Essays on precision agriculture technology adoption and agricultural cooperative mergers

by

Eric Kwesi Makafui Ofori

B.Sc., University of Ghana, 2013
M.S., Mississippi State University, 2017

AN ABSTRACT OF A DISSERTATION

submitted in partial fulfillment of the requirements for the degree

DOCTOR OF PHILOSOPHY

Department of Agricultural Economics
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Abstract

Understanding how differences in precision agriculture (PA) technology adoption may impact crop productivity is important for assisting farmers to make more informed adoption choices. Also, examining if strategic alliances amongst agricultural cooperatives can provide benefits to farmers is relevant. This dissertation therefore consists of three essays that provide insights into how PA technology adoption choices may improve crop productivity, and how mergers or other forms of strategic alliances amongst agricultural cooperatives can provide additional benefits to cooperative-member farms.

The first study of this dissertation evaluates potential crop productivity improvements that can be attributed to adoption of PA technologies. In this study, treatment effect estimators are incorporated into a stochastic frontier analysis framework to estimate the impact of PA technology adoption on technical inefficiency of corn production. Empirical estimations utilize data from the Kansas Farm Management Association consisting of 444 farms between 2002 to 2015. This includes non-adopters and adopters of two PA technologies: precision soil sampling (PSS) and variable rate technology (VRT).

The sample data is pre-processed by using propensity score matching to account for potential underlying differences between adopters and non-adopters that may have spillover effects on the outcome of interest, technical inefficiency. Results suggest that adoption of PA technologies had no statistically significant impact on reducing technical inefficiency of corn production, in the presence of some degree of covariate imbalance.

In the first study, differences amongst adopters are not considered, that is whether farms adopt PSS only or both PSS and VRT. However, estimates of technical inefficiency reductions

may be masked by differences in adoption choices. The results of the first study therefore inspire the second study of this dissertation.

The second study, accounts for differences in PA technology adoption choices by grouping adopters as either adopters of PSS only or adopters of both PSS and VRT. The methodology and data of the first study are adapted to estimate the impact of PA technology adoption on technical inefficiency of corn production under each adoption choice. In the presence of some degree of covariate imbalance, results suggest that, regardless of adoption choice (i.e., whether farms adopt PSS only or both PSS and VRT), adoption had no statistically significant effect on reducing technical inefficiency of corn production.

The third study of this dissertation examines potential gains that agricultural cooperatives may accrue from mergers. An ex-ante data envelopment analysis approach is employed. Empirical estimations utilize data from CoBank, consisting of 749 midwestern agricultural cooperative observations from 2011 to 2015. Potential overall merger effects are decomposed into learning effects, scope effects, and scale effects.

Findings show that generally, there are non-trivial overall potential gains from mergers. Overall merger gains are primarily driven by improvements due to learning effects and scope effects. Scale effect on the other hand tends to work against all merger combinations, with higher associated revenue reductions (or cost increases) for mergers between larger sized cooperatives compared to mergers between smaller cooperatives.

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Dedication

To God and family

Chapter 1 - Introduction

There is a growing interest in how site-specific farm level data can be leveraged to improve productivity (Yu and Hendricks, 2019); reduce movement of soil nutrients into ground water (Paudel and Crago, 2020); mitigate emission of greenhouse gases (Balafoutis et al., 2017); and even for improving the accuracy of predicting agricultural commodity prices and services or products such as crop insurance (Woodard and Verteramo-Chiu, 2017). Precision agriculture (PA) technologies enable adopter-farms to collect data on changing production conditions at site-specific levels to adjust farming practices such as soil nutrient application and seeding rates; this provides potential benefits to farmers and has positive environmental outcomes.

While the use of PA technologies seem promising and beneficial, previous studies show that adoption rates remain significantly low (Schimmelpfennig, 2016). Whether and how farms adopt these technologies is complex and may not be easily nor uniquely unraveled. However, cost of technologies has been identified as one of the major barriers to adoption (Lambert, Paudel and Larson, 2015). Agricultural cooperatives may reduce cost barriers and promote adoption by making these technologies available (Hogeland, 2006). However, the use of such services may remain accessible to cooperative-member farms only. In such instances, consolidations and other forms of strategic alliances amongst cooperatives have been suggested as being potentially useful for helping farms access previously unavailable services such as the use of PA technologies (Briggeman et al., 2016).

Quantifying the benefits that farmers may accrue from adopting PA technologies is important for promoting more adoption. Furthermore, understanding how differences in adoption choices may affect potential benefits from adoption is even more important for helping farmers to make informed adoption choices. Also, examining if strategic alliances amongst agricultural cooperatives can provide benefits to farmers is relevant. This dissertation therefore consists of three essays that provide insights into how PA technology adoption choices may improve crop productivity, and how mergers or other forms of strategic alliances amongst agricultural cooperatives can provide additional benefits to cooperative-member farms.

The first study in Chapter 2 evaluates the potential productivity improvements that can be attributed to adoption of PA technologies. Previous studies have examined the extent to which adoption of PA technologies impact crop yields, cost savings and input use. More recently, there has been a growing interest in examining how adoption of PA technologies impact the (in)effectiveness with which inputs are combined to produce outputs (DeLay, Thompson and Mintert, 2021; and McFadden, Rosburg and Njuki, 2021). Advancements in quasi-experimental methods and the availability of a unique dataset from the Kansas Farm Management Association (KFMA) present an opportunity to contribute to the literature by re-evaluating the impacts of PA technology adoption on crop productivity.

In this study, treatment effect estimators are incorporated into a stochastic frontier analysis (SFA) framework to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production; and (ii) determine the effect of other farm/farmer characteristics on technical inefficiency.[1] Empirical estimations utilize data from the KFMA consisting of 444 farms between 2002 to 2015. This includes non-adopters and adopters of PA technologies: precision soil sampling (PSS) and variable rate technology (VRT).

[1] Technical (in)efficiency captures the (in)effectiveness in converting a given set of inputs to produce an output. Under a given production technology, a unit/farm is said to be technically efficient if the unit/farm is producing the maximum quantity of output from the minimum quantity of inputs.

The sample data is pre-processed by using propensity score matching (PSM) to account for potential underlying differences between adopters and non-adopters that may have spillover effects on the outcome of interest, that is technical inefficiency.[2] Results suggest that adoption of PA technologies had no statistically significant impact on reducing technical inefficiency of corn production, in the presence of some degree of covariate imbalance.

In Chapter 2, differences amongst adopters are not considered, that is whether farms adopt PSS only or both PSS and VRT. However, estimates of technical inefficiency reductions may be masked by differences in adoption choices. The results of Chapter 2 therefore inspire the second study of this dissertation.

The second study, Chapter 3, accounts for differences in PA technology adoption choices by grouping adopters as either adopters of PSS only or adopters of both PSS and VRT. The methodology and data of Chapter 2 are adapted to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production under each adoption choice; and (ii) determine if outcomes are different under varying adoption choices. In the presence of some degree of covariate imbalance, results suggest that, regardless of the adoption choice (i.e., whether farms adopt PSS only or both PSS and VRT), adoption had no statistically significant effect on reducing technical inefficiency of corn production.

The first two studies are not conclusive in terms of the relationship between PA technology adoption and technical inefficiency reductions, due to underlying differences between adopters

[2] The term “pre-processed” is used to describe creating a sub-sample from the initial study sample, by matching comparable adopters to non-adopters, such that there is balance in pre-treatment covariates as outlined in Bravo-Ureta et al. (2020). The “pre-processed” data is then used to estimate the outcome of interest, under the assumption that there are no underlying spillover effects, given that there is covariate balancing between the treated and non-treated groups.

and non-adopters. Furthermore, event-study findings suggest that PSS only adopters potentially belong to the same distribution as non-adopters. On the other hand, adopters of both PSS and VRT are found to be potentially systematically different from non-adopters.

The third study, Chapter 4, utilizes data from CoBank, consisting of 749 midwestern agricultural cooperative observations from 2011 to 2015, to investigate potential gains from mergers. Ex-ante merger analyses are conducted from both cost and revenue orientations, along with considerations for cooperative size, defined by total assets. Potential gains from mergers are decomposed into learning effect and pure merger effect, which is further decomposed into scale and scope effects, following Bogetoft and Wang (2005).

Bogetoft and Wang (2005) introduced an ex-ante data envelopment analysis (DEA) approach for estimating potential gains from mergers. Potential gains from mergers were decomposed into learning effects, scale (size) effects, and scope (synergy, harmony, or mix) effects. Learning effects capture potential gains or losses that may accrue to decision making units (DMUs) if each DMU learns best practices but operates as an independent unit (Shi et al., 2017). Scope effects capture the portion of merger gains or losses that can be attributed to re-allocation of input-output mixes (Flokou, Aletras and Niakas, 2017). Scale effects capture the merger gains or losses that may be attributed to operating at full or integrated scale compared to operating at the average scale of merger candidate DMUs (Bogetoft and Wang 2005).

The findings of this study show that, there are non-trivial overall potential gains from mergers based on both cost and revenue orientations. Overall merger gains are primarily driven by improvements due to learning effects and scope effects. Scale effect on the other hand tends to work against mergers, with higher associated cost increases (or revenue losses) for mergers between larger sized cooperatives compared to mergers between smaller cooperatives. Also, findings show that, on average, overall merger gains from the revenue orientation are relatively higher than from the cost orientation.

Finally, baseline (pre-merger) profits are benchmarked against endline (post-merger) profits. Results show that, less of other unique merger costs such as legal fees, non-trivial profits may accrue to cooperatives due to mergers, with smaller sized cooperatives benefiting more from mergers than larger sized cooperatives.

The findings of the studies in this dissertation have implications for farm management, policy, agricultural cooperative strategy as well as for future research. These are extensively discussed in Chapter 5 which concludes and provides a summary of this dissertation.

Chapter 2 - Adoption of precision agriculture technologies and productivity effects

2.1 Introduction

Increasing the accuracy of soil nutrient application provides several benefits to farmers and has positive environmental outcomes. Key amongst these benefits are increased input use efficiency for farmers (Yu and Hendricks, 2019); reduction in the movement of nutrients into groundwater (Paudel and Crago, 2020); and mitigation of greenhouse gas (GHG) emissions (Balafoutis et al., 2017). Site-specific crop management technologies, popularly known as precision agriculture (PA) technologies create the means for farmers to collect detailed georeferenced data on field-specific soil quality and nutrient contents. This enables adjustments in input use to match spatial variability in soil conditions more precisely (Khanna, 2001).

By definition, and intent of its innovators, PA technologies are designed to give adopters an edge over non-adopters by helping adopter-farms collect data on changing production conditions to adjust farming practices (Schimmelpfennig, 2016). Therefore, given farm-specific economic, environmental, and managerial conditions, a rational farmer that desires to maximize the present value of expected gains from crop production over a given period will choose adoption over non-adoption.

Previous empirical studies such as Khanna (2001); Schimmelpfenning and Ebel (2016); DeLay, Thompson and Mintert (2021); and McFadden, Rosburg and Njuki (2021) document positive to no significant gains from adopting PA technologies, under different farm and farmer conditions. For example, Khanna (2001) finds that, when farms have less than average soil quality before adoption of PA technologies, there are statistically significant increases in yield per amount of nitrogen fertilizer utilized. There are however no statistically significant effects when adopter-farms have above-par soil quality. Schimmelpfenning and Ebel (2016) also find that adoption of PA technologies may provide additional production cost savings by enabling adopter-farms to gather more detailed information and improving application control. Yet, assessing the (in)effectiveness with which a given set of inputs can be converted to produce the maximum output possible through the adoption of PA technologies is even more relevant.

McFadden, Rosburg and Njuki (2021) examine how adoption of mapping technologies impacts technical (in)efficiency of corn production. The study utilizes 2010 and 2016 data from the U.S. Department of Agriculture's (USDA) Agricultural Resource Management Survey (ARMS) to determine if information inputs such as yield and soil maps that are obtained from PA technology use significantly improve technical efficiency. A stochastic frontier analysis (SFA) framework approach is employed such that a farmer's dichotomous choice of map adoption is incorporated into the estimation equation. It is found that the use of information inputs from mapping technology adoption significantly lower technical inefficiency for adopters (McFadden, Rosburg and Njuki, 2021).

While comparing differences in technical efficiency between adopters and non-adopters of PA technologies is important, it is also relevant to understand if adopters realize improvements in technical (in)efficiency after adoption. Advancements in quasi-experimental methods and the availability of a unique dataset from the Kansas Farm Management Association (KFMA) therefore present an opportunity to contribute to the literature. In this study, treatment effect estimators are incorporated into a stochastic frontier analysis (SFA) framework to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production; and (ii) determine the effect of other farm/farmer characteristics on technical inefficiency. Empirical estimations utilize a dataset from the KFMA consisting of 444 farms between 2002 to 2015. This includes 267 non-adopters and 177 adopters of PA technologies: precision soil sampling (PSS) and variable rate technology (VRT). The use of SFA allows for evaluating the relationship between output and input use due to adoption, rather than estimating production and input use effects separately. This relationship is measured as technical (in)efficiency, which captures the (in)effectiveness in converting a given set of inputs to produce the maximum output possible.

Much of the methodological efforts in studies on the impact of agricultural technology adoption have focused on addressing the endogeneity of farmers' adoption decisions. A farmer's adoption decision may be endogenous to crop productivity, such that estimates of the impact of adoption on productivity are biased without controlling for potential endogeneities. For instance, McFadden, Rosburg and Njuki (2021) note that map adoption is potentially associated with unobserved factors such as farmer's managerial skills, which are also correlated with technical efficiency. Within an SFA framework a two-step approach is utilized to correct for possible endogenous map adoption choice. In the first step, a bivariate probit model is estimated to explain map adoption. In the second step, estimated generalized residuals are incorporated in the SFA equation, with the expectation that their coefficients will be statistically significant in the presence of endogeneity (McFadden, Rosburg and Njuki, 2021). Khanna (2001) studied the impact of adopting PA technologies on nitrogen productivity. A two-step selectivity approach is used to correct for potential selection bias. Schimmelpfenning and Ebel (2016) studied plausible pathways of adopting PA technologies, and how input costs can be decreased by enabling farmers to collect more detailed data, as well as facilitate effective and efficient application of inputs. Potential selection bias is accounted for by utilizing a treatment effects approach.

Previous studies such as Sanglestsawai, Rejesus and Yorobe (2014); Mayen, Balagtas and Alexander (2010); and Bravo-Ureta et al. (2020) also examine how other forms of agricultural technologies or policies impact productivity, by utilizing statistical matching techniques and quasi-experimental methods. Sanglestsawai, Rejesus and Yorobe (2014) studied the impact of adopting an improved crop hybrid, Bt corn, on yields. Using instrumental variable quantile regression with propensity score matching, their study found that Filipino farmers that have a priori lower yields, benefit more from adopting Bt corn through the realization of significantly higher yields due to adoption (Sanglestsawai, Rejesus and Yorobe, 2014). Mayen, Balagtas and Alexander (2010) studied the impact of organic farming on the technical efficiency and productivity of dairy farms. Selection bias was corrected for by using propensity score matching. Utilizing the 2005 ARMS data on Dairy Costs and Returns Report, the study found that organic dairy technology is less productive than the conventional technology (Mayen, Balagtas and Alexander, 2010).

Finally, Bravo-Ureta et al. (2020) combine propensity score matching and difference-in-differences (DiD) approaches within a stochastic frontier framework (SFF) to study the impact of a rural environmental development program implemented in Nicaragua between 2012 and 2016. The analysis showed relatively low levels of technical efficiency with no significant variation across models, time, and treatment status. However, negative effects were significantly lower for beneficiaries of the program compared to the control group (Bravo-Ureta et al., 2020).

In this study, methods similar to Bravo-Ureta et al. (2020) are employed. Like Bravo-Ureta et al. (2020), this study combines quasi-experimental methods within an SFF to estimate the impact of the treatment (adoption of PA technologies) on technical (in)efficiency. This study however differs from Bravo-Ureta et al. (2020) in two main areas, besides the obvious difference in treatment. The first is primarily due to the difference in the design of the datasets used in both studies. In this study adopters of PA technologies are treated at different times within the sample period, where as in the study by Bravo-Ureta et al. (2020) treatment (the environmental development program) occurred at only one time within the study period. Given this set up, the canonical DiD design that is used in Bravo-Ureta et al. (2020) is not applicable, thus different treatment effect estimators including a two-way fixed effect model and an event-study design are explored. Also, in Bravo-Ureta et al. (2020) the treatment is modeled to impact the outcome through the production function of the SFF, however, in this study the treatment is modeled to impact the outcome through the inefficiency function as in McFadden, Rosburg and Njuki (2021). It is assumed that adoption will not have a direct impact on production, however improvements in technical efficiency through the use of adopted PA technologies will ultimately affect total production.

The initial sample data is pre-processed by using propensity score matching as in Bravo-Ureta et al. (2020) to account for potential underlying differences between adopters and non-adopters that may have spillover effects on the outcome of interest, technical inefficiency reductions due to adoption. The total number of observations in the initial sample data reduces to 2253 because the matching process identifies and keeps only statistically comparable adopter and non-adopter observations in the matched sample. Next, the estimation strategy, treatment effect estimators which are incorporated into an SFF, is employed using the matched sample to identify the impact of adoption on technical inefficiency reductions.

Findings of this study suggest that adoption of PA technologies had no statistically significant impact on reducing technical inefficiency of corn production in the presence of some degree of covariate imbalance. In this study, differences amongst adopters are not considered that is whether farms adopt PSS only or both PSS and VRT. However, estimates of technical inefficiency reductions may be masked by differences in adoption choices. The possibilities for differences in technical inefficiency reduction effects due to varying adoption choices are explored in Chapter 3 of this dissertation. Additional findings of this study show that technical inefficiency is significantly influenced by share of irrigated land, and farm size.

The remainder of this chapter is organized as follows. The next section describes the methods, while section three introduces the data used in this study. In section four, the empirical estimations are outlined, and the main results are presented in section five. Finally, section six concludes.

2.2 Methods

The goal of this study is to estimate the impact of PA technology adoption on reducing technical inefficiency. Treatment effect estimators are incorporated into a stochastic frontier framework (SFF) to estimate the impact of adoption on technical inefficiency. In the first subsection of this section, a review of the SFF as well as a justification to why it is the preferred method of estimation for this study is provided. The next subsection follows up with some background on treatment effects estimations and focuses on difference-in-differences (DiD), two-way fixed effects model, and event-study design. Finally, a review of the matching estimation techniques that are used in this study is provided.

2.2.1 Stochastic frontier framework

Theoretically, given a set of inputs, a production function outlines the maximum output possible. The stochastic frontier framework (SFF) differs from its common regression counterpart because it outlines a boundary or "frontier", deviations from which can be interpreted as inefficiency. The stochastic nature of production is accounted for under this approach, and categorical variables can also be included in the estimation equation to characterize technology

(Aigner, Lovell and Schmidt, 1977; Meeusen and van den Broeck, 1977). Following Kumbhakar and Lovell (2000) the output-oriented stochastic frontier model is specified as:

$$\ln y_{it} = \ln y_{it}^{*} - u_{it}, \qquad u_{it} \geq 0 \tag{2.1}$$

$$\ln y_{it} = f(\boldsymbol{x_{it}}; \boldsymbol{\beta}) + v_{it} - u_{it} \tag{2.2}$$

where y_{it} represents the observed output of farm *i* in year *t*. y_{it}^{*} is the frontier (maximum possible) level of output, such that, $\ln y_{it}^{*} = f(\boldsymbol{x_{it}}; \boldsymbol{\beta}) + v_{it}$. $\boldsymbol{x_{it}}$ is a vector of variables representing production inputs, $\boldsymbol{\beta}$ is a vector of parameters to be estimated, v_{it} is the random error term that denotes statistical noise, and u_{it} is a nonnegative stochastic component which represents production inefficiency. Equation 2.2 outlines the stochastic frontier function. Given the vector of production inputs $(\boldsymbol{x})$, the frontier represents the maximum level of output possible, and it is stochastic because of the inefficiency term u_{it}. The observed output (y_{it}) is restricted below the frontier output level (y_{it}^{*}) since $u_{it} \geq 0$. That is, the term (u_{it}) specified in equation 2.1 is the difference between the log of the maximum output and the log of the observed output (i.e., $u_{it} = \ln y_{it}^{*} - \ln y_{it}$). Rearranging equation 2.1, we have: $\exp(-u_{it}) = \frac{y_{it}}{y_{it}^{*}}$. Thus, $\exp(-u_{it})$ represents the ratio of observed output to the maximum possible output, which is referred to as the technical efficiency of farm *i* in year *t*. Since $u_{it} \geq 0$, the ratio is restricted between 0 and 1, with a value of 1, signifying that the production unit is fully technically efficient, and a value of 0, implying that the unit is fully technically inefficient. Therefore, if $\exp(-u_{it}) \times 100\% = 95\%$, it implies that the production unit is producing only 95% of the maximum output possible.

Estimation of the stochastic production frontiers (SPF) require the imposition of specific production functional forms. While a set of production frontier functional forms exist, the most widely used in the literature are the Cobb-Douglas and translog functions, expressed in general terms in equations 2.3 and 2.4 respectively:

$$lny_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it} \tag{2.3}$$

$$lny_{it} = \beta_0 + \sum_{j=1}^{n} \beta_j ln\boldsymbol{x}_{jit} + \frac{1}{2}\sum_{j=1}^{n}\sum_{k=1}^{n} \beta_{jk} ln\boldsymbol{x}_{jit} ln\boldsymbol{x}_{kit} + v_{it} - u_{it} \tag{2.4}$$

where y_{it} represents output in unit i at time t, $\boldsymbol{x}_{ijt}$ are input variables, v_{it} and u_{it} represent the random error term and technical inefficiency respectively. It is important to note that the Cobb-Douglas form is nested in translog form (i.e., when the second order coefficients in translog functional form are set to zero).

The use of either translog or Cobb-Douglas production functions can be tested for, under the hypothesis that if $\beta_{jk} = 0$ in equation 2.4, then the Cobb-Douglas functional form will be considered as adequate in comparison to the alternative (Asante, Villano and Battese, 2017; Danso-Abbeam and Baiyegunhi, 2019). Other studies have used the Cobb-Douglas without conducting functional form tests (e.g. Mayen, Balagtas and Alexander, 2010; McFadden, Rosburg and Njuki, 2021). The assumption made in these studies is that the large number of variables required in the translog production function may cause estimation challenges if data is limited. In such instances the simpler Cobb-Douglas functional form is preferred. This study utilizes the Cobb-Douglas form primarily because of its ability to capture the production process given the available data.

Following the assumption of an appropriate functional form, a distributional assumption must be made about the inefficiency component, u_{it}. Four main distributional assumptions have been used in the literature: an exponential distribution i.e. $u_{it} \approx \exp(\theta)$ (Meeusen and van den Broeck, 1977); a truncated normal distribution, for example, $u_{it} \approx |N(\mu_{it}, \sigma_u^2)|$ (Aigner, Lovell and Schmidt, 1977); a half-normal distribution i.e. $u_{it} \approx |N(0, \sigma_u^2)|$ (Jondrow et al., 1982); and a gamma/normal distribution (Greene, 1990). There are advantages and shortfalls of each distributional form, thus selecting one form over the other is primarily ad hoc (Coelli et al., 2005). In this study, v_{it} and u_{it} are assumed to be normally and truncated-normally distributed, respectively, following previous studies such as Asante, Villano and Battese (2017); Danso-Abbeam and Baiyegunhi (2019); and McFadden, Rosburg and Njuki (2021).

It is also appropriate to check the validity of using the stochastic production frontier model based on the data for this study (Coelli, 1995; Asante, Villano and Battese, 2017; Danso-Abbeam and Baiyegunhi, 2019). Therefore, it is examined if technical inefficiency plays a significant role in the variation of production. This is a very important hypothesis to test because failure to reject the null of no inefficiency implies the stochastic frontier model reduces to an ordinary least squares (OLS) estimation. This hypothesis is evaluated by using the generalized likelihood-ratio test, which is specified as:

$$LR(\lambda) = -2[\{lnL(H_0)\} - \{lnL(H_1)\}] \tag{2.5}$$

where $L(H_0)$ is the likelihood function under the null hypothesis (OLS) and $L(H_1)$ is the likelihood function under the alternative hypothesis (stochastic frontier). If the null hypothesis is rejected, it implies that the test statistic (λ) is greater than the critical value, given a chi-square distribution with degrees of freedom defined as the difference between the estimated parameters under null (H_1) and alternative (H_0) hypotheses (Danso-Abbeam and Baiyegunhi, 2019).

2.2.2 Treatment effects

The treatment effects literature focuses on evaluating the average causal effect of a "treatment", such as adoption of new technologies or some intervention, on an outcome variable such as production or environmental pollution. The concept of 'treatment effect' originated from the medical literature, with the goal of estimating the causal effects of 'treatments', such as a new surgical technique or trial drug. Treatment effects are estimated by comparing a control group that does not receive an assigned treatment to a treated experimental group, such that any difference in outcomes between both groups can be attributed solely to the treatment. In economics, the concept has been used much more generally to refer to the causal effect of some policy intervention on an outcome of interest. Earlier studies examining the causal effects of training programs are perhaps the most widely analyzed treatment effects in economics (e.g. Ashenfelter, 1978; Heckman and Robb, 1985).

The Rubin causal model (RCM) provides a theoretical foundation for computing causal estimates (Rubin, 1977; and Holland, 1986). The goal of the RCM is to estimate the effect that the treatment has on an outcome variable of interest (Y). To understand the set-up of treatment effect models, let i denote units and D_i represent a treatment indicator, which is equal to 1 if a unit is treated, and 0 if a unit is untreated. For example, in this study, $D_i = 1$ is an indicator for farms that adopt precision agriculture technologies. To describe the treatment effect, assume that Y_{i1} represents the potential outcome that would occur when unit i is treated, that is $D_i = 1$. Also assume that Y_{i0} denotes the potential outcome when the unit is not treated, that is $D_i = 0$. Since both potential outcomes are not observed at the same time, the observed outcome will be defined as:

$$Y_i = D_i Y_{i1} + (1 - D_i) Y_{i0} \tag{2.6}$$

Thus, the treatment effect for unit i is specified as:

$$\delta = Y_{i1} - Y_{i0} \tag{2.7}$$

The defined object, treatment effect (δ) in equation 2.7 is not identified since only one of the potential outcomes can be observed. Given some assumptions, other practical objects may be easily identified. These include the average treatment effect (ATE), which is defined as:

$$ATE \stackrel{\text{def}}{=} E[\delta] \tag{2.8}$$

This captures the difference in mean effects between the treated and untreated group over a sample. The average effect of treatment on the treated (ATT) is an alternative empirical object, which is also defined as:

$$ATT \stackrel{\text{def}}{=} E[\delta|D = 1] \tag{2.9}$$

This captures the mean effects of the treatment over the subsample of the treated units. The ATT is of particular interest when treatment assignment is non-random since the estimated effect of the treatment on untreated units is generally not relevant outside of prediction applications. Researchers get to observe the treated state of the outcome variable for units in the treatment group, and untreated outcome variables for units in the control group. They do not get to observe the counterfactual outcomes, the untreated outcome variable for the treatment group and the treated outcomes for the control groups. While these outcomes are not observable, researchers can estimate treatment effects under the assumption of random assignments to treatment (Angrist, Imbens and Rubin, 1996). Units must be randomly assigned to the treatment and control groups to ensure that all units are identical in distributions of potential outcomes as well as covariates. Given random assignments of treatment, the mean effect for the treated units can serve as an appropriate counterfactual for the mean effect in the control units (Holland, 1986).

The difference-in-differences (DiD) method is one way to estimate treatment effects. The canonical DiD is a panel approach in which there are two distinct groups and time periods. In the first period, all units are untreated. In the second period, certain units are treated, referred to as the treated group. All other remaining units are not treated, known as the control group. The first difference represents the before and after treatment outcome differences for both the treated and control groups. The second difference represents the difference in the differenced outcomes for the treated and control groups. Table 2.1 provides an illustration of the description above, where Y represents the average treatment outcome. The first two rows describe the first differences, and the last row describes the second differencing. Under the assumption of parallel trends, that is if the average outcomes for the control and treated groups would have followed parallel paths over a period in the absence of treatment, δ is considered as a credible estimate of the ATT (Abadie, 2005).

Table 2.1: Illustration of difference-in-differences

	Pre-treatment	Post-treatment	Difference
Treated group	Y_{T0}	Y_{T1}	$\Delta Y_T = Y_{T1} - Y_{T0}$
Control group	Y_{C0}	Y_{C1}	$\Delta Y_C = Y_{C1} - Y_{C0}$
Difference			$\delta = \Delta Y_T - \Delta Y_C$

The illustration above provides a simple mechanics of the DiD design. However, to provide a better understanding of what exactly δ maps onto, the expected causal effect of the treatment for units in the treated grouped or the ATT as shown in equation 2.9 can be decomposed more meaningfully as:

$$E[\delta|D = 1] = E[Y_T - Y_C|D = 1] = E[Y_T|D = 1] - E[Y_C|D = 1]. \tag{2.10}$$

Equation 2.10 highlights the counterfactual nature of a causal effect. Y_T, and Y_C are the average outcomes of the treated and control groups respectively. Y_T is a potentially observed outcome, whereas Y_C cannot be observed. However, by utilizing appropriate econometric and statistical modelling strategies, an appropriate counterfactual can be assumed to provide a consistent estimate. Thus, equation 2.10 can be practically decomposed as:

$$\begin{aligned} E[\delta|D = 1] &= E[Y_T|D = 1] - E[Y_C|D = 0] \\ &= E[Y_T|Y_C|D = 1] + \{E[Y_C|D = 1] - E[Y_C|D = 0]\} \end{aligned} \tag{2.11}$$

This decomposition shows that the DiD estimator will isolate the ATT (the first term) if and only if the second term (non-parallel trends bias) zeroes out. This equals zero if $E[Y_C|D = 1] = E[Y_C|D = 0]$, that is if the average outcome of the untreated group can be a good stand-in (counterfactual) for the outcome of the treated had they not been treated (Abadie, 2005). The concept of parallel trends, counterfactual, and treatment effect are visually illustrated in figure 2.1. The treatment outcome (technical inefficiency) is the difference between the observed post-treatment outcome and the predicted counterfactual (illustrated with dashed red lines) of the treated group in the post treatment period. It also graphically shows the parallel trend assumption at work as the treatment effect is estimated as the difference between the realized and assumed parallel counterfactual trend.

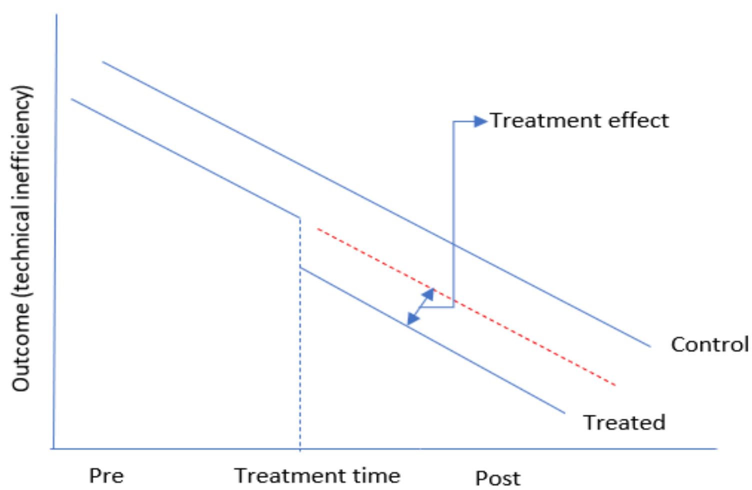

Figure 2.1: Graphical illustration of difference-in-differences design

This study deviates from the standard DiD setup because adoption of precision agriculture (PA) technology in the study sample happens at different time periods. In such instances a variant of the standard two-period/two-group DiD approach which is known as the two-way fixed effects

(TWFE) model is recommended (Goodman-Bacon, 2018). The standard DiD model is presented in equation 2.12 as:

$$y_{it} = \alpha_0 + \alpha_1 T_i + \alpha_2 P_i + \alpha_3 (T_i \times P_i) + \boldsymbol{X_{it}} + \varepsilon_{it} \tag{2.12}$$

where T_i represents an indicator for the treated group, P_i is an indicator for the post treatment period, y_{it} is the outcome variable and ε_{it} is the error term.

In the TWFE model, both time and unit/group fixed effects are included to account for the differences in timing of the treatment. In equation 2.13, the TWFE model is presented:

$$y_{it} = \mu_g + \tau_t + \beta_1 T_{it} + \boldsymbol{X_{it}\gamma} + \epsilon_{it} \tag{2.13}$$

where T_{it} represents an indicator for treatment, μ_g is unit/group fixed effects, τ_t is time fixed effects and ϵ_{it} is the error term.

For illustration purposes, a graphical representation of the TWFE design is provided. Consider a dataset with sample period from 2000 to 2015. There are "early" adopters who adopt in 2005 and "late" adopters who adopt in 2010. This data set by design allows for two distinct DiD comparisons (Jakiela, 2019). Assuming we want to estimate the impact of adoption on reducing technical inefficiency (the outcome of interest), first, let's focus on the left panel of figure 2.2. In the period from 2000 to 2009, the late adopters are not yet treated, therefore they can be considered as controls to estimate adoption impacts on technical inefficiency in the early adopter group. However, a second DiD treatment effect of adoption can also be considered by focusing on periods from 2006 to 2015. At this point, the treatment status of the early adopters remains unchanged (i.e., they stay treated for the entire study period), thus they can be considered as controls to estimate adoption impacts on technical inefficiency in the late adopter group as illustrated in the right panel of figure 2.2.

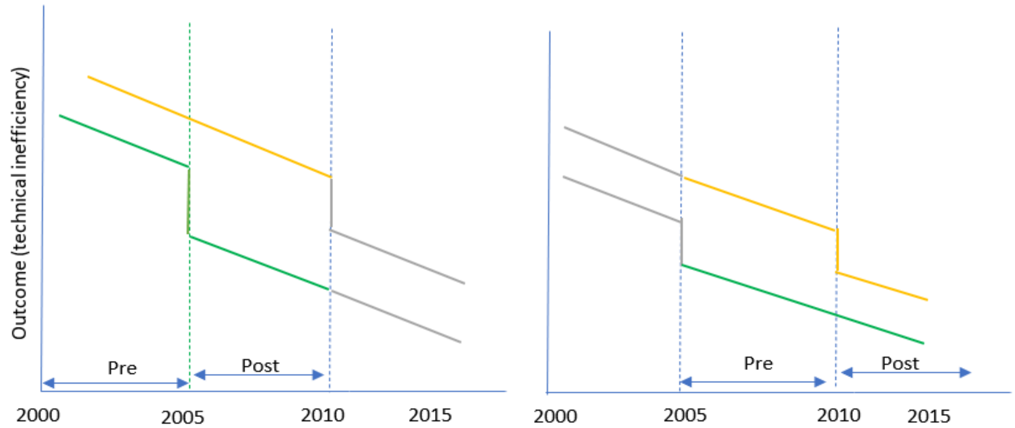

Figure 2.2: Graphical illustration of two-way fixed effects model decomposition

Goodman-Bacon (2018) shows that the TWFE model is a weighted average of every potential two-period/two-group DiD estimator that compares treatment timing groups, where weights are based on group sizes and variance in treatment. In the illustration above in figure 2.2, the TWFE estimate of the DiD can be decomposed as a weighted average of (i) assessments between early adopters and late adopters during time periods when the late adopters are yet to be treated, (ii) assessments between early adopters and late adopters over time periods when the early adopters are treated, thus are exploited as controls for the late adopters, and (iii) assessments between the different treatment timing groups, that is the early or late adopters, and the never treated group (Jakiela, 2019).

Though this illustration provides an intuitive decomposition, it also presents some important implications. The first is that treatment effects may be heterogeneous across units, thus those that have more variance in treatment status (typically those in the middle of the panel) receive relatively higher weights. Therefore, some sort of re-weighting is required to produce a more accurate estimate of the treatment effect. Secondly, when there are time-varying treatment effects within units, the DiD estimate tends to be biased because units that are already treated are exploited as controls in some of the two-period/two-group DiDs that define the weighted average. In this study, treatment effects are likely to vary over time, that is, the impact of adoption on technical inefficiency in the year of adoption is likely to differ from technical inefficiency impacts, say three years after adoption. This may be due to improvements in soil nutrients over time or potential learning curves associated with using the adopted technology.

Goodman-Bacon (2018) shows that, under these scenarios, the TWFE estimator may not be appropriate, thus recommends alternative approaches such as event-study estimations (Jacobson, LaLonde and Sullivan, 1993). The event-study design includes leads and lags of the treatment variable instead of a single indicator for treatment.

2.2.3 Matching Methods

Matching can be used to correct non-parallel trends (Ryan et al., 2019). Matching conditions on observables under the assumption that units in the treated and control groups are not systematically different, or in other words that both groups come from the same distribution (Ryan, Burgess and Dimick, 2015; O'Neill et al., 2016). Several matching procedures exist; thus, key matching procedures that have been widely used in the literature are outlined and justification for the choice of matching procedure that is used in this study is provided. The first step in any matching procedure is deciding which metric to use, that is whether matching will be based on propensity scores or weighted distances of covariates such as Mahalanobis distance matching. While studies may present one matching metric as superior to the other and vice versa, the ultimate measure of superiority is based on balancing in covariates. The next step will be to select a matching method such as nearest neighbor matching to create a sub-sample of matched units for estimation of treatment effects. This study compares balancing in covariates based on both propensity score and Mahalanobis distance metrics with $k{:}\,1$ nearest neighbor matching. The method which generates the best balancing in covariates is the preferred matching method.

2.3 Data

The main data source for this study is the Kansas Farm Management Association (KFMA) which maintains a database of financial and production data for member farms in Kansas. In 2015, KFMA economists updated records on precision agriculture (PA) technology adoption by Kansas farmers (Griffin et al., 2017). Data collected includes the use of technologies such as global navigation satellite system enabled yield monitors (GNSSYM), lightbar (LB), variable rate technology (VRT), automated guidance (AGS), precision soil sampling (PSS), and automated section control (ASC). This study focuses on two main technologies: PSS (a diagnostic technology) and VRT (an application technology), because of their specific and interrelated roles in improving site-specific soil quality and nutrient conditions. Typically, a farmer would use PSS to diagnose the soil quality of farmland and then use VRT to apply the appropriate distribution of farm inputs across the field thus ensuring efficient use of inputs (i.e., fertilizer and/or lime).

The main KFMA dataset was merged with data on PA technology adoption. Given that this study only focuses on corn production, farms that do not produce corn were removed. Also, observations with negative values for input variables were removed because negative input use is not expected. Finally, since this study focuses on adopters of PSS only and adopters of both PSS and VRT, adopters of VRT only were removed. This yields a sample dataset consisting of 3,907 observations of 444 farms (267 non-adopters and 177 adopters) between 2002 to 2015.[3] In figure

[3] The data on PA technology adoption provides information about the year adoption starts for each PA technology by each farm. Information is also provided for the year adoption ends for some farms, however for most farms there are

2.3, the percentage of adopters relative to all farms in the study sample at the county level are presented. While data on adoption rates across counties is quite sparse in the entire study sample, it is more pronounced towards the southwestern part of the state where no PA data was collected. This is unfortunately a factor of the dataset and should not be interpreted that PA technology was not adopted across the state.

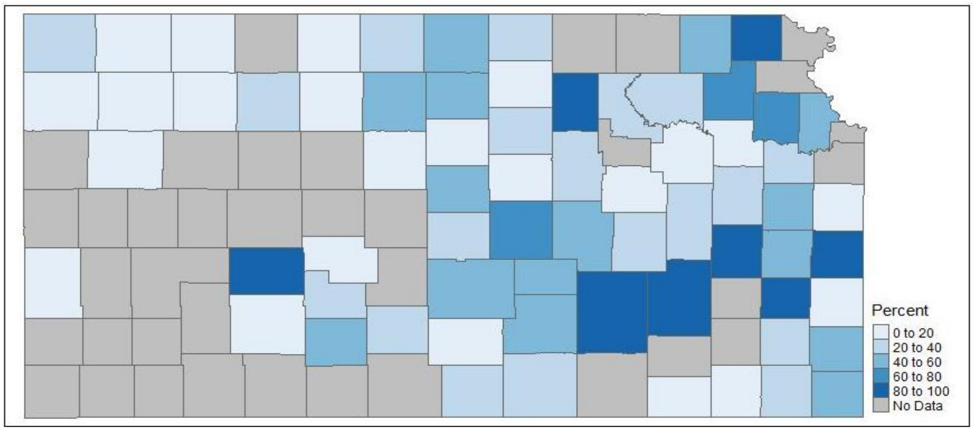

Figure 2.3: Adoption rate of PA technologies by county in sample data

Notes: This figure shows the distribution of adopter-farms relative to all farms in the study sample across Kansas counties, and it is not necessarily representative of actual adoption rates.

The second dataset used in this study is annual national-level prices obtained from the United States Department of Agriculture-National Agriculture Statistics Service (USDA-NASS) to construct quantity indexes for some input expense variables, following Yeager and Langemeier (2017). The KFMA database primarily includes financial variables thus indices are used to proxy

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no explicitly stated end of adoption years. Thus, the assumption made in this dissertation is that if a farm adopts a PA technology, it is considered as having adopted beginning the year it indicates adoption and for all remaining years in the study period. Farms that have an explicit end of adoption year in the dataset are dropped from the study sample to avoid being considered as having adopted in periods when it is clearly known that they do not adopt PA technologies.

input quantities that are utilized in estimations. In the next sections, brief descriptions as well as justification where necessary of variables used directly in estimations are provided. This is followed with descriptive statistics for variables of interest.

2.3.1 Outcome variables

The main outcome variable that is used in the stochastic frontier framework (SFF) is the total corn production (in bushels) for each individual farm *i* in year *t*. This includes both irrigated and non-irrigated corn production. The outcome variable of interest is, however, the technical inefficiency which is jointly estimated within the SFF. Technical inefficiency captures the ineffectiveness in converting a given set of inputs (outlined in Section 2.3.2) to produce the maximum corn output possible.

2.3.2 Input variables

Conventional inputs that are typically utilized in a production function of an SFF are included for estimations. The productive inputs used in this study are land (measured as total corn acres, including both irrigated and non-irrigated corn acres), total number of workers (which captures labor), capital, fertilizer, and *other* (which includes seeds and miscellaneous crop inputs). Capital, fertilizer, and *other* are available in the KFMA dataset as total expense, measured in dollars, thus, quantity indices are constructed by dividing the input expense variables by their corresponding national-level USDA input price indices. Also given that, labor, capital, fertilizer, and *other* are available in the KFMA dataset for entire farm operation, these production input variables are standardized by corn acres to total crop acres to account for that.

2.3.3 Inefficiency variables

These variables are used to capture sources of technical inefficiency. In this study, the variable that captures adoption of precision agriculture (PA) technology is the primary variable used to account for technical inefficiency. The other variables that account for technical inefficiency include farms' share of irrigated acres, share of rented acres, and crop labor percentage, farm size, and location. Since the outcome variable in the production function, that is corn production, includes both irrigated and non-irrigated acres, it is important to account for inefficiency differences that might be due to the proportion of land acres that are irrigated relative to the total land acres, thus the inclusion of share of irrigated acres as an inefficiency variable. Share of rented acres is also included to account for inefficiency due to farming on potentially marginalized rented land. Crop labor percentage which captures the proportion of labor that is solely dedicated to crop production is also included to account for inefficiency differences due to labor used in non-crop production activities.

Farm size which is categorized into small, medium, and large based on corn acres is used to capture inefficiencies associated with operating either too small or too large farms as suggested by Mugera and Langemeier (2011). In this study, farms below the 33.33rd percentile (i.e., between 3 and 171 corn acres) are classified as small-size farms. Farms within the 33.33rd and 66.66th percentile (i.e., between 171 and 452 corn acres) are classified as medium-size farms, and those above the 66.66th percentile (i.e., between 452 and 5,606 corn acres) are classified as large-size farms. Location which is defined in this study as whether the farm is in the east, west or central part of Kansas is used as proxy to account for potential differences in soil characteristics which may be associated with varying inefficiencies in production. Accounting for location related factors is also very important in this study because of the sparse nature of adoption data in the sample of study especially towards the southwestern part of the state (shown in figure 2.3).

2.3.4 Matching variables

The key assumption for determining which variables to include in a matching procedure is that, conditional on observable covariates, there are no unobservable differences between the treated and control groups. Given that this is a strong assumption, it is recommended that all variables that plausibly impact both the treatment assignment and the outcome be used in the matching process (Stuart, 2010). Therefore, all variables in the stochastic frontier model (i.e., input and inefficiency variables previously described) that may impact the outcome of interest are included as matching variables. Other key variables include age of farm operator, and net farm income. Age of farm operator is included as a proxy for farming experience and technological savviness. Studies such as Watcharaanantapong et al. (2014) and Ofori, Griffin and Yeager (2020) show that younger farmers tend to adopt PA technologies sooner compared to their older counterparts. Net farm income has also been found as a major driver of adoption of technologies in general, including PA technologies (e.g. Lambert, Paudel and Larson, 2015).

2.3.5 Summary statistics

Summary statistics are presented in table 2.2 categorized by data for adopters and non-adopters. As shown in the table, adopters on average have higher corn production compared to non-adopters, but they also have higher input use such as land and fertilizer compared to non-adopters. On average, adopters are younger than non-adopters. Also, adopters have higher net farm incomes compared to non-adopters.

It is important to state that, capital, fertilizer, and *other* are indices because financial data for those variables are divided by their respective price data (provided in Appendix table A.1), to obtain quantity values for estimations. Share of irrigated and share of rented land are all indices, as they represent proportions of irrigated corn land and rented corn land to total corn land acres respectively. Farm size is based solely on corn acres. More adopters have larger farms compared to non-adopters.

Table 2.2: Summary statistics of variables of interest

Variables (units)	Non-adopters (N=2,264)		Adopters (N=1,643)	
	Mean	SD	Mean	SD
Output variable				
Corn production (bushels)	36,117	47,364	59,311	58,992
Input variables				
Land (corn acres)	326	333	549	469
Labor (no. of workers)	0.35	0.34	0.63	0.83
Capital (index)	6,964	10,152	11,483	14,575
Fertilizer (index)	198	287	393	461
Other (index)	142	191	273	274
Inefficiency variables				
Irrigated (ratio)	0.13	0.30	0.11	0.26
Rented (ratio)	0.63	0.36	0.72	0.31
Crop labor percentage (ratio)	0.81	0.19	0.85	0.19
Farm size (% of group)				
Small (3 – 171 corn acres)	42.76		19.61	
Medium (171 – 452 corn acres)	32.95		33.07	
Large (452 – 5606 corn acres)	24.29		47.32	
Location (% of group)				
Central	21.64		28.97	
West	11.88		1.22	
East	66.48		69.81	
Matching variables				
Age of farmer (years)	56	11	52	11
Net farm income ($)	105,621	148,562	174,028	233,616

Notes: N implies number of observations. SD implies standard deviation. “Irrigated” and “Rented” represent share of irrigated corn acres and share of rented corn acres to total corn acres respectively. Land acres are total corn acres only, and all other production input variables are standardized to account for that. “Other” includes seeds and miscellaneous crop inputs. Statistics are based on unmatched sample. Two-sample t tests show that the difference of means in all continuous variables of interest are statistically different from zero between adopters and non-adopters at 0.05 significance level.

2.4 Empirical estimation

Now that all variables of interest have been described, the empirical analysis begins by estimating the average treatment effect (ATE) of adoption on technical inefficiency. An indicator for treatment group is incorporated into the stochastic frontier framework (SFF), thus the proposed model is presented in equation 2.14 as:

$$lny_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it}$$

$$u_{it} = \alpha_0 + \sum_{j=1}^{3} \alpha_j F_{jit} + \rho T_i + \mu_{it} \tag{2.14}$$

where y_{it} represents total corn production in bushels of farm i, in year t. $\boldsymbol{x}_{ijt}$ represents conventional inputs usually used in crop production, namely, quantity of land, labor, capital, fertilizer, and *other*. T_i is an indicator of treatment group (which is equal to 1 if a farm adopts PA technologies, and 0 otherwise) for each farm i. v_{it} is statistical noise, $u_{it} \geq 0$ represents technical inefficiency, with a random term μ_{it}, defined by a truncated normal distribution (Battese and Coelli, 1995). F_{jit} denote farm-level inefficiency variables, as previously defined in the data section. α_0, β_0, α_j, and β_j are parameters to be estimated. ρ is the parameter of interest which elicits the ATE.

Next, the average treatment effect on the treated (ATT) of adoption on technical inefficiency is estimated by incorporating an indicator for treatment (which is equal to 1 only in periods when a farm is treated, and 0 otherwise) into an SFF. Group and year fixed effects are also included to account for variations in treatment timing, thus readily allows for estimation of a two-way fixed effects (TWFE) model estimand, presented in equation 2.15 as:

$$lny_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it}$$

$$u_{it} = \alpha_0 + \sum_{j=1}^{3} \alpha_j F_{jit} + a_g + \tau_t + \delta T_{it} + \mu_{it} \quad (2.15)$$

where a_g and τ_t represent group and year fixed effects respectively. T_{it} is an indicator for treatment (which is equal to 1 only in periods when a farm is treated) for each farm i, in year t. δ is the parameter of interest which elicits the ATT. All other variables and parameters are as previously outlined.

In addition, the ATT is estimated by incorporating an event-study design into the SFF, presented in equation 2.16 as:

$$lny_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it}$$

$$u_{it} = \alpha_0 + \sum_{j=1}^{3} \alpha_j F_{jit} + a_g + \tau_t + \sum_{k=\underline{c}}^{\overline{c}} \gamma_k D_{it}^k + \mu_{it} \quad (2.16)$$

where D_{it}^k are event-time dummies defined as $D_{it}^k := 1[t = \tau_i + k] \quad \forall k \;\; s.t. \; \underline{c} < k < \overline{c}$, $D_{it}^{\overline{c}} = 1[t \geq \tau_i + \overline{c}]$, $D_{it}^{\underline{c}} = 1\left[t \leq \tau_i + \underline{c}\right]$ (where 1[.] is the indicator function and τ_i is the year when farm i adopts or gets treated). Based on the study sample, $\underline{c}$ and $\overline{c}$ are set to -2 and +2 respectively. γ_k are parameters of interest which indicate the impact of adoption on technical inefficiency relative to non-adoption, in year $\tau_i + k$. All other variables and parameters are as previously outlined.

A key advantage of the event-study design is that it helps for validation of the identification strategy used in the study, since pre-adoption effects are not expected to be statistically significantly different from zero. That is to say, γ_k should be statistically equal to zero for periods when $D_{it}^{c} = 1[t \leq \tau_i + \underline{c}]$. The results of the event-study estimations will also be useful for understanding if the impacts of adoption change over time.

As stated earlier, a core identifying assumption for the validity of the effect estimates in all the models is that inefficiency for adopters would have followed a trend along a path parallel to non-adopters in the absence of adopting PA technologies. To provide support to this assumption, adopters are matched to non-adopters based on their pre-adoption input use levels as well as farm/farmer characteristics as recommended by Ryan et al. (2019). Both propensity score metrics (PSM), and Mahalanobis distance metrics (MDM) with k: 1 nearest neighbor matching techniques are explored to provide the appropriate counterfactual of the trend that adopters would have followed if they had not adopted PA technologies.

The covariates included in the matching procedure are pre-adoption input, inefficiency, and matching variables described in the data section. The assumption here is that, if adopters and non-adopters are statistically similar in characteristics and input use levels pre-adoption, then change in input use levels after adoption and its consequent impact on production and subsequent estimates of technical inefficiency reduction is due to adoption (Brown, Lambert and Wojan, 2019).

A preferred matching estimator is then selected based on tests of balancing that compare the standardized difference in means and variances between adopters and non-adopters, for all covariates included in the matching procedure. Finally, all models are re-estimated using the matched sample based on the preferred matching estimator.

2.5 Results

2.5.1 Matching results

To begin this section, results from the matching estimations are presented. As stated earlier, the validity of the results of this study hinges on the assumption that adopters and non-adopters of PA technologies have parallel pre-adoption trends. Figure 2.4 presents trends in corn yields and fertilizer use in Panels A and B respectively, between adopters and non-adopters. Panel A of figure 2.4 suggests that adopters of PA technologies realize higher yields after adoption compared to non-adopters. The figure also shows that adopters have lower yields prior to adoption compared to non-adopters, with yields of adopters surpassing those of non-adopters after adoption. On the other hand, Panel B of figure 2.4 shows that adopters have higher fertilizer use than non-adopters.

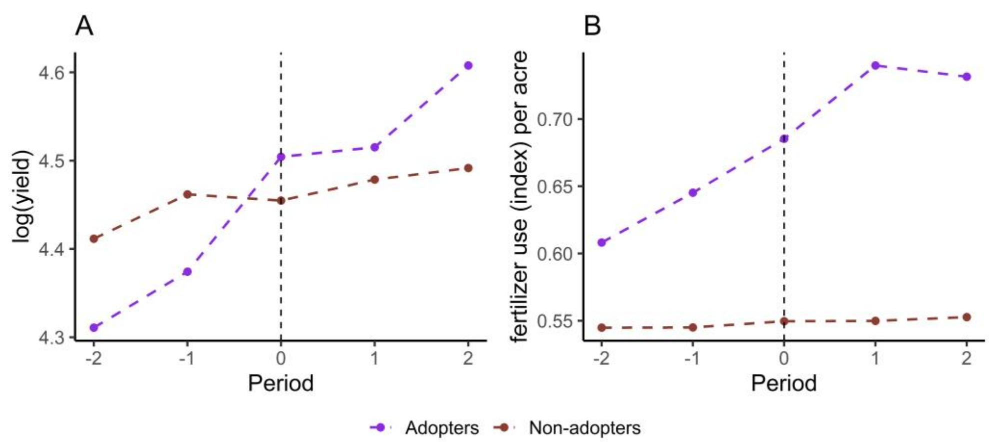

Figure 2.4: Trends in corn yields and fertilizer use between adopters and non-adopters

Notes: This figure shows trends in mean corn yields and fertilizer use per acre for adopters in each period *i* juxtaposed with non-adopters in the same periods. Period -2 and Period -1 imply two years and a year respectively before adoption. Period 0 implies the year of adoption. Period 1 and Period 2 imply a year and two years respectively after adoption.

To account for potential bias from spillover effects in pre-adoption trends, adopters are matched to non-adopters. In Appendix tables A2-A3, the standardized differences and variance ratios for the matched and unmatched samples as shown by Austin (2011) are presented, using propensity score metrics (PSM) and Mahalanobis distance metrics (MDM) with k: 1 nearest neighbor matching techniques. The results show that matching substantially improves covariate balancing under PSM than MDM, as the standardized differences and variances ratios of covariates are closer to 0 and 1 respectively under PSM than MDM. To assess covariate imbalance, Rubin (2001) recommends bounds of less than 0.25 for standardized differences, and variance ratios between 0.5 and 2.0. Other studies such as Cohen (1988) and Normand et al. (2001) recommend standardized differences cut-offs of 0.20 and 0.10 respectively. Taking all recommendations into consideration, it can be observed that PSM with 4:1 nearest neighbor matching provides the most improvements in covariate balancing. However, depending on which cut-offs are chosen, others may argue that there is still some degree of covariate imbalance. In table 2.3, the standardized differences and variance ratios for the matched and unmatched samples using the preferred matching technique (i.e., PSM with 4:1 nearest neighbor matching) are presented. Subsequent analyses in this study are based on the preferred matched sample.

Table 2.3: Balance in covariates

Variables	Standardized differences Unmatched	Standardized differences Matched	Variance ratio Unmatched	Variance ratio Matched
Age of farmer	0.229	0.051	0.950	1.296
log (Net farm income)	0.746	0.164	0.913	2.388
Farm size (Reference: Small)				
Medium	0.148	0.231	1.092	1.106
Large	0.424	0.089	1.319	1.086
Location (Reference: East)				
Central	0.290	0.028	1.348	1.036
West	0.442	0.027	0.097	0.931
Share of irrigated land	0.124	0.265	0.633	1.412
Share of rented land	0.207	0.077	0.797	1.189
Crop labor percentage	0.148	0.217	1.154	0.868
log (Land)	0.663	0.276	0.674	0.732
log (Labor)	0.530	0.145	0.889	0.852
log (Capital)	0.701	0.318	0.631	0.521
log (Fertilizer)	0.624	0.266	0.718	0.667
log (Other)	0.562	0.126	0.719	1.295
N	3,907	2,253	3,907	2,253

Notes: This table presents results for the balance of covariates test from the PSM with 4: 1 nearest neighbor matching technique. The absolute value of standardized differences and variance ratios for covariates between treatment (adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in the data section. "Other" includes seeds and miscellaneous crop inputs.

2.6.2 Main results

In this section, the results of the study's empirical estimations are presented. To begin, results from the stochastic frontier models in equations 2.14, 2.15, and 2.16 are presented in table 2.4, and discussed. In the bottom section of the table, results for hypothesis tests which validate the use of stochastic frontier framework (SFF) are provided. In all estimated models, λ is statistically different from zero at the 1% significance level. Therefore, this suggests that technical inefficiency plays a significant role in the variation of observed production in all models, thus validating the use of SFF.

Across all models, land and fertilizer are shown to have positive and statistically significant effects on production. Capital on the other hand, shows positive and statistically significant effects on production only in models (2) and (3). These results are consistent with other studies such as

Mayen, Balagtas and Alexander (2010); Bravo-Ureta et al. (2020); DeLay, Thompson and Mintert (2021) which show that traditional inputs such as labor, land capital, and fertilizer have positive relationships with output. In this study, however, estimates for labor show a negative relationship with output, which is inconsistent with these prior studies. This may reflect the fact that adoption of PA technologies provides other assistance to farmers such as field navigation, thus more human intervention could potentially be counterproductive. *Other*, which captures seeds and other miscellaneous crop inputs is also shown to have positive and statistically significant effects on production only in models (2) and (3).

Also, results show that technical inefficiency decreases as share of irrigated acres increases, with statistically significant results in model (3). Relative to being a small-size farm, being a medium or large-size farm, decreases technical inefficiency. Other variables also show inconsistent signs and statistically insignificant results across models. For example, share of rented land is shown to have a negative but statistically insignificant effect on technical inefficiency in models (2) and (3), but a positive and statistically insignificant effect in model (1). On the other hand, crop labor percentage is shown to have a positive but statistically insignificant effect on technical inefficiency in models (2) and (3), but a negative and statistically insignificant effect in model (1).

Table 2.4: Stochastic frontier estimates

Variables	Model (1)	(2)	(3)
<u>Production</u>			
Land	0.983***	0.930***	0.943***
	(0.021)	(0.021)	(0.019)
Labor	-0.032**	-0.015	-0.027**
	(0.014)	(0.014)	(0.013)
Capital	-0.012	0.026**	0.022**
	(0.008)	(0.011)	(0.009)
Fertilizer	0.044***	0.040***	0.040***
	(0.012)	(0.011)	(0.011)
Other	0.014	0.032***	0.022**
	(0.010)	(0.010)	(0.009)
<u>Technical inefficiency</u>			
Share of irrigated land	-88.983		-5.018***
	(65.900)		(0.547)
Share of rented land	1.039	-0.234	-0.065
	(1.512)	(0.170)	(0.087)
Crop labor percentage	-0.335	0.096	0.161
	(0.134)	(0.288)	(0.157)
Farm size (Reference: Small)			
Medium	1.517	-0.380**	-0.150*
	(1.586)	(0.155)	(0.081)
Large	2.532	-0.435**	-0.066
	(2.290)	(0.175)	(0.096)
Location (Reference: East)			
Central	7.179	0.078	0.487***
	(5.105)	(0.128)	(0.074)
West	16.119	1.917***	2.106***
	(11.412)	(0.669)	(0.376)
Fixed effects		Yes	Yes
λ	19.985***	4.663***	4.004***
	(1.185)	(0.062)	(0.027)
σ_u	3.256***	0.958***	0.659***
	(1.188)	(0.064)	(0.028)
σ_v	0.163***	0.205***	0.164***
	(0.008)	(0.008)	(0.008)
Log likelihood	-1286	-813	-613
N	2,246	2,246	2,246

Notes: (1), (2), and (3) represent models from equations 2.14, 2.15, and 2.16 respectively. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. If parameter estimate is not provided, it means the associated variable was dropped to allow convergence due to near-collinearity. "Other" includes seeds and other crop inputs. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

Next, results for the main variable of interest (i.e., adoption of PA technologies) for this study are presented in models (1) and (2) of table 2.5 from equations 2.14 (i.e. average treatment effect model) and 2.15 (i.e., average treatment effect on the treated model, using TWFE design) respectively. In figure 2.5, the results for model (3) which represents equation 2.16 (i.e., average treatment effect on the treated model, using an event-study design) are also presented. Results for the first two models as presented in table 2.5 show that, adoption of PA technologies had no statistically significant effect on technical inefficiency of corn production. In addition, event-study results as presented in figure 2.5 show that there are no statistically significant effects of adoption of PA technologies on technical inefficiency.

Table 2.5: Impact of adoption on technical inefficiency

	Model	
	(1)	(2)
Technical inefficiency effect	-0.224	-0.127
	(0.880)	(0.214)
Fixed effects		Yes
N	2,246	2,246

Notes: (1) and (2) represent models from equations 2.14 and 2.15 respectively. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

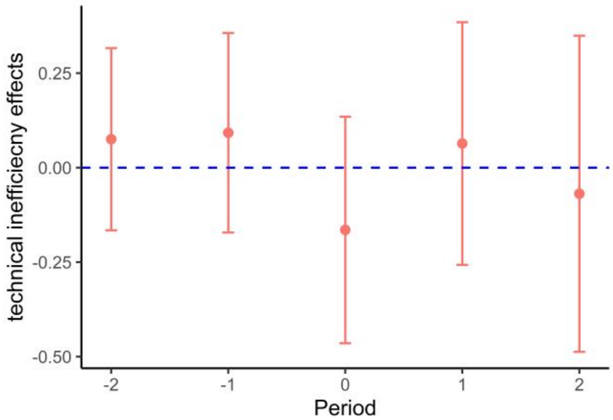

Figure 2.5: Event-study results

Notes: Results are from the estimation of equation 2.16. The dotted points represent the mean estimates, and the whiskers represent the lower and upper bounds at 95% confidence interval. Period -2 and Period -1 imply two years and a year respectively before adoption. Period 0 implies the year of adoption. Period 1 and Period 2 imply a year and two years respectively after adoption.

2.7 Conclusion

This study builds on the existing literature that examines the impact of precision agriculture (PA) technology adoption on agricultural productivity, by estimating the impact of adoption on technical inefficiency of corn production. Treatment effect estimators are incorporated into a stochastic frontier framework (SFF), along with propensity score matching to estimate the impact of PA technology adoption on technical inefficiency. The main dataset for this study is from the Kansas Farm Management Association (KFMA) which includes a total of 3,907 observations, for 444 corn farms over 14 years from 2002 to 2015, consisting of 267 non-adopters and 177 adopters of PA technologies (i.e., precision soil sampling (PSS), and variable rate technology (VRT)).

The initial sample data is pre-processed by using propensity score matching as in Bravo-Ureta et al. (2020) to account for potential underlying differences between adopters and non-adopters, that may have spillover effects on the outcome of interest, that is technical inefficiency reductions due to adoption. The total number of observations in the initial sample data reduces to 2,253 because the matching process identifies and keeps only statistically comparable adopter and non-adopter observations in the matched sample. Next, the estimation strategy, that is treatment effects estimators which are incorporated into an SFF are employed, using the matched sample to identify the impact of adoption on technical inefficiency reductions.

In the presence of potential covariate imbalance, results suggest that adoption of PA technologies had no statistically significant effect on reducing technical inefficiency of corn production. Other factors that influence technical inefficiency were also identified. Technical inefficiency is shown to decrease as share of irrigated land increases. Also, relative to small-size farms, medium and large-size farms are associated with decreases in technical inefficiency. Conventional inputs such as land, capital, and fertilizer are shown to increase production, consistent with studies such as Mayen, Balagtas and Alexander (2010); Bravo-Ureta et al. (2020); DeLay, Thompson and Mintert (2021). However, findings of this study show that labor has a negative relationship with production, which is inconsistent with these prior studies. This may reflect the fact that, adoption of PA technologies provides other assistance to farmers such as field navigation, thus more human intervention could potentially be counterproductive.

It is important to note that in this study, how adopters choose to utilize available sets of PA technologies is not considered. Prior studies such as Khanna (2001); Schimmelpfenning and Ebel (2016); and DeLay, Thompson and Mintert (2021) show that farmers may adopt technologies individually or in bundles, in recognition of their complementarity. Therefore, estimates of technical inefficiency reductions may be masked by differences in adoption choices. In the next chapter of this dissertation, possibilities for differences in technical inefficiency reduction effects due to varying adoption choices are explored.

Chapter 3 - Heterogeneous adoption patterns of precision agriculture technologies and productivity effects

3.1 Introduction

This study engages the concept that changes in productivity effects may vary given heterogeneous adoption patterns of precision agriculture (PA) technologies. Assume that a rational farmer that has a discrete choice set of two technologies, a diagnostic technology such as precision soil sampling (PSS) and an application technology such as variable rate technology (VRT). The farmer desires to maximize the present value of expected gains from production over a given period. First, the farmer decides to adopt one or both PA technologies if the expected benefit from some combination of technologies is greater than non-adoption. Given possible combinations and farm-specific economic, environmental, or managerial constraints; the farmer would choose some pattern of technology adoption.

Previous empirical studies such as Khanna (2001); and Schimmelpfenning and Ebel (2016); document positive to no significant gains from adopting PA technologies, depending on the type of technologies adopted and/or the pattern of adoption, as well as farm and farmer characteristics. For example, Khanna (2001) finds significant improvements in nitrogen productivity for adopter-farms with below-average soil quality but statistically insignificant improvements for farms with above-average soil quality. Further analyses also showed that, adopters of PSS only realized greater improvements in productivity than their counterparts that adopted both PSS and VRT. Schimmelpfenning and Ebel (2016) find that when VRT is combined with soil mapping, there are additional production cost savings, but not when combined with yield mapping alone.

This study adopts the methods and data used in Chapter 2 to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production under each adoption choice; and (ii) determine if outcomes are different under varying adoption choices. The initial sample data is pre-processed by using propensity score matching as in Bravo-Ureta et al. (2020) to control for potential underlying differences between non-adopters and each group of adopters (i.e., adopters of PSS only, and adopters of both PSS and VRT). This is to account for potential spillover effects on the outcome of interest, that is technical inefficiency reductions due to adoption choice. The total number of observations in the initial sample data reduces to 1,650 for the sample which considers adoption of PSS only as the treatment, and 1,587 for the sample that considers adoption of both PSS and VRT as the treatment. In each matched sample, only statistically comparable adopter and non-adopters remain. Next, the estimation strategy, that is treatment effect estimators which are incorporated into an SFF are employed. Each matched sample is used separately to identify the impacts on technical inefficiency reduction given adoption choice.

In the presence of some degree of covariate imbalance, the findings of this study suggest that, regardless of adoption choice (i.e., whether farms adopt PSS only or both PSS and VRT), adoption of PA technologies had no statistically significant effect on reducing technical inefficiency of corn production. This study also provides evidence that there are underlying differences amongst farm/farmers that may influence adoption choices. While PSS only adopters are found to potentially belong to the same distribution as non-adopters, adopters of both PSS and VRT are found to be potentially systematically different from non-adopters. This finding is consistent with Khanna (2001) which shows that, farmers that adopt both PSS and VRT are more technically competent, educated, and operate on larger scales compared to those who adopt only PSS.

The remainder of this chapter is organized as follows. The next section describes the methods and data used in this study. In section three, the empirical estimations are outlined, and the main results are presented in section four. Finally, section five concludes.

3.2 Methods and data

This study adopts the methods and utilizes the data variables as outlined in Chapter 2 of this dissertation: they may be reviewed for reference. However, given that adopters are now grouped as PSS only adopters and adopters of both PSS and VRT, differences that exist between groups are presented in table 3.1, and discussed. As shown in the table, non-adopters have lower corn production compared to PSS only adopters, and adopters of both PSS and VRT. Meanwhile, adopters of both PSS and VRT have higher average corn production compared to PSS only adopters. Input variables including land, labor, capital, fertilizer, and *other*, follow the same trends as production, with lower input use for non-adopters compared to PSS only adopters, who also have lower input use compared to adopters of both PSS and VRT.

On average, non-adopters have a higher share of irrigated land compared to adopters of PSS only. On the other hand, adopters of both PSS and VRT have a higher share of irrigated land compared to non-adopters. Also, both groups of adopters a have higher share of rented land and crop labor percentage compared to non-adopters. On average, adopters of PSS only are younger and have higher net farm income compared to non-adopters. Meanwhile, adopters of both PSS and VRT are younger and have higher net farm income compared to PSS only adopters.

Table 3.1: Summary statistics of variables of interest by adoption group

Variables (units)	Non-adopters (N=2,264)		PSS only adopters (N=815)		PSS+VRT adopters[4] (N=828)	
	Mean	SD	Mean	SD	Mean	SD
Output variable						
Corn production (bushels)	36,117	47,364	47,942	49,781	70,502	64,944
Input variables						
Land (acres)	326	333	480	456	617	472
Labor (no. of workers)	0.35	0.34	0.58	0.61	0.69	0.99
Capital (index)	6,964	10,152	9,496	12,076	13,440	16,447
Fertilizer (index)	198	287	363	507	422	408
Other (index)	142	191	240	250	306	293
Inefficiency variables						
Irrigated (ratio)	0.13	0.30	0.08	0.22	0.15	0.29
Rented (ratio)	0.63	0.36	0.68	0.34	0.76	0.28
Crop labor percentage (ratio)	0.81	0.19	0.86	0.18	0.83	0.20
Farm size (% of group)						
Small (3 – 171 corn acres)	42.76		22.85		16.43	
Medium (171 – 452 corn acres)	32.95		36.00		30.19	
Large (452 – 5606 corn acres)	24.29		41.15		53.38	
Location (% of group)						
Central	21.64		24.29		33.57	
West	11.88		0.00		2.42	
East	66.48		75.71		64.01	
Matching variables						
Age of farmer (years)	56	11	53	11	51	12
Net farm income ($)	105,621	148,562	155,368	214,005	192,394	250,203

Notes: N implies number of observations. SD implies standard deviation. “Irrigated” and “Rented” represent share of irrigated corn acres and share of rented corn acres to total corn acres respectively. Land acres are total corn acres only, and all other production input variables are standardized to account for that. “Other” includes seeds and miscellaneous crop inputs. Statistics are based on unmatched sample.

[4] Adopters of both PSS and VRT are labelled as “PSS+VRT adopters” for ease of writing and may be used interchangeably throughout the rest of this dissertation.

3.3 Empirical estimation

In this section, the empirical analysis begins by estimating the average treatment effect (ATE) of adoption on technical inefficiency, by incorporating an indicator for treatment group into the stochastic frontier framework (SFF). The proposed model is presented in equation 3.1 as:

$$
\begin{aligned}
lny_{it} &= \beta_0 + \sum_{j=1}^{5} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it} \\
u_{it} &= \alpha_0 + \sum_{j=1}^{3} \alpha_j F_{jit} + \rho T_{ih} + \mu_{it}
\end{aligned}
\tag{3.1}
$$

where, y_{it} represents total corn production in bushels of farm i, in year t. $\boldsymbol{x}_{ijt}$ represents conventional inputs usually used in crop production, namely, quantity of land, labor, capital, fertilizer, and seeds. T_{ih} is an indicator of treatment group (which is equal to 1 if a farm is treated, and zero otherwise) for each farm i. As stated earlier, there are two different treatment assignments in this study, a treatment assignment for PSS only adopters, and a treatment assignment for PSS+VRT adopters. Equation 3.1 is estimated separately for each treatment assignment. v_{it} is statistical noise, $u_{it} \geq 0$ represents technical inefficiency, with a random term μ_{it}, defined by a truncated normal distribution (Battese and Coelli, 1995). F_{jit} denote farm-level inefficiency variables as previously defined in the data section. α_0, β_0, α_j, and β_j are parameters to be estimated. ρ is the parameter of interest which elicits the ATE.

Next, the average treatment effect on the treated (ATT) of adoption on technical inefficiency is estimated by incorporating an indicator for treatment (which is equal to 1 only in periods when a farm is treated) into an SFF. Group and year fixed effects are also included to account for variations in treatment timing, thus readily allowing for estimation of a two-way fixed effects (TWFE) model estimand, presented in equation 3.2 as:

$$lny_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it}$$

$$u_{it} = \alpha_0 + \sum_{j=1}^{3} \alpha_j F_{jit} + a_g + \tau_t + \delta T_{iht} + \mu_{it} \tag{3.2}$$

where a_g and τ_t represent group and year fixed effects respectively. T_{iht} is an indicator for treatment (which is equal to 1 only in periods when a farm is treated) for each farm i, in year t. δ is the parameter of interest which elicits the ATT. All other variables and parameters are as previously outlined.

In addition, the ATT is estimated by incorporating an event-study design into the SFF, presented in equation 3.3 as:

$$lny_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j ln\boldsymbol{x}_{jit} + v_{it} - u_{it}$$

$$u_{it} = \alpha_0 + \sum_{j=1}^{3} \alpha_j F_{jit} + a_g + \tau_t + \sum_{k=\underline{c}}^{\overline{c}} \gamma_k D_{iht}^{k} + \mu_{it} \tag{3.3}$$

where D_{iht}^{k} are event-time dummies defined as $D_{iht}^{k} := 1[t = \tau_i + k] \quad \forall k \;\; s.t. \, \underline{c} < k < \overline{c}, D_{iht}^{\overline{c}} = 1[t \geq \tau_i + \overline{c}]$, $D_{iht}^{\underline{c}} = 1\left[t \leq \tau_i + \underline{c}\right]$ (where 1[.] is the indicator function and τ_i is the year when farm i adopts or gets treated). Based on the study sample, $\underline{c}$ and $\overline{c}$ are set to -2 and +2 respectively. γ_k are parameters of interest which indicate the impact of adoption on technical inefficiency relative to non-adoption, in year $\tau_i + k$. All other variables and parameters are as previously outlined.

3.4 Results

3.4.1 Matching results

To begin this section, results from the matching estimations are presented. The validity of the results of this study hinges on the assumption that adopters and non-adopters of PA technologies have parallel pre-adoption trends. On the left panel of figure 3.1, trends in corn yields between PSS only adopters and non-adopters suggest that, PSS only adopters realize higher yields after adoption compared to non-adopters. A similar trend is observed when PSS+VRT adopters are compared to non-adopters (as shown in the right panel of figure 3.1). It can also be observed that PSS+VRT adopters have higher yields than PSS only adopters in periods after adoption, however pre-adoption trends vary. This suggests that potential non-parallel pre-adoption trends between adopters and non-adopters exist, and differ by treatment groups, thus must be independently accounted for.

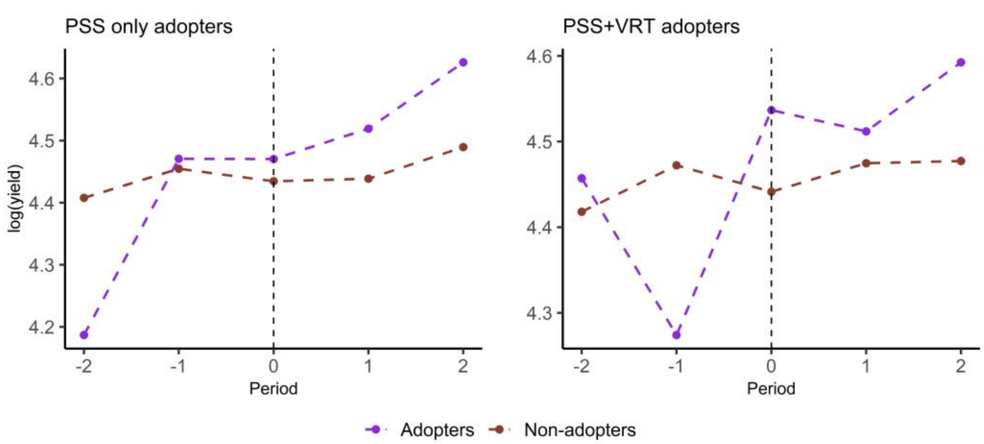

Figure 3.1: Trends in corn yields between adopters and non-adopters by adoption group

Notes: This figure shows trends in mean corn yields for adopters (i.e., PSS only adopters and PSS+VRT adopters) in each period *i* juxtaposed with non-adopters in the same periods. Period -2 and Period -1 imply two years and a year respectively before adoption. Period 0 implies the year of adoption. Period 1 and Period 2 imply a year and two years respectively after adoption.

To account for potential bias from spillover effects in pre-adoption trends, each group of adopters are matched to non-adopters independently. In Appendix tables B5-B8, the standardized differences and variance ratios for the matched and unmatched samples as shown by Austin (2011) are presented, using propensity score metrics (PSM) and Mahalanobis distance metrics (MDM) with k: 1 nearest neighbor matching techniques. As in Chapter 2, results show that PSM with 4:1 nearest neighbor matching provides the most improvements in covariate balancing across all treatments. In tables 3.2 and 3.3, the standardized differences and variance ratios for matched and the unmatched samples under PSS only and PSS+VRT treatment groups respectively are presented. All subsequent analyses in this study are based on matched samples.

Table 3.2: Balance in covariates under PSS only treatment

	Standardized differences		Variance ratio	
	Unmatched	Matched	Unmatched	Matched
Age of farmer	0.208	0.327	0.822	0.951
log (Net farm income)	0.631	0.262	1.073	2.829
Farm size (Reference: Small)				
Medium	0.211	0.102	1.114	1.057
Large	0.447	0.039	1.423	1.049
Location (Reference: East)				
Central	0.165	0.021	1.191	0.975
Share of irrigated land	0.017	0.332	0.973	2.224
Share of rented land	0.147	0.068	0.795	1.037
Crop labor percentage	0.352	0.027	0.798	1.075
log (Land)	0.733	0.234	0.534	0.651
log (Labor)	0.530	0.287	0.727	0.751
log (Capital)	0.780	0.322	0.587	0.754
log (Fertilizer)	0.672	0.327	0.629	0.636
log (Other)	0.626	0.221	0.527	0.965
N	3,079	1,650	3,079	1,650

Notes: This table presents results for the balance of covariates test from the PSM with 4: 1 nearest neighbor matching technique. The absolute value of standardized differences and variance ratios for covariates between treatment (PSS only adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. Observations for the location indicator -West are dropped because they perfectly predict the outcome. This may be associated with the small number of observations in the West relative to the entire sample size, thus potentially creating extremes in the sample distribution. "Other" includes seeds and other crop expense.

Table 3.3: Balance in covariates under PSS+VRT treatment

	Standardized differences		Variance ratio	
	Unmatched	Matched	Unmatched	Matched
Age of farmer	0.283	0.043	1.081	1.641
log (Net farm income)	0.931	0.211	0.727	0.790
Farm size (Reference: Small)				
Medium	0.066	0.275	1.054	1.124
Large	0.473	0.045	1.335	1.047
Location (Reference: East)				
Central	0.352	0.007	1.406	1.009
West	0.379	0.015	0.202	1.037
Share of irrigated land	0.047	0.255	0.713	1.334
Share of rented land	0.259	0.016	0.786	0.958
Crop labor percentage	0.021	0.244	1.504	0.843
log (Land)	0.686	0.234	0.847	0.738
log (Labor)	0.535	0.093	1.061	0.659
log (Capital)	0.677	0.376	0.709	0.379
log (Fertilizer)	0.617	0.159	0.830	0.586
log (Other)	0.514	0.108	0.935	1.110
N	3,092	1,587	3,092	1,587

Notes: This table presents results for the balance of covariates test from the PSM with 4: 1 nearest neighbor matching technique. The absolute value of standardized differences and variance ratios for covariates between treatment (PSS+VRT adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. “Other” includes seeds and other crop expense.

3.4.2 Main results

In this section, the results of the study’s empirical estimations are presented. Estimates from the stochastic frontier models in equations 3.1, 3.2, and 3.3 are presented in the Appendix B, as results are very similar to those presented in table 2.4 of Chapter 2, this allows for a focus on the main variables of interest in this study. These results are presented in models (1) and (2) of table 3.4 from equations 3.1 (i.e., average treatment effect model) and 3.2 (i.e., average treatment effect on the treated model, using TWFE design) respectively for each treatment group. In figure 3.2, the results for model (3) which represents equation 3.3 (i.e., average treatment effect on the treated model, using an event-study design) are also presented. Results as provided in models (1) and (2) of table 3.4 show that, adoption of PA technologies had no statistically significant effect on technical inefficiency for PSS only adopters as well as PSS+VRT adopters.

In addition, event-study results as presented in figure 3.2 show that across all treatment groups, there are no statistically significant effects of adoption of PA technologies on technical inefficiency in periods after adoption. The figure also shows that, for PSS+VRT adopters there is a significant increase in technical inefficiency in the period prior to adoption. This provides evidence that some adopters, that is specifically PSS+VRT adopters may be systematically different from non-adopters in the presence of some degree of covariate imbalance.

Table 3.4: Impact of adoption on technical inefficiency by treatment group

	Treatment group			
	PSS only		PSS+VRT	
	(1)	(2)	(1)	(2)
Technical inefficiency effect	-0.601	0.233	0.298	-0.351
	(1.503)	(0.196)	(0.718)	(0.239)
Fixed effects		Yes		Yes
N	1381	1381	1303	1303

Notes: (1) and (2) represent models from equations 3.1 and 3.2 respectively. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

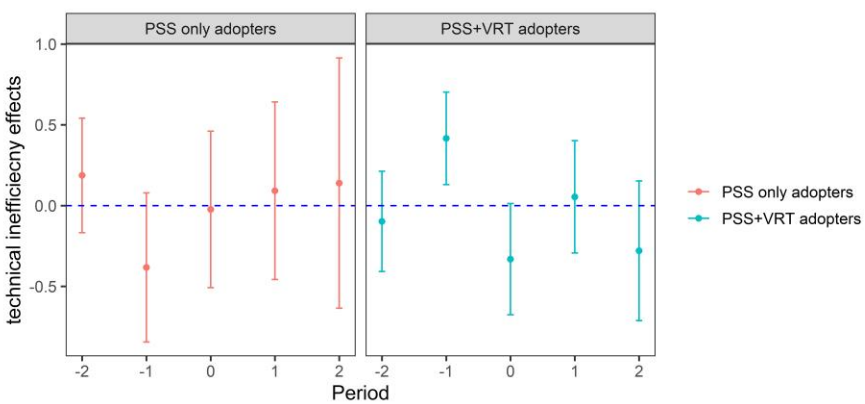

Figure 3.2: Event-study results by treatment group

Notes: Results are from the estimation of equation 3.3. The dotted points represent the mean estimates, and the whiskers represent the lower and upper bounds at 95% confidence interval. Period -2 and Period -1 imply two years and a year respectively before adoption. Period 0 implies the year of adoption. Period 1 and Period 2 imply a year and two years respectively after adoption.

3.5 Conclusion

This study builds on Chapter 2 of this dissertation as well as existing literature that examines how differences in adoption choices of precision agriculture (PA) technologies impact agricultural productivity. The methods and data used in Chapter 2 are adapted to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production under each adoption choice; and (ii) determine if outcomes are different under varying adoption choices. The initial sample data is pre-processed by using propensity score matching as in Bravo-Ureta et al. (2020) to control for potential underlying differences between non-adopters and each group of adopters (i.e., adopters of PSS only, and adopters of both PSS and VRT). This is to account for potential spillover effects on the outcome of interest, that is technical inefficiency reductions due to adoption choice. The total number of observations in the initial sample data reduces to 1,650 for the sample which considers adoption of PSS only as the treatment, and 1,587 for the sample that considers adoption of both PSS and VRT as the treatment. In each matched sample, only statistically comparable adopter and non-adopters remain. Next, the estimation strategy, that is treatment effect estimators which are incorporated into a stochastic frontier framework (SFF) are employed. Each matched sample is used separately to identify the impacts on technical inefficiency reduction given adoption choice.

In the presence of some degree of covariate imbalance, results suggest that adoption of PA technologies had no statistically significant effect on reducing technical inefficiency of corn production. Specifically, two-way fixed effects estimates show that, for PSS only adopters as well as adopters of both PSS and VRT, adoption had no statistically significant effect on reducing technical inefficiency for corn production. Event-study findings provide evidence that PSS only adopters potentially belong to the same distribution as non-adopters. However, adopters of both

PSS and VRT are found to be systematically different from non-adopters. This finding is consistent with Khanna (2001) which shows that, farmers that adopt both PSS and VRT are more technically competent, educated, and operate on larger scales compared to those who adopt only PSS.

Despite that this study is not conclusive in terms of the relationship between PA technology adoption and technical inefficiency reductions, findings which show that some adopters are potentially systematically different from non-adopters may prove useful. Identifying and understanding the characteristic differences amongst adopters, as well as between adopters and non-adopters can help in designing technology adoption support programs that are more targeted. This will also be useful for disentangling the actual effect of PA technology adoption on outcomes of interest versus spillover effects due to potential systematic differences between adopters and non-adopters in future research as more data becomes available.

Chapter 4 - Estimating potential gains from agricultural cooperative mergers

4.1 Introduction

Agricultural cooperatives have developed throughout history; responding to socio-economic distress in order to benefit members and communities. In 1922, the enactment of the Capper-Volstead Act permitted farmers to take collective actions that might be beneficial to members and rural communities while upholding antitrust laws (Zeuli and Cropp, 2004). The number of new agricultural cooperatives began to increase in the early years after the Capper-Volstead Act was enacted and then slowly began to decrease, from about 12,000 in 1930 to 1,871 in 2017 (left y-axis of figure 4.1). On the other hand, gross business volumes increased from 2.5 billion dollars to 197.1 billion dollars within the same period (right y-axis of figure 4.1). The decrease in the number of agricultural cooperatives was largely due to merger activity and some dissolutions (USDA, 2018).

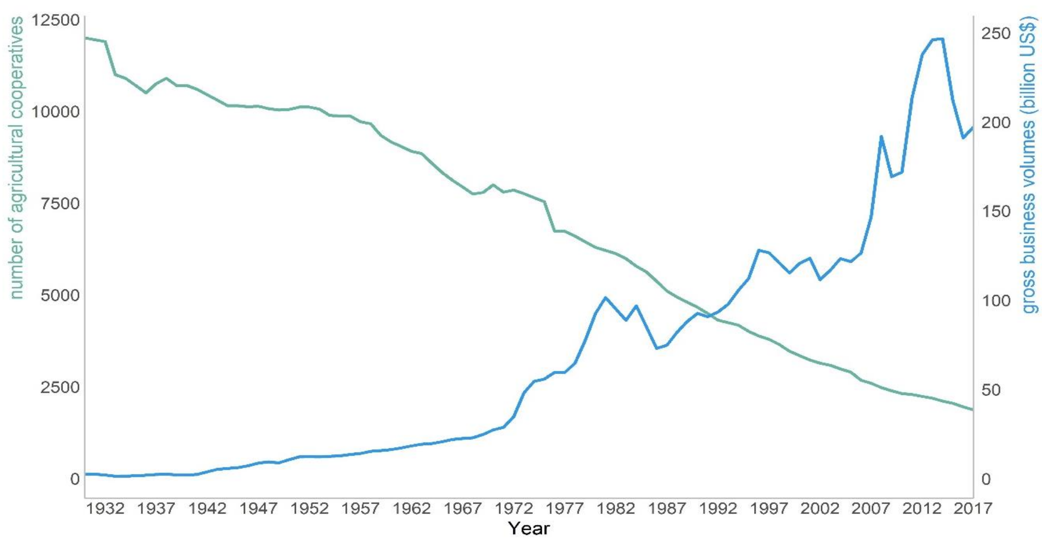

Figure 4.1: Agricultural cooperatives in the United States, 1930-2017

Data source: USDA Statistics

Mergers of agricultural cooperatives are still ongoing and appear to be largely motivated by the need to circumvent capital constraints, and improve economies of scale and scope (Demko, 2018). It is assumed that cooperative mergers can create larger scale regionally located facilities which tend to achieve scale and scope economies that generate higher profitability and allow for rapid allocation of equity (Briggeman et al., 2016). However, there is also ample evidence suggesting that not all agricultural cooperative mergers are successful at achieving these objectives (e.g. Schroeder, 1992; Richards and Manfredo, 2003; Briggeman et al., 2016).

During a period of considerable mergers, Schroeder (1992) finds evidence of firm-wide economies of scale and scope for agricultural cooperatives. Significant economies of scope were found for all products considered. However, for some specific products such as chemical sales, there were no scale economies. The study suggests that, cooperatives may benefit from engaging in strategic alliances that expand their scope of products/services. Furthermore, full-scale mergers may persist if scale economies have not been exhausted (Schroeder 1992). Richards and Manfredo (2003) examined the post-merger performance of agricultural cooperatives and concluded that, mergers allow newly formed cooperative entities to have access to more capital and to increase sales. However, it is also found that full-scale mergers may reduce profitability due to redundant administrative costs (Richards and Manfredo, 2003).

These studies suggest that identifying the sources of potential gains or losses, pre-merger may serve as a useful resource when cooperative managers and directors are considering engaging in mergers or other strategic alliances. Therefore, the objectives of this study are to (i) estimate the potential overall gains or losses that may accrue to agricultural cooperatives due to mergers; (ii) determine how much different sources of merger effects may contribute to overall merger gains or losses; and (iii) determine if differences in merger effects exist based on size of cooperatives, defined by total assets.

In other sectors such as banking, several studies have been conducted to measure potential gains from mergers (e.g. Seiford and Zhu, 1999; Bogetoft and Wang, 2005; Färe, Grosskopf and Margaritis, 2011; Wu, Zhou and Birge, 2011; Lozano, 2013; Shi et al., 2017). These studies suggest that not all mergers will be successful at cost reduction and/or improvements in profit. However, equivalent assessment for agricultural cooperatives is scanty. This study contributes to the limited literature on agricultural cooperative mergers by investigating potential gains of cooperatives pre-merger

Using data from CoBank for 749 midwestern agricultural cooperative observations from 2011 to 2015, this study investigates potential gains from mergers. Ex-ante merger analyses are conducted from both cost and revenue orientations, along with considerations for cooperative size, defined by total assets. Potential gains from mergers are decomposed into learning effect and pure merger effect, which is further decomposed into scale and scope effects, following Bogetoft and Wang (2005).

Bogetoft and Wang (2005) introduced an ex-ante data envelopment analysis (DEA) approach for estimating potential gains from mergers. Potential gains from mergers were decomposed into learning effects, scale (size) effects, and scope (synergy, harmony, or mix) effects. Learning effects capture potential gains or losses that may accrue to decision making units (DMUs) if each DMU learns best practices but operates as an independent unit (Shi et al., 2017). Scope effects capture the portion of merger gains or losses that can be attributed to re-allocation of input-output mixes (Flokou, Aletras and Niakas, 2017). Scale effects capture the merger gains or losses that may be attributed to operating at full or integrated scale compared to operating at the average scale of merger candidate DMUs (Bogetoft and Wang 2005).

The findings of this study show that, there are non-trivial overall potential gains from mergers based on both cost and revenue orientations. Overall merger gains are primarily driven by improvements due to learning effects and scope effects. Scale effect on the other hand tends to work against mergers, with higher associated cost increases (or revenue losses) for mergers between larger sized cooperatives compared to mergers between smaller cooperatives. Also, findings show that, on average, overall merger gains from the revenue orientation are relatively higher than from the cost orientation. Finally, baseline (pre-merger) profits are benchmarked against endline (post-merger) profits. Estimates show that, less of other unique merger costs such as legal fees, non-trivial profits may accrue to cooperatives due to mergers, with smaller sized cooperatives benefiting more from mergers than larger sized cooperatives.

The rest of this study is organized as follows. In the following section, the methodology that is utilized is discussed. Next, data and descriptive statistics as well as preliminary data considerations are provided. The empirical estimation is then presented, followed by the results. Finally, this chapter concludes by discussing the major findings of this study as well as implications for agricultural cooperative management and policy.

4.2 Methodology

4.2.1 Data envelopment analysis

Data envelopment analysis (DEA) is a commonly used method for assessing efficiency. Charnes, Cooper and Rhodes (1978) first introduced this approach in their seminal paper, as an advancement of earlier work by (Farrell, 1957) and was later extended by Banker, Charnes and

Cooper (1984). DEA can be applied to decision making units (DMUs) which convert multiple inputs into multiple outputs, such that each DMU's efficiency is maximized, defined by the ratio of the weighted sums of outputs to inputs (Yeager and Langemeier, 2017). This approach allows for the production inputs and outputs of each DMU to be weighted relative to a set of DMUs such that a benchmark frontier is defined. Based on this benchmark frontier, DMUs can be classified as either technically efficient (also referred to as best practice DMUs) or inefficient. The DMUs that are fully efficient define the efficiency frontier and all other DMUs that are below this frontier are considered as inefficient. DMUs that are fully efficient are assigned a value of 1, while all other DMUs are assigned non-negative values less than 1, with lower values implying the DMU is farther away from the frontier, thus more technically inefficient. The efficiency of a DMU can be expressed from input and output orientations. From the input orientation, efficiency is measured as the minimum production input, given a fixed level of output (Färe, Grosskopf and Margaritis, 2011). Similarly, from the output orientation, efficiency reflects the maximum output, given a fixed level of input (Coelli et al., 2005). While an alternative method of estimation might be stochastic frontier analysis, DEA may be preferred because it relies on less a priori restrictions. Another advantage of the DEA approach is its ability to handle multiple inputs as well as multiple outputs (Yeager and Langemeier, 2017).

4.2.2 Measuring potential gains from mergers

Based on the data envelopment analysis (DEA) methodology, Bogetoft and Wang (2005) proposed a framework that can be used to examine hypothetical cases of consolidations between decision making units (DMUs). By presenting an approach for examining potential gains from mergers a prior rather than ex-post, this framework provides a means for gauging which mergers will be successful.

The notation and concepts as used by Bogetoft and Wang (2005); and Flokou, Aletras and Niakas (2017) are followed such that, DMU^i denotes a decision making unit of n total DMUs, $i \in I = \{1,2,3,\dots,n\}$ that converts p inputs $x^i = (x_1^i, x_2^i, x_3^i, \dots, x_p^i) \in \mathbb{R}_+^p$ into q outputs $y^i = (y_1^i, y_2^i, y_3^i, \dots, y_q^i) \in \mathbb{R}_+^q$.

Also, let T be a production possibility set which represents the set of all possible feasible combinations of inputs and outputs: $T = \{(x, y) \in \mathbb{R}_+^{p+q} | x\ can\ produce\ y\}$.

The underlying production technology T can be estimated by using the DEA approach, such that an empirical reference technology set T^* is constructed based on the observed data points, given some assumptions about the technology. The estimation of T^* is derived according to the minimum extrapolation principle which states that, T^* is the smallest subset of $\mathbb{R}_+^{p+q}$ that (i) contains the observed production plans (x^i, y^i), $i \in I$ and (ii) also satisfies the underlying technological assumptions (Flokou, Aletras and Niakas, 2017).

After deriving T^*, the relative efficiency of DMU^i within T^* may then be measured either from the input or output orientation, defined by (Farrell, 1957) as:

$E^i = \min\{E \in \mathbb{R}_+ | (Ex^i, y^i) \in T^*\}$ or $F^i = \max\{F \in \mathbb{R}_+ | (x^i, Fy^i) \in T^*\}$ respectively.

E^i denotes (for any given y^i) the maximum contraction factor inputs x^i that are feasible in T^* for DMU^i. Similarly, F^i denotes (for any given x^i) the maximum expansion factor of outputs y^i that are feasible in T^* for DMU^i. The imposed assumptions on T are:

Assumption 1 (disposability): less can be produced with more:

$(x', y') \in T\ and\ x'' \geq x'\ and\ y'' \leq y' \Rightarrow (x'', y'') \in T$.

Assumption 2 (convexity): the convex combination (i.e., weighted average) of two feasible production plans is also feasible:

$(x', y') \in T \; and \; (x'', y'') \in T \Rightarrow \lambda(x', y') + (1 - \lambda)(x'', y'') \in T, \; \forall \lambda \in [0,1]$.

Assumption 3 (s-return to scale): defines the nature of possible rescaling of the production plans:

$(x', y') \in T \Rightarrow k(x', y') \in T \quad for \; k \in K(s)$

where $s = "crs" \; or \; "vrs"$ corresponding to constant or variable returns to scale respectively; and $K(crs) = [0, +\infty]$, implying any rescaling is possible, and $K(vrs) = \{1\}$, implying no rescaling is possible.

Assumptions 1 and 2 in combination with the assumption for the returns to scale of Assumption 3 lead to the empirical reference technology $T^*(s)$ described by the following set:

$T^*(s) = \{(x, y) \in \mathbb{R}_+^p \times \mathbb{R}_+^q | \exists \boldsymbol{\lambda} = (\lambda^1, \lambda^2, \lambda^3, \dots, \lambda^n)$

$\in \Lambda(n, s): x \geq \sum_{i=1}^{n} \lambda^i x^i \, , y \leq \sum_{i=1}^{n} \lambda^i y^i\}$

where

$\Lambda(n, crs) = \left\{\lambda \in \mathbb{R}_+^n \middle| \sum_i \lambda^i \geq 0\right\}$,

$\Lambda(n, vrs) = \{\lambda \in \mathbb{R}_+^n | \sum_i \lambda^i = 1\}$.

Thus, when applying the Farrell (1957) definition of efficiency for DMU^r, $r \in \{1,2,3, \dots, n\}$, producing at point (x^r, y^r) within $T^*(s)$ the following DEA linear programming problems are obtained:

$E_{(s)}^r = \min\left\{E \in \mathbb{R}_+ \middle| Ex^r \geq \sum_{i=1}^{n} \lambda^i x^i \, ; y^r \leq \sum_{i=1}^{n} \lambda^i y^i \, ; \boldsymbol{\lambda} = (\lambda^1, \lambda^2, \lambda^3, \dots, \lambda^n) \in \Lambda(n, s)\right\}$

$F_{(s)}^r = \max\left\{F \in \mathbb{R}_+ \middle| x^r \geq \sum_{i=1}^{n} \lambda^i x^i \, ; Fy^r \leq \sum_{i=1}^{n} \lambda^i y^i \, ; \boldsymbol{\lambda} = (\lambda^1, \lambda^2, \lambda^3, \dots, \lambda^n) \in \Lambda(n, s)\right\}$,

such that $E_{(s)}^r \leq 1$ and $F_{(s)}^r \geq 1$ (Flokou, Aletras and Niakas, 2017). The programs above define the reference (efficient) unit $(\sum_{i=1}^{n} \lambda^i x^i \, , \sum_{i=1}^{n} \lambda^i y^i)$, which is basically a convex combination of the existing DMUs, against which DMU^r is compared. The DMUs that contribute to the construction of the benchmark unit (i.e., the units with $\lambda^i > 0$) are called "peer units", which form the "peer group" of DMU^r.

Peer group of $DMU^r = \{DMU^i, i \in \{1,2,3,\dots,n\} | \lambda^i > 0\}$.

Another important concept is the most productive scale size (MPSS), outlined by Banker, Charnes and Cooper (1984) as: a production possibility $(x^0, y^0) \in T^*$ is an MPSS for its output and input combination, if and only if for all $(ax^0, \beta y^0) \in T^*$, such that $a \geq \beta$. The MPSS is located on the frontier and it matches the point where the average productivity for its output and input combination is maximized. That is, at MPSS the maximum average output is achieved, thus any deviation from this point of production would result in a lower-than-average output. Scale efficiency (SE^r) is another concept that captures the cost from not operating at MPSS, which for a DMU^r, $r \in \{1,2,3,\dots,n\}$, operating at point (x^r, y^r) is specified as: $SE^r = \frac{E^r_{crs}}{E^r_{vrs}}$ (Flokou, Aletras and Niakas, 2017).

The proposition which connects MPSS to scale efficiency states that: a production possibility $(x^0, y^0) \in T^*$ is an MPSS for its output and input combination, if and only if $E^r_{(vrs)} = 1$, and $SE^r = 1$ (i.e., $E^r_{(crs)} = 1$). Thus, if $(x^0, y^0) \in T^*$ is an MPSS then constant returns to scale prevails at (x^0, y^0). Moreover, the convexity of the vrs production possibility set allows for all points that are defined by increasing returns to scale (irs) precede whilst the ones characterized by decreasing returns to scale (drs) follow the MPSS along the efficient benchmark. The scale efficiency represents the distance between the crs and vrs frontiers, hence underscores the propinquity of a technically efficient DMU (i.e., $E^r_{(vrs)} = 1$) to the MPSS, which basically mirrors the improvements from adjusting its production scale to match that of the MPSS. It is important to note however that, for each output and input combination, the MPSS that is outlined, depends on the specific direction in the output and input space.

Super efficiency is another relevant concept that originated from advancements in DEA modelling. Super efficiency models are derived by omitting DMU^r under assessment from the formulation of the empirical technology set $T^*(s)$, defined as:

$$T^{*r}(s) = \{(x,y) \in \mathbb{R}_+^p \times \mathbb{R}_+^q | \exists\, \boldsymbol{\lambda} = (\lambda^1, \lambda^2, \lambda^3, \dots, \lambda^{n-1}) \in \Lambda(n-1,s): x \geq \sum_{\substack{i=1 \\ i \neq r}}^{n} \lambda^i x^i\, , y \leq \sum_{\substack{i=1 \\ i \neq r}}^{n} \lambda^i y^i\}$$

As observed, the empirical technology set $T^{*r}(s)$ is not necessarily common to every DMU. Therefore, super efficiency models deviate slightly from the standard DEA linear programming problems, defined from the input and output orientation respectively as:

$$E_{(s)}^{SE-r} = min \left\{ E \in \mathbb{R}_+ \middle| Ex^r \geq \textstyle\sum_{\substack{i=1 \\ i \neq r}}^{n} \lambda^i x^i\, ;\ y^r \leq \sum_{\substack{i=1 \\ i \neq r}}^{n} \lambda^i y^i\, ; \boldsymbol{\lambda} = (\lambda^1, \lambda^2, \dots, \lambda^{n-1}) \in \Lambda(n-1,s) \right\}$$

$$F_{(s)}^{SE-r} = \max \left\{ F \in \mathbb{R}_+ \middle| x^r \geq \textstyle\sum_{\substack{i=1 \\ i \neq r}}^{n} \lambda^i x^i\, ;\ Fy^r \leq \sum_{\substack{i=1 \\ i \neq r}}^{n} \lambda^i y^i\, ; \boldsymbol{\lambda} = (\lambda^1, \lambda^2, \dots, \lambda^{n-1}) \in \Lambda(n-1,s) \right\}$$

The concept of super efficiency is known to have been first proposed by Andersen and Petersen (1993) under the assumption of crs, to reorder DMUs by considering that all fully efficient DMUs have an efficiency score which is strictly equal to 1. By not including the DMU under consideration in the technology set $T^*(s)$ implies that, the super efficiency scores from output (input) orientation do not necessarily have to be bounded below (above) by unity as in conventional DEA models. Therefore, the efficient DMUs can be reordered according to their super efficiency score. This approach may however result in programs without feasible solutions when the vrs assumption is considered.

Assume that a hypothetical merger of DMUs in a subset J of the set I ($J \subseteq I$) is a direct pooling of inputs and outputs such that the merged DMU uses $x_J = \sum_{j \epsilon J} x^j$ to produce $y_J = \sum_{j \epsilon J} y^j$. The hypothetically merged unit is therefore defined as: $DMU^J = (\sum_{j \epsilon J} x^j\, , \sum_{j \epsilon J} y^j)$.

From the input orientation, a measure of the potential overall gains from merging the J-$DMUs$ is defined as:

$E^J = \min\{E \in \mathbb{R}_+ | (E[\sum_{j\epsilon J} x^j], \sum_{j\epsilon J} y^j) \in T^*\}.$

E^J represents the maximum proportional reduction in the pooled inputs $\sum_{j\epsilon J} x^j$ that enables the production of the corresponding pooled outputs $\sum_{j\epsilon J} y^j$. If $E^J > 1$, the merger is considered as costly, with efficiency losses of up to $(E^J - 1)$. On the other hand, if $E^J < 1$, it implies that the merger can potentially be beneficial, with efficiency gains of up to $(1 - E^J)$.

Similarly, from the output orientation, a measure of the potential overall gains from merging the J-$DMUs$ is defined as:

$F^J = \max\{F \in \mathbb{R}_+ | (\sum_{j\epsilon J} x^j, F[\sum_{j\epsilon J} y^j]) \in T^*\}.$

F^J represents the maximum proportional expansion of the pooled output $\sum_{j\epsilon J} y^j$ that is feasible in the merged DMU, with pooled input $\sum_{j\epsilon J} y^j$. If $F^J > 1$, the merger is considered as beneficial, with potential gains of up to $(1 - F^J)$. On the other hand, if $F^J < 1$, it implies that the merger can potentially be costly, with efficiency losses of up to $(F^J - 1)$.

It is important to note that a solution to the DEA merger problem is not always feasible. To allow for feasible solutions, a sufficient condition is the replicability or additivity assumption for the empirical reference technology T^* which is defined as:

Assumption 4 (additivity): the sum of any two feasible production plans is also feasible:

$(x', y') \in T \text{ and } (x'', y'') \in T \Rightarrow (x' + x'', y' + y'') \in T.$

Thus, there is always a solution under the assumption of crs, but not always for the case of vrs assumption.

E^J and F^J are measures of overall merger effects, which encompass several effects. Bogetoft and Wang (2005) decompose these overall effects into learning effects, and pure merger effects, which is further decomposed into scale (size), and scope (harmony, synergy, or mix) effects. These decompositions are discussed in the next subsections.

4.2.2.1 Learning effect

There may be some technically inefficient units in subset J. This may be captured in the overall merger effects, E^J and F^J, that is, from input and output orientations respectively. Take for example that, a merger brings in a more experienced management, this may enable the purging of inefficiencies. Also, technical inefficiencies can be reduced through other means such as "learning from" the more efficient peer units. Thus, overall merger effects must be adjusted to account for these learning (peer) effects. To do this, the pre-merger units are projected to the production possibility frontier, such that the projected plans are used as the benchmark for assessing the residual effects from the merger. Therefore, if each original unit (x^j, y^j) in subset J is projected to $(E^j x^j, y^j)$, where E^j is the conventional DEA efficiency score from the input orientation for DMU^j, the projected plans $(E^j x^j, y^j)$, $j \in J$, can be used as the basis for estimating the adjusted pure merger effects defined as:

$E^{*J} = \min\{E \in \mathbb{R}_+ | (E[\sum_{j\epsilon J} E^j x^j],\ \sum_{j\epsilon J} y^j) \in T^*\}$.

The learning effect can therefore be calculated as $LE_E^J = \frac{E^J}{E^{*J}}$, which can be rearranged as $E^J = LE_E^J \times E^{*J}$. This shows that the learning effect component reflects potential savings by eliminating individual inefficiencies due to peer effects of the units in subset J.

Similarly, from the output orientation, if each original unit (x^j, y^j) in subset J is projected to $(x^j, F^j y^j)$, where F^j is the conventional DEA efficiency score for DMU^j, the projected plans

$(x^j, F^j y^j)$, $j \in J$, can be used as the basis for estimating the adjusted pure merger effects defined as:

$F^{*J} = \max\{F \in \mathbb{R}_+ | (\sum_{j \epsilon J} x^j,\ F[\sum_{j \epsilon J} F^j y^j]) \in T^*\}$.

The learning effect can similarly be calculated as $LE_F^J = \frac{F^J}{F^{*J}}$, and rearranged as $F^J = LE_F^J \times F^{*J}$.

After adjusting for individual technical inefficiencies, two more evident merger effects labelled as scale (size) effect, and scope (harmony, synergy, or mix) effect are present. These two effects underscore the direct pooling of outputs and inputs to produce a merged unit that operates at a large scale, with different input and output mixes. Thus, contingent on the scale properties of the underlying production technology, and the direction of the input-output space taken by the merged unit, these effects may or may not be beneficial. It is therefore useful to investigate whether the merged unit lies within the input-output space in a relatively more efficient portion of the production possibility set. If this assumption holds, then it is also important to determine to what extent merger effects can be associated with the new direction of production, and what portion of merger effects can be ascribed to the large scale of production. In the next subsections, how these effects are measured is outlined and discussed.

4.2.2.2 Scope effect

Scope effect SpE^J, also referred to as mix, synergy, or harmony effect, measures what portion of merger effects can be attributed to re-allocation of inputs and outputs among decision making units (DMUs) in J, such that all DMUs can operate with the exact same mixes as in the corresponding aggregated unit. To capture this effect, consider that the effects of all J different units are replaced by J identical "arithmetic average" DMUs after adjustments for learning effects, then from the input orientation, scope effects can be defined as:

$SpE_E^J = \min\{SpE_E \in \mathbb{R}_+ | (SpE_E[|J|^{-1} \sum_{j\epsilon J} E^j x^j],\ |J|^{-1} \sum_{j\epsilon J} y^j) \in T^*\}$

where $|J|$ is the number of elements in J. It is important to note that, at this point, the sizes of the pre-merger units are considered to be identical to the "arithmetic average" units. It is however admissible that, this is not the always case, that is units in J may be significantly different in sizes to begin with. In the case of considerable differences in sizes, scope effects may be picking up scale effects. $SpE_E^J < 1$ implies potential cost savings, with savings of up to $(1 - SpE_E^J)$ due to an enhanced scope of operation, otherwise if $SpE_E^J > 1$, merging can be potentially costly, with losses up to $(1 - SpE_E^J)$.

Similarly, from the output orientation, scope effect is defined as:

$SpE_F^J = \max\{SpE_F \in \mathbb{R}_+ | ((|J|^{-1} \sum_{j\epsilon J} x^j,\ SpE_F[|J|^{-1} \sum_{j\epsilon J} F^j y^j]) \in T^*\}.$

$SpE_F^J > 1$ indicates potential revenue gains, with gains up to $(SpE_F^J - 1)$ due to improved scope, otherwise if $SpE_F^J < 1$, merging can be potentially costly, with losses up to $(SpE_F^J - 1)$.

4.2.2.3 Scale effect

After adjusting for scope/mix effects, scale effect SlE^J, also referred to as size effect can be measured by comparing potential gains from operating at full scale rather than at average scale. Thus, the scale effect from the input orientation is given by:

$SlE_E^J = \min\{SlE_E \in \mathbb{R}_+ | (SlE_E[SpE_E \sum_{j\epsilon J} E^j x^j],\ \sum_{j\epsilon J} y^j) \in T^*\}.$

$SlE_E^J < 1$ indicates rescaling is advantageous, with potential cost savings up to $(1 - SlE_E^J)$ due to economies of scale, otherwise if $SlE_E^J > 1$, it implies that larger DMUs are not favored for the given returns to scale property, thus full mergers that produce such large units can be potentially costly, with losses of up to $(1 - SlE_E^J)$.

Similarly, from the output orientation, scale effect is defined as:

$SlE_F^J = \max\{SlE_F \in \mathbb{R}_+ \big| \big(\sum_{j\epsilon J} x^j\ ,\ SlE_F[SpE_F \sum_{j\epsilon J} F^j y^j]\big) \in T^*\}$.

$SlE_F^J > 1$ indicates rescaling is advantageous, with potential revenue gains of up to $(SlE_F^J - 1)$ due to economies of scale, otherwise if $SlE_F^J < 1$, it implies that the return to scale property does not favor larger DMUs thus full mergers that produce such large units can be potentially costly, with losses $(SlE_F^J - 1)$.

In summary, the three immediate past subsections illustrate the decomposition of the overall potential gains from mergers, in the form of cost savings (from the input orientation) captured by $E^J = LE_E^J \times E^{*J} = LE_E^J \times SpE_E^J \times SlE_E^J$, and in the form of revenue gains (from the output orientation) captured by $F^J = LE_F^J \times F^{*J} = LE_F^J \times SpE_F^J \times SlE_F^J$.

The learning effect captures what can be potentially gained by making individual DMUs fully efficient through learning from the practices and procedures of the more efficient units. After adjusting for individual unit inefficiencies, the remaining effect defined as pure merger effect is captured by scope and scale effects. Scope effect captures potential gains due to reallocating of outputs and inputs among units to create advanced input combinations and produced more improved outputs. This is measured by comparing what can be gained by a hypothetical DMU of equal size to that of the original units which utilize the same mixes of outputs and inputs as those in the merged DMU. Thus, the scale effect captures what can be gained by operating at full scale rather than at average scale.

4.3 Data

CoBank maintains financial statement data on farmer cooperatives and agricultural businesses across the United States. This study utilizes a subset of CoBank data, consisting of 749 farm supply and marketing cooperative observations from 2011 to 2015 across 5 midwestern states: Kansas, Nebraska, Oklahoma, Missouri, and Colorado. Input and output measures used in analysis are similar to Russell, Briggeman and Featherstone (2017). Labor, capital, and other (variable) expense are the three input variables utilized in this study. Output variables include grain sales, farm input supply sales, service (operating) income, and other product sales. Agricultural cooperatives may market or supply all these outputs, or a subset.

Output and input variables are provided in the CoBank data as dollar values, thus are converted into quantity indexes, by dividing dollar values by their corresponding price indexes. Annual national-level producer price indices for inputs and outputs are obtained from U.S. Department of Labor (2019). US real interest rate, used as the price of capital is obtained from the World Bank (2019).

4.3.1 Input variables

The three inputs used for the analysis in this study include capital, labor, and variable expense. Labor expense is made up of expenses on fringe benefits and wages. A quantity index for labor is constructed by dividing labor expense by average hourly earnings for the manufacturing sector (U.S. Department of Labor, 2019). The quantity of capital is captured by total assets, and the U.S. real interest rate (World Bank, 2019) is considered as the cost of capital. Thus, capital expense is calculated as the product of total assets and real interest rate. The final input is variable expense, which includes expenses for utility, advertising, telephone, collection, lease, and rent. The quantity index variable is constructed by dividing variable expense by general producer price index (U.S. Department of Labor, 2019). In the first panel of table 4.1, summary statistics of input variables are presented as expenses. On average, capital expense accounts for more than 90% of total input expenses. The corresponding quantity indexes follow a similar trend as input expenses and are also presented in the first panel of table 4.2.

4.3.2 Output variables

The four output variables that are used for the analysis in this study include grain sales (aggregated sales for commodities and grain), service income (aggregate of storage, and handling revenues, as well as revenue from other services), farm input supply sales (aggregate of fertilizer, chemicals, petroleum, feed, and other farm input sales), and finally other product sales. These output variables are expressed in dollars; thus, they are converted to output quantity indexes. To obtain output quantity indexes, grain sales, service income, farm input supply sales, and other product sales are divided by producer price indices for grains, finished goods, crude materials for further processing, and general producer price index respectively (U.S. Department of Labor, 2019). In the second panel of table 4.1, summary statistics of output variables are presented as revenues. As shown, revenue from grain sales is the highest contributor to the total revenue of agricultural cooperatives. The corresponding quantity indexes follow a similar trend as output revenues and are also presented in the second panel of table 4.2.

Table 4.1: Summary statistics of annual input expense and output revenue variables

Variables (dollars)	N	Mean	Std dev.
Input expense			
Labor	749	3,399,421	5,587,599
Capital	749	57,796,889	97,541,391
Other inputs	749	814,433	1,413,494
Output revenue			
Grain sales	749	67,853,226	126,980,948
Farm-supply sales	749	25,770,173	41,917,366
Service income	749	2,881,668	5,116,672
Other sales	749	3,188,332	5,568,538

Note: Std. dev. stands for standard deviation, N is number of agricultural cooperative observations.

Table 4.2: Summary statistics of annual input and output quantity indexes

Variables (index)	N	Mean	Std dev.
Input quantities			
Labor	749	175,547	286,775
Capital	749	40,352,571	63,020,828
Other inputs	749	4,249	7,348
Output quantities			
Grain	749	322,697	619,225
Farm-supply	749	107,674	175,673
Service	749	15,045	26,973
Other outputs	749	16,316	28,411

Note: Std. dev. Stands for standard deviation, N is number of agricultural cooperative observations.

4.3.3 Preliminary considerations

Cooperatives are categorized into small, medium, and large-size entities based on total assets. Cooperatives below the 33.33rd percentile (i.e., below $ 9,533,757 in total assets) are classified as small-size cooperatives. Cooperatives within the 33.33rd and 66.66th percentile (i.e., between $9,533,757 and $26,647,057 in total assets) are classified as medium-size cooperatives, and those above the 66.66th percentile (i.e., above $26,647,057 in total assets) are classified as large-size cooperatives. Summary statistics of input and output expenses as well as their corresponding quantity indexes are presented in tables 4.3 and 4.4 respectively. Both tables show that on average, as the size of a cooperative increases, input use and output increase.

Table 4.3: Summary statistics of annual input expense and output revenue variables by total asset categorization

Variables (dollars)	Small			Medium			Large		
	N	Mean	Std dev.	N	Mean	Std dev.	N	Mean	Std dev.
Input expense									
Labor	250	826,619	497,711	249	1,787,760	809,154	250	7,577,436	8,131,427
Capital	250	8,128,354	3,946,411	249	22,399,147	8,636,129	250	142,721,576	132,364,208
Other inputs	250	196,829	179,965	249	391,227	208,374	250	1,853,550	2,068,844
Output revenue									
Grain sales	250	6,536,398	9,332,159	249	17,498,208	20,813,551	250	179,323,651	170,682,884
Farm-supply sales	250	7,714,034	8,166,473	249	15,225,324	11,532,311	250	54,328,983	61,819,845
Service income	250	635,341	638,178	249	1,755,149	1,383,725	250	6,250,008	7,655,409
Other sales	250	1,611,707	3,395,589	249	2,217,823	2,795,085	250	5,731,584	7,994,217

Note: Std. Dev. stands for standard deviation, N is number of agricultural cooperative observations.

Table 4.4: Summary statistics of annual input and output quantity indexes by total asset categorization

Variables (index)	Small			Medium			Large		
	N	Mean	Std dev.	N	Mean	Std dev.	N	Mean	Std dev.
Input expense									
Labor	250	42,810	25,762	249	92,470	41,792	250	391,028	416,457
Capital	250	5,801,064	2,360,589	249	15,875,671	4,770,422	250	99,283,071	81,351,804
Other inputs	250	1,027	942	249	2,041	1,091	250	9,671	10,739
Output revenue									
Grain	250	29,997	42,298	249	82,198	98,981	250	854,935	843,824
Farm-supply	250	32,124	33,988	249	63,512	47,989	250	227,208	259,290
Service	250	3,314	3,333	249	9,152	7,217	250	32,645	40,480
Other input	250	8,258	17,417	249	11,369	14,408	250	29,302	40,690

Note: Std. dev. stands for standard deviation, N is number of agricultural cooperative observations. Quantity indexes are constructed by dividing expense values by their price indices.

A hypothetical merger cooperative is defined as a combination of two candidate cooperatives. Examples include a combination of two small cooperatives (small-small); a small and large cooperative (small-large); or a medium and large cooperative (medium-large). Potential mergers are constrained so that candidate cooperatives in Kansas can merge with any candidate cooperative located in Nebraska, Oklahoma, Missouri, or Colorado. However, candidate cooperatives located in Nebraska, Oklahoma, Missouri, and Colorado can only merge with other cooperatives within state. If candidate cooperatives are too far from each other, then it becomes difficult for some farmers to access facilities and services provided by the merged cooperative post-merger. Thus, it makes "organizational sense" to consider these proximity restrictions.

After clearly categorizing cooperatives, merger candidates are paired, and simulations are conducted on an annual basis. Simulations are based on 1,000 bootstrapped samples to improve the accuracy of estimates (Simar and Wilson, 1998). Merger candidate pairs are assigned without consideration for size of cooperatives. This implies that without location restrictions, there are C_2^{yt} mergers for each simulation, where yt is the number of cooperative observations for each bootstrapped sample in year t.

4.4 Empirical Estimation

To evaluate potential gains from mergers, the DEA approach is used to estimate both cost and revenue functions. DEA compares the relative use of inputs by decision making units (DMUs) and resulting output levels to estimate a benchmark frontier (Charnes, Cooper and Rhodes, 1978). When input prices are known, cost efficiency can be estimated under the assumption that DMUs are cost minimizers. On the other hand, when output prices are known, revenue efficiency can be estimated under the assumption that DMUs are revenue maximizers. Also, under the assumption that there are both advantages and disadvantages of either being too small or too large, technologies can be investigated under variable returns to scale (VRS) (Banker, Charnes and Cooper, 1984). Hence, the cost and revenue functions for estimating efficiency outcomes can be expressed under VRS in equations 4.1 and 4.2 respectively as follows:

$$C(y_0, w) = min_{\lambda,x} wx$$

$$s.t.$$

$$\sum_{k=1}^{n} x_k \lambda_k - x \leq 0$$

$$\sum_{k=1}^{n} y_k \lambda_k - y_0 \geq 0$$

$$\sum_{k=1}^{n} \lambda_k = 1 \tag{4.1}$$

where x is a vector of quantity index inputs including labor, capital, and other variable expenses, y is a vector of quantity index outputs including grain sales, farm input supply sales, service income, and other product sales, and w is a vector of input prices, all as described in the data section. λ measures the intensity of use of the *k*-th DMU's technology, and *k* denotes the number of DMUs.

$$R(x_0, p) = max_{\lambda,y} py$$

$$s.t.$$

$$\sum_{k=1}^{n} x_k \lambda_k - x_0 \leq 0$$

$$\sum_{k=1}^{n} y_k \lambda_k - y \geq 0$$

$$\sum_{k=1}^{n} \lambda_k = 1 \tag{4.2}$$

where p is a vector of output prices, and all other variables are as described earlier.

Next, the cost and revenue efficiencies for each DMU i is calculated in equation 4.3 and 4.4 respectively as follows:

$$CE_{\boldsymbol{i}} = C(y_i, w)/wx_i \tag{4.3}$$

which is the ratio of the minimum (frontier) cost of production to the observed cost. Thus, cost efficiency ($CE_{\boldsymbol{i}}$) provides a measure of the relative distance from the cost frontier, such that, an efficiency score of one implies that the DMU is fully efficient. A non-negative efficiency score of less than one, indicates that the DMU is cost inefficient, with lower scores implying more inefficiency.

$$RE_{\boldsymbol{i}} = R(x_i, p)/py_i \tag{4.4}$$

which is the ratio of the maximum (frontier) revenue from production to the observed revenue. Thus, revenue efficiency ($RE_{\boldsymbol{i}}$) provides a measure of the relative distance from the revenue frontier, such that, an efficiency score of one implies that the DMU is fully efficient. If an efficiency score is greater than one, it indicates that the DMU is revenue inefficient, with higher scores implying more inefficiency.

Now, following Bogetoft and Wang (2005), possible mergers of candidate DMUs are considered to form merged DMUs denoted as DMU_J. DMU_J is a direct pooling of inputs and outputs such that the merged DMU uses $x_J = \sum_{j \epsilon J} x_j$ to produce $y_J = \sum_{j \epsilon J} y_j$, $j \geq 2$, and $J = \{1,2, \dots, h\}$; where h is the total number of merged DMUs. This is parallel to having a fully decentralized organization in which the decentralized units correspond to the h merged DMUs.

Therefore, the overall merger effects of each hypothetical DMU_J from the cost orientation can be calculated in equation 4.5 as follows:

$$ME_C^J = C(y_J, w)/wx_J \tag{4.5}$$

where ME_C^J captures the maximum reduction in cost of aggregated input x_J that allows the production of the aggregated output y_J, and w is vector of input prices. If $ME_C^J < 1$, this implies that there is a potential cost saving from merging, since the minimum possible cost, $C(y_J, w)$ is less than the observed cost, wx_J. On the other hand, if $ME_C^J > 1$, the merger is costly. For example, a score of $ME_C^J = 0.9$, suggests that the merged unit DMU_J could potentially produce the same level of outputs with 10 percent lower costs. Likewise, a score of $ME_C^J = 1.1$, suggests that the merged unit DMU_J could potentially produce the same level of outputs with 10 percent higher costs, thus a merger would not be recommended.

According to Bogetoft and Wang (2005), the overall merger cost effects can be decomposed into learning effect and pure merger effect; which is further decomposed into size (scale) and scope (synergy, harmony, or mix) effects in equation 4.6 as follows:

$$ME_C^J = LE_C^J \times ME_C^{*J} = LE_C^J \times SpE_C^J \times SlE_C^J \tag{4.6}$$

The decomposed effects are defined in following equations as:

$$LE_C^J = \sum_{j \in J} C(y_j, w)\,/wx_J \tag{4.7}$$

where the learning effect LE_C^J captures the reduction in costs if each DMU learns best practices but remains an independent entity. Thus, lower efficiency scores imply higher potential reductions in cost if DMUs learn best practices from more efficient DMUs.

$$ME_C^{*J} = C(y_J, w)\Big/\sum_{j \in J} C(y_j, w) \tag{4.8}$$

which is the pure merger effect, and it captures potential cost reductions from merging after accounting for individual learning.

$$SpE_C^J = \frac{C\left(y_J/h, w\right)}{\sum_{j\in J} C\left(y_j, w\right)/h} \tag{4.9}$$

where scope effect SpE_C^J measures the minimum cost of the average output mix compared to the average of the costs after adjusting for individual learning. This therefore captures what portion of merger effects can be attributed to re-allocation of inputs among DMUs in J, such that all DMUs can operate with the exact same mixes as in the corresponding aggregated unit. If $SpE_C^J < 1$, it implies that scope effects favor the merger. On the other hand, if $SpE_C^J > 1$, it indicates scope effects work against the merger.

$$SlE_C^J = \frac{C\left(y_J, w\right)}{h \times C\left(y_J/h, w\right)} \tag{4.10}$$

where scale effect SlE_C^J measures the cost of operating at the full or integrated scale compared to the average scale of candidate units. Scale effects are considered to favor the merger if $SlE_C^J < 1$. On the other hand, if $SlE_C^J > 1$, it implies that scale effects work against the merger. Given that full-scale mergers are not always feasible, the decomposition of potential merger gains is important for identifying alternative organizational reforms or strategies that may be more practical to implement.

Similarly, the overall merger effects of each hypothetical DMU_J from the revenue orientation can be calculated in equation 4.11 as follows:

$$ME_R^J = R\left(x_J, p\right)/py_J \tag{4.11}$$

where ME_R^J captures the maximum increase in revenue from aggregated outputs y_J, produced from the aggregated inputs x_J, and p is vector of output prices. If $ME_R^J < 1$, this implies that there is a potential revenue reduction from merging, since the maximum possible revenue, $R(x_J, p)$ is less than the observed revenue, py_J. On the other hand, if $ME_R^J > 1$, the merger could potentially increase revenue. For example, a score of $ME_R^J = 0.9$, suggests that the merged unit DMU_J could potentially generate 10 percent lower revenue using the same level of inputs. Likewise, a score of $ME_C^J = 1.1$, suggests that the merged unit DMU_J could potentially generate 10 percent more revenue using the same level of inputs.

Overall merger revenue effect is decomposed into learning effect and pure merger effect, which is further decomposed into size (scale) and scope (synergy, harmony, or mix) effects in equation 4.12 as follows:

$$ME_R^J = LE_R^J \times ME_R^{*J} = LE_R^J \times SpE_R^J \times SlE_R^J \tag{4.12}$$

The decomposed effects are defined in following equations as:

$$LE_R^J = \sum_{j \in J} R(x_j, p) / py_J \tag{4.13}$$

where learning effect LE_R^J measures the increase in revenue if each DMU learns best practices but remains an independent unit. Thus, higher efficiency scores imply higher potential increases in revenue if DMUs learn best practices from more efficient DMUs.

$$ME_R^{*J} = R(x_J, p) \Big/ \sum_{j \in J} R(x_J, p) \tag{4.14}$$

which is the pure merger effect, and it measures potential revenue increases from merging after accounting for individual learning.

$$SpE_R^J = \frac{R(x_J/h, p)}{\sum_{j \in J} R(x_j, p) / h} \tag{4.15}$$

where scope effect SpE_R^J measures the maximum revenue of the average input vector compared to the average of the revenue adjusted for individual learning. This therefore captures what portion of merger effects can be attributed to re-allocation of outputs among DMUs in J, such that all DMUs can operate with the exact same mixes as in the corresponding aggregated unit If $SpE_R^J > 1$, the scope effect favors the merger. If $SpE_R^J < 1$, the scope effect works against the merger.

$$SlE_R^J = \frac{R(x_j, p)}{h \times R(x_J/h, p)} \tag{4.16}$$

where scale effect SlE_R^J measures the revenue generated from operating at the full (integrated) scale compared to the average scale of candidate DMUs. If $SlE_R^J > 1$, the scale effect favors the merger. If $SlE_R^J < 1$, the scale effect works against the merger.

Finally, additional analysis is conducted to determine how merger gains can potentially translate into profitability, as a measure of financial performance. This is done by comparing the baseline profits of cooperatives pre-merger to their respective endline profits, defined in equation 4.17 as:

$$\vartheta_g^{\Delta} = \frac{\vartheta_g^{*} - \vartheta_g^{0}}{\vartheta_g^{0}} \times 100\% \tag{4.16}$$

where ϑ_g^{Δ} is the percentage change in profits due to merger for each specific merger group g, ϑ_g^{0} is the baseline profit, and ϑ_g^{*} is the endline profit.

Profit is defined as the difference between total revenue and total cost. Total cost and total revenue are the sums of all input expense and output revenue variables respectively, as defined in table 4.3 for each merger group. ϑ_g^{*} is calculated from both the cost and revenue orientations based on overall merger cost reductions and revenue gains from tables 4.5 and 4.6 respectively. Thus, ϑ_g^{Δ} is also calculated under both cost and revenue orientations.

4.5 Results

In this section, estimates of potential gains from mergers decomposed into various effect components are presented. From the cost orientation, a score of less than 1 indicates a potential cost reduction, and a score above 1 indicates an estimated potential cost increase. On the other hand, from the revenue orientation, a score of less than 1 indicates a potential revenue reduction, and a score above 1 indicates an estimated potential revenue increase.

Results in table 4.5 show that from the cost orientation, there are non-trivial overall potential cost reductions from mergers. Overall potential cost reductions range from a maximum of 27.6% to a minimum of 0.3%, with higher overall potential cost reductions in mergers between smaller cooperatives compared to mergers between larger cooperatives. For example, a merger between a small and medium cooperative (i.e., small-medium) could potentially produce overall cost savings of 27.6%, compared to overall cost savings of 17.8% for a merger between a medium and large cooperative (i.e., medium-large).

Overall merger gains are primarily driven by improvements due to learning effects and scope effects. Across all merger combinations, potential improvements due to scope effects (average of about 9.5%) are less than improvements due to learning effects (average of about 35.4%). Scale effects on the other hand tend to work against all types of mergers, with higher associated cost increases for mergers between larger sized cooperatives compared to mergers between smaller cooperatives. For example, a merger between a small and small cooperative (i.e., small-small) could potentially produce scale effect cost increases of 11.7%, compared to scale effect cost increases of 65.4% for a merger between two large cooperatives (i.e., large-large).

Compared to learning and scale effects, there is less variation in the magnitude of scope effects across merger combinations. This corroborates that cooperatives primarily provide similar services to farmers, hence using comparable input-output mixes. The scale effect results of this study reiterate similar results by Bogetoft and Wang (2005) which indicate that full-scale mergers are not always recommendable given potential cost increases. In these instances, cooperatives may engage in other strategic alliances such as sharing technical expertise or knowledge without having to undertake a full-scale merger.

Table 4.5: Cost oriented merger effects

Mergers	ME_c^J	LE_c^J	ME_c^{*J}	SpE_c^J	SlE_c^J
Small-Small	0.739	0.694	1.053	0.936	1.117
	(0.590)	(0.724)	(0.129)	(0.075)	(0.725)
Small-Medium	0.724	0.640	1.103	0.925	1.207
	(0.412)	(0.484)	(0.135)	(0.073)	(0.527)
Small-Large	0.784	0.641	1.204	0.852	1.419
	(0.557)	(0.607)	(0.157)	(0.091)	(0.617)
Medium-Medium	0.742	0.621	1.165	0.924	1.282
	(0.327)	(0.312)	(0.144)	(0.078)	(0.398)
Medium-Large	0.822	0.640	1.276	0.883	1.452
	(0.386)	(0.429)	(0.146)	(0.080)	(0.454)
Large-Large	0.997	0.643	1.526	0.919	1.654
	(1.240)	(1.464)	(0.141)	(0.074)	(1.470)

Note: Variables ME_c^J, LE_c^J, ME_c^{*J}, SpE_c^J, and SlE_c^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are averages of annual cost-oriented merger effect estimations from a 1,000 bootstrap samples, from 2011 to 2015. Standard deviations in parentheses.

In table 4.6, similar results are presented, but from the revenue orientation. There are non-trivial overall potential revenue increases from mergers. Overall potential revenue increases range from a maximum of 68.8% to a minimum of 11.5%, with higher overall potential revenue increases in mergers between smaller cooperatives compared to mergers between larger cooperatives. For example, a merger between a small and medium cooperative (i.e., small-medium) could potentially produce overall revenue increases of 54.3%, compared to overall revenue increases of 25.7% for a merger between a medium and large cooperative (i.e., medium-large).

Similar to the cost orientation, overall merger gains are primarily driven by improvements due to learning effects and scope effects. There is less variation in the magnitude of scope effects across merger combinations, averaging out to about 9.7%. Mergers between same-size cooperatives have potentially higher individual learning improvements, compared to mergers between cooperatives of different sizes. For example, a merger between a small and small cooperative (i.e., small-small) could potentially produce learning effect revenue increases of 61.9%, compared to learning effect revenue increases of 45.5% for a merger between a small and large cooperative (i.e., small-large).

Scale effect on the other hand tends to work against all merger combinations, with higher associated revenue reductions for mergers between larger sized cooperatives compared to mergers between smaller cooperatives. For example, a merger between a small and small cooperative (i.e., small-small) could potentially produce scale effect revenue reductions of 6.2%, compared to scale effect revenue reductions of 21.5% for a merger between two large cooperatives (i.e., large-large).

Scope and scale effect outcomes from the revenue orientation mirror outcomes from the cost orientation. However, overall merger gains from the revenue orientation on average are relatively higher than from the cost orientation.

Table 4.6: Revenue oriented merger effects

Mergers	ME_R^J	LE_R^J	ME_R^{*J}	SpE_R^J	SlE_R^J
Small-Small	1.688	1.619	1.038	1.109	0.938
	(0.637)	(0.198)	(0.436)	(0.148)	(0.133)
Small-Medium	1.543	1.657	0.929	1.107	0.842
	(0.437)	(0.087)	(0.410)	(0.087)	(0.074)
Small-Large	1.343	1.455	0.923	1.147	0.808
	(0.287)	(0.067)	(0.292)	(0.089)	(0.050)
Medium-Medium	1.405	1.631	0.862	1.074	0.803
	(0.383)	(0.068)	(0.420)	(0.066)	(0.053)
Medium-Large	1.257	1.439	0.874	1.090	0.803
	(0.251)	(0.061)	(0.273)	(0.074)	(0.042)
Large-Large	1.115	1.335	0.829	1.057	0.785
	(0.244)	(0.081)	(0.228)	(0.068)	(0.061)

Note: Variables ME_R^J, LE_R^J, ME_R^{*J}, SpE_R^J, and SlE_R^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are averages of annual revenue-oriented merger effect estimations from a 1,000 bootstrap samples, from 2011 to 2015. Standard deviations in parentheses.

Finally, potential percentage changes in profits due to mergers are presented in table 4.7. Results are presented from both the cost and revenue orientations. As shown in the table, potential profits that may accrue to cooperatives due to mergers are higher from the revenue orientation than from the cost orientation. But more importantly, it is also shown that smaller cooperatives may benefit the most from mergers. For example, for mergers between two small-size cooperatives, percentage changes in profits may range from 32.5% to 154.5%, from the cost and revenue orientations respectively. On the other hand, for mergers between two large-size cooperatives, percentage changes in profits may range from 0.49% to 30.2%, from the cost and revenue orientations respectively.

It is important to note that these estimations do not consider other costs that go into a merger process such as legal fees. Thus, potential percentage changes in profits may be less than estimated if other costs are considered. Costs such as legal fees for merger processes are not readily available, hence are not accounted for in this study. However, cooperative directors and managers may use these estimates as benchmarks, while accounting for other unique costs when considering mergers.

Table 4.7: Potential percentage changes in profits due to mergers

Mergers	$\vartheta^{\Delta}_{gC}(\%)$	$\vartheta^{\Delta}_{gR}(\%)$
Small-Small	32.52	154.52
Small-Medium	47.83	148.40
Small-Large	34.56	89.17
Medium-Medium	52.33	122.64
Medium-Large	29.79	68.71
Large-Large	0.49	30.22

Note: ϑ^{Δ}_{gC} and ϑ^{Δ}_{gR} represent percentage changes in profits from the cost and revenue orientations respectively. ϑ^{Δ}_{g} is calculated as defined in equation 4.17.

4.6 Conclusion

Mergers can be a very useful strategy for agricultural cooperatives to improve scale and scope economies, reduce costs of production and/or gain improvements in revenue (Demko, 2018). However, there is also ample evidence suggesting that not all agricultural cooperative mergers are successful at achieving these objectives (e.g. Schroeder, 1992; Richards and Manfredo, 2003; Briggeman et al., 2016). Identifying the sources of potential gains or losses, as well as mergers that are more likely to be successful, pre-merger may serve as a useful resource when cooperative managers and directors are considering engaging in mergers or other strategic alliances.

This study utilizes data from CoBank of 749 midwestern agricultural cooperative observations from 2011 to 2015, to investigate potential gains from mergers. Ex-ante merger analyses are conducted from both cost and revenue orientations, along with considerations for cooperative size, defined by total assets. Potential gains from mergers are decomposed into learning effect and pure merger effect, which is further decomposed into scale and scope effects, following Bogetoft and Wang (2005).

Bogetoft and Wang (2005) introduced an ex-ante data envelopment analysis (DEA) approach for estimating potential gains from mergers. Potential gains from mergers were decomposed into learning effects, scale (size) effects, and scope (synergy, harmony, or mix) effects. Learning effects capture potential gains or losses that may accrue to decision making units (DMUs) if each DMU learns best practices but operates as an independent unit (Shi et al., 2017). Scope effects capture the portion of merger gains or losses that can be attributed to re-allocation of input-output mixes (Flokou, Aletras and Niakas, 2017). Scale effects capture the merger gains or losses that may be attributed to operating at full or integrated scale compared to operating at the average scale of merger candidate DMUs (Bogetoft and Wang 2005).

The findings of this study show that, there are non-trivial overall potential gains from mergers based on both cost and revenue orientations. Overall merger gains are primarily driven by improvements due to learning effects and scope effects. Scale effect on the other hand tends to work against mergers, with higher associated cost increases (or revenue losses) for mergers between larger sized cooperatives compared to mergers between smaller cooperatives. Also, findings show that, on average, overall merger gains from the revenue orientation are relatively higher than from the cost orientation.

Finally, baseline (pre-merger) profits are benchmarked against endline (post-merger) profits. Results show that, less of other unique merger costs such as legal fees, non-trivial profits may accrue to cooperatives due to mergers, with smaller sized cooperatives benefiting more from mergers than larger sized cooperatives.

Chapter 5 - Summary

This dissertation consists of three essays that provide insights into how precision agriculture (PA) technology adoption choices may improve crop productivity, and how mergers or other forms of strategic alliances amongst agricultural cooperatives can provide additional benefits to cooperative-member farms. Motivation is drawn from the growing interest in how site-specific farm level data can be leveraged to improve productivity and environmental outcomes (Balafoutis et al., 2017; Woodard and Verteramo-Chiu, 2017; Yu and Hendricks, 2019; and Paudel and Crago, 2020). PA technologies enable adopter-farms to collect data on changing production conditions at site-specific levels to adjust farming practices such as soil nutrient application and seeding rates; this provides productivity improvements and has positive environmental outcomes.

While the use of PA technologies seem promising and beneficial, previous studies show that adoption rates remain significantly low (Schimmelpfennig, 2016). Whether and how farms adopt these technologies is complex and may not be easily nor uniquely unraveled. However, cost of technologies has been identified as one of the major barriers to adoption (Lambert, Paudel and Larson, 2015). Agricultural cooperatives may reduce cost barriers and promote adoption by making these technologies available (Hogeland, 2006). However, the use of such services may remain accessible to cooperative-member farms only. In such instances, consolidations and other forms of strategic alliances amongst cooperatives have been suggested as being potentially useful for helping farms access previously unavailable services such as the use of PA technologies (Briggeman et al., 2016).

Quantifying the benefits that farmers may accrue from adopting PA technologies is important for promoting more adoption. Furthermore, understanding how differences in adoption choices may affect potential benefits from adoption is even more important for helping farmers to make informed adoption choices. Also, examining if strategic alliances amongst agricultural cooperatives can provide benefits to farmers is relevant.

The first study in Chapter 2 evaluates the potential productivity improvements that can be attributed to adoption of PA technologies. Previous studies have examined the extent to which adoption of PA technologies impact crop yields, cost savings and input use. More recently, there has been a growing interest in examining how adoption of PA technologies impact the (in)effectiveness with which inputs are combined to produce outputs. Advancements in quasi-experimental methods and the availability of a unique dataset from the Kansas Farm Management Association (KFMA) present an opportunity to contribute to the literature by re-evaluating the impacts of PA technology adoption on crop productivity. In this study, treatment effect estimators are incorporated into a stochastic frontier analysis (SFA) framework to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production; and (ii) determine the effect of other farm/farmer characteristics on technical inefficiency. Empirical estimations utilize data from the KFMA consisting of 444 farms between 2002 to 2015. This includes non-adopters and adopters of PA technologies: precision soil sampling (PSS) and variable rate technology (VRT). The sample data is pre-processed by using propensity score matching (PSM) to account for potential underlying differences between adopters and non-adopters that may have spillover effects on the outcome of interest, that is technical inefficiency. Results suggest that adoption of PA technologies had no statistically significant impact on reducing technical inefficiency of corn production, in the presence of some degree of covariate imbalance.

In Chapter 2, differences amongst adopters are not considered, that is whether farms adopt PSS only or both PSS and VRT. However, estimates of technical inefficiency reductions may be masked by differences in adoption choices. The results of Chapter 2 therefore inspire the second study of this dissertation. The second study in Chapter 3, accounts for differences in PA technology adoption choices by grouping adopters as either adopters of PSS only or adopters of both PSS and VRT. The methodology and data of Chapter 2 are adapted to (i) estimate the impact of PA technology adoption on technical inefficiency of corn production under each adoption choice; and (ii) determine if outcomes are different under varying adoption choices. In the presence of some degree of covariate imbalance, results suggest that adoption of PA technologies had no statistically significant effect on reducing technical inefficiency of corn production. Specifically, two-way fixed effects estimates show that, for PSS only adopters as well as adopters of both PSS and VRT, adoption had no statistically significant effect on reducing technical inefficiency for corn production. Furthermore, event-study findings provide evidence that PSS only adopters potentially belong to the same distribution as non-adopters. However, adopters of both PSS and VRT are found to be systematically different from non-adopters.

The findings in Chapters 2 and 3 have several implications for farm policy and future research. First, though findings on technical inefficiency reductions due to PA technology adoption are not conclusive, this study shows that adopters of both PSS and VRT may be systematically different from non-adopters. This finding is consistent with Khanna (2001) which shows that, farmers that adopt both PSS and VRT are more technically competent, educated, and operate on larger scales. Identifying and understanding the characteristic differences amongst adopters, as well as between adopters and non-adopters can help in designing technology adoption support programs that are more targeted. This will also be useful for disentangling the actual effect of PA technology adoption on outcomes of interest versus spillover effects due to potential systematic differences between adopters and non-adopters in future research as more data becomes available.

The third study in Chapter 4 examines potential gains that agricultural cooperatives may accrue from mergers. An ex-ante data envelopment analysis approach proposed by Bogetoft and Wang (2005) is utilized to estimate potential gains from mergers of agricultural cooperatives. The empirical analysis leverages data from CoBank, consisting of 749 midwestern agricultural cooperative observations from 2011 to 2015. Merger analyses are conducted from both cost and revenue orientations, along with considerations for cooperative size, defined by total assets. Potential gains from mergers are decomposed into learning effect and pure merger effect, which is further decomposed into scale and scope effects, following Bogetoft and Wang (2005).

Bogetoft and Wang (2005) introduced an ex-ante data envelopment analysis (DEA) approach for estimating potential gains from mergers. Potential gains from mergers were decomposed into learning effects, scale (size) effects, and scope (synergy, harmony, or mix) effects. Learning effects capture potential gains or losses that may accrue to decision making units (DMUs) if each DMU learns best practices but operates as an independent unit (Shi et al., 2017). Scope effects capture the portion of merger gains or losses that can be attributed to re-allocation of input-output mixes (Flokou, Aletras and Niakas, 2017). Scale effects capture the merger gains or losses that may be attributed to operating at full or integrated scale compared to operating at the average scale of merger candidate DMUs (Bogetoft and Wang 2005).

The findings of this study show there are non-trivial overall potential gains from mergers based on both cost and revenue orientations. Overall merger gains are primarily driven by improvements due to learning effects and scope effects. Scale effect on the other hand tends to work against mergers with higher associated cost increases (or revenue losses) for mergers between larger sized cooperatives compared to mergers between smaller cooperatives. Also, findings show on average overall merger gains from the revenue orientation are relatively higher than from the cost orientation.

Finally, baseline (pre-merger) profits are benchmarked against endline (post-merger) profits. Findings show that less of other unique merger costs such as legal fees, non-trivial profits may accrue to cooperatives due to mergers with smaller sized cooperatives benefiting more from mergers than larger sized cooperatives. The findings of this study will give cooperative directors and managers corporate foresight when considering mergers as strategies to potentially provide better services to cooperative members and to improve the overall financial standing of agricultural cooperatives.

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Appendix A - Appendices for Chapter 2

A.1 Additional table and figures

Table A.1: Summary statistics of financial and price variables

	Total Expense ($)		Price (Index)	
Variables	Mean	SD	Mean	SD
Capital	1,012,660	1,192,069	171	97.91
Fertilizer	21,945	32,570	76.81	25.44
Other	16,668	22,351	82.64	27.28

Notes: SD implies standard deviation. Summary statistics are from farm-level data from 2000 to 2015 for 444 farms. Total expense variables data were obtained from the Kansas Farm Management Association (KFMA) and price index data was obtained from the United States Department of Agriculture-National Agriculture Statistics Service (USDA-NASS). Total expense variables are standardized by the ratio corn to total crop acres. Value for "Other" include seeds other miscellaneous crop expense.

A.2 Additional results over unmatched samples

Table A.2: Stochastic frontier estimates over unmatched sample

	Model		
Variables	(1)	(2)	(3)
Production			
Land	1.014***	0.988***	0.988***
	(0.015)	(0.014)	(0.014)
Labor	-0.047***	-0.050***	-0.050***
	(0.010)	(0.010)	(0.010)
Capital	-0.009	0.013*	0.013*
	(0.006)	(0.007)	(0.007)
Fertilizer	0.052***	0.050***	0.050***
	(0.010)	(0.009)	(0.009)
Other	0.001	0.008	0.008
	(0.009)	(0.008)	(0.008)
Technical inefficiency			
Share of irrigated land	-100.848	-5.783***	-5.760***
	(70.676)	(0.462)	(0.460)
Share of rented land	2.171	0.206***	0.205***
	(1.788)	(0.072)	(0.072)
Crop labor percentage	0.199	0.086	0.082
	(2.020)	(0.132)	(0.132)
Farm size (Reference: Small)			
Medium	-0.064***	-0.163***	-0.166***
	(0.918)	(0.062)	(0.062)
Large	0.321	-0.186**	-0.185**
	(1.131)	(0.075)	(0.075)
Location (Reference: East)			
Central	6.257	0.506***	0.503***
	(4.231)	(0.064)	(0.064)
West	11.760	1.271***	1.266***
	(7.748)	(0.126)	(0.126)
Fixed effects		Yes	Yes
λ	19.024***	4.392***	4.390***
	(1.213)	(0.025)	(0.025)
σ_u	3.516***	0.753***	0.752***
	(1.215)	(0.025)	(0.025)
σ_v	0.185***	0.172***	0.171***
	(0.007)	(0.006)	(0.006)
Log likelihood	-2413	-1519	-1518
N	3875	3875	3875

Notes: (1), (2), and (3) represent models from equations 2.14, 2.15, and 2.16 respectively over unmatched sample. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. If parameter estimate is not provided, it means the associated variable was dropped to allow convergence due to near-collinearity. "Other" includes seeds and other crop expense. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

Table A.3: Impact of adoption on technical inefficiency over unmatched sample

	Model	
	(1)	(2)
Technical inefficiency effect	-0.874	0.052
	(0.991)	(0.113)
Fixed effects		Yes
N	3875	3875

Notes: (1) and (2) represent models from equations 2.14 and 2.15 respectively over unmatched sample. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

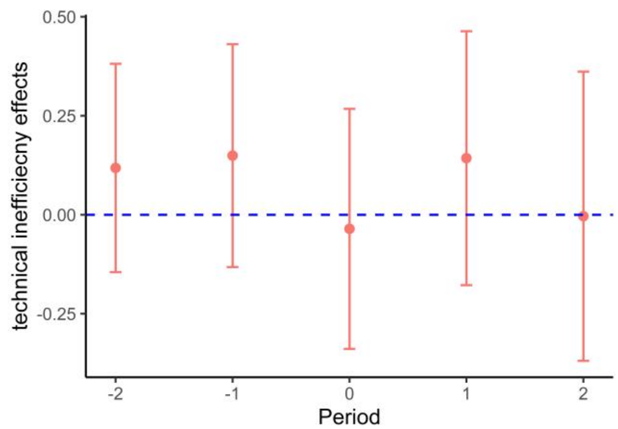

Figure A.1: Event-study results over unmatched sample

Notes: Results are from the estimation of equation 2.16 over unmatched sample. The dotted points represent the mean estimates, and the whiskers represent the lower and upper bounds at 95% confidence interval. Period -2 and Period -1 imply two years and a year respectively before adoption. Period 0 implies the year of adoption. Period 1 and Period 2 imply a year and two years respectively after adoption.

A.3 Additional matching results

Table A.4: Balance in covariates under PSM

	Standardized differences					Variance ratio				
		Matched					Matched			
Variables	Unmatched	(1:1)	(2:1)	(3:1)	(4.1)	Unmatched	(1.1)	(2:1)	(3:1)	(4:1)
Age of farmer	0.229	0.305	0.194	0.121	0.051	0.950	1.115	1.213	1.216	1.296
log (Net farm income)	0.746	0.242	0.200	0.185	0.164	0.913	4.137	3.427	2.696	2.388
Farm size (Reference: Small)										
Medium	0.148	0.151	0.172	0.220	0.231	1.092	1.081	1.087	1.103	1.106
Large	0.424	0.165	0.136	0.117	0.089	1.319	1.150	1.128	1.112	1.086
Location (Reference: East)										
Central	0.290	0.024	0.041	0.001	0.028	1.348	1.031	1.052	0.999	1.036
West	0.442	0.075	0.052	0.009	0.027	0.097	1.198	1.137	0.978	0.931
Share of irrigated land	0.124	0.293	0.247	0.294	0.265	0.633	1.498	1.428	1.450	1.412
Share of rented land	0.207	0.165	0.085	0.044	0.077	0.797	0.967	1.028	1.152	1.189
Crop labor percentage	0.148	0.184	0.211	0.192	0.217	1.154	0.964	0.921	0.860	0.868
log (Land)	0.663	0.335	0.292	0.313	0.276	0.674	0.812	0.761	0.744	0.732
log (Labor)	0.530	0.249	0.157	0.223	0.145	0.889	0.762	0.803	0.827	0.852
log (Capital)	0.701	0.378	0.322	0.320	0.318	0.631	0.514	0.537	0.532	0.521
log (Fertilizer)	0.624	0.349	0.267	0.330	0.266	0.718	0.658	0.676	0.665	0.667
log (Other)	0.562	0.350	0.171	0.272	0.126	0.719	0.850	1.113	1.047	1.295

Notes: This table presents results for the balance of covariates test from the PSM with k: 1 nearest neighbor matching procedure, with $k = 1, 2, 3,4$. The absolute value of standardized differences and variance ratios for covariates between treatment (all adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. "Other" includes seeds and other crop expense.

Table A.5: Balance in covariates under MDM

	Standardized differences					Variance ratio				
		Matched					Matched			
Variables	Unmatched	(1:1)	(2:1)	(3:1)	(4.1)	Unmatched	(1.1)	(2:1)	(3:1)	(4:1)
Age of farmer	0.229	0.154	0.170	0.159	0.156	0.950	0.836	0.802	0.776	0.766
log (Net farm income)	0.746	0.488	0.528	0.550	0.569	0.913	0.588	0.571	0.566	0.573
Farm size (Reference: Small)										
Medium	0.148	0.135	0.178	0.205	0.223	1.092	1.075	1.091	1.100	1.105
Large	0.424	0.173	0.204	0.223	0.235	1.319	1.155	1.176	1.188	1.195
Location (Reference: East)										
Central	0.290	0.053	0.052	0.050	0.045	1.348	1.068	1.067	1.065	1.059
West	0.442	0.166	0.186	0.248	0.286	0.097	0.595	0.549	0.416	0.339
Share of irrigated land	0.124	0.070	0.092	0.135	0.160	0.633	0.748	0.715	0.632	0.587
Share of rented land	0.207	0.092	0.132	0.137	0.141	0.797	0.739	0.713	0.713	0.710
Crop labor percentage	0.148	0.169	0.215	0.237	0.248	1.154	0.895	0.804	0.760	0.730
log (Land)	0.663	0.354	0.428	0.471	0.498	0.674	0.753	0.689	0.652	0.630
log (Labor)	0.530	0.273	0.324	0.363	0.388	0.889	0.741	0.688	0.666	0.657
log (Capital)	0.701	0.403	0.454	0.493	0.515	0.631	0.564	0.559	0.551	0.551
log (Fertilizer)	0.624	0.304	0.385	0.438	0.472	0.718	0.695	0.646	0.615	0.599
log (Other)	0.562	0.359	0.437	0.486	0.519	0.719	0.725	0.654	0.615	0.588

Notes: This table presents results for the balance of covariates test from the MDM with k: 1 nearest neighbor matching procedure, with $k = 1, 2, 3, 4$. The absolute value of standardized differences and variance ratios for covariates between treatment (all adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. “Other” includes seeds and other crop expense.

A.4 Technical change and efficiency change

Technical change and efficiency change can be estimated by a parametric stochastic meta-frontier method or a non-parametric Malmquist productivity index (MPI). The dataset used in this study best fits MPI, thus it is considered for estimating productivity changes, that allows for decomposition into technical change and efficiency change.

Assuming that for each period $t = 1, \dots, T$, $x^t \in \mathbb{R}_+^N$ inputs are converted into outputs $y^t \in \mathbb{R}_+^N$ given the production technology G^t, then following Fare et al. (1994), the output distance functions for every two periods are defined as:

$$E_0^t(x^{t+1}, y^{t+1}) = \max\{\delta: (x^{t+1}, y^{t+1}/\delta) \in G^{t+1}\} \qquad (A.1)$$

$$E_0^{t+1}(x^t, y^t) = \max\{\delta: (x^t, y^t/\delta) \in G^t\} \qquad (A.2)$$

where the distance function $E_0^t(x^{t+1}, y^{t+1})$ measures the maximal proportional change in output required to make (x^{t+1}, y^{t+1}) feasible relative to the technology at period t. Likewise, the distance function $E_0^{t+1}(x^t, y^t)$ measures the maximal proportional change in output required to make (x^t, y^t) feasible relative to the technology at period $t+1$. Following that, the Malmquist index (MI), which measures productivity change between periods t and $t+1$ is given as:

$$M_0(x^{t+1}, y^{t+1}, x^t, y^t) = \frac{E_0^{t+1}(x^{t+1}, y^{t+1})}{E_0^t(x^t, y^t)} \times \left[\left(\frac{E_0^t(x^{t+1}, y^{t+1})}{E_0^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{E_0^t(x^t, y^t)}{E_0^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \qquad (A.3)$$

where MI is a product of efficiency change and technical change defined in equations A.4 and A.5 respectively as:

$$\text{Efficiency change} = \frac{E_0^{t+1}(x^{t+1}, y^{t+1})}{E_0^t(x^t, y^t)} \qquad (A.4)$$

$$\text{Technical change} = \left[\left(\frac{E_0^t(x^{t+1}, y^{t+1})}{E_0^{t+1}(x^{t+1}, y^{t+1})}\right)\left(\frac{E_0^t(x^t, y^t)}{E_0^{t+1}(x^t, y^t)}\right)\right]^{\frac{1}{2}} \qquad (A.5)$$

Efficiency change measures the change in relative distance of observed production from the maximum potential production between periods t and $t+1$. Technical change captures the shift in production technology between periods t and $t+1$. If the value of an index (i.e., Malmquist productivity change, efficiency change, technical change) is greater than 1, it implies that there is progress between periods t and $t+1$. On the other hand, a value less than 1 (equal to 1) implies that there is deterioration (no change) between periods t and $t+1$.

Table A.6: Malmquist productivity changes between adopters and non-adopters of precision agriculture technologies.

	Non-adopters			Adopters		
Year	$Malmq$	$Effch$	$Tech$	$Malmq$	$Effch$	$Tech$
2003	1.254	0.845	1.455	1.199	0.855	1.427
2004	3.013	1.930	1.583	3.154	1.868	1.641
2005	0.798	0.786	1.027	0.817	0.758	1.088
2006	0.901	0.828	1.094	0.919	0.919	1.038
2007	1.366	1.808	0.765	1.183	1.546	0.789
2008	1.286	1.111	1.153	1.299	1.149	1.139
2009	1.063	1.046	1.022	0.984	0.963	1.027
2010	0.518	0.702	0.742	0.552	0.805	0.700
2011	0.736	0.845	0.864	0.573	0.675	0.838
2012	1.045	1.415	0.754	1.321	1.780	0.774
2013	3.525	3.197	1.087	3.297	3.029	1.089
2014	1.432	1.220	1.171	1.427	1.259	1.152
2015	0.965	0.932	1.035	0.918	0.879	1.047
Average	1.377	1.282	1.058	1.357	1.268	1.058

Notes: Variables $Malmq$, $Effch$, and $Tech$ represent Malmquist productivity index, efficiency change, and technical change. Estimates are based on a balanced panel from 2002 to 2015. Given that, the productivity measures represent changes between periods t and $t+1$, there are no estimates for the first year of the balanced panel (i.e., 2002).

Appendix B - Appendices for Chapter 3

Table B.1: Stochastic frontier estimates from equation 3.1

	Unmatched sample		Matched sample	
Variables	(1)	(2)	(1)	(2)
Production				
Land	1.012***	1.024***	0.966***	0.996***
	(0.018)	(0.017)	(0.027)	(0.025)
Labor	-0.040***	-0.047***	0.021	-0.036**
	(0.013)	(0.011)	(0.018)	(0.016)
Capital	-0.011	-0.014**	-0.021**	-0.029***
	(0.007)	(0.007)	(0.010)	(0.010)
Fertilizer	0.052***	0.054***	0.056***	0.058***
	(0.011)	(0.012)	(0.016)	(0.017)
Other	-0.002	0.000	-0.004	0.003
	(0.011)	(0.010)	(0.015)	(0.013)
Technical inefficiency				
Share of irrigated land	-83.376	-43.310**	-116.220	-67.331
	(56.987)	(17.527)	(78.448)	(50.655)
Share of rented land	1.843	1.173*	-0.431	0.210
	(1.524)	(0.665)	(2.194)	(1.115)
Crop labor percentage	-0.476	-0.054	-3.274	-0.300
	(1.975)	(0.967)	(4.820)	(1.901)
Farm size (Reference: Small)				
Medium	-0.211	0.207	0.585	0.737
	(0.869)	(0.445)	(1.969)	(1.072)
Large	1.069	0.479	3.348	1.430
	(1.232)	(0.568)	(3.133)	(1.493)
Location (Reference: East)				
Central	-4.735	2.846**	9.214	4.679
	(3.132)	(1.103)	(6.116)	(3.264)
West	9.749	5.349***		17.553
	(6.187)	(1.949)		(17.025)
λ	16.737***	13.063***	21.376***	16.260***
	(1.074)	(0.447)	(1.221)	(0.914)
σ_u	3.210***	2.305***	3.689***	2.518***
	(1.077)	(0.450)	(1.222)	(0.918)
σ_v	0.192***	0.176***	0.173***	0.155***
	(0.007)	(0.008)	(0.010)	(0.011)
Log likelihood	-1974	-1898	-803	-698
N	3052	3063	1381	1303

Notes: (1) and (2) represent models with treatment assignments: PSS only adopters, and PSS+VRT adopters respectively. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. If parameter estimate is not provided, it means the associated variable was dropped to allow convergence due to near-collinearity. "Other" includes seeds and other crop expense.

Table B.2: Stochastic frontier estimates from equation 3.2

	Unmatched sample		Matched sample	
Variables	(1)	(2)	(1)	(2)
Production				
Land	0.988***	1.000***	0.921***	0.923***
	(0.017)	(0.016)	(0.024)	(0.028)
Labor	-0.042***	-0.050***	0.033**	0.011
	(0.012)	(0.010)	(0.016)	(0.018)
Capital	0.010	0.005	0.022*	-0.024*
	(0.008)	(0.008)	(0.011)	(0.012)
Fertilizer	0.053***	0.054***	0.043***	0.062***
	(0.010)	(0.011)	(0.014)	(0.017)
Other	0.004	0.005	0.005	0.023*
	(0.010)	(0.009)	(0.012)	(0.014)
Technical inefficiency				
Share of irrigated land	-5.747***	-5.606***	-5.577***	-11.378***
	(0.536)	(0.468)	(0.927)	(2.249)
Share of rented land	0.166**	0.226***	-0.157	0.138
	(0.078)	(0.076)	(0.127)	(0.185)
Crop labor percentage	-0.021	0.152	-0.113	0.396
	(0.157)	(0.139)	(0.252)	(0.300)
Farm size (Reference: Small)				
Medium	-0.164**	-0.089	-0.317***	-0.212
	(0.069)	(0.064)	(0.116)	(0.161)
Large	-0.101	-0.125	-0.107	-0.174
	(0.084)	(0.079)	(0.131)	(0.177)
Location (Reference: East)				
Central	0.499***	0.520***	0.532***	0.646***
	(0.071)	(0.068)	(0.106)	(0.151)
West	-1.251***	-1.243***		-17.693
	(0.130)	(0.122)		(141.102)
Fixed effects	Yes	Yes	Yes	Yes
λ	4.246***	4.553***	3.853***	2.825***
	(0.028)	(0.026)	(0.041)	(0.057)
σ_u	0.755***	0.741***	0.696***	0.731***
	(0.029)	(0.027)	(0.041)	(0.057)
σ_v	0.178***	0.163***	0.181***	0.259***
	(0.006)	(0.007)	(0.007)	(0.007)
Log likelihood	-1281	-1237	-372	-453
N	3052	3063	1381	1303

Notes: (1) and (2) represent models with treatment assignments: PSS only adopters, and PSS+VRT adopters respectively. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. If parameter estimate is not provided, it means the associated variable was dropped to allow convergence due to near-collinearity. “Other” includes seeds and other crop expense. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

Table B.3: Stochastic frontier estimates from equation 3.3

	Unmatched sample		Matched sample	
Variables	(1)	(2)	(1)	(2)
Production				
Land	0.988***	0.960***	0.921***	0.953***
	(0.017)	(0.018)	(0.024)	(0.023)
Labor	-0.042***	-0.036***	0.034**	-0.030**
	(0.012)	(0.012)	(0.016)	(0.015)
Capital	0.010	0.009	0.022*	-0.005
	(0.008)	(0.009)	(0.011)	(0.011)
Fertilizer	0.053***	0.069***	0.043***	0.060***
	(0.010)	(0.011)	(0.014)	(0.015)
Other	0.004	0.025***	0.005	0.010
	(0.010)	(0.009)	(0.013)	(0.011)
Technical inefficiency				
Share of irrigated land	-5.754***		-5.610***	-5.019***
	(0.537)		(0.936)	(0.578)
Share of rented land	0.170**	0.183	-0.148	0.021
	(0.078)	(0.190)	(0.127)	(0.103)
Crop labor percentage	-0.016	-0.545*	-0.102	0.188
	(0.157)	(0.320)	(0.251)	(0.167)
Farm size (Reference: Small)				
Medium	-0.171**	-0.235	-0.336***	-0.089
	(0.069)	(0.157)	(0.116)	(0.088)
Large	-0.109	-0.597***	-1.131	-0.073
	(0.084)	(0.197)	(0.131)	(0.102)
Location (Reference: East)				
Central	0.496***	-0.102	0.522***	0.542***
	(0.071)	(0.156)	(0.105)	(0.084)
West	1.251***	-0.674**		0.844
	(0.130)	(0.263)		(0.740)
Fixed effects	Yes	Yes	Yes	Yes
λ	4.237***	5.797***	3.825***	3.985***
	(0.028)	(0.085)	(0.041)	(0.028)
σ_u	0.754***	1.233***	0.694***	0.584***
	(0.029)	(0.086)	(0.041)	(0.028)
σ_v	0.178***	0.213***	0.181***	0.147***
	(0.006)	(0.008)	(0.007)	(0.009)
Log likelihood	-1279	-1638	-370	-306
N	3052	3063	1381	1303

Notes: (1) and (2) represent models with treatment assignments: PSS only adopters, and PSS+VRT adopters respectively. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. If parameter estimate is not provided, it means the associated variable was dropped to allow convergence due to near-collinearity. “Other” includes seeds and other crop expense. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

Table B.4: Impact of adoption on technical inefficiency by treatment group over unmatched samples

	Treatment group			
	PSS only		PSS+VRT	
	(1)	(2)	(1)	(2)
Technical inefficiency effect	-0.412	0.192	-0.669	-0.081
	(0.857)	(0.164)	(0.508)	(0.139)
Fixed effects		Yes		Yes
N	3052	3052	3063	3063

Notes: (1) and (2) represent models from equations 3.1 and 3.2 respectively over unmatched samples. Standard errors are in parenthesis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Fixed effects include year and group (level of aggregation at which treatment/adoption occurs) fixed effects.

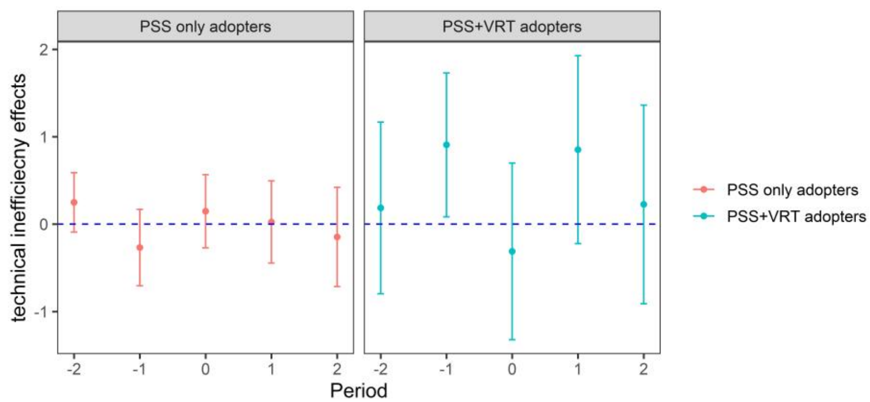

Figure B.1: Event-study results by treatment group over unmatched samples

Notes: Results are from the estimation of equation 3.3 over unmatched samples. The dotted points represent the mean estimates, and the whiskers represent the lower and upper bounds at 95% confidence interval. Period -2 and Period -1 imply two years and a year respectively before adoption. Period 0 implies the year of adoption. Period 1 and Period 2 imply a year and two years respectively after adoption.

Table B.5: Balance in covariates under PSM with PSS only adopters as treatment

	Standardized differences					Variance ratio				
		Matched					Matched			
Variables	Unmatched	(1:1)	(2:1)	(3:1)	(4.1)	Unmatched	(1.1)	(2:1)	(3:1)	(4:1)
Age of farmer	0.208	0.443	0.445	0.355	0.327	0.822	0.922	0.925	0.964	0.951
log (Net farm income)	0.631	0.189	0.349	0.297	0.262	1.073	2.161	3.867	3.095	2.829
Farm size (Reference: Small)										
Medium	0.211	0.028	0.098	0.134	0.102	1.114	0.981	1.055	1.070	1.057
Large	0.447	0.053	0.059	0.041	0.039	1.423	1.064	1.072	1.051	1.049
Location (Reference: East)										
Central	0.165	0.145	0.030	0.005	0.021	1.191	1.157	1.035	1.006	0.975
Share of irrigated land	0.017	0.478	0.330	0.393	0.332	0.973	3.040	2.378	2.429	2.224
Share of rented land	0.147	0.168	0.153	0.069	0.068	0.795	1.005	1.026	1.106	1.037
Crop labor percentage	0.352	0.069	0.138	0.084	0.027	0.798	1.073	0.980	1.006	1.075
log (Land)	0.733	0.197	0.248	0.259	0.234	0.534	0.684	0.666	0.626	0.651
log (Labor)	0.530	0.203	0.261	0.283	0.287	0.727	0.779	0.769	0.754	0.751
log (Capital)	0.780	0.098	0.272	0.282	0.322	0.587	0.992	0.848	0.789	0.754
log (Fertilizer)	0.672	0.280	0.361	0.362	0.327	0.629	0.601	0.640	0.606	0.636
log (Other)	0.626	0.017	0.206	0.240	0.221	0.527	1.479	1.072	1.018	0.965

Notes: This table presents results for the balance of covariates test from the PSM with k: 1 nearest neighbor matching procedure, with $k = 1, 2, 3, 4$. The absolute value of standardized differences and variance ratios for covariates between treatment (PSS only adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. Observations for the location indicator -West are dropped because they perfectly predict the outcome. This may be associated with the small number of observations in the West relative to the entire sample size, thus, potentially creating extremes in the sample distribution. “Other” includes seeds and other crop expense.

Table B.6: Balance in covariates under PSM with PSS+VRT adopters as treatment

	Standardized differences					Variance ratio				
		Matched					Matched			
Variables	Unmatched	(1:1)	(2:1)	(3:1)	(4.1)	Unmatched	(1.1)	(2:1)	(3:1)	(4:1)
Age of farmer	0.283	0.207	0.113	0.006	0.043	1.081	1.755	1.578	1.553	1.641
log (Net farm income)	0.931	0.146	0.158	0.227	0.211	0.727	1.318	1.063	0.846	0.790
Farm size (Reference: Small)										
Medium	0.066	0.404	0.181	0.191	0.275	1.054	1.130	1.101	1.103	1.124
Large	0.473	0.005	0.225	0.085	0.045	1.335	1.006	1.196	1.086	1.047
Location (Reference: East)										
Central	0.352	0.180	0.075	0.031	0.007	1.406	1.230	1.100	1.042	1.009
West	0.379	0.022	0.238	0.075	0.015	0.202	0.945	1.605	1.189	1.037
Share of irrigated land	0.047	0.008	0.346	0.358	0.255	0.713	0.955	1.558	1.480	1.334
Share of rented land	0.259	0.385	0.008	0.055	0.016	0.786	1.283	1.051	1.038	0.958
Crop labor percentage	0.021	0.505	0.398	0.209	0.244	1.504	0.661	0.695	0.852	0.843
log (Land)	0.686	0.195	0.322	0.202	0.234	0.847	0.703	0.745	0.758	0.738
log (Labor)	0.535	0.256	0.040	0.037	0.093	1.061	0.954	0.811	0.687	0.659
log (Capital)	0.677	0.310	0.302	0.327	0.376	0.709	0.413	0.406	0.386	0.379
log (Fertilizer)	0.617	0.032	0.143	0.134	0.159	0.830	0.673	0.650	0.593	0.586
log (Other)	0.514	0.392	0.061	0.014	0.108	0.935	1.930	1.406	1.167	1.110

Notes: This table presents results for the balance of covariates test from the PSM with k: 1 nearest neighbor matching procedure, with $k = 1, 2, 3,4$. The absolute value of standardized differences and variance ratios for covariates between treatment (PSS+VRT adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. “Other” includes seeds and other crop expense.

Table B.7: Balance in covariates under MDM with PSS only adopters as treatment

	Standardized differences					Variance ratio				
		Matched					Matched			
Variables	Unmatched	(1:1)	(2:1)	(3:1)	(4.1)	Unmatched	(1.1)	(2:1)	(3:1)	(4:1)
Age of farmer	0.208	0.135	0.108	0.101	0.098	0.822	0.677	0.660	0.648	0.646
log (Net farm income)	0.631	0.455	0.527	0.555	0.583	1.073	0.587	0.562	0.559	0.549
Farm size (Reference: Small)										
Medium	0.211	0.272	0.327	0.343	0.355	1.114	1.108	1.111	1.111	1.110
Large	0.447	0.124	0.169	0.199	0.221	1.423	1.144	1.190	1.218	1.238
Location (Reference: East)										
Central	0.165	0.009	0.011	0.001	0.009	1.191	1.010	1.013	0.999	0.990
Share of irrigated land	0.017	0.037	0.067	0.084	0.094	0.973	0.791	0.713	0.657	0.632
Share of rented land	0.147	0.099	0.114	0.120	0.123	0.795	0.658	0.670	0.658	0.644
Crop labor percentage	0.352	0.268	0.323	0.351	0.366	0.798	0.855	0.754	0.703	0.675
log (Land)	0.733	0.419	0.498	0.537	0.568	0.534	0.511	0.486	0.475	0.465
log (Labor)	0.530	0.347	0.385	0.407	0.428	0.727	0.455	0.474	0.487	0.484
log (Capital)	0.780	0.588	0.628	0.651	0.679	0.587	0.424	0.441	0.443	0.444
log (Fertilizer)	0.672	0.354	0.435	0.477	0.511	0.629	0.521	0.492	0.478	0.473
log (Other)	0.626	0.396	0.483	0.523	0.553	0.527	0.514	0.466	0.446	0.433

Notes: This table presents results for the balance of covariates test from the MDM with k: 1 nearest neighbor matching procedure, with $k = 1, 2, 3, 4$. The absolute value of standardized differences and variance ratios for covariates between treatment (PSS only adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. Under PSS, observations for the location indicator -West are dropped because they perfectly predict the outcome. This may be associated with the small number of observations in the West relative to the entire sample size, thus potentially creating extremes in the sample distribution. The same variable is also dropped here for uniformity. “Other” includes seeds and other crop expense.

Table B.8: Balance in covariates under MDM with PSS+VRT adopters as treatment

	Standardized differences					Variance ratio				
		Matched					Matched			
Variables	Unmatched	(1:1)	(2:1)	(3:1)	(4.1)	Unmatched	(1.1)	(2:1)	(3:1)	(4:1)
Age of farmer	0.283	0.227	0.245	0.258	0.263	1.081	0.889	0.825	0.797	0.787
log (Net farm income)	0.931	0.665	0.715	0.735	0.749	0.727	0.512	0.491	0.494	0.496
Farm size (Reference: Small)										
Medium	0.066	0.210	0.222	0.235	0.246	1.054	1.106	1.110	1.114	1.117
Large	0.473	0.251	0.283	0.291	0.296	1.335	1.217	1.235	1.240	1.242
Location (Reference: East)										
Central	0.352	0.084	0.084	0.083	0.080	1.406	1.109	1.109	1.108	1.105
West	0.379	0.136	0.158	0.223	0.267	0.202	0.674	0.625	0.483	0.394
Share of irrigated land	0.047	0.079	0.094	0.144	0.178	0.713	0.741	0.717	0.622	0.557
Share of rented land	0.259	0.148	0.159	0.178	0.185	0.786	0.789	0.763	0.747	0.746
Crop labor percentage	0.021	0.171	0.198	0.211	0.211	1.504	0.706	0.649	0.623	0.614
log (Land)	0.686	0.544	0.601	0.624	0.640	0.847	0.771	0.722	0.696	0.684
log (Labor)	0.535	0.364	0.407	0.434	0.452	1.061	0.813	0.765	0.742	0.735
log (Capital)	0.677	0.489	0.527	0.545	0.569	0.709	0.585	0.588	0.602	0.594
log (Fertilizer)	0.617	0.491	0.556	0.594	0.621	0.830	0.709	0.657	0.632	0.627
log (Other)	0.514	0.517	0.576	0.607	0.621	0.935	0.744	0.678	0.644	0.640

Notes: This table presents results for the balance of covariates test from the MDM with k: 1 nearest neighbor matching procedure, with $k = 1, 2, 3,4$. The absolute value of standardized differences and variance ratios for covariates between treatment (PSS+VRT adopters) and the control (non-adopters) are computed as in Austin (2011). All variables are as previously discussed in data section. “Other” includes seeds and other crop expense.

Table B.9: Malmquist productivity changes between different groups of adopters and non-adopters of precision agriculture technologies.

	Non-adopters			PSS only adopters			PSS+VRT adopters		
Year	$Malmq$	$Effch$	$Tech$	$Malmq$	$Effch$	$Tech$	$Malmq$	$Effch$	$Tech$
2003	1.254	0.845	1.455	1.340	0.942	1.449	1.002	0.734	1.395
2004	3.013	1.930	1.583	3.354	1.952	1.672	2.874	1.749	1.598
2005	0.798	0.786	1.027	0.804	0.742	1.089	0.837	0.781	1.088
2006	0.901	0.828	1.094	0.941	0.965	1.016	0.888	0.855	1.070
2007	1.366	1.808	0.765	1.228	1.627	0.787	1.119	1.432	0.793
2008	1.286	1.111	1.153	1.084	1.004	1.101	1.600	1.352	1.193
2009	1.063	1.046	1.022	1.057	1.027	1.033	0.882	0.874	1.019
2010	0.518	0.702	0.742	0.526	0.791	0.689	0.588	0.825	0.716
2011	0.736	0.845	0.864	0.621	0.731	0.837	0.504	0.596	0.841
2012	1.045	1.415	0.754	1.141	1.496	0.778	1.574	2.180	0.768
2013	3.525	3.197	1.087	3.029	2.721	1.110	3.674	3.462	1.059
2014	1.432	1.220	1.171	1.424	1.287	1.122	1.431	1.219	1.195
2015	0.965	0.932	1.035	0.948	0.912	1.041	0.872	0.833	1.056
Average	1.377	1.282	1.058	1.346	1.246	1.056	1.373	1.299	1.061

Notes: Variables $Malmq$, $Effch$, and $Tech$ represent Malmquist productivity index, efficiency change, and technical change. Estimates are based on a balanced panel from 2002 to 2015. Given that, the productivity measures represent changes between periods t and $t + 1$, there are no estimates for the first year of the balanced panel (i.e., 2002).

Appendix C - Appendices for Chapter 4

Table C.1: Cost oriented merger effects, 2011

Mergers	ME_c^J	LE_c^J	ME_c^{*J}	SpE_c^J	SlE_c^J
Small-Small	0.700	0.539	1.242	0.921	1.325
	(0.870)	(1.357)	(0.143)	(0.105)	(1.349)
Small-Medium	0.682	0.528	1.235	0.913	1.391
	(0.572)	(0.841)	(0.145)	(0.093)	(0.920)
Small-Large	0.708	0.549	1.273	0.821	1.578
	(0.419)	(0.546)	(0.160)	(0.116)	(0.576)
Medium-Medium	0.730	0.527	1.326	0.910	1.509
	(0.495)	(0.610)	(0.155)	(0.099)	(0.840)
Medium-Large	0.787	0.557	1.393	0.856	1.653
	(0.496)	(0.567)	(0.154)	(0.099)	(0.674)
Large-Large	0.890	0.552	1.560	0.900	1.740
	(1.068)	(1.250)	(0.148)	(0.084)	(1.280)

Note: Variables ME_c^J, LE_c^J, ME_c^{*J}, SpE_c^J, and SlE_c^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average cost-oriented merger effect estimations from a 1,000 bootstrap samples for 2011. Standard deviations in parentheses.

Table C.2: Cost oriented merger effects, 2012

Mergers	ME_c^J	LE_c^J	ME_c^{*J}	SpE_c^J	SlE_c^J
Small-Small	0.782	0.617	1.198	0.945	1.259
	(0.914)	(1.077)	(0.149)	(0.075)	(1.110)
Small-Medium	0.735	0.603	1.171	0.938	1.256
	(0.533)	(0.625)	(0.138)	(0.063)	(0.660)
Small-Large	0.817	0.607	1.310	0.863	1.499
	(1.027)	(1.165)	(0.165)	(0.066)	(1.163)
Medium-Medium	0.750	0.605	1.199	0.934	1.293
	(0.302)	(0.235)	(0.152)	(0.068)	(0.272)
Medium-Large	0.821	0.617	1.328	0.898	1.470
	(0.461)	(0.618)	(0.149)	(0.057)	(0.623)
Large-Large	1.107	0.631	1.701	0.937	1.795
	(2.952)	(3.404)	(0.143)	(0.052)	(3.406)

Note: Variables ME_c^J, LE_c^J, ME_c^{*J}, SpE_c^J, and SlE_c^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average cost-oriented merger effect estimations from a 1,000 bootstrap samples for 2012. Standard deviations in parentheses.

Table C.3: Cost oriented merger effects, 2013

Mergers	ME_c^J	LE_c^J	ME_c^{*J}	SpE_c^J	SlE_c^J
Small-Small	0.714	0.713	0.979	0.940	1.036
	(0.458)	(0.470)	(0.129)	(0.057)	0.464
Small-Medium	0.661	0.631	1.025	0.933	1.102
	(0.250)	(0.271)	(0.118)	(0.055)	(0.288)
Small-Large	0.750	0.605	1.194	0.863	1.383
	(0.591)	(0.635)	(0.145)	(0.102)	(0.629)
Medium-Medium	0.642	0.598	1.052	0.935	1.135
	(0.223)	(0.190)	(0.133)	(0.059)	(0.237)
Medium-Large	0.742	0.597	1.224	0.879	1.394
	(0.341)	(0.408)	(0.133)	(0.104)	(0.397)
Large-Large	0.924	0.590	1.571	0.901	1.734
	(0.751)	(1.226)	(0.143)	(0.115)	(1.233)

Note: Variables ME_c^J, LE_c^J, ME_c^{*J}, SpE_c^J, and SlE_c^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average cost-oriented merger effect estimations from a 1,000 bootstrap samples for 2013. Standard deviations in parentheses.

Table C.4: Cost oriented merger effects, 2014

Mergers	ME_c^J	LE_c^J	ME_c^{*J}	SpE_c^J	SlE_c^J
Small-Small	0.709	0.766	0.914	0.944	0.969
	(0.401)	(0.409)	(0.126)	(0.057)	(0.417)
Small-Medium	0.702	0.670	1.020	0.920	1.121
	(0.283)	(0.276)	(0.127)	(0.070)	(0.317)
Small-Large	0.795	0.690	1.126	0.855	1.327
	(0.418)	(0.394)	(0.163)	(0.085)	(0.401)
Medium-Medium	0.714	0.632	1.102	0.924	1.204
	(0.246)	(0.195)	(0.132)	(0.073)	(0.245)
Medium-Large	0.817	0.675	1.194	0.885	1.358
	(0.296)	(0.262)	(0.149)	(0.071)	(0.277)
Large-Large	0.941	0.699	1.320	0.918	1.436
	(0.444)	(0.405)	(0.137)	(0.066)	(0.398)

Note: Variables ME_c^J, LE_c^J, ME_c^{*J}, SpE_c^J, and SlE_c^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average cost-oriented merger effect estimations from a 1,000 bootstrap samples for 2014. Standard deviations in parentheses.

Table C.5: Cost oriented merger effects, 2015

Mergers	ME_c^J	LE_c^J	ME_c^{*J}	SpE_c^J	SlE_c^J
Small-Small	0.789	0.836	0.933	0.930	0.994
	(0.307)	(0.308)	(0.101)	(0.081)	(0.287)
Small-Medium	0.841	0.770	1.064	0.921	1.166
	(0.421)	(0.408)	(0.146)	(0.081)	(0.449)
Small-Large	0.851	0.752	1.115	0.858	1.309
	(0.331)	(0.294)	(0.155)	(0.084)	(0.315)
Medium-Medium	0.875	0.747	1.148	0.917	1.270
	(0.370)	(0.331)	(0.148)	(0.090)	(0.395)
Medium-Large	0.945	0.753	1.240	0.897	1.384
	(0.334)	(0.293)	(0.142)	(0.069)	(0.301)
Large-Large	1.124	0.745	1.481	0.941	1.567
	(0.984)	(1.034)	(0.135)	(0.052)	(1.035)

Note: Variables ME_c^J, LE_c^J, ME_c^{*J}, SpE_c^J, and SlE_c^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average cost-oriented merger effect estimations from a 1,000 bootstrap samples for 2015. Standard deviations in parentheses.

Table C.6: Revenue oriented merger effects, 2011

Mergers	ME_R^J	LE_R^J	ME_R^{*J}	SpE_R^J	SlE_R^J
Small-Small	1.883	1.926	0.970	1.142	0.855
	(0.669)	(0.185)	(0.527)	(0.182)	(0.125)
Small-Medium	1.626	1.877	0.864	1.136	0.765
	(0.477)	(0.085)	(0.503)	(0.102)	(0.074)
Small-Large	1.384	1.554	0.892	1.154	0.775
	(0.292)	(0.063)	(0.322)	(0.087)	(0.047)
Medium-Medium	1.411	1.779	0.794	1.076	0.739
	(0.399)	(0.062)	(0.498)	(0.070)	(0.043)
Medium-Large	1.281	1.517	0.845	1.087	0.779
	(0.261)	(0.054)	(0.303)	(0.065)	(0.040)
Large-Large	1.151	1.398	0.814	1.067	0.764
	(0.282)	(0.085)	(0.267)	(0.068)	(0.070)

Note: Variables ME_R^J, LE_R^J, ME_R^{*J}, SpE_R^J, and SlE_R^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average revenue-oriented merger effect estimations from a 1,000 bootstrap samples for 2011. Standard deviations in parentheses.

Table C.7: Revenue oriented merger effects, 2012

Mergers	ME_R^J	LE_R^J	ME_R^{*J}	SpE_R^J	SlE_R^J
Small-Small	1.668	1.719	0.963	1.089	0.885
	(0.626)	(0.146)	(0.543)	(0.124)	(0.091)
Small-Medium	1.520	1.689	0.894	1.088	0.824
	(0.395)	(0.068)	(0.387)	(0.070)	(0.057)
Small-Large	1.389	1.518	0.915	1.120	0.818
	(0.317)	(0.051)	(0.341)	(0.058)	(0.043)
Medium-Medium	1.383	1.637	0.840	1.062	0.792
	(0.381)	(0.055)	(0.416)	(0.052)	(0.040)
Medium-Large	1.290	1.475	0.873	1.069	0.818
	(0.274)	(0.045)	(0.304)	(0.045)	(0.036)
Large-Large	1.135	1.351	0.834	1.043	0.799
	(0.251)	(0.073)	(0.239)	(0.043)	(0.061)

Note: Variables ME_R^J, LE_R^J, ME_R^{*J}, SpE_R^J, and SlE_R^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average revenue-oriented merger effect estimations from a 1,000 bootstrap samples for 2012. Standard deviations in parentheses.

Table C.8: Revenue oriented merger effects, 2013

Mergers	ME_R^J	LE_R^J	ME_R^{*J}	SpE_R^J	SlE_R^J
Small-Small	1.708	1.633	1.030	1.080	0.954
	(0.627)	(0.153)	(0.443)	(0.101)	(0.123)
Small-Medium	1.634	1.713	0.949	1.088	0.876
	(0.419)	(0.081)	(0.399)	(0.077)	(0.075)
Small-Large	1.381	1.483	0.932	1.179	0.794
	(0.278)	(0.101)	(0.266)	(0.144)	(0.054)
Medium-Medium	1.551	1.737	0.894	1.073	0.834
	(0.400)	(0.069)	(0.437)	(0.064)	(0.060)
Medium-Large	1.321	1.498	0.883	1.128	0.787
	(0.254)	(0.091)	(0.264)	(0.151)	(0.045)
Large-Large	1.149	1.393	0.820	1.078	0.763
	(0.257)	(0.099)	(0.240)	(0.134)	(0.062)

Note: Variables ME_R^J, LE_R^J, ME_R^{*J}, SpE_R^J, and SlE_R^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average revenue-oriented merger effect estimations from a 1,000 bootstrap samples for 2013. Standard deviations in parentheses.

Table C.9: Revenue oriented merger effects, 2014

Mergers	ME_R^J	LE_R^J	ME_R^{*J}	SpE_R^J	SlE_R^J
Small-Small	1.688	1.523	1.099	1.108	0.992
	(0.626)	(0.240)	(0.385)	(0.122)	(0.195)
Small-Medium	1.559	1.626	0.951	1.108	0.859
	(0.484)	(0.091)	(0.426)	(0.079)	(0.070)
Small-Large	1.332	1.427	0.931	1.137	0.820
	(0.304)	(0.061)	(0.305)	(0.072)	(0.048)
Medium-Medium	1.432	1.627	0.878	1.068	0.822
	(0.402)	(0.064)	(0.421)	(0.054)	(0.046)
Medium-Large	1.251	1.425	0.877	1.083	0.811
	(0.264)	(0.051)	(0.286)	(0.051)	(0.038)
Large-Large	1.091	1.300	0.833	1.051	0.792
	(0.225)	(0.077)	(0.215)	(0.051)	(0.054)

Note: Variables ME_R^J, LE_R^J, ME_R^{*J}, SpE_R^J, and SlE_R^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average revenue-oriented merger effect estimations from a 1,000 bootstrap samples for 2014. Standard deviations in parentheses.

Table C.10: Revenue oriented merger effects, 2015

Mergers	ME_R^J	LE_R^J	ME_R^{*J}	SpE_R^J	SlE_R^J
Small-Small	1.492	1.295	1.130	1.124	1.003
	(0.639)	(0.265)	(0.282)	(0.212)	(0.132)
Small-Medium	1.376	1.380	0.987	1.116	0.889
	(0.410)	(0.112)	(0.333)	(0.107)	(0.092)
Small-Large	1.229	1.292	0.948	1.143	0.832
	(0.244)	(0.058)	(0.228)	(0.082)	(0.056)
Medium-Medium	1.248	1.374	0.906	1.093	0.831
	(0.332)	(0.092)	(0.330)	(0.089)	(0.075)
Medium-Large	1.142	1.281	0.890	1.084	0.823
	(0.204)	(0.063)	(0.212)	(0.058)	(0.051)
Large-Large	1.047	1.235	0.842	1.044	0.806
	(0.205)	(0.070)	(0.177)	(0.044)	(0.057)

Note: Variables ME_R^J, LE_R^J, ME_R^{*J}, SpE_R^J, and SlE_R^J represent overall merger effects, learning effects, pure merger effects, scope effects, and scale effects respectively. Values are annual average revenue-oriented merger effect estimations from a 1,000 bootstrap samples for 2015. Standard deviations in parentheses.