results.

Our initial regression suggests that drone use plan and proportional output scaling factor are positively correlated. In other words, farmers who plan to use drones are likely to be more technically efficient. The result was robust after the inclusion of additional covariates. The bootstrap estimates for drone use plan also share similarity with the initial regression findings. Besides, the confidence intervals were different than zero and contained the actual regression estimate and bootstrap estimates, adding strength to our findings. We also revealed a non-linear relationship between age and proportional output scaling factor scores and the finding was also robust with bootstrapping. With respect to the convergence rates of our estimates, it ranged from 0.75 to 0.89 for our coefficients. This rate is higher than theoretical rate of 0.5, however not infeasible. This suggests that our estimates are stabilizing at a faster rate, indicating a higher level of precision and reliability in our bootstrap inference.

While our finding is communicating a crucial aspect of drone use attitude and efficiency, it is entitled to certain limitations, which should be addressed in future research. First, our study could not use the ideal data to identify any causal relationship. One can replicate this research to an ideal one by having multiple years of farm-level data. A well-structured panel dataset would allow researchers to track changes in efficiency over time and control unobserved heterogeneity across farms, thus improving the reliability of causal claims. Additionally, ensuring the presence of comparable control and treatment groups—such as farms that adopt drones versus those that do not—would be crucial for mitigating selection bias. In addition, having information on a greater number of farmers would be great, as it will capture more variability compared to our study, where we have only 363 observations. By addressing these data limitations, future research could employ more sophisticated econometric techniques, such as difference-in-differences (DID) to isolate the causal effect of drone use on efficiency.

Second, we do not have any information on farmers' current drone adoption. Ideally it would be more intuitive to study the effect of current drone use on current technical efficiency, as this would allow us to capture the direct, real-time impact of the technology on farm performance. Without data on actual adoption, we are left to infer potential effects based on farmers' stated intentions or future plans. While these intentions may signal openness to innovation, they do not provide conclusive evidence of behavioral change or operational shifts resulting from drone use. As a result, our interpretation of the link between drone-related planning and current efficiency must be made with caution, recognizing the possibility that efficiency gains could be driven by other underlying factors rather than drone usage itself.

Despite these limitations, this study opens up a new avenue for economics of PA research. This study should be replicated for the United States. There is so much growing evidence on the potential of drone use in agriculture; however, little is known about its economic viability. Future research should build on this foundation to further explore the economic feasibility of drone adoption in different agricultural settings, helping more informed policy and investment decisions.

CHAPTER FIVE

CONCLUSION

This thesis explores the economics of PA in the United States by analyzing its adoption patterns, policy impacts, and efficiency implications across multiple scales. The findings from Chapter 2 reveal that PA adoption in the U.S. is geographically clustered, with the Midwest leading in usage, particularly among larger farms and operations cultivating crops like corn, wheat, and cotton. The role of ownership structure and financial capacity further emphasizes that PA adoption is often driven by economic scale and institutional support. While data limitations prevent causal inference in the U.S. context, Canadian econometric evidence supports the hypothesis that larger farm size and capital intensity promote PA adoption, suggesting similar dynamics likely apply to the U.S. as well. Chapter 3 contributes the first empirical analysis of a state-level PA incentive policy in the U.S.—Virginia's tax credit for conservation tillage and PA equipment—by employing a natural experiment framework using neighboring North Carolina as a control. The results indicate a modest but statistically significant decrease in insurance coverage rates post-policy, offering early insights into how financial incentives may influence farmers' risk management behavior. However, limited post-policy years and aggregate data constrain broader generalizability. Chapter 4, although based on Australian data, offers valuable lessons for the U.S. by examining the relationship between drone adoption plans and technical efficiency. The findings indicate a strong positive association, suggesting that forward-thinking, technology-inclined farmers are more efficient—a dynamic likely relevant in the U.S. context given its growing drone technology ecosystem in agriculture. Taken together, these chapters underscore the importance of scale, capital, and institutional design in driving PA outcomes in the U.S. While current data limitations hinder stronger causal claims domestically, the thesis provides a roadmap for future U.S.-focused research through the collection of longitudinal and farm-level data. Ultimately, this work highlights the transformative potential of PA for enhancing U.S. agricultural sustainability, efficiency, and resilience—especially if supported by targeted policy and robust evidence-based strategies.

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APPENDICES

APPENDIX A

US AND CANADA STUDY

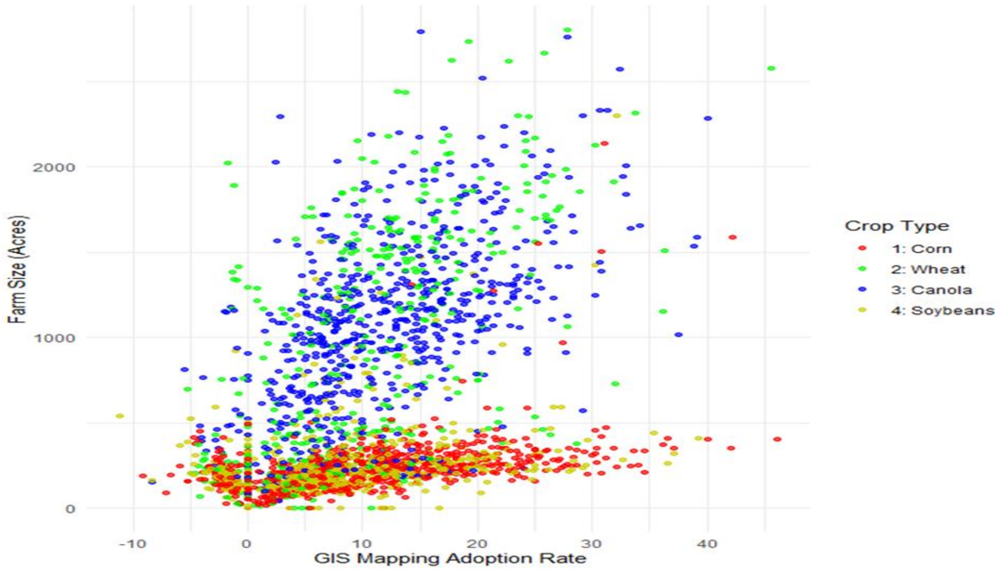


Figure A.1 Relationship between Farm Size and GIS Mapping Adoption, Broken-down by Major Crops

Table A.2 2SLS Regression Results for Canada with Province FE

Dependent variable: Adoption of GIS Mapping

	(1)	(2)	(3)
Farm Size	2.499***	0.710***	0.747***
	(0.135)	(0.070)	(0.046)
Age	0.095	-1.355	-1.348
	(0.572)	(1.092)	(0.961)
Age^2	-0.066	1.246	1.304
	(0.572)	(1.100)	(0.956)
Partnership	0.308***	0.008	-0.084
	(0.062)	(0.072)	(0.057)
Female	-0.068	0.057	0.187***
	(0.062)	(0.070)	(0.067)
CAR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No of Obs.	1061	363	611

Table A.3 RLM 2SLS Regression Results for Canada with Province FE

Dependent variable: Adoption of GIS Mapping			
	(1)	(2)	(3)
Farm Size	2.534***	0.714***	0.754***
	(0.124)	(0.069)	(0.045)
Age	0.186	-1.527	-1.162
	(0.533)	(1.026)	(0.939)
Age^2	-0.158	1.435	1.112
	(0.533)	(1.034)	(0.937)
Partnership	0.341***	0.0330	-0.071
	(0.057)	(0.067)	(0.056)
Female	-0.091	0.0436	0.177***
	(0.057)	(0.066)	(0.068)
CAR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No of Obs.	1061	363	611

Table A.4 2SLS Regression Results for Canada Controlling Capital

Dependent variable: Adoption of GIS Mapping			
	(1)	(2)	(3)
Farm Size	0.809***	0.527***	0.796 ***
	(0.231)	(0.118)	(0.126)
Capital	0.382***	0.255*	-0.007
	(0.049)	(0.103)	(0.119)
Age	0.035	-1.147	-0.679
	(0.531)	(4.207)	(1.105)
Age^2	-0.075	1.003	0.674
	(0.532)	(1.470)	(1.098)
Partnership	0.157**	-0.007	-0.159 *
	(0.064)	(0.012)	(0.066)
Female	-0.166***	0.002	0.195**
	(0.053)	(0.003)	(0.067)
CAR FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No of Obs.	1061	363	611

APPENDIX B

VIRGINIA STUDY

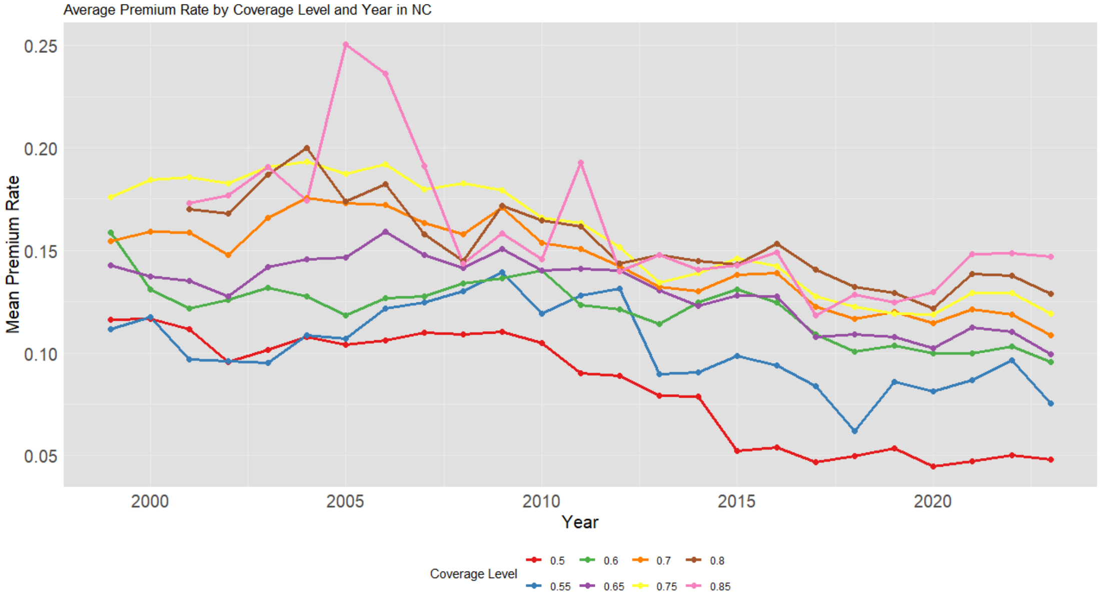


Figure B.1 Trend in Premium Rates by Coverage Level in North Carolina

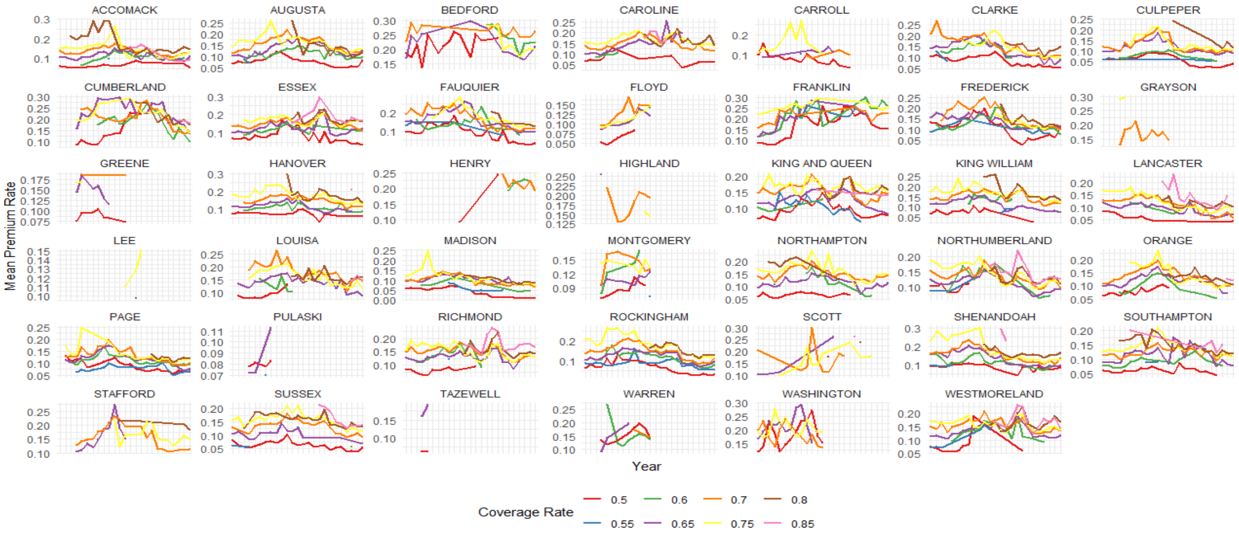


Figure B.2 Average Premium Rate by Coverage Level and Year in Virginia

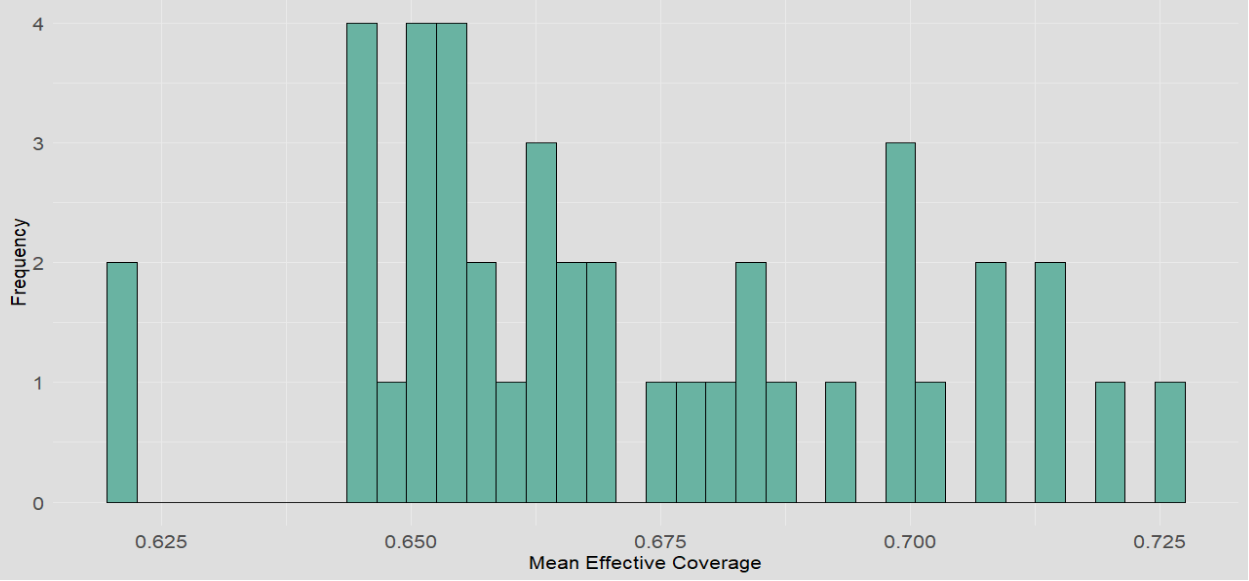


Figure B.3 Distribution of Mean Acres Weighted Coverage (Before Policy)

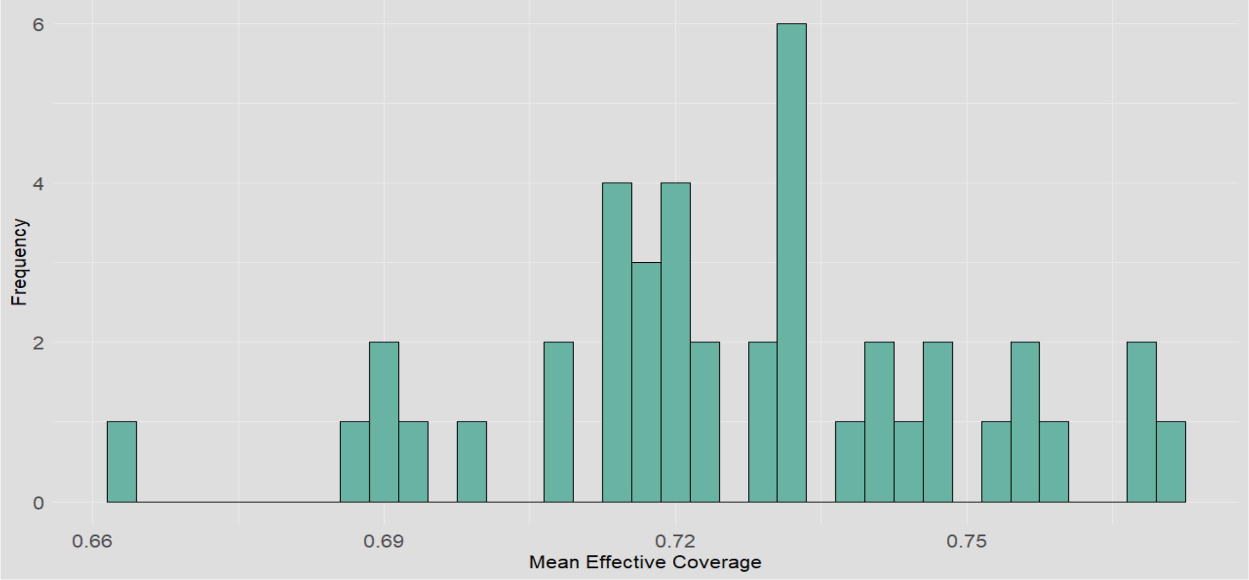
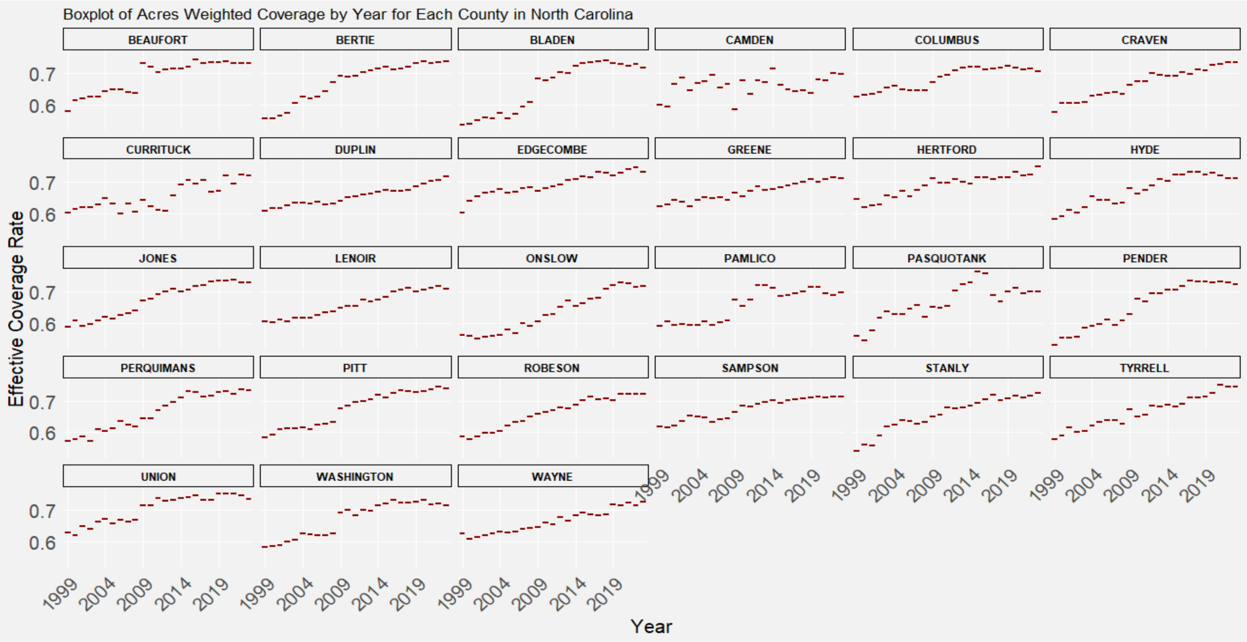


Figure B.4 Distribution of Mean Acres Weighted Coverage (After policy)



B.5 Trend in Effective Coverage Rate by County in North Carolina