THE EFFECTS OF GOVERNMENT FARM SUPPORT PROGRAMS ON THE ADOPTION OF FARM TECHNOLOGY AND SUSTAINABLE PRODUCTION PRACTICES

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To my wife, Sierra, for her constant support of my passions.

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ABSTRACT

This paper examines the relationship between the Federal Crop Insurance Program (FCIP) participation and technology adoption patterns, using farm-level data from the United States Department of Agriculture (USDA) Agricultural Resource Management Survey (ARMS). Participation in the federally subsidized crop insurance program may be correlated with technology adoption and other various risk management practices. Existing studies indicate that the subsidized FCIP may disincentivize producers from utilizing technology as a risk management tool. Empirical results indicate that producers enrolled in federal crop insurance programs may be more likely to have adopted PATs earlier than producers who were not enrolled in the FCIP. This could indicate that producers may not view the FCIP as a substitute for other risk management options, or that these producers may not view these technologies in the same risk-reducing lens as they may view the FCIP.

1. INTRODUCTION AND LITERATURE REVIEW

Agricultural production has long been considered an industry with a high level of risk. Producers are exposed to a multitude of perils, many of which are unpredictable and potentially catastrophic. There is an increasing body of research that suggests these types of risks are likely to increase in frequency and magnitude due to climate change (Schneider et al. 2007; Karl, Meehl, and Miller 2008; Schoengold et al. 2014; Woodard and Verteramo-Chiu, 2017). Another potential cause of future price volatility is increased demand for agricultural products for non-food items such as ethanol, plastics, and animal by-products. Due to this increased volatility, agricultural risk management is consistently one of the highest congressional legislative priorities.

In response to these increased risks, various technological advancements have been made to assist farmers with risk reduction and to bolster efficient production methods. Implementing improved irrigation technology has become an increasingly popular practice to combat drought, weather, and crop price fluctuations. Improved irrigation technology has been shown to use water in a more efficient manner than traditional water management methods, leading to higher average profits with less variance in non-irrigating operations (Koundouri et al. 2006; Foudi and Erdlenbruch 2011). Similarly, implementing a subsurface tile-drainage system may help operations better control water quality and flooding issues. While the use of fertilizers and pesticides has been known to increase yields, there are concerns that over application of inputs and application in the face of uncertainty causes greater variability in crop yields (Paulson and Babcock 2010; Just and Pope 1979). Skip-row planting methods have been shown to better facilitate soil moisture and have shown promise to mitigate drought risk in dryer climates (Woodard et al. 2012). Additionally, progress has been made in modifying existing crop strands to utilize inputs more efficiently and better handle extreme weather fluctuations. Emerick et al. (2016) studied a new variation of rice and found it better withstood flooding hazards. Additionally, genetically modified (GM) corn hybrids containing the Bacillus thuringiensis (Bt) gene were found to increase yields and reduced risk exposure (Chavas and Shi, 2015).

Precision agriculture technologies (PATs) are classified as a suite of technologies that use site-specific information to improve field management techniques. The most common PATs include yield monitors, soil and yield mapping using a global positioning system (GPS), GPS based tractor guidance systems, variable rate technology (VRT), and aerial technology such as drones and satellite imagery. PATs have been linked to higher yields, higher net returns, and more efficient allocation of inputs (Schimmelpfennig, 2016). These benefits may be associated with increased risk-mitigation due to their data-based methods for nutrient applications and crop management. PAT adopting farms experience a $66 average per acre increase to farm operating profit (Schimmelpfennig, 2016). However, this average is taken across farms of different sizes and thus could be reflecting economies of scale for adopters. A study conducted by Griffin et al. (2004) summarized results from many PAT studies and concluded that out of the 87 studies included, 73% reported net benefits from adopting PATs.

The technologies this thesis will focus on are GPS guidance systems, VRT (fertilizer, pesticide, and seeding) systems, and subsurface tile-drainage. Figure A.1 shows the relative adoption rates of GPS guidance, VRT, and subsurface tile-drainage on both soybean farms and soybean acres as of 2018 (the last time ARMS conducted studies on soybeans). We can see that as of 2018, 54% of total soybeans acres had adopted a GPS guidance system, while 37% of soybean farms had adopted. The magnitude of this gap indicates that more larger sized farms have adopted this technology. GPS guidance has the largest adoption pattern of the three technologies, with subsurface tile-drainage following with 40% of cropland acres having adopted by 2018, and 33% of farms having adopted. VRT systems rounded out the group with 32% of acres having adopted, while only 28% of soybean farms have adopted. In each case the proportion of soybean acres having adopted these technologies is larger than the percentage of soybean farms having adopted, indicating economies of scale.

While each technology was released on a different date, GPS guidance systems were first adopted on a commercial level (albeit a very small level) around 1990 while VRT systems were first adopted on a commercial level around 1998. Figure A.2 shows the relative adoption paths for both of these technologies on soybean farms over time (between 1990 - 2018). We can see that GPS guidance auto-steering claims a larger adoption proportion when compared to VRT systems, and that gap does not appear to be narrowing. However, we can also see that for both of these technologies, the rate of adoption appears to be plateauing slightly. The most rapid increase in adoption for these technologies occurs after 2010. The exact reason for this is unknown, but there are a number of factors, such as increased broadband internet access, increased efficiency of production leading to lower adoption costs, and increased reliability of these systems, that could explain this increase. It should be noted that Figure A.2 is based on data from the 2018 USDA ARMS Phase II. More specifically, the survey questions used are based on each reported number of years these technologies have been adopted (if at all). This alters the reported statistics between Figure A.1 and Figure A.2, as Figure A.1 is based on whether or not the technology had been adopted by 2018. Similarly, Figure A.3 depicts the proportion of soybean farms adopting subsurface tile-drainage systems between 1900 - 2018. This technology has been commercially adopted since 1900, significantly longer than GPS guidance or VRT systems. These tiles were originally made of clay which were prone to cracking, but have since been replaced by sturdy plastic tubes. It appears that the most rapid increase of subsurface tile-drainage systems occurred between 2000 - 2015. We can see that adoption appears to be slightly plateauing, but is still rising at a steeper rate than GPS guidance and VRT systems.

U.S. farm policy has increasingly relied on the Federal Crop Insurance Program (FCIP) as the main source of risk-management for agriculture. The FCIP is managed, regulated, and administered by the United States Department of Agriculture (USDA) Risk Management Agency (RMA), whose mission is to assist agricultural producers in mitigating risk from various natural perils (climatic, sanitary, geological, market, man-made, etc). In 2021, 444 million acres were enrolled in the FCIP (USDA RMA, 2021). This number doesn't include commodities not measured in acres, such as fruits, nuts, meat, milk, and honey. The four largest enrolled commodities were corn, soybeans, wheat, and cotton. In the year 2021, 83.3 million (90%) of corn acres, 36.6 million (78%) of wheat acres, 78.9 million (90%) of soybean acres, and 10.7 million (91%) of cotton acres were all enrolled in the FCIP (USDA RMA, 2021; NASS, 2022). Table B.1 and figure A.4 describes the major crops and livestock products that were insured in 2021. We can see that this table supports our above analysis that row crops occupy a majority of insured acres, liability dollars, and number of policies sold.

The two most common insurance policies are yield protection and revenue protection. In 1990, all policies offered by the FCIP were yield protection policies (Glauber 2013). Yield protection policies will trigger an indemnity payment when actual yield drops below the average historical yield multiplied by the coverage level (Yu et al. 2017). Producers select the percentage of yields to insure (coverage level), between 55-75 percent (in some areas, 85 percent). In addition to selecting the percentage of yields, a projected price following the Commodity Exchange Price Commissions is used to determine the price level. Producers select the percentage of the projected price they wish to insure, within a range of 55-100 percent. Revenue protection insurance products were first introduced in 1996 as an alternative to yield protection insurance products. Revenue protection policies trigger an indemnity payment when current total crop revenue (actual yield multiplied by harvest price) drops below historical average crop revenue multiplied by the coverage level. Historical average crop revenue is the historical average yield multiplied by the greater of either projected price or the harvest price (Yu et al. 2017). Producers select the percentage of average yield they wish to insure, between 50-75 percent (up to 85 in some areas). Table B.2 breaks down the FCIP policies purchased in 2021. Revenue protection contains the largest share of policies purchased (71%), while yield protection follows with only 13% of total policies sold. Similarly, revenue protection policies also occupied the largest amount of total acres insured and total liabilities (46% and 65%, respectively).

The FCIP subsidizes crop insurance premiums in order to incentivize participation by reducing farmers' out-of-pocket crop insurance costs. While actual portions of covered premiums are determined by the respective policy, 60% of premium costs are covered by the federal government on average. Subsidy rates react inversely to coverage levels (the selected percentage of insurance). As a producer increases coverage, the subsidy rate decreases, resulting in a higher out-of-pocket cost for the producer. This has been a policy objective of the U.S. government since the passage of the Federal Crop Insurance Act of 1980, with the hope that crop insurance would replace ad-hoc disaster payments, due to the decreased comparative cost of the crop insurance program (Glauber et al. 2002). The current FCIP operates as a public-private partnership. Private vendors, also known as Approved Insurance Providers (AIPs), must be approved by the FCIP to market and sell crop insurance policies, while the federal government sets pricing for policies and subsidizes premium costs for producers. The Federal Crop Insurance Corporation (FCIC) is wholly government-owned and reimburses AIPs for subsidized premiums, delivery costs, and reinsurance costs.

The modern FCIP program was developed through The Federal Crop Insurance Act of 1980 and was intended to supplant all other forms of catastrophic risk coverage. However, the only way this new program could achieve this goal was through producer participation (Glauber 2013). In order to encourage producer enrollment, insurance premiums were subsidized, and some current programs were substituted. Prior to 1980, all delivery costs were handled and financed by the federal government (mainly USDA employees) or contracted out to private insurers. After the 1980 Act, delivery of the FCIP was passed onto private insurance corporations in an effort to boost participation via a more active sales force (Glauber 2013). However, these changes did little to boost participation.

Between 1981 and 1988, eligible acres enrolled increased from 16% to 25%, which was far less than the goal of 50%. Currently, private insurers provide marketing and delivery services while the federal government reimburses their administrative, operational, and reinsurance costs, and subsidizes insurance premiums (USDA, RMA, "Summary Of Business 2021"). Additionally, the RMA determines actuarially fair premium rates per dollar of insured liability. While premiums vary by the respective policy coverage level and product selected, they are determined by estimating the expected value of loss cost (total indemnity per unit of liability) using historical weighted average crop yield data. Woodard et al. (2012) explores the effect of actuarially fair premium design with respect to skip row planting adoption and finds that this risk reducing technology could be crowded out if these insurance schemes are designed poorly.

While various aspects of the federal crop insurance program are handled by private insurance companies, there is currently no major private crop insurance market that is fully independent from the FCIP, except certain hail insurance products. During the 1920's, there was access to various private agricultural insurance products, namely catastrophic insurance (fires, droughts, etc.). However, severe drought and fires caused widespread crop losses throughout Montana and the Dakotas. These private insurance companies were unprepared for such widespread losses, and were unable to provide indemnifications, resulting in devastating losses for these producers and a decreased confidence in these private insurance markets (Valgren, 1922).

While it is possible that private insurance markets may currently be crowded out by subsidized crop insurance products, it is unclear whether a viable market-based alternative would emerge in the absence of our current system for the aforementioned reasons. Another potential reason for the absence of private crop insurance markets is the relatively low historical demand for crop insurance due to other risk management tools that could act in competition with crop insurance. Only when heavy subsidies were introduced into the crop insurance program did participation rates begin to climb significantly (Glauber et al. 2002). In fact, it has been found that risk aversion was a minor reason in producers' rationale for crop insurance participation. Rather, their motives were driven by the expected size of premium subsidy payout (Just et al. 1999).

On the supply side, the viability of private insurance markets has been brought into question due to the various moral hazard, adverse selection, and general risk of the agriculture industry (Ahsan et al. 1982; Chambers, 1989; Nelson and Loehman, 1987). Moral hazard and adverse selection are endemic to insurance markets and have received a great deal of attention in the crop insurance literature. Adverse selection is an issue of 'hidden information' while moral hazard is an issue of 'hidden characteristics' (Quiggin, Karagiannis, and Stanton, 1993). Moral hazard suggests that an insured producer's optimal decision may change because of the insurance coverage. Because insurance reduces a producer's loss associated with the insured event, changes in behavior could increase the probability of the event occurring and increase the severity of any losses associated with the insured event (Quiggin, Karagiannis, and Stanton, 1993). Essentially, moral hazard describes a situation in which a producer who adopts insurance to mitigate risk will begin making riskier decisions.

Adverse selection suggests that people who are more likely to suffer losses will be more inclined to insure (Just et al. 1999). This can become costly if the insurer does not predict and account for this information. Due to the high levels of FCIP participation, adverse selection is no longer a major concern. Formal analysis of insurance effects has attempted to separate moral hazard and adverse selection to determine an adequate solution. However, these two effects are often intertwined, thus making an individual analysis of either moral hazard or adverse selection exceeding difficult (Quiggin, Karagiannis, and Stanton, 1993).

Generally, insurance contracts attempt to account for these issues with deductibles, co-payments, and other provisions that attempt to share risk between the insurer and insured. However, due to the high cost of monitoring these provisions throughout agricultural production, private crop insurance would most likely require high deductibles, or high premium costs (Glauber et al., 2002). Combining this information with the Just et al. (1999) study leads one to believe that a market under these constraints would have a difficult time sustaining.

Participation in the federal crop insurance program has continually increased over time. Figure A.5 depicts the increase of insured acres, rising from 206 million acres in 2000 to more than 444.5 million insured acres in 2021, a two-fold increase (USDA, RMA, "Summary of Business 2000-2021"). As participation has increased, associated liabilities, premiums, and premium subsidies have also risen. As portrayed in Figure A.5, total premiums have risen from $2.5 billion in 2000 to $14.3 billion in 2021 (USDA, RMA, "Summary of Business 2000-2021"). Premium subsidies have risen eight-fold from $951 million in 2000 to $8.8 billion in 2021 (USDA, RMA, "Summary of Business 2000-2021"). Liabilities have ballooned from $34.4 billion in 2000 to $150.8 billion in 2021 (USDA, RMA, "Summary of Business 2000-2021"). I should note that total premiums increased by 37.5% between 2020 and 2021 alone. The same can be said for premium subsidies (36.7%), and liabilities (18.4%). RMA does disclose that the COVID-19 pandemic did lead to an increase in additional subsidy amounts, and one can speculate that this drastic increase in subsidy and liabilities was pandemic related, but the exact reason is not known. Figure A.5 does not account for delivery costs, which accounted for roughly 47% of the total insurance costs between 1990 and 2011 (Glauber 2013). Additionally, the above tables do not take the entire private portion of the FCIP into account. If an underwriting profit is recorded, then the AIP is entitled to a portion of the proceeds. This process also works inversely if an underwriting loss is recorded. In this case, the AIP is liable for a specific portion of the losses and essentially compensates the federal government.

These facts have led to criticisms regarding the efficiency of the FCIP when compared to other government programs, such as the Conservation Reserve Program (CRP), and direct payment programs that managed to deliver benefits to producers at lower delivery costs (Glauber 2013; Hart et al. 2006). Due to this inflating cost, a number of studies examine the elements driving crop insurance participation, its effect on farm efficiency, and producer management decisions.

A formal crop insurance participation model was developed by Coble et al. (1996) using cross-sectional farm level data and found statistically significant effects of market return and return to insurance on participation rates. This indicates that farms expecting more frequent, but smaller losses were more likely to participate, whereas operations that experienced fewer but large losses were less likely to participate. Large losses are often attributed to major weather events, such as drought, while smaller losses are often attributed to individual farm error. This seems to be counter-intuitive to the original purpose of the FCIP, which was to protect producers from risk inducing events beyond their control.

There has been evidence suggesting that crop insurance rules may have incentive-distorting impacts (Goodwin and Smith, 2013; Glauber et al. 2002; Schoengold et al. 2014). For example, Woodard et al. (2012) found that crop insurance may disincentivize the adoption of skip-row planting, an agricultural risk management practice that has been shown to lead to better soil health and moisture retention. If crop insurance rules remain relatively consistent, then adoption of risk mitigating technology and practices that otherwise would be optimal for farms may be crowded out by the FCIP. Additionally, data has suggested that an increase in insured acres can have a negative impact on CRP enrollment, which could potentially place the FCIP at odds with conservation programs (DeLay 2019).

Evidence has shown that participating in revenue and yield crop insurance schemes could act as a substitute for fertilizer applications, leading to lower chemical use (Babcock and Hennessey 1996; Smith and Goodwin 1996; Goodwin et al. 2004). This finding has garnered mixed reviews, with some highlighting the potential moral hazard issues and others citing the potential environmental benefits of decreased fertilizer application.

In addition to the FCIP, producers can manage risk through various other methods, such as: implementing precision agriculture technologies (PATs), using new crop varietals, crop and livestock diversification, using alternative tillage practices, savings accumulation, off-farm activities, adjusting the intensification of production, and developing early warning weather systems (Smit and Skinner, 2002). In addition to assisting producers with risk management, these practices can also have an impact on conservation and sustainability practices, providing a positive externality that extends beyond the individual producer.

Throughout the literature, there has been mixed evidence regarding the relationship between crop insurance markets and technology adoption. This relationship was examined in Chile, with results indicating that those who adopt improved irrigation technology were less likely to adopt crop insurance, indicating that these farmers viewed the two as substitutes (Salazar et al. 2019). There is also evidence that participation in the FCIP dis-incentivized skip-row planting, a method that has been linked to higher yields and increased drought resistance (Woodard et al. 2012). Different crop insurance structures have also been proposed as a possible solution. Various index-based insurance studies have been conducted and found positive relationships between this form of crop insurance and technology adoption. Tang et al. (2019) analyzed the effects of weather index-based insurance schemes on technology adoption in China. They concluded that increased adoption of weather index-based insurance exhibited a positive impact on the adoption of improved seeds. Carter et al. (2016) examined the effects of an index-based insurance plan on improved technology adoption in western Africa and concluded that in certain scenarios this alternate form of insurance can aid in promoting improved technology adoption.

This paper examines the effects of the FCIP on farm technology adoption. Specifically, GPS guidance systems, VRT (fertilizer, pesticide, and seeding) systems, and subsurface tile-drainage. By doing this, the hope is to further understand the relationship between government risk protection programs and farm risk mitigating practices. There may be tension between farmer adoption of capital-intensive farm technologies and federal crop insurance programs due to the subsidized nature of the FCIP system. While a plethora of research has been devoted to the role of subsidized crop insurance on various aspects of risk-mitigating practices, there exists a gap in the literature on the effects of the FCIP on a suite of various risk mitigating technologies, such as PATs and the management practices mentioned above, within the United States. This paper aims to add to the existing literature by analyzing the effects of the FCIP on farm risk mitigating technology adoption and farming practices in the United States.

2. ECONOMIC FRAMEWORK

It is assumed that a representative producer is risk averse and makes production decisions that will maximize total profit from a combination of production revenue and government payments. For the purposes of this analysis, crop insurance is considered to be the only source of government payments, as emergency disaster payments and other government support programs are excluded. It is assumed that adopting advanced farm technology and production methods incurs an additional cost relative to not adopting, but also reduces production profit variance. If various stochastic production shocks (weather, market volatility, etc) are beneficial to the production operation, then it is assumed that they are positively correlated with production profit and negatively correlated with crop insurance indemnity payments. Similarly, it is assumed that negative production shocks are negatively correlated to production profit and positively correlated to crop insurance indemnity payments.

For the purposes of this model, total income is solely the sum of production profits and government payments (indemnity payments and subsidized premiums). Let x denote the total amount of traditional inputs used in production (fertilizer, water, pesticides, etc), with a higher value of x representing a greater amount of these inputs being used. Additionally, let z represent the total amount of technology adoption, with a higher value of z representing an increased amount of technology adoption. The stochastic production shocks are denoted by Θ, which is non-positive, and has a range of $[\Theta, 0]$. A lower (more negative) value of Θ represents stochastic shocks that correlate to lower production levels, with $\Theta = 0$ being the most optimal production level. A Just and Pope (1979) production function is used to incorporate these variables, which specifies that the output function can be split into two distinct parts: a deterministic function of the input variable and the technology variable, and a stochastic function of the production shock variable.

$$y(x, z, \Theta) = f(x, z) + g(z)\Theta \tag{2.1}$$

The deterministic portion of the production function is $f(x, z)$ and represents the maximum possible yield with x number of inputs and z amount of technology adopted. Both of the partial derivatives can be described as $\frac{\partial f}{\partial x} > 0$ and $\frac{\partial f}{\partial z} > 0$ since an increase in either of the choice variables will lead to an increase in production. It is assumed that the deterministic production function is twice differentiable, with $\frac{\partial^2 f}{\partial x^2} < 0$ and $\frac{\partial^2 f}{\partial z^2} < 0$ as the production function is expected to exhibit decreasing returns to scale, as yield will begin to become less affected by marginal additions of inputs. Furthermore, it is assumed that $\frac{\partial^2 f}{\partial x \partial z} > 0$ as more technology is adopted (an increase in z), the yield impact of each additional unit of input x increases. The stochastic portion of the production function is $g(z)\Theta$. Higher technology adoption can mitigate yield risks from various stochastic production shocks. It is assumed that $g(z)$ is positive with a range of $(0, 1]$, and $g'(z) < 0$. Use of the technology attenuates the negative effects of the production shock on yield toward zero, i.e., $g(z)$ approaches 0 as z increases. Using no technology means the production shock will have its full negative effect on yield, that is $g(0) = 1$.

Adopting these risk mitigating technologies requires additional costs, such as capital required for technology adoption, adjustment costs, and other various costs that may arise with the addition of inputs. These costs are represented by $wx+mz+hk$, where w is the unit cost of applied inputs (x), m is the unit cost of adopted technology (z), h is the depreciated investment cost, k is an indicator variable that is dependent on the value of z and takes a value of 0 if no technology is adopted and 1 otherwise. The depreciated investment cost variable, h, can be considered quasi-fixed as it does not change with every hour used but does change with every new technology adopted. Additionally, this cost is assumed to be a fixed cost in the short run while in the long run this cost is assumed to be marginal.

Indemnity payments are based on yield or revenue loss in a given crop year. For simplicity, this economic framework is modeled around yield insurance schemes. However, this model can be easily adapted for revenue insurance plans. Because these yield losses are in part dependent on stochastic shocks and the adopted production technology used to mitigate these shocks, these indemnity payments will be denoted as $I(z, \Theta) = max\{0, p(\mu\bar{y} - y)\}$. Historical average yield is represented by $\bar{y}$, observed yield is represented by y, the chosen crop insurance coverage level is denoted by μ, and the price that the insurance policy pays out is denoted by p. If the observed yield is greater than the guaranteed yield ($\mu\bar{y}$), then the respective policy will not pay anything out. If the observed yield is lower than the guaranteed yield, then the respective policy will pay the difference times the contract price, p.

Due to the subsidized nature of the crop insurance program, the premium subsidy rate must also be considered. Since the subsidy level (denoted as γ) must be between 0 and 1, the subsidized premium cost to the producer is represented as $(1-\gamma)\bar{I}(z)$, where $\bar{I}(z)$ represents the expected value of the indemnity payment and is a function of the amount of technology adopted. In an actuarily fair insurance market, the value of the premium payment should equal the expected value of the indemnity payment, conditional on the production technology level z chosen. Insurance premiums can be influenced by production technology adopted by the producer, as is the case with irrigation technology. There are premium differences for those operations that use irrigation technology as a risk management tool as compared to those operations that do not use irrigation technology. Expected indemnity payments are denoted as: $\int_0^{\mu\bar{y}} p(\mu\bar{y} - y)t(y)\,dy$, with μ being the chosen level of insurance coverage, $\bar{y}$ being the historical yield average, y being the observed yield, p being the contract price, $\mu\bar{y}$ being the guaranteed yield, and $t(y)$ being the yield probability distribution. The integral is taken from 0 to $\mu\bar{y}$ because this study is interested in the positive expected value up until the guaranteed production level and yield realizations above $\mu\bar{y}$ result in no indemnity payments.

This model implements a basic profit equation:

$$\Pi(x, z; w, m, h, k, p, \Theta, \gamma) = py - (wx + mz + hk) + I(z, \Theta) - (1-\gamma)\bar{I}(z). \tag{2.2}$$

Where p is the output price, y is the production function, $(wx+mz+hk)$ is the cost function, $I(z, \Theta)$ is the received indemnity payment, and $(1-\gamma)\bar{I}(z)$ is the premium cost with the subsidy level considered. The defined production function is then substituted into (2.2) to arrive at:

$$\begin{aligned}\Pi(x, z; w, m, h, k, p, \Theta, \gamma) = p(f(x, z) + g(z)\Theta) - (wx + mz + hk) \\ + I(z, \Theta) - (1-\gamma)\bar{I}(z).\end{aligned} \tag{2.3}$$

Further, output price (p) is taken as given and normalized to 1. Upon doing so, the net profit equation (2.4), expected value equation (2.5), and variance equation (2.6) can be formed:

$$\Pi(x, z; w, m, h, k, \Theta, \gamma) = f(x, z) + g(z)\Theta - (wx + mz + hk) + I(z, \Theta) - (1 - \gamma)\bar{I}(z). \quad (2.4)$$

$$E[\Pi(x, z; w, m, h, k, \Theta, \gamma)] = f(x, z) + g(z)\bar{\Theta} - (wx + mz + hk) + \gamma\bar{I}(z). \quad (2.5)$$

$$Var[\Pi(x, z; \Theta, \gamma] = [g(z) + \frac{\partial I}{\partial \bar{\Theta}}]^2\sigma^2 = \sigma^2_{\Pi}. \quad (2.6)$$

Incorporating both the expected value of profit and the variance of profit will capture the effects of stochastic risks on both the average levels of profit and the variance between these levels. In forming the utility function, a mean-variance approach was implemented. This form was outlined in Meyer (1987), and applied by Schoengold et al. (2014), Isik and Khanna (2003), and Serra et al. (2011). This functional form approach gives a greater flexibility in the assumptions made and allows for the incorporation of different utility function forms while still maintaining validity. Additionally, this function form was used because producers care about both the expected value of profit and the variance of those expected profits. Using this intuition, the utility function takes the form of $U(\bar{\Pi}, \sigma^2_{\Pi})$ where $\bar{\Pi}$ is the expected value of profit and σ^2_{Π} is the variance of profit. It is assumed that $U_{\Pi} > 0$ and $U_(\sigma^2) < 0$. Therefore, the optimization problem is as follows:

$$MaxU(\Pi) = \bar{\Pi} - \frac{\alpha}{2}(\sigma^2_{\Pi}). \quad (2.7)$$

Producer's risk aversion preferences, α, are factored in and represent the amount of expected profit a producer is willing to change for a change in profit variance. Essentially, a greater value of (α) corresponds to greater risk aversion preferences. Further, equations (2.5) and (2.6) can be substituted into (2.7) to explicitly express the optimization problem.

$$MaxU(\Pi) = (f(x,z) + g(z)\bar{\Theta} - (wx + mz + hk) + \gamma \bar{I}(z)) \\ - \frac{\alpha}{2}([g(z) + I_{\Theta}(\bar{\Theta}, z)]^2 \sigma^2). \quad (2.8)$$

The optimization problem is a function of Π at its expected value and variance. The optimization problem is solved for the technology variable, z, and the first-order condition (FOC) is expressed.

$$\frac{\partial \bar{\Pi}}{\partial z} - \frac{\alpha}{2}(\frac{\partial \sigma_{\Pi}^2}{\partial z}) = 0. \quad (2.9)$$

Substituting the expected value of profit and variance of profit functions from equations (2.5) and (2.6) into (2.9), the first-order condition with respect to z can be explicitly expressed.

$$[\frac{\partial f}{\partial z} + g'(z)\bar{\Theta} - m + \gamma \bar{I}'(z)] - \alpha[(g(z) + I_{\Theta})(g'(z) + \frac{\partial^2 I}{\partial \Theta \partial z})]\sigma^2 = 0. \quad (2.10)$$

It is assumed that $\frac{\partial^2 I}{\partial \Theta \partial z} > 0$ since the effect of stochastic shocks (Θ) on indemnities is reduced as more technology is adopted. The first-order condition can also be expressed with respect to x.

$$\frac{\partial f}{\partial x} - w = 0. \quad (2.11)$$

Expression (2.11) represents the optimal amount of inputs (x) where the marginal revenue product of (x) is equal to its marginal cost. Taking the fully expressed FOC, comparative statics can be used to determine the effects of the interest variables on technology adoption decisions. In particular, the stochastic shock variable, (Θ), subsidy variable (γ), risk variable (α), technology unit cost variable (m), and the variability of these shocks (σ^2), and their respective relationships with technology adoption. If there is a connection between stochastic shocks and increased crop insurance enrollment or increased technology adoption as these shocks negatively affect production, then there may be implications for policy makers. Similarly, if there is a connection between the crop insurance variables and technology adoption, then there may be evidence of moral hazard and adverse selection. There is evidence that producers view both crop insurance program and agriculture technology as risk management tools, but it is less clear whether these two options can be used as complements or substitutes. Equation (2.10) is totally differentiated with respect to the interest variables and the second-order condition (SOC) is expressed. While the SOC will not be fully expressed in this paper, it should be noted that if the producer is a utility maximizer, then the SOC must be negative ($SOC < 0$).

Using comparative statics via the implicit function theorem, the relationship between the variables of interest and the adoption of farm technology can be evaluated:

$$\frac{\partial z}{\partial m} = \frac{1}{SOC_z} < 0 \tag{2.12}$$

$$\frac{\partial z}{\partial w} = \frac{1}{\frac{\partial^2 f}{\partial x \partial z}} > 0 \tag{2.13}$$

$$\frac{\partial z}{\partial \bar{\Theta}} = \frac{g'(z)}{SOC_z} < 0 \tag{2.14}$$

$$\frac{\partial z}{\partial \sigma^2} = \frac{\alpha(g(z) + I_\Theta)(g'(z) + \frac{\partial^2 I}{\partial \Theta \partial z})}{SOC_z} \tag{2.15}$$

$$\frac{\partial z}{\partial \alpha} = \frac{(g(z) + I_\Theta)(g'(z) + \frac{\partial^2 I}{\partial \Theta \partial z})\sigma^2}{SOC_z} \tag{2.16}$$

$$\frac{\partial z}{\partial \gamma} = \frac{\bar{I}'(z)}{SOC_z} < 0 \tag{2.17}$$

These comparative statics show some interesting results, with 4 out of the 6 comparative statics equations being unambiguous. Equation (2.12) explains that as the cost of adopting technology increases, the willingness of producers to acquire new technologies will decrease. Inversely, equation (2.13) shows that as the unit cost of inputs increase, the likelihood of producers adopting new technologies increases, possibly with hopes that their purchased input will be used more efficiently. This showcases a possible substitution effect between the cost of inputs and technology adoption, as producers exhibit a willingness to substitute inputs with technology to maintain optimal profitability. Equation (2.14) shows that as the average stochastic shock value increases (in this case, this indicates a lesser impact on yields and risk due to the negative Θ value) the need to adopt new technology decreases.

Equation (2.15) is ambiguous and ultimately depends on the relative sizes of $\frac{\partial^2 I}{\partial \Theta \partial z}$, $g'(z)$, $g(z)$, and I_Θ. Due to the complexity of equation (2.15), a definitive inequality cannot be determined. One can say that since indemnity payments are more likely to decrease as stochastic risk conditions improve (Θ approaching 0), the partial derivative of indemnity payments with respect to Θ will be less than 0. However, $g(z)$ is a positive term, so it is unknown which term will ultimately dictate the sign of equation (2.15). While the overall sign of equation (2.15) is unknown and will need to be determined empirically, one can deduce that this expression is based on the relationship between exposed risk, indemnity payment amount, and farm-level technology adoption.

Equation (2.16) uses the same intuition, as it can be seen that the direction of this equation is ambiguous and dependent on the relative sizes of $\frac{\partial^2 I}{\partial \Theta \partial z}$, $g'(z)$, $g(z)$, and I_Θ. As with equation (2.16), empirical testing will be needed to determine its direction. It is known that the main difference between equation (2.15) and equation (2.16) is that while equation (2.15) is related to actual exposed risk variance, equation (2.16) isolates a producer's risk preferences (in which it is assumed that most producers are risk-averse). This expression's sign will be based on indemnity payments, stochastic risk, technology adoption, and producer risk-preferences.

Lastly, equation (2.17) shows that as the premium subsidy rate increases, the likelihood that producers will adopt new technologies decreases. This final equation is of particular interest and showcases the concerns that increasing the subsidy rate on crop insurance premiums could lead to moral hazard and adverse selection issues. These comparative statics results highlight the possible role that these government programs could play in acting as substitutes for other risk reducing behavior and practices.

3. EMPIRICAL ESTIMATION STRATEGY

The empirical estimation strategy was formulated to measure the effects of government farm support program payments on the adoption of farm technology and sustainable management practices. Using a variation of Heckman's estimator (Heckman, 1979) time to adoption of various farm technologies are formally analyzed following the direction of Greene (2012, 880-883) and Terza (1998). Heckman's method used two different equations to model sample selection bias, one equation to model the participation decision and an equation dependent on the outcome of the first to model the extent of participation (in years), referred to here as intensity. Traditionally, Heckman's method began with a probability model (typically either probit or logit) to model the binary outcome, followed by a linear regression (OLS) to model the positive outcomes. However, the dependent variables (number of years a technology has been adopted) is considered to be "count data". Count data are a statistical data type in which the variables of interest are non-negative integers which must be counted (1,2,3, etc) instead of measured. A linear regression might not be appropriate for count data as its linear modeling for the conditional outcome variable does not restrict the predicted values to positive integers and thus could predict negative values, which is not possible for count data. To address this issue, a Poisson regression was applied as this solution is common when dealing with count data models.

In this case, a probit selection model is implemented to ascertain whether an operation has adopted certain technologies by 2018, followed by a Poisson intensity equation to estimate the extent of that adoption (in years) and to gain a better understanding of the thought process behind these adoption decisions. Van de Ven and van Praag (1981) used a similar framework to model consumer insurance purchases, and were among the first to apply this selection methodology to a non-linear model. Boyes, Hoffman, and Low (1989) applied a similar model to model loan defaults, while Greene (1998) applied a similar model to credit card scoring. Additionally, Mohanty (2002) also used a similar framework to analyze teen employment in California.

The positive count outcome is based around the dependent variable representing the number of years a specific technology has been adopted for, y_i, which has a Poisson distribution and is dependent on a vector of covariates, x_i, and a vector of coefficients, β. In this case, the primary function can be modeled as the following:

$$Prob(Y = y_i|x_i', \epsilon_i) = \frac{e^{-\lambda_i}\lambda_i^{y_i}}{y_i!} \tag{3.1}$$

with conditional mean

$$E(y_i|x_i', \epsilon_i) = \lambda_i = exp(x_i'\beta + \sigma\epsilon_i) = exp(\mu_i). \tag{3.2}$$

where $\epsilon_i \sim N[0, \sigma^2]$. However, whether or not y_i is observed depends upon the selection variable, s_i. This selection variable represents whether or not the technology has been adopted by 2018. is equal to 1 (which indicates the technology has been adopted by 2018). This selection variable models the binary selection outcome (also referred to as the participation decision), which is modeled with a vector of covariates, z_i, a vector of coefficients, γ, and adheres to the following:

$$s_i = \begin{cases} 1, & \text{if } z_i'\gamma + u_i > 0 \\ 0, & \text{otherwise} \end{cases} \tag{3.3}$$

Where u_i is an error term that follows $u_i \sim N(0, 1)$. As laid out in Terza (1998) and Greene (2012), this selection equation will consist of a probit model. In order to account for the potential sample selection of s_i, the error terms [ϵ_i,u_i] are assumed to possess a joint-normal distribution with a zero conditional mean, correlation such that $corr(\epsilon_i, u_i) = \rho$, and variance-covariance matrix as shown below:

$$\begin{bmatrix} \sigma^2 & \sigma\rho \\ \sigma\rho & 1 \end{bmatrix}$$

The main diagonal represents the variances of the two error terms (σ^2, 1) and the cross diagonal represents the co-variances between the error terms ($\sigma\rho$). It should be noted that per the traditional definition of bivariate normal distribution, the most common way to visualize the co-variance terms is $\sigma_1\sigma_2\rho$, with σ_1 representing the standard deviation of ϵ_i,

σ_2 representing the standard deviation of u_i, and ρ possessing the same interpretation as above. However, since in this case σ_2=1, this term has been omitted from the matrix. The log-likelihood function for this model will consist of the joint density for all of the observed data. The joint density function can be defined by integrating the joint probability for both $s_i = 1$ and $s_i = 0$ via $Pr(y_i, s_i = 1|x_i, z_i)$ and $Pr(y_i, s_i = 0|z_i)$. The $s_i = 1$ case is shown below.

$$Pr(y_i, s_i = 1|x_i, z_i) = \int_{-\infty}^{\infty} Pr(y_i, s_i|x_i, z_i, \epsilon_i) f(\epsilon_i) d\epsilon_i. \tag{3.4}$$

The integral is conditioned upon ϵ_i, s_i, and y_i being independent. The joint density can be expressed as the following product

$$Pr(y_i, s_i = 1|x_i, z_i, \epsilon_i) = f(y_i|x_i' + \sigma\epsilon_i) Prob(s_i = 1|z_i, \epsilon_i). \tag{3.5}$$

By joint normality, $f(u_i|\epsilon_i) = N[\rho\epsilon_i, (1 - \rho^2)]$, so $u_i|\epsilon_i = \rho\epsilon_i + (u_i - \rho_i) = \rho\epsilon_i + v_i$, with $E[v_i] = 0$ and $Var[v_i] = (1 - \rho^2)$. Therefore,

$$Prob(s_i = 1|z_i, \epsilon_i) = \Phi(\frac{z_i'\gamma + \rho\epsilon_i}{\sqrt{1 - \rho^2}}). \tag{3.6}$$

Where Φ represents the standard normal cumulative density function. To formulate the unconditional joint density, the above terms are combined

$$p(y_i, s_i = 1|x_i, z_i) = \int_{-\infty}^{\infty} f(y_i|x_i'\beta + \sigma\epsilon_i)\Phi(\frac{z_i\gamma + \rho\epsilon_i}{\sqrt{1 - \rho^2}})\frac{exp(-\epsilon_i^2/2)}{\sqrt{2\pi}} d\epsilon_i. \tag{3.7}$$

Where $\frac{exp(-\epsilon_i^2/2)}{\sqrt{2\pi}}$ is the standard normal density function and is commonly represented with ϕ. The other side of the likelihood function for observations $s_i = 0$ looks similarly

$$\begin{aligned} Prob(s_i = 0|z_i') &= \int_{-\infty}^{\infty} Prob(s_i = 0|z_i', \epsilon_i)\phi(\epsilon_i/\sigma)d\epsilon_i \\ &= \int_{-\infty}^{\infty} [1 - \Phi(\frac{z_i\gamma + \rho\epsilon_i}{\sqrt{1-\rho^2}})]\phi(\epsilon_i/\sigma)d\epsilon_i \\ &= \int_{-\infty}^{\infty} \Phi(-\frac{(z_i\gamma + \rho\epsilon_i)}{\sqrt{1-\rho^2}})\frac{exp(-\epsilon_i^2/2)}{\sqrt{2\pi}}d\epsilon_i. \end{aligned} \tag{3.8}$$

Using the invariance principle, the likelihood function can be redefined in terms of $\alpha = \gamma/\sqrt{1-\rho^2}$ and $\tau = \rho/\sqrt{1-\rho^2}$. When the previous terms are combined, the log-likelihood function to be maximized is expressed

$$\begin{aligned} ln(L(\theta)) = \sum_{i=1}^{N} [s_i * ln\{Prob(y_i, s_i = 1)|x_i, z_i, \theta\}] \\ + (1 - s_i) * ln\{Prob(s_i = 0|z_i, \theta)\}]. \end{aligned} \tag{3.9}$$

Where θ represents $(\beta, \gamma, \rho, \sigma)$ for simplicity. The log-likelihood function can be further defined as follows

$$ln(L) = \sum_{i=1}^{n} \int_{-\infty}^{\infty} [(1 - s_i) + s_i f(y_i|x_i'\beta + \sigma\epsilon_i)]\Phi[(2z_i - 1)(z_i'\alpha + \tau\epsilon_i)]\phi(\epsilon_i)d\epsilon_i. \tag{3.10}$$

This function can be maximized with respect to $(\beta, \sigma, \alpha, \tau)$ using Gauss-Hermite quadrature. After maximizing, ρ can be recovered from $\rho = \tau/(1+\tau^2)^{1/2}$ and γ from $\gamma = (1-\rho^2)^{1/2}\alpha$. While other specifications may be used for this estimation, this particular specification and estimation method was laid out in Terza (1998) and Greene (2012).

4. DATA AND VARIABLES

Data and variables for this study have been obtained from the Agricultural Resource Management Survey (ARMS), which is administered and maintained jointly through the USDA Economic Research Service (ERS) and the National Agricultural Statistical Service (NASS). This survey provides a comprehensive, nation-wide overview of the production practices, resource use, and economic situations of farm operations. Because ARMS is not a random sample, the dataset includes expansion weights for all observations, which indicates the number of fields each specific farm represents. USDA sets the weights so that each sample represents the given population and meets certain criteria such as number of farms by state, harvested acres for major crops, and total production by commodity. These sample weights ensure that the ARMS survey is nationally representative, despite only surveying certain operations. First administered in 1996, this yearly survey rotates through various crops and livestock operations. ARMS is administered in three phases, with each phase pertaining to a different set of farm characteristics. Phase I is an initial screening to determine the crop produced as each year ARMS surveys a different set of crops. Phase II focuses on field level characteristics such as various production practices, field topography, and technology adoption. Phase II is where the technology and crop insurance questions are located. Phase III surveys operation wide characteristics, such as farm assets, farm debts, and total acres operated.

2018 will be the survey year of focus for this study, which used soybeans as the surveyed crop. The 2018 survey was selected due to the inclusion of time-related questions in addition to binary response questions pertaining to the adoption of various technologies. These time-related questions will serve as the basis for the intensity equations, while the binary response questions will serve as the selection equations.

The pertinent technology questions for this study include sub-surface tile drainage systems, GPS based guidance auto-steering, and variable rate applicators (seeding, fertilizer/lime applications, and pesticide applications). The survey questions first ask whether the respective technology was used during 2018 (these binary variables will be used as the dependent variable in the selection equation). If the answer is "yes" then several follow-up questions are given, one of which asks in what year the respective technology was first adopted. Another variable was then then created that contained the number of years each technology has been adopted in accordance to the original year of adoption. The variable rate applicator questions were originally separated based on function. These different applications were then combined to determine if any of the variations had been adopted. Sample weights have also been applied to these summary statistics to ensure the data-set is nationally representative. All summary statistics have applied these sample weights to calculate the means and all standard errors have been formulated using the jack knife replication process. Table B.3 contains the summary statistics for these variables.

Figure A.6 provides a visual for the number of years a subsurface tile-drainage system has been installed. It can be seen that this graph follows a Poisson distribution, as the outcome is count and the distribution is right-skewed. It can also be seen that the median number of years for this data-set is 18 years. This figure shows the wide variation among the years adopted, with some producers have had a subsurface tile-drainage system installed for upwards of 100 years. Figure A.7 contains data related to the number of years a guidance auto-steering system has been implemented. This figure is also right-skewed and appears to follow a Poisson distribution. The median number of years adopted for this technology is 5 years, considerably lower than subsurface tile-drainage. However, this is to be expected since subsurface tile-drainage systems have been commercially available for a longer period of time than guidance auto-steering systems. Figure A.8 contains data related to the number of years a VRT system for any purpose has been installed. This technology has a median of 4 years, which is the lowest out of the three technologies. It also appears to be right-skewed and following a Poisson distribution. While figure A.8 is fairly similar to figure A.7, both figures contain lower median years of adoption compared to figure A.6. While other technologies are present in the 2018 survey, these technologies contained information related to the both the presence of adoption and the extent (in years) of adoption. It is not uncommon for ERS and NASS to expand the survey questions from year to year, so additional applications of this study will become possible if time-related adoption questions are further expanded upon in future surveys.

The crop insurance variables are derived from Phase II of the 2018 ARMS survey. A time-based variable has been included that represents the number of years a producer has possessed multi-peril crop insurance, (*Multi-Peril Adoption (Years)*). Also included is a variable representing the selected coverage-level, (*Coverage Level*). This variable incorporates both the percentage of yield coverage and revenue coverage (dependent on the producer's crop insurance product selection decision). While it is not correct to directly speculate as to the subsidy-amount based on the coverage level, it is well-known that as producers elect higher coverage levels, the subsidy rate decreases. This indicates that as the coverage level variable increases, one can expect a lower subsidy rate. However, this lower rate will be applied to higher premiums, so the total subsidy dollars allocated could increase. Due to multi-collinearity issues, only the crop insurance variables mentioned above were included. Figure A.9 contains data related to the number of years a multi-peril crop insurance plan has been used. With a median of 13 years, this figure also appears to be slightly skewed to the left. For a producer to have adopted multi-peril insurance around the median, they would need to have adopted around 2005. Table B.4 contains the summary statistics for these variables.

The exogenous variables are derived from both Phase II and Phase III of the 2018 ARMS survey. Table B.5 contains the summary statistics for these variables. Included are a couple of basic characteristic control variables, such the age of the principle operator in years (*Age*) and a binary response variable for education, where 1 indicates the primary operator has at least some college experience, 0 otherwise (*College*). Variables that represent an operations total dollar amount of farm assets (*Farm Assets*) and farm debts (*Farm Debt*) are also included. It is anticipated that as a farm assets relative to its debts increase, the ability to adopt new technologies will increase. Additionally, a variable representing the average interest-rate of the producer listed loans (*Interest Rate*) is accounted for. It is suspected that as borrowing becomes more expensive, the ability to adopt new technologies will decrease. Variables indicating the total number of acres operated (*Total Acres Operated*) are also incorporated, along with another variable indicating how many acres are being rented as a percentage of total acres (*Percentage of Rented Acres*).

ERS splits the United States into 9 “Farm Resource Regions”. These regions have been incorporated to measure differences in adoption based off of location. This variable will represent the risk variance comparative static outlined in the Economic Framework section, and is shown in Figure B.10. These 9 different sectors are defined as follows: (1) Heartland, (2) Northern Crescent, (3) Northern Great Plains, (4) Prairie Gateway, (5) Eastern Uplands, (6) Southern Seaboard, (7) Fruitful Rim, (8) Basin and Range, and (9) Mississippi Portal. The Heartland region contains the highest number of farms (22%), along with the highest value of production (23%), and the most cropland (27%). The Northern Crescent region houses 15% of farms worth 15% of total production value, and contains 9% of total cropland. The Northern Great Plains region contains the smallest population, largest farms, a small number of farms (5%), 6% of total production value, and 17% of cropland.

The Prairie Gateway region contains 13% of farms, 12% of production value, and 17% of cropland. The Eastern Uplands region contains the smallest farm-size of any other region, 15% of the total number of farms, 5% of production value, and 6% of cropland. The Southern Seaboard region is a mix of small and large farms, contains 11% of the total number of farms, 9% of total production value, and 6% of cropland. The Fruitful Rim region contains 10% of farms, 22% of total production value, and 8% of cropland. The Basin and Range region represents the smallest share of U.S. cropland (roughly 4 %), but the largest share of non-family farms, around 4% of farms, 4% of production value, and 4% of cropland. The Mississippi Portal region represents 5% of farms, 4% of total production value, and 5% of cropland.

Other exogenous variables include the total dollar amount spent on chemical and fertilizer expenses (*Chemical Expense*). As the price of inputs increases, the demand for a more efficient applicators may rise. A crucial aspect of the comparative static section within the economic framework is the producer's reaction to risk. In an attempt to incorporate this factor, It was decided to add county-level RMA data that tracks various crop insurance characteristics, such as premium levels, indemnity amounts, and total liabilities. This data-set is readily available on the RMA website and contains county-level information from 1989 - 2020.

To incorporate a variable for risk levels, a county-level historical average of the loss-cost ratio (LCR) was included and is represented as (*Loss-Cost Ratio*). The average LCR method was used in Goodwin (1993) and can be calculated as follows: *LCR = total indemnity / total liabilities*. A loss cost ratio of 1 means that total indemnity payments equals total liabilities, a total loss. Similarly, a value less than 1 would indicate total liabilities were greater than indemnity payments received. This value was averaged by county from the years 1989 - 2017 in order to generate a reliable measure of a respective county's riskiness over time. If producers in a particular county are consistently receiving large indemnities, then one can reason that this county is more frequently exposed to various risks. This term will incorporate risk independently of that risk's source, whether it be weather variation, market turbulence, or from another source. This characteristic is valuable in that will allow us to control for any number of risks, not just one particular type, as would be the case with many other weather based risk-controlling variables. Table B.6 contains the summary statistics for these variables.

Another potential driver of farm technology adoption is labor. Total dollar amount of labor costs (*Labor Costs*) an operation incurs, as well as the total number of unpaid labor hours (*Unpaid Labor*) it incurs have been included. One can reasonably suspect that unpaid labor is largely attributed to labor on behalf of the operator's family or close circle, and can reason that as this increases, the desire for new technology may increase. Likewise, if labor costs increase, this may add new strain on an operation and make the capital cost of new technology appear more favorable. Also included is a binary variable that equals 1 if any portion of the selected field (covered in Phase II of ARMS), is classified as Highly Erodible Land (*HEL*). As determined in Shoengold et al. (2014), the presence of highly erodible land may lead to an increased demand for more efficient methods and technologies. This variable is mainly applied to the subsurface tile drainage model. Another indicator variable included is equal to 1 if the primary operator has concerns about poor drainage (*Poor Drainage*) throughout his/her fields. If the operator is concerned with poor drainage, it reasons that they may take steps to address this issue through subsurface tile drainage. Likewise, an indicator variable equal to 1 if the primary operator has concerns about soil compaction (*Soil Compaction*) is included. Poor soil compaction can be caused through increased equipment size or increased precipitation. As the soil compacts, the pore size within the soil is decreased, decreasing its ability to effectively drain and aerate. A common solution to compacted soils is improved tile drainage.

(*Wetland*) is an indicator variable equal to 1 if the field chosen for the Phase II contains a wetland. This variable will be helpful for the drainage model in that if a field does contain a wetland, implementing a tile-drainage system would be logical. Also included is (*Water Erosion Issues*), an indicator variable equal to 1 if the producer has any water erosion issues amongst his/her fields. (*Water Quality Issues*) is another environmental indicator variable equal to 1 if the producer has any concerns related to water-quality throughout his/her fields. This variable was used within the VRT model. If a producer has concerns about water-quality, then it may be in their best interest to apply chemicals in a more efficient method, such as with a VRT applicator. A categorical variable is included that describes the slope of the selected field in Phase II (*Slope of the Field*). Producers have five different categories to place their field based on the variability and extent of the slope. (1) "Nearly level 0-2%", (2) "Even, Moderate Grade (3-9%)", (3) "Variable, Moderate Grade", (4) "Even, Steep Grade (Over 10%)", (5) "Variable, Steep Grade". This variable could prove useful in the Guidance model, because if a field contains either a variable or steep slope, then auto-steering features might prove either less effective or even present more risks to the operation. (*Soil Texture*) is another categorical variables used to determine the soil composition of the Phase II selected field. Producer's have five options to describe the primary soil texture: (1) Loam, (2) Clay, (3) Sandy, (4) Mixed, and (5) Silty. This variable will be useful within the VRT model as fields with different soil textures are more likely to benefit from variable application, whether that be derived from a sensor or from a pre-determined map based applicator. Collection and use of farm-level data, (*Data-Collection*), has also been controlled for. This indicator variable is equal to 1 if the operator has stored and accessed data via paper-copy, personal computer, or mobile device. This variable works in conjunction with (*Data-Tools*, as this indicator variable is equal to 1 if the operator has made use of any data collection tools (yield monitor, GPS mapping, etc). As these technologies increase in complexity, more tech-savvy operators may favor adoption when compared to less technology inclined operators.

5. RESULTS

Tables B.7, B.8, and B.9 contain the results from a Poisson model with sample selection for dependent variables *Guidance, Variable Rate Technology, and Drainage*, respectively. However, due to the non-linear estimation for both the selection and intensity equations, the values of the coefficients cannot be directly interpreted. To address this, the average marginal effects for the main intensity equation were included. Average marginal effects were calculated according to the traditional Average Marginal Effect (AME) framework. This method makes use of numerical derivatives for every covariate across all observations. Every observation change is averaged and replicated for all three technology models in order to compare the effects of the covariates across technologies.

Increasing the number of years a producer has adopted a multi-peril crop insurance plan by 10 units (years), implies an increase of the likelihood of adopting a guidance system by 0.99 additional years, 0.71 additional years for a VRT system, and 5.43 additional years for a subsurface tile-drainage system. It should also be noted that all of these effects are statistically significant at least at the 5% level, with the drainage estimate being significant at the 1% level. This result is surprising, as the theoretical framework predicted that adopting multi-peril crop insurance would act as a deterrent to increased adoption of these technologies. One possible explanation is the income effect generated by increased efficiency (yield gains) from using these technologies. A producer may begin to see these two options as compliments rather than substitutes if the combination of yield gains and crop insurance subsidy rates are strong enough to induce dual adoption. It could also be the case that early adopters of crop insurance are more likely to be early adopters of technology. On the other hand, as coverage level selections increase by one percentage point, results indicate a decrease -0.131 additional years for guidance systems, an increase of 0.035 additional years in VRT, and an increase of 0.069 additional years in subsurface tile-drainage systems. These results are significant at the 5% level for guidance systems, and not significant for VRT systems nor for subsurface tile-drainage systems.

While it is normally best to err on the side of caution when interpreting and applying the coefficient and average marginal effects, the general sign on both of these terms is helpful, especially for guidance systems. Both the coefficient and average marginal effect possess negative (-) signs, indicating an inverse relationship between the premium coverage level selection and the number of years a guidance system has been adopted. This adds an interesting layer to the relationship between crop insurance and the adoption of guidance systems, as the number of years a producer has possessed crop insurance was positively related to the number of years a guidance system has been adopted. Putting these two aspects together can potentially indicate that while adopting crop insurance as a whole has a positive effect on adopting guidance systems, a producer will potentially not have adopted guidance systems for the same period of time as they select higher coverage levels (which typically correlate to lower subsidy levels).

Another surprising result was that of *Age*. One would initially suspect that the relationship between the age of the producer and the number of years these technologies have been adopted for would be significant, but the results do not paint this picture. Amongst guidance systems and subsurface tile-drainage, *Age* is positively related to years of adoption, but this finding is not significant for any model. This finding makes intuitive sense, the longer a producer has been alive, the more opportunities they may have had to adopt in comparison to those younger producers. Unlike guidance systems and subsurface tile-drainage, *Age* has an inverse relationship with VRT systems. One possible explanation for this phenomenon is that VRT is arguably the most data intensive technology out of the three. If it is assumed that younger producers may possess a higher inclination to incorporate data intensive methods into their operations, this finding makes sense. However, the data-based coefficients will be needed to further analyze this possibility.

One of the main new developments within production agriculture is the use of data. Improved data collection abilities are the foundation that supports the application of these technologies. Therefore, it was anticipated that including variables accounting for the use of data-collecting devices and the form of data access would prove significant. The results for *Data Tools* indicate a positive relationship with VRT adoption. This shows that producers who use data tools have likely had a VRT system installed for a greater number of years than producers who do not use these data tools. This result is coupled with a positive selection coefficient that indicates producers who use data tools were also more likely to adopt a

VRT system in 2018. Producers who used data tools were less likely to have adopted a subsurface tile-drainage system before producers who did not report using data tools. This is an interesting result, but it is contention with the selection equation finding, which reports that producers who use data tools are more likely to adopt a subsurface tile-drainage system by 2018. Unfortunately, It was not possible to add this variable into the guidance model due to concavity issues. *Data Collection* does not tell a similar story. Subsurface tile-drainage producers who collected and accessed field level data were less likely to have adopted subsurface tile-drainage systems for as long as those who did not (this result was significant at the 1% level). This could be evidence that producers prefer to contract out this task to either the technology supplier or a third party rather than collect it themselves. Again, this variable was excluded from the guidance equation due to concavity issues with that model.

It is well known that soil is incredibly diverse in its composition, needs, and advantages. While data collection ability may expedite this process, there still could be an advantage to spending more time operating a field. This is accounted for with *Years Operated*, but only for VRT and subsurface tile-drainage as the guidance model could not account for this variable due to concavity issues. This could be due to a multitude of reasons, such as a producer becoming increasingly inexorable the longer they've been in business. Another could be that those producers who have been operating the same field have already figured out a good balance of irrigation water, seeding rates, and chemicals to apply and therefore don't see a need to acquire a VRT system to help with these issues. As the number of years a producer has been operating the same field increases, they are less likely to adopt a VRT system in 2018. This reasoning is similar to that described above. It is also found that as producers increase the number of years they have operated the same field, they are less likely to have adopted drainage for a longer period of time (this result is significant at the 1% level). This result was surprising, and it may be because of the inexorability of these producers as well. However, the results also indicate that as the number of years a producer has been operating a specific field increases, they are more likely to adopt a subsurface tile-drainage system at all (this result is significant at the 1% level). This could mean that these producers are facing differing weather patterns, or the results of this technology are being diffused, causing others who are typically resistant to change to consider adopting. One must also keep in mind that some of the operators have been in business for decades, while the development of these technologies is relatively new (except subsurface tile-drainage). A plateau effect could occur for at least some of these producers due to this fact. It is also possible that the previous owners of the field installed a subsurface tile-drainage system, so one was already present when the current operator began producing.

Another operator-specific characteristic that was controlled for is *College*. As described in the *Data and Variables* section, *College* is a binary variable equal to 1 if the primary producer has at least some college credit, and 0 otherwise. The number of years of formal education is thought to be positively related to technology adoption. Results indicate that this is the case for guidance and VRT systems, with the coefficient indicating a positive but not significant, and a positive and significant (at the 10% level) average marginal effect for guidance systems. This indicates that those producers who have at least some college credits could be more inclined to adopt guidance systems when compared to those producers who have no formal college credit. It is also worth mentioning that *College* is significant at the 10% level within the selection equation, indicating that completing at least some college credit could lead to a higher probability of adopting guidance systems by 2018 when compared to those producers who have no college experience. An interesting caveat for *College* lies with subsurface tile-drainage systems, as the two are inversely related with the intensity equation and average marginal effects (and significant at the 1% level). This indicates that those who have at least some college credit could be less likely to have adopted subsurface tile-drainage systems, and with the average marginal effect coefficient being -13.933 (indicating a 13.9 year difference in subsurface tile-drainage adoption years between those with some college credit and those with none). While education is certainly no perfect proxy for intelligence or ability, one can reasonably expect that producers who have completed higher levels of education could be more likely to be comfortable adopting complicated methods. This could be one possible explanation for this finding as subsurface tile-drainage is the least technologically complicated technology being investigated. Interestingly, the *College* coefficient for the subsurface tile-drainage system selection equation is positive (and significant at the 1% level), indicating that producers who have at least some college credit could be more likely to adopt this technology by 2018.

The economic framework showed that as the cost of farm inputs increases, the likelihood of technology adoption will increase (Equation 2.13 shows the comparative static). This theory is tested empirically using the variable *Chemical Expense*. As described in the *Data and Variables* section, this variable accounts for a producers input expense (fertilizer, pesticides, herbicides, other chemicals, etc). In particular, VRT would be considered the most relevant technology for this variable, as the main uses of a VRT system are for seeding, chemical applications, and irrigation. Results for VRT proved insignificant for this variable, so they cannot be interpreted them with much confidence. *Chemical Expense* was also included in the drainage equation, where it has a significant (at the 1% level) and negative relationship with with the intensity equation. This indicates that as chemical and fertilizer expenses increase, the average number of years a producer is likely to have adopted a subsurface tile-drainage system could decrease. The reasoning behind this finding is a little more unclear, because chemical and fertilizer use is not considered to be a main driver behind the adoption of subsurface tile-drainage systems. Typically, these systems are adopted due to various field and weather characteristics, such as field flooding tendency or heavy rains, in order to protect crop yields. However, subsurface tile-drainage has been connected to increased nutrient runoff, so one could potentially make a case for fields that don't experience severe flooding (but enough to warrant contemplating a drainage system) may care more about keeping chemicals in field as the price of these chemicals increases, and would therefore hold off on adopting until either weather conditions decline further or the cost of these chemicals decreases. Additionally, *Chemical Expense* is the reported chemical expenses for 2018, and it is difficult to explain the past adoption of a technology based on current expenses.

Equation (2.15) of the economic framework describes the anticipated effect of risk variability on the adoption of farm technology. Though the equation is ambiguous, risk variability has been accounted for through a location variable that takes into account 9 different regions as defined by the USDA ERS. These regions are discussed in detail within the *Data and Variables* section, but it should be noted that not all of the ERS regions are included in the coefficients to be analyzed. This is due to the model basing the region coefficients on "base" categories that are subsequently omitted from the results. The omitted regions are the Fruitful Rim, Heartland, and Basin and Range. However, it should be noted that the base region is the Heartland, while the Fruitful Rim and Basin and Range regions were omitted due to collinearity. Conveniently, the same regions are omitted throughout the three models, so as not to cause confusion in the interpretation. Upon comparing these regions, one must keep the differing characteristics of each region in mind with respect to technology adoption. For example, it can be seen that those producers in the Eastern Uplands region are less likely to adopt guidance systems by 2018 when compared to those producers operating out of the Heartland. This makes intuitive sense especially when comparing to the Heartland region because that area is characterized as flat, operations are typically larger, and soybeans are more prominent within the heartland region than any other region - whereas the Eastern Uplands could have less ideal topography which could hinder guidance systems.

Additionally, producers in the Mississippi Portal region are more likely to have adopted guidance systems for a greater number of years when compared to those producers in the Heartland (this result is significant at the 10% level). For similar reasons described above, this finding makes intuitive sense. The Mississippi Portal region could possess more topographic variability that might hinder guidance auto-steering systems. Producers in the Northern Great Plains have a greater likelihood of adopting guidance systems by 2018. Inversely, producers within the Southern Seaboard region could be less likely to adopt guidance systems by 2018 (this result is significant at the 1% level).

The results for VRT systems with respect to risk variability appear to be less telling. Producers within the Prairie Gateway region appear to have possibly adopted VRT systems for a longer number of years when compared to those producers within the Heartland. This result makes sense given that this region typically is drier than the Heartland region and could potentially benefit through increased efficiency of chemicals (to avoid water contamination) (this result is significant at the 5% level and the average marginal effect is significant at the 10% level). It could be anticipated that those regions which experience water issues, weather variability, and other risk-related issues could be more prone to having adopted VRT systems for a greater number of years. Evidence of this can be seen from the producers within the Prairie Gateway.

Producers adopting subsurface tile-drainage systems have also had risk variability accounted for. Two relatively distinct groups are present: those in rain heavy areas and those in drier conditions. Producers in the Northern Crescent, Southern Seaboard, and Mississippi Portal all have positive coefficients and average marginal effects (and all are significant at the 1% level). Considering the topographic characteristics of these areas, a possibly greater affinity to have adopted subsurface tile-drainage systems earlier when compared to those producers in the Heartland region makes sense. These regions, especially the Southern Seaboard and Mississippi Portal, are lower to sea-level, potentially more likely to get precipitation, and could have greater soil-compaction issues. All of these characteristics could warrant a subsurface tile-drainage system. An interesting caveat is the magnitude of the average marginal effects. All three region's marginal effects are over 20 years, which is a considerable amount of time. However, this technology has been commercially available for decades longer than the other two technologies. Conversely, those producers in the Northern Great Plains, Eastern Uplands, and Prairie Gateway all have negative coefficients, which suggests that these regions could be less likely to have adopted a subsurface tile-drainage system by 2018 when compared to the Heartland region. This also makes sense, since these regions could be better insulated from some of the water issues mentioned above. While these coefficients were significant at the 1% level, only the Eastern Uplands region contained a coefficient that was significant in the intensity equation.

Equation (2.14) of the economic framework describes the relationship between stochastic risks and the adoption of farm technology. This equation came to the conclusion that as the riskiness of an area decreases (in this case, an increase in the value of $\bar{\Theta}$), the need to adopt new technologies could decrease. To test this empirically, *Loss Cost Ratio* was implemented to measure a county's loss cost ratio averaged between 1989 - 2017 (this variable is described in greater detail in the *Data and Variables*). An increase in this variable's value indicates a higher level of riskiness over time (at the county level). Results indicate that as this variable increases, the likelihood that producers will adopt any of the three technologies by 2018 decreases (this result is significant at the 5% level for guidance systems). This result was surprising, as Equation (2.14) came to the opposite conclusion. One can potentially interpret this as farmers being satisfied with the increased indemnity payments received as relative risk increases, enough so to disincentivize the further adoption of guidance systems. Another possible explanation is simply that environmental risk could not play as significant of a role in the adoption of these technologies.

One of the perceived benefits of adopting a guidance system is the producers' ability to allow a piece of equipment steer without a human operator manually steering. Following this logic, it seems reasonable that as the number of acres operated increases, the stronger that benefit becomes. The *Total Acres Operated* coefficient is positive within the selection equation, suggesting that those producers who operate more acres could be more likely to adopt a guidance system by 2018. The selection equation coefficient is also significant at the 1% level while the intensity equation coefficient is not significant and the average marginal effect is significant at the 10% level. The effects for VRT and Drainage systems were both insignificant, but did differ in direction from each other.

Pivoting from *Total Acres Operated*, the effect of renting versus owning operated land differs between the three technologies. *Percentage of Rented Acres* displays negative for the guidance intensity coefficient, meaning that as the proportion of rented acres to operated acres increases, there's a lower likelihood that producers could have had a guidance system for as long. However, the coefficient for the selection equation remains positive and significant at the 1% level, which indicates that those same producers could be more likely to adopt this technology by 2018. For subsurface tile-drainage systems, the selection coefficient is positive, indicating that producers who rent more of their operation's land could be more likely to have had these technologies adopted by 2018 when compared to producers in other situations.

It stands to reason that as farms acquire more assets, less debt, or better interest rates, they could be more likely to at least consider adopting improvements for the business. The results indicate that as *Farm Assets* increases, these operations are more likely to had adopted a VRT system for a greater number of years, although this finding is only significant at the 10% level for the VRT selection equation. The opposite appears to be true for guidance systems - as assets increase, these producers have potentially had a guidance system for a lesser number of years, but are more likely to have adopted this technology by 2018 (all of these coefficients are significant at least the 5% level).

As described in the *Data and Variables* section, various field characteristics are accounted for. Every producer faces different challenges, and these technologies are intended to address some of these issues. Most of these field characteristics are. used as the exclusion variable, since they are relevant to the selection equation, but possibly not as relevant for the intensity equation. This is due to the fact that these characteristics could not change over time (unless these technologies alter them permanently). For example, *Slope of the Field* is a categorical variable that accounts for different grade levels as well as if the field is level or variable in its grade. Using "Nearly Level 0 - 2%" as the base level, producers operating on a field that is characterized as "Variable, Steep Grade" may be less likely to adopt guidance systems when compared to the base category. This finding is in line with the hypothesis that guidance systems may look less attractive if the field is not level or even. This could be due to worries on behalf of the operator that a malfunction could cause overturns, or other accidents due to the inconsistency of the land. Additionally, for every other slope category, producers are less likely to adopt guidance systems when compared to producers on an even and flat field. This also makes sense for the reasons presented above. It should also be noted that producers within the "Variable, Moderate Grade" category presented results that were significant at the 5% level. *Poor Drainage Concerns* indicates that producers with these concerns could be more likely to adopt a drainage system by 2018 when compared to those producers who do not share those concerns. This result is intuitive, as a drainage system could be an effective answer to a field with poor drainage (this result was also significant at the 10% level).

These results also highlight the differences between subsurface tile-drainage and guidance/VRT systems. There were more significant variables throughout the subsurface tile-drainage model when compared to the other two, and it is possible this fact showcases the fundamental differences between these technologies. Per the increased significance, the tile-drainage model was better able to identify factors that affect adoption of this technology with confidence. One possible explanation for this is the greater number of years tile-drainage has been on the market compared to the other technologies. Another is that subsurface tile-drainage is a technology that is installed and not touched (unless something breaks). It is also implemented to fix specific issues within a field: poor drainage quality. When comparing this technology to VRT, its clear that they are very different. A producer can easily visualize a field draining after installation of a tile-draiange system. However, implementing a VRT system is intended to increase average yields and decrease the variability of these yields, which is not as easily visualized. These difference could provide some possible explanations for the discrepancy between the covariates within these models.

6. CONCLUSION

This thesis examines the role that the federal crop insurance program, among other factors, plays on the adoption of Precision Agriculture Technologies (PATs) and sustainable farming practices. While other studies have examined the role of subsidized crop insurance schemes on other farming methods, this is paper is the first to extend those results to PATs within the United States. Public crop insurance markets have been examined at length, with many studies concluding that while subsidization increases enrollment, subsidization can also catalyze the presence of moral hazard. Therefore, this thesis is relevant not only for soybean producers, but for insurance administrators and policy makers as well.

The Agriculture Resource Management Survey (ARMS) was used to measure and test the theoretical framework empirically. Combining this survey with county-level data administered through the Risk Management Agency (RMA), a model was formulated to examine the relationships of these programs on PAT adoption. The empirical results show that there is evidence that producers enrolled in federal crop insurance programs could be more likely to have adopted PATs earlier than producers who were not enrolled in a crop insurance program. This could indicate that producers do not view the FCIP as a substitute for other risk management options, or that these producers may not view these technologies in the same risk-reducing lens as they may view the FCIP.

Additionally, counties that received increased levels of indemnity payments could be less likely to have had PATs adopted for a longer period of time as compared to less risky counties. This is significant if we are to assume that the average level of riskiness is likely to increase due to climate change. Results also indicate mixed results for producers who elected a higher coverage level (which possesses an inverse relationship with subsidy level), as this could potentially lead to an increased number of years of VRT and subsurface tile-drainage adoption (in comparison to producers who elected lower coverage levels), but resulted in a potentially lower number of years for guidance auto-steering adoption.

Various field specific characteristics could also potentially influence the adoption of PATs. Poor drainage concerns, moisture level, and erodibility all led to potential increases in the number of years PATs could have been adopted for (among other field characteristics). Location of the operation also led to mixed results in PAT adoption, which is understandable considering the vastly different circumstances these producers encounter. Operator specific characteristics such as age, education level, assets, debts, and aptitude with technology also contribute to the likelihood of adoption, with mixed results. This is expected and likely plays a large role in these decisions.

These results can provide useful information in understanding the decision making process for PAT adoption. These results are relevant for policy makers, as it can highlight the possible substitution effects for risk management between government sponsored programs and alternate farm specific risk management decisions. However, there are some aspects of this thesis that could be further addressed. The guidance model could not accommodate several variables that could have provided valuable information, and this issue should be addressed through future research. While using ARMS provided a rich, nationally representative data set, inclusion of more time-based technology variables could provide additional models that could also glean some more information about PAT adoption decisions. We must also remember that while a great deal of research has been dedicated to PAT adoption and benefits, they are still a relatively young suite of technologies. As PATs further develop and pass various market tests, more opportunities will arise for continued study into producer risk management decisions. While this study found a positive relationship between crop insurance participation and length of PAT adoption, there are many other aspects of the crop insurance program that were not included within this study. The inclusion of disaster payments, other crop insurance choices, and other important aspects of the FCIP could be fruitful future research endeavors.

Despite some of these minor imperfections and areas for future research, this study found that increases in enrollment years may be positively correlated with increases in the average time of adoption for these PATs. Results indicate that producers may not view the FCIP as a substitute for other risk-reducing practices as originally thought, or that the FCIP may be viewed as a risk management tool to be used in conjuncture with other risk-reducing practices and technologies. Another possibility is that producers may not view PATs with the same risk-reducing lens as they may view the FCIP. These different scenarios highlight the importance of further study to understand the basis of these participation and adoption decisions. As producers continue to face market volatility, climate change impacts, and risk fluctuations, the need to make use of different forms of risk-management practices and technologies will become increasingly crucial to agricultural production systems.

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A. FIGURES

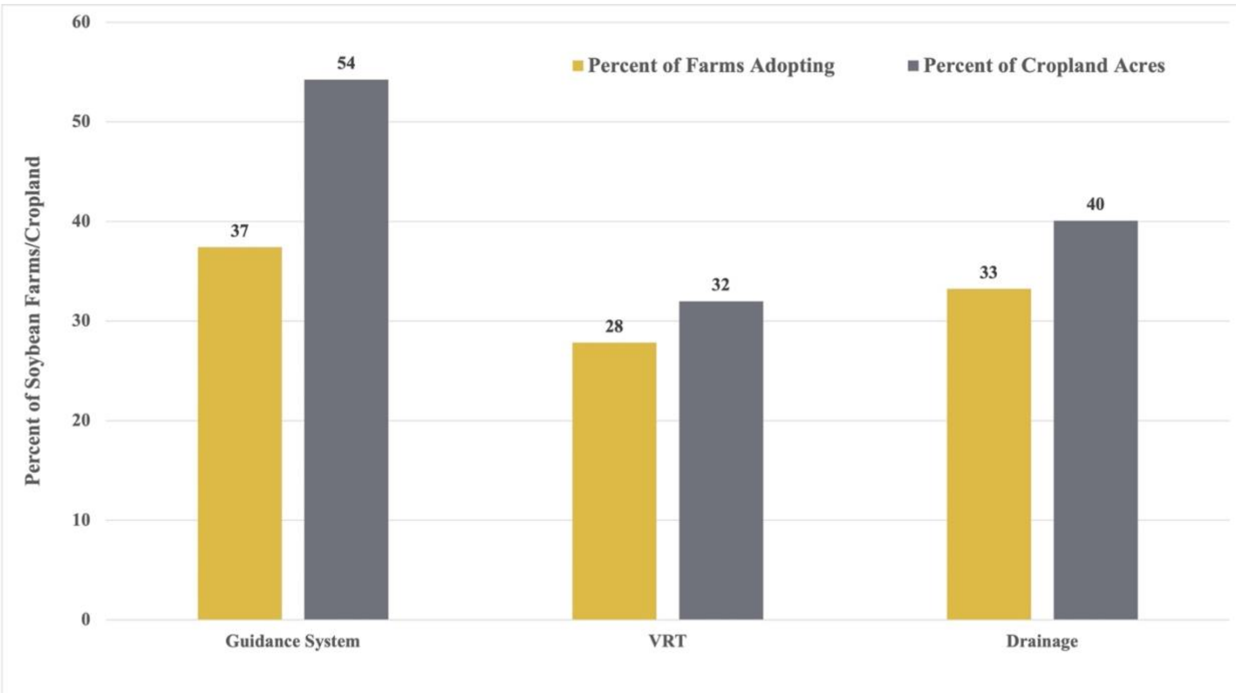

Figure A.1 Technology Adoption on Soybean Farms/Cropland Acres, 2018.

Source: USDA, ERS, “2018 Agricultural Resource Management Survey, Phase II.”

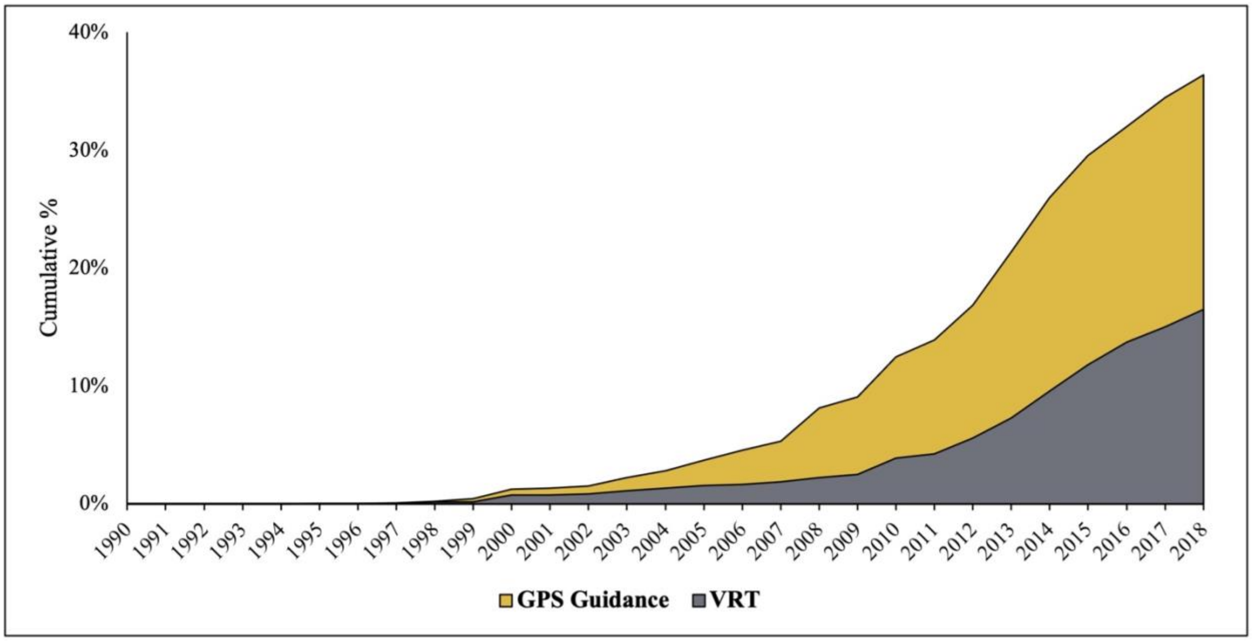

Figure A.2. Proportion of Soybean Farms Adopting Precision Agriculture Technology, 1990 - 2018.

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II."

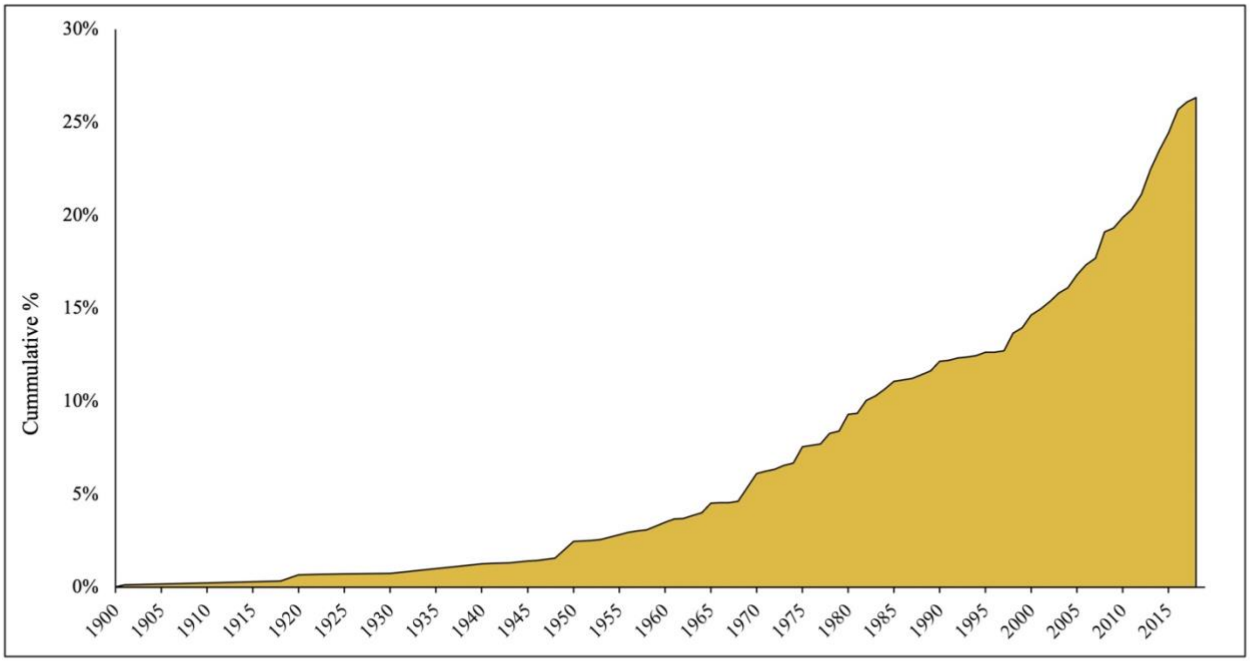

Figure A.3. Proportion of Soybean Farms Adopting Subsurface Tile Drainage, 1900 - 2018.

Source: USDA, ERS, “2018 Agricultural Resource Management Survey, Phase II.”

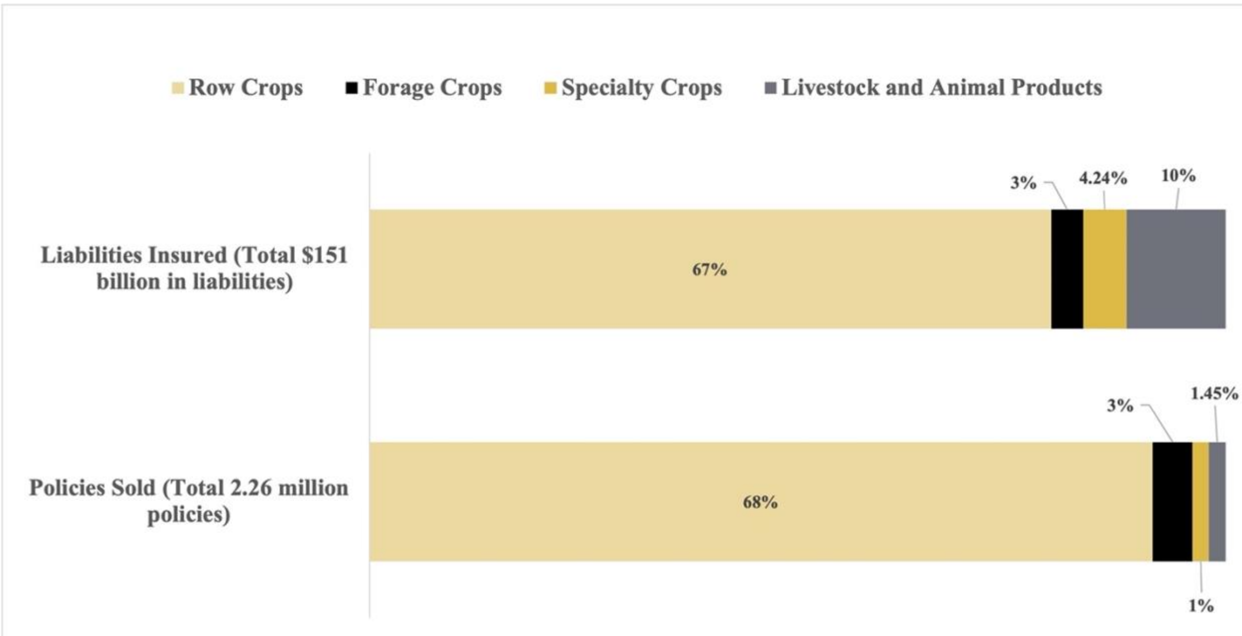

Figure A.4. Liabilities Insured and Policies Sold in 2021, by Commodity Type.

Source: USDA, RMA, “Summary of Business, 2000 – 2021.”

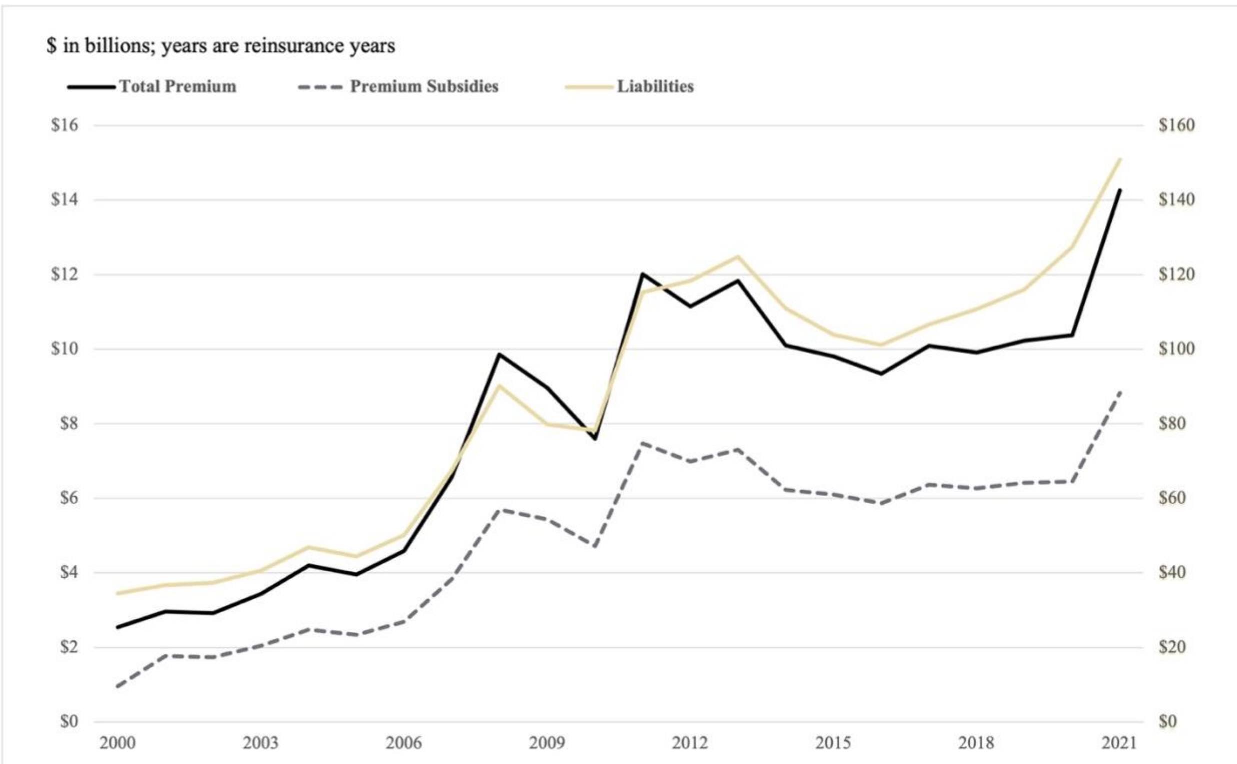

Figure A.5. Annual FCIP Total Premium, Premium Subsidies, and Liabilities, 2000 - 2021.
Source: USDA, RMA, “Summary of Business, 2000 – 2021.”

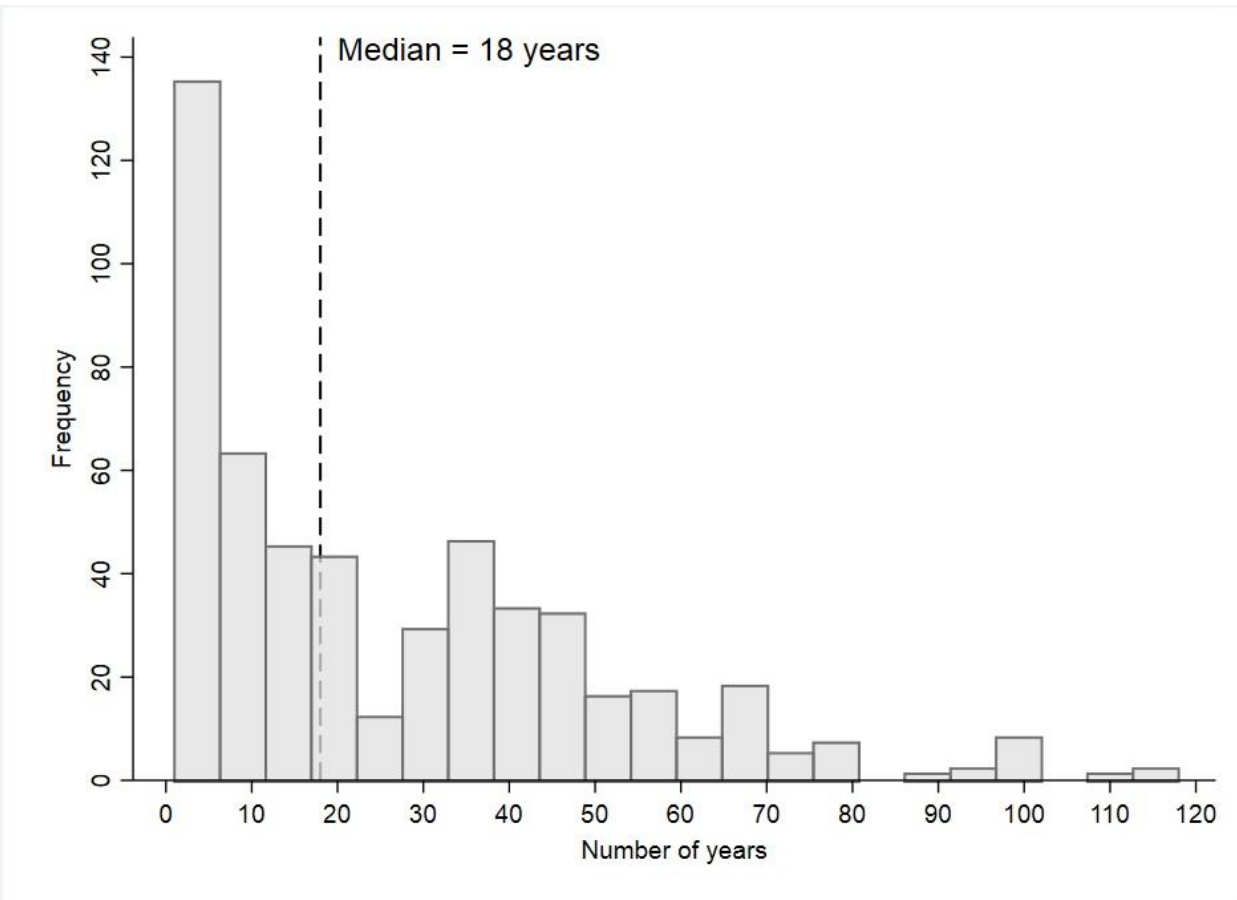

Figure A.6. Number of Years a Subsurface Tile Drainage System has been Installed.

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II."

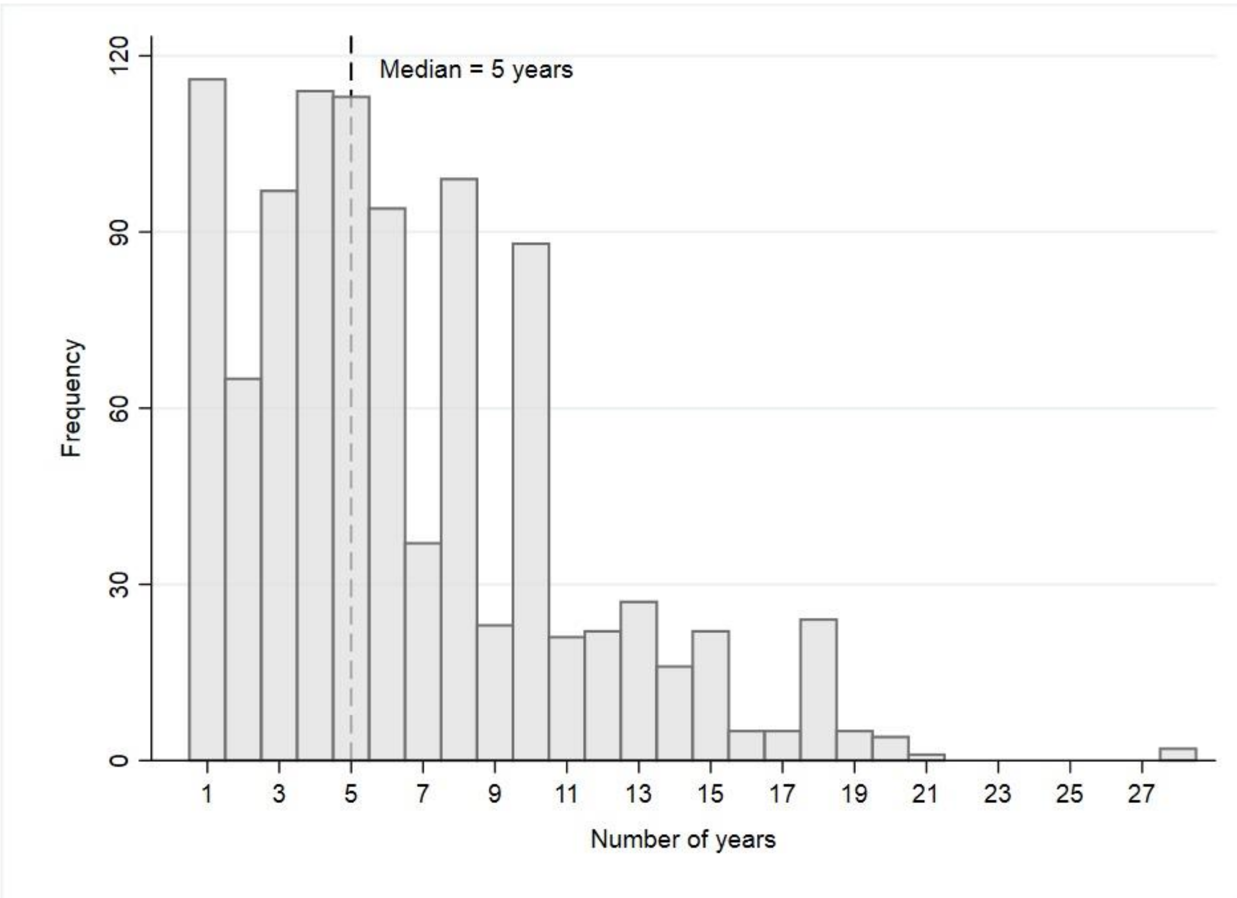

Figure A.7. Number of Years a GPS Guidance Auto-Steering System has been Installed.

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II."

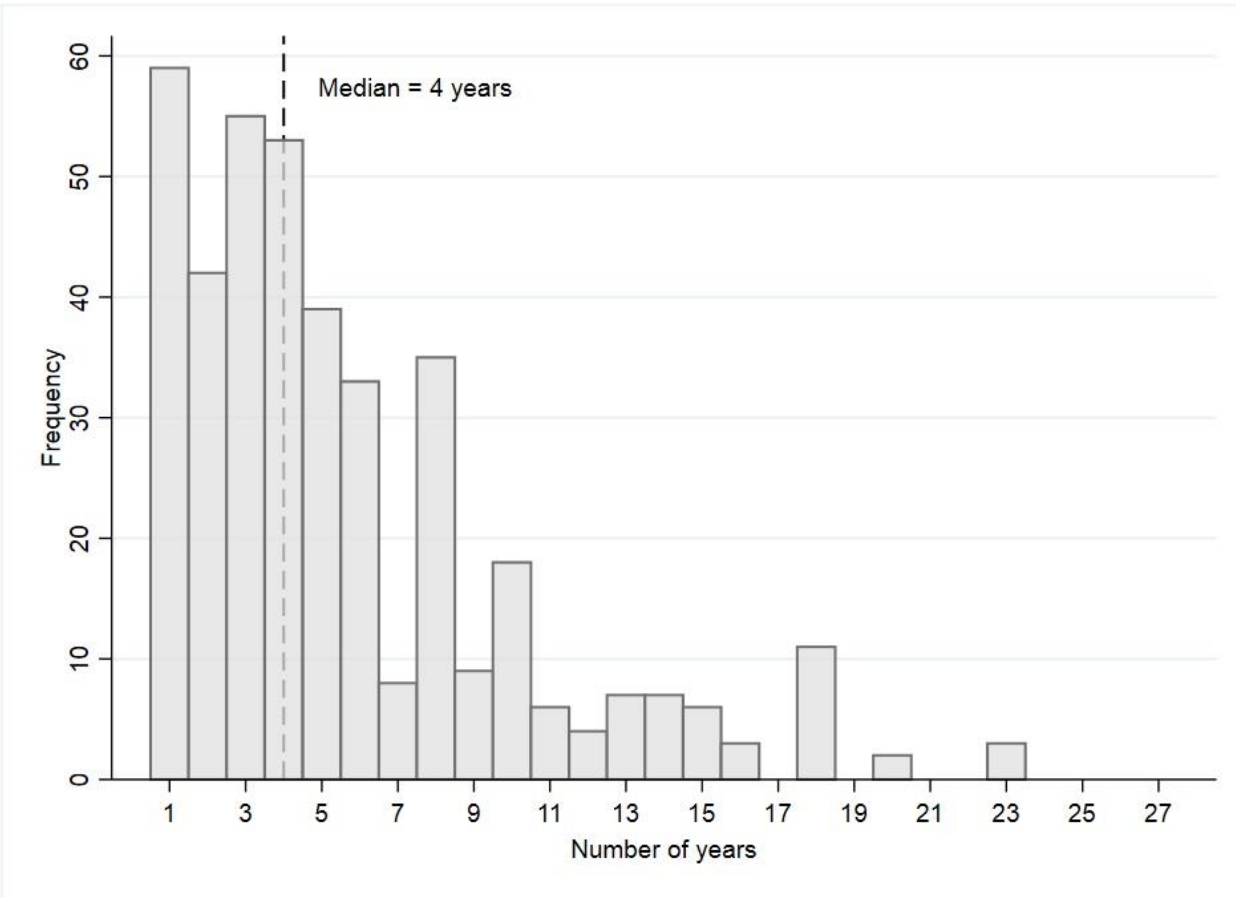

Figure A.8. Number of years a Variable Rate Technology (VRT) system has been installed.

Source: USDA, ERS, “2018 Agricultural Resource Management Survey, Phase II.”

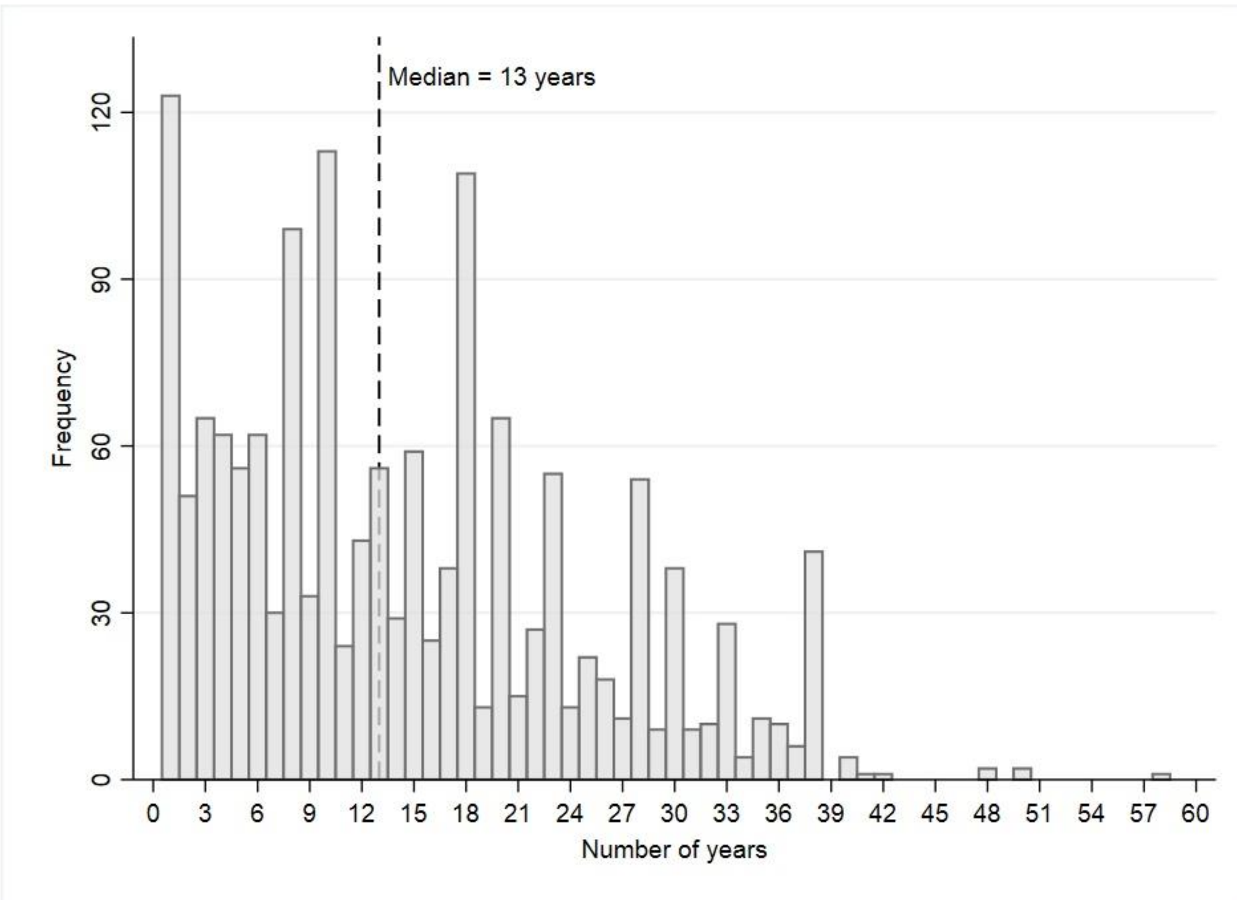

Figure A.9. Number of Years a Multi-Peril Crop Insurance Policy has been Adopted.

Source: USDA, ERS, “2018 Agricultural Resource Management Survey, Phase II.”

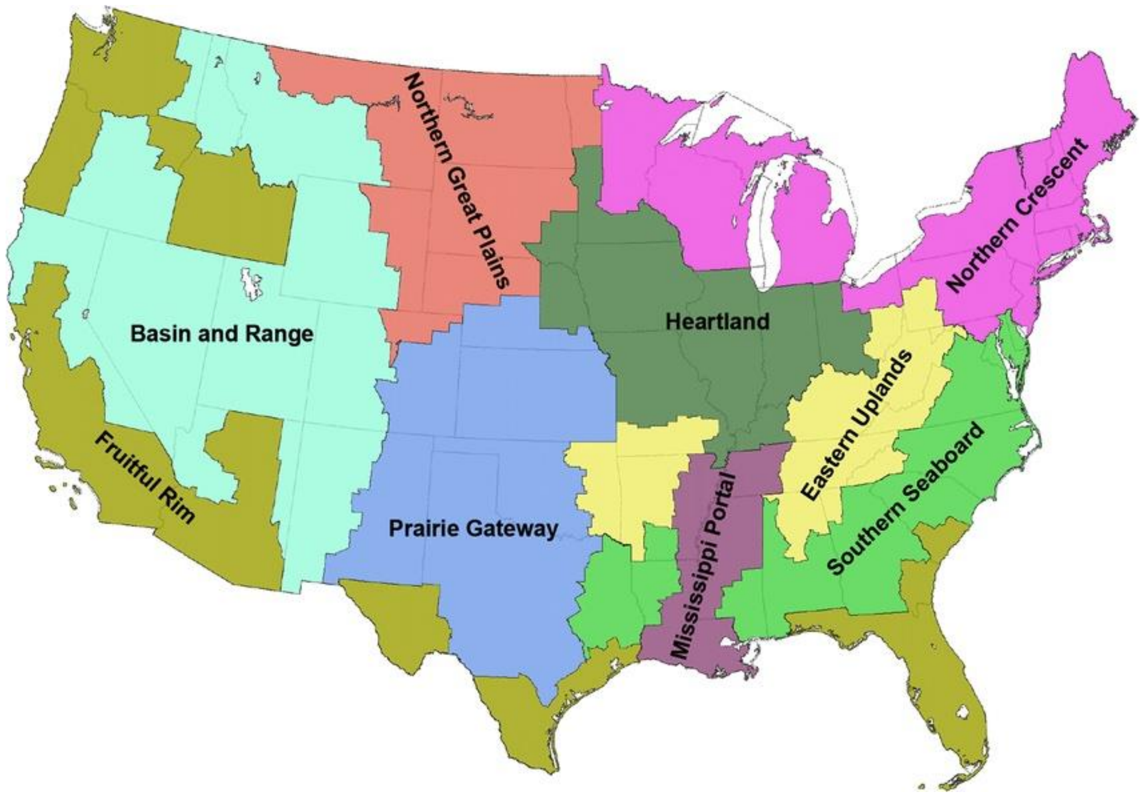

Figure A.10. ERS Farm Resource Regions.

Source: USDA, ERS, https://www.ers.usda.gov

B. TABLES

Table B.1. Major Crops, Livestock, and Livestock Products Insured in 2021

Commodity Type	Commodity	Share of Total Policies Sold	Share of Total Insured Acres	Share of Total Insured Liabilities
Row Crops	Corn	26%	19%	35%
	Soybeans	24%	18%	24%
	Wheat	13%	8%	5%
	Cotton	5%	2%	3%
Forage Crops	All Forage Crops	3%	47%	3%
Specialty Crops	Almonds	1%	0.36%	0.17%
	Grapes	0.28%	0.14%	2%
	Nursery	0.06%	N/A	1%
	Apples	0.13%	0.05%	1%
Animal Products	Milk	0.25%	N/A	7%
	Bees	0.21%	N/A	0.20%
	Cattle	1%	N/A	1%
	Swine	0.06%	N/A	1%

Source: 2021 USDA, RMA, "Summary of Business."
Note: Cattle includes dairy, feeder, and fed cattle. Corn includes sweet corn.

Table B.2. FCIP Policies Purchased in 2021

Policies Type	Share of Total Policies Sold	Share of Total Acres Insured	Share of Total Liabilities Insured
Revenue Protection	71%	46%	65%
Actual Production History	9%	2%	10%
Yield Protection	13%	5%	6%
Dairy Revenue Protection	0.25%	N/A	7%
Rainfall Index	3%	46%	0.37%
Whole-Farm Revenue Protection	0.09%	N/A	1%
All Other Policies	4%	0.19%	10%

Source: 2021 USDA, RMA, "Summary of Business."

Table B.3. Summary Statistics For Technology Variables

Variable	Description	Mean	Standard Error	95% Confidence Interval	95% Confidence Interval	Number of Observations	Survey Population Size
Guidance (=1)	Equals 1 if a GPS guidance auto-steering system was adopted by 2018, 0 otherwise	0.374	0.020	0.333	0.416	1,505.000	1,073,300.000
VRT (=1)	Equals 1 if a VRT (for any application) system was adopted by 2018, 0 otherwise	0.278	0.016	0.245	0.311	1,505.000	1,073,300.000
Drainage (=1)	Equals 1 if subsurface tile drainage was adopted by 2018, 0 otherwise	0.332	0.019	0.293	0.372	1,505.000	1,073,300.000
Guidance Years	Number of years a GPS guidance auto-steering system has beeen adopted	6.358	0.257	5.832	6.884	649.000	374,874.660
VRT Years	Number of years any VRT system has been adopted	6.240	0.330	5.565	6.914	254.000	181,690.560
Drainage Years	Number of years subsurface tile drainage has been adopted	27.136	1.357	24.361	29.911	344.000	292,659.160

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II and III."
Notes: These summary statistics were generated with 30 replications and 29 design degrees of freedom.

Table B.4. Summary Statistics For Crop-Insurance Variables

Variable	Description	Mean	Standard Error	95% Confidence Interval	95% Confidence Interval	Number of Observations	Survey Population Size
Multi-Peril Years	Number of years multi-peril insurance has been adopted	14.349	0.486	13.355	15.343	1,008.000	730,195.220
Coverage Level	The selected crop insurance coverage level	75.405	0.418	74.551	76.259	927.000	674,939.260

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II and III."
Notes: These summary statistics were generated with 30 replications and 29 design degrees of freedom.

Table B.5. Summary Statistics for Exogenous Variables Included in Poisson Models.

Variable	Description	Mean	Standard Error	95% Confidence Interval	95% Confidence Interval	Number of Observations	Survey Population Size
Age	Age of primary farm operator	58.082	0.513	57.032	59.129	1,505.000	1,073,300.000
Interest Rate	Interest rate (%) paid on farm debt	1.306	0.049	1.205	1.471	1,505.000	1,073,300.000
Education (=1)	Equals 1 if producer has at least some college experience, 0 otherwise	0.574	0.020	0.533	0.615	1,505.000	1,073,627.000
ERS Region	Represents various locations based on ERS Farm Resource Regions						
1	Heartland ERS region	0.492	0.015	0.461	0.522	1,505.000	1,073,300.000
2	North Crescent ERS region	0.138	0.016	0.106	0.170	1,505.000	1,073,300.000
3	North Plains ERS region	0.061	0.005	0.051	0.071	1,505.000	1,073,300.000
4	Prairie Gate ERS region	0.053	0.006	0.040	0.066	1,505.000	1,073,300.000
5	Eastern Uplands ERS region	0.052	0.011	0.029	0.074	1,505.000	1,073,300.000
6	Southern Seaboard ERS region	0.104	0.013	0.079	0.130	1,505.000	1,073,300.000
9	Mississippi Portal ERS region	0.101	0.008	0.084	0.117	1,505.000	1,073,300.000
Chemical Expense	Total amount of fertilizer and chemical expense	169,407.000	9382.497	150217.7	188596.4	1,505.000	1,073,300.000
Total Acres	Total acres operated by the farmer across all crops	1,527.204	67.518	1389.114	1665.295	1,505.000	1,073,300.000
Percent Rented	Percentage of total operated acres that are rented from others	0.548	0.014	0.520	0.577	1,505.000	1,073,300.000
Farm Assets	Total amount ($) of farm assets	3,263,209.000	273781.100	2703264.000	3823155.000	1,392.000	1,020,229.000
Farm Debt	Total amount ($) of farm debt	483,823.200	39094.900	403865.100	563781.200	1,392.000	1,020,229.000
Labor Cost	Total cost ($) of labor	45,907.330	5664.394	34322.350	57492.320	1,505.000	1,073,300.000
HEL (=1)	Equals 1 if any part of field is classified as "Highly Erodible Land", 0 otherwise	0.188	0.018	0.151	0.224	1,505.000	1,073,300.000
Poor Drainage (=1)	Equals 1 if producer has concerns about poor drainage, 0 otherwise	0.241	0.018	0.203	0.278	1,398.000	1,006,108.000
Wetland (=1)	Equals 1 if selected field contains a wetland	0.038	0.007	0.023	0.053	1,504.000	1,072,916.000
Soil Compaction (=1)	Equals 1 if producer has concerns about soil compaction, 0 otherwise	0.277	0.020	0.237	0.317	1,399.000	1,007,683.000
Data Tools (=1)	Equals 1 if operator used any tools to collect data, 0 otherwise	0.545	0.022	0.500	0.591	1,505.000	1,073,300.000
Data Collection (=1)	Equals 1 if operator accessed data, 0 otherwise	0.752	0.019	0.713	0.792	1,505.000	1,073,300.000
Slope							
1	Nearly level, 0-2%	0.465	0.018	0.429	0.501	1,501.000	1,071,857.000
2	Even, moderate grade 3-9%	0.333	0.017	0.298	0.368	1,501.000	1,071,857.000
3	Variable, moderate grade	0.170	0.015	0.139	0.201	1,501.000	1,071,857.000
4	Even, steep grade over 10%	0.019	0.006	0.006	0.032	1,501.000	1,071,857.000
5	Variable, steep grade	0.013	0.004	0.005	0.020	1,501.000	1,071,857.000
Primary Soil Texture							
1	Loam	0.362	0.014	0.333	0.391	1,502.000	1,072,504.000
2	Clay	0.173	0.016	0.140	0.207	1,502.000	1,072,504.000
3	Sandy	0.063	0.007	0.049	0.078	1,502.000	1,072,504.000
4	Mixed	0.371	0.021	0.327	0.415	1,502.000	1,072,504.000
5	Silty	0.030	0.006	0.018	0.042	1,502.000	1,072,504.000
Water Quality (=1)	Equals 1 if producer has concerns about water quality, 0 otherwise	0.065	0.009	0.046	0.084	1,381.000	993,369.370

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II and III."
Notes: These summary statistics were generated with 30 replications and 29 design degrees of freedom.

Table B.6. Summary Statistics for RMA Variables

Table 4. Summary Statistics on RMA County-Level Variables

Variable	Description	Mean	Standard Deviation	Number of Observations
Indemnity	Average value ($) of total county indemnity payments between 1989 - 2017	1,918,131.000	3,953,200.000	76,016.000
Premium	Average value ($) of total county premium payments between 1989 - 2017	1,917,756.000	3,638,036.000	76,016.000
Liability	Average value ($) of total county liability payments between 1989 - 2017	20,800,000.00	42,900,000.00	76,016.000
Average Loss Cost Ratio	Average loss cost ratio (per county) between 1989 - 2017	0.105	0.001	1,505.000

Source: USDA, Risk Management Agency, 1989-2017

Table B.7. Results from a Poisson Model with Sample Selection on GPS Guidance Auto-Steering

	Intensity Equation	Selection Equation	Marginal Effects
Variable Name	Coefficient	Coefficient	Coefficient
Multi-Peril Adoption (Years)	0.007**	-0.002	0.099**
	(0.003)	(0.003)	(0.047)
Age	0.004	-0.004*	0.063
	(0.003)	(0.002)	(0.042)
College	0.111	0.132**	1.517*
	(0.068)	(0.065)	(0.920)
ERS REGION			
Northern Crescent	-0.230	-0.073	-3.028
	(0.153)	(0.174)	(1.854)
Northern Great Plains	-0.107	0.790***	-1.496
	(0.110)	(0.112)	(1.516)
Prairie Gateway	-0.140	0.075	-1.924
	(0.130)	(0.139)	(1.722)
Eastern Uplands	0.027	-0.571***	0.405
	(0.199)	(0.196)	(3.013)
Southern Seaboard	0.168	-0.436***	2.699
	(0.141)	(0.116)	(2.412)
Mississippi Portal	-0.183*	0.104	-2.471*
	(0.109)	(0.112)	(1.429)
Coverage Level	-0.009**	0.013***	-0.131**
	(0.004)	(0.004)	(0.059)
Loss Cost Ratio	-1.424	-5.687**	-19.709
	(2.775)	(2.695)	(38.329)
Total Acres Operated (in 100,000's)	-0.323*	1.224***	-4.470*
	(0.188)	(0.188)	(2.681)
Percentage of Rented Acres	-0.102	0.724***	-1.411
	(0.127)	(0.134)	(1.776)
Farm Assets (in $10 millions)	-0.196**	1.220***	-2.710**
	(0.089)	(0.103)	(1.280)
Total Labor Costs (in $1 millions)	0.097	0.271	1.34
	(0.109)	(0.284)	(1.510)
SLOPE OF THE FIELD			
Even, Moderate Grade (3-9%)	(ommitted)	-0.013	(ommitted)
		(0.078)	
Variable, Moderate Grade	(ommitted)	-0.178**	(ommitted)
		(0.083)	
Even, Steep Grade (Over 10%)	(ommitted)	-0.012	(ommitted)
		(0.183)	
Variable, Steep Grade	(ommitted)	-0.415**	(ommitted)
		(0.168)	
Constant	2.978***	-1.197***	(ommitted)
	(0.460)	(0.377)	
Number of Observations	769		
Selected	413		
Non-selected	356		
Log-Likelihood	-1574.652		
Wald-$\chi^2(19)$	39.34		
Prob > χ^2	0.0006***		
ρ	-0.994		
σ	0.787		
Wald test of indep. eqns. ($\rho = 0$): $\chi^2(1) = 116.93$; Prob > $\chi^2 = 0.000$***			

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II and III."
Note: Significance at the 0.01, 0.05, and 0.10 levels are represented by ***, **, and * respectively.

Table B.8. Results from a Poisson Model with Sample Selection on VRT.

Variable	Intensity Model Coefficient	Selection Model Coefficient	Marginal Effects Coefficient
Multi-Peril Adoption (Years)	0.029**	0.011	0.071**
	(0.012)	(0.009)	(0.031)
Age	-0.005	-0.011*	-0.013
	(0.007)	(0.006)	(0.017)
Interest Rate	-0.045	-0.018	-0.110
	(0.061)	(0.053)	(0.149)
College	0.132	0.164	0.319
	(0.172)	(0.137)	(0.412)
ERS REGION			
Northern Crescent	-0.068	-0.108	-0.162
	(0.265)	(0.226)	(0.616)
Northern Great Plains	-0.314	-0.231	-0.665
	(0.291)	(0.232)	(0.565)
Praiaire Gateway	0.558**	0.398	1.843*
	(0.262)	(0.251)	(1.062)
Eastern Uplands	0.274	0.373	0.778
	(0.409)	(0.356)	(1.273)
Southern Seaboard	0.185	0.140	0.503
	(0.366)	(0.317)	(1.079)
Mississippi Portal	-0.156	0.080	-0.357
	(0.262)	(0.211)	(0.580)
Coverage Level	0.014	0.018*	0.035
	(0.013)	(0.009)	(0.032)
Chemical Expense (in $10 millions)	0.076	1.100	0.188
	(3.680)	(3.190)	(9.060)
Loss Cost Ratio	-5.115	-6.408	-12.609
	(5.561)	(5.101)	(14.087)
Total Acres Operated (in 10,000's)	-0.424	-0.416	-1.045
	(0.668)	(0.572)	(1.626)
Percentage of Rented Acres	0.282	0.090	0.696
	(0.273)	(0.231)	(0.693)
Farm Assets (in $100 millions)	1.590	2.800*	3.920
	(1.860)	(1.650)	(4.620)
Farm Debts (in $10 millions)	0.673	-0.0485	1.660
	(0.868)	(0.846)	(2.150)
Total Labor Cost (in $1 millions)	1.120	0.819	2.770
	(0.944)	(0.795)	(2.270)
Data Tools	0.736**	1.009***	1.581***
	(0.333)	(0.167)	(0.468)
Data Collection	-0.351	-0.003	-0.984
	(0.291)	(0.200)	(0.915)
Years Operating	-0.012	-0.016**	-0.030
	-0.01	(0.007)	(0.024)
SOIL TEXTURE TYPE			
Clay	(ommitted)	-0.169	(ommitted)
		(0.166)	
Sandy	(ommitted)	-0.027	(ommitted)
		(0.255)	
Mixed	(ommitted)	-0.056	(ommitted)
		(0.138)	
Silty	(ommitted)	-0.037	(ommitted)
		(0.384)	
SLOPE OF THE FIELD			
Even, Moderate Grade (3-9%)	(ommitted)	-0.179	(ommitted)
		(0.136)	
Variable, Moderate Grade	(ommitted)	0.009	(ommitted)
		(0.172)	
Even, Steep Grade (Over 10%)	(ommitted)	0.626	(ommitted)
		(0.402)	
Variable, Steep Grade	(ommitted)	-0.207	(ommitted)
		(0.533)	
Water Quality Concerns	(ommitted)	0.171	(ommitted)
		(0.221)	
Highly Erodible Land	(ommitted)	0.255	(ommitted)
		(0.161)	
Constant	-0.379	-1.610	(ommitted)
	(1.343)	(0.998)	
Number of Observations	641.000		
Selected	137.000		
Non-selected	504.000		
Log-likelihood	-639.160		
Wald-$\chi^2(19)$	29.960		
Prob > χ^2	0.0929*		
ρ	0.894		
σ	0.806		
Wald test of indep. eqns. ($\rho = 0$): $\chi^2(1) = 3.54$; Prob > $\chi^2 = 0.0600$*			

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II and III."
Note: Significance at the 0.01, 0.05, and 0.10 levels are represented by ***, **, and * respectively.

Table B.9. Results from a Poisson Model with Sample Selection on Subsurface Tile-Drainage

	Intensity Equation	Selection Equation	Marginal Effects
Variable	Coefficient	Coefficient	Coefficient
Multi-Peril Adoption (Years)	0.014***	-0.005	0.543***
	(0.002)	(0.008)	(0.100)
Age	0.002	-0.013**	0.096
	(0.002)	(0.006)	(0.076)
Interest Rate	0.013	-0.021	0.520
	(0.018)	(0.055)	(0.733)
College	-0.344***	0.387***	-13.933***
	(0.049)	(0.137)	(2.291)
ERS REGION			
Northern Crescent	0.715***	-0.303*	31.758***
	(0.071)	(0.183)	(3.384)
Northern Great Plains	-0.415	-1.978***	-10.326
	(0.625)	(0.306)	(12.585)
Prairie Gateway	-0.070	-1.304***	-2.049
	(0.174)	(0.264)	(4.957)
Eastern Uplands	-1.646*	-1.483***	-24.529***
	(0.865)	(0.413)	(5.189)
Southern Seaboard	0.549***	-1.718***	22.238**
	(0.203)	(0.347)	(10.623)
Mississippi Portal	0.737***	-2.013***	33.129***
	(0.206)	(0.301)	(12.671)
Coverage Level	0.002	0.035***	0.069
	(0.003)	(0.010)	(0.129)
Chemical Expense (in $1 millions)	-0.822***	0.426	-53.600***
	(0.332)	(0.495)	(21.700)
Loss Cost Ratio	-3.353	0.638	-132.908
	(2.286)	(5.139)	(90.526)
Total Acres Operated	0.00002	-0.0001*	0.0009
	(0.0001)	(0.0001)	(0.002)
Percentage of Rented Acres	0.177**	-0.369	7.028**
	(0.082)	(0.234)	(3.321)
Farm Assets (in $100 millions)	0.150	2.170	9.760
	(0.888)	(1.840)	(57.900)
Farm Debts (in $10 millions)	-0.484	1.220	-14.500
	(0.353)	(0.970)	(2.310)
Total Labor Costs (in $100,000's)	-0.131	-0.031	-8.530
	(0.049)	(0.066)	(3.460)
Years Operated	-0.005***	0.016***	-0.202***
	(0.002)	(0.006)	(0.078)
Data Tools	-0.004	0.416***	-0.159
	(0.070)	(0.151)	(2.773)
Data Collection Type	-0.244***	-0.027	-10.446***
	(0.058)	(0.183)	(2.792)
Wetland	(ommitted)	0.191	(ommitted)
		(0.320)	
Soil Compaction Issues	(ommitted)	-0.011	(ommitted)
		(0.154)	
Poor Drainage Concerns	(ommitted)	0.295*	(ommitted)
		(0.154)	
Highly Erodible Land	(ommitted)	-0.265	(ommitted)
		(0.162)	
Constant	3.395***	-2.353**	(ommitted)
	(0.421)	(1.011)	
Number of Observations	681		
Selected	201		
Non-selected	480		
Log likelihood	-1082.188		
Wald-χ^2(19)	313.2		
Prob > χ^2	0.000		
ρ	-0.357		
σ	0.956		
Wald test of indep. eqns. ($\rho = 0$): $\chi^2(1) = 13.52$; Prob > χ^2 = 0.0002***			

Source: USDA, ERS, "2018 Agricultural Resource Management Survey, Phase II and III."
Note: Significance at the 0.01, 0.05, and 0.10 levels are represented by ***, **, and * respectively.