Effects of Crop Insurance on Farm Survival

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Abstract

Over the last two decades, the U.S. federal crop insurance program expanded rapidly and about 300 million acres of farmland are insured by the program today. Despite growing importance of crop insurance programs, little is known about the relationship between crop insurance and farm survival. We first conceptually describe how crop insurance can affect farm survival to motivate our empirical strategy. Using a farm-level panel dataset, we parametrically and semi-parametrically estimate the effects of crop insurance on farm survival with several different identification strategies. Our preferred specification using propensity score matching method indicates that crop insurance lengthens farm survival year by seven years and reduces the probability of farm exit by about 70%. The positive and significant effect of crop insurance on farm survival remain robust across different specifications.

Key words: Crop insurance, farm survival, survival analysis, propensity score matching

JEL codes: Q12, Q18

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Introduction

Producers face various risks in their revenue stream due to unexpected changes in price and quantity brought about by exogenous factors such as adverse weather, crop pests or diseases, and unpredictable changes in demand. Over the past 20 years, the U.S. federal crop insurance program expanded rapidly and more than 298 million acres of farmland with liabilities in excess of $102 billion are covered by crop insurance as of 2015 (Risk Management Agency 2015). Globally, many countries support crop insurance programs that can assist farmers to cope with such risks (Mahul and Stutley 2010). Despite global expansion of crop insurance programs, little is known about how crop insurance affects farm survival.

This article investigates how crop insurance affects farm survival. By using a farm-level panel dataset from the Kansas Farm Management Association (KFMA), we provide empirical evidences on positive effects of crop insurance on farm survival from parametric and semi-parametric estimations. We carefully identify the effects of crop insurance on farm survival by employing propensity score matching.

The Crop Insurance Reform Act of 1994 required farms to participate in the federal crop insurance program in order to be eligible for the farm bill commodity programs. The mandatory provision of crop insurance was later repealed in 1996. Therefore, farms were required to have crop insurance to receive government payments in 1995, but not in years following 1995. Thus, we compare farms that participated in the federal crop insurance program in 1996 to those farms that did not participate in the program in 1996. In other words, we investigate survivability rates for farms that instantly opted out from the federal crop insurance program in 1996 versus farms that participated.

Crop insurance can lengthen farm survival time by providing indemnity payments when farms have financial shocks from declines in crop prices or yields. This argument is supported by previous research that find financial constraints are likely to increase the probability of firm’s exiting the market (Vartia 2004; Bridges and Guariglia 2008; Musso and Schiavo 2008). Hence, some argue that crop insurance can ultimately increase farm survivability.

On the other hand, others may argue that crop insurance does not affect survivability. For example, the government offers disaster assistance to help producers recover financially from natural disaster events. The continuation of ad hoc disaster assistance has prevented the need for crop insurance adoption (Harwood and Novak 2001), which is consistent with Innes (2003) that *ex ante* crop insurance deters *ex post* disaster relief. Additionally, producers have other means to manage risk through contracts, diversification, government programs, off-farm income, savings, and storage. Thus, crop insurance may be mostly used as a way to transfer money rather than reducing risks.

There have been several studies that have explored factors that influence farm survival. These factors include farm characteristics (Kimhi and Bollman 1999; Weiss 1999; Glauben, Tietje, and Weiss 2006; Breustedt and Glauben 2007), subsidy decoupling (Kazukauskas et al., 2013), marketing strategy (Foltz 2004), state aid (Heim et al. 2017), cooperative extension (Goetz and Davlasheridze 2017), and government payments (Ahearn, Yee, and Korb 2005; Key and Roberts 2006). However, little is known how crop insurance impacts survival of individual farms. To date, this research is unique as it is the first to assess the effect of crop insurance on farm business survivability.

The remaining sections of the paper are structured as follows. Next, we provide a conceptual framework on how crop insurance affects farm survival. This is followed by discussion of our data and definition of a farm exit. Then, the empirical framework is presented and potential endogeneity problem is discussed. Subsequently, propensity score matching methods are described. The estimated effects of crop insurance on farm survival from Ordinary Least Squares and the Cox proportional hazards model are presented. Finally, we conclude by describing the implication of the results.

How Crop Insurance Affects Farm Survival

Empirical studies reveal that firm-level financial distress is likely to decrease the probability of firm survival in the market. Musso and Schiavo (2008) found that financial constraints, a synthetic index incorporating seven different variables – size, profitability, liquidity, cash flow generating ability, solvency, trade credit over total assets and repaying ability – significantly impact the probability of exiting the market. Vartia (2004) indicates that financial distress in Finnish manufacturing reduce the probability of firm survival. Bridges and Guariglia (2008) argued that lower collateral and higher leverage increases the probability of firm failure in the UK and emphasized the role of global engagement to shield firms from financial constraints.

Previous studies have established conceptual frameworks for the role of a risk management tool. Risk management aids in the reduction of various cost by providing stable internal cash flows such as expected costs of financial distress (Mayer and Smith 1982), the financing cost (Froot, Scharfstein, and Stein 1993).

An agricultural producer has the option of using several risk management tools to reduce production or yield risk, and crop insurance is known as the key risk management tool for producers. Crop insurance reduces loan losses for agricultural lenders (Lee and Djogo 1984) and improves liquidity and farm survival for a representative highly leveraged farm

(Pfleuger and Barry 1987). Thus, from past research, we can deduce that crop insurance, as a risk management tool, may allow producers to stay in business longer by mitigating a farm's financial distress.

To motivate the empirical approaches, we conceptually describe how crop insurance affects farm survival using a simple stochastic dynamic model. We utilize a real option approach developed by Dixit (1989). For the illustrative purpose, we assume the exogenous assignment of crop insurance.[1] We describe how crop insurance changes the revenue threshold that triggers exit of farms.

Suppose a farm has two states: an active state $(s = 1)$ and an idle state $(s = 0)$. Here, we only consider the exit threshold, R_L, that triggers a change in states from $(s = 1)$ to $(s = 0)$. We assume that the revenue of the farm follows a geometric Brownian motion. Thus, the stochastic revenue of the farm follows

(1) $$dR(t) = \alpha R(t)dt + \sigma R(t)dz$$

where $R(t)$ is the revenue of the farm, α is the drift parameter, σ is the variance parameter, dt is the increment in time, and dz is the increment of a Wiener process.

The expected net present value of farming in the idle state $(s = 0)$, $V_0(R)$, can be expressed as

(2) $$V_0(R) = A_1 R^{\beta_1} + A_2 R^{\beta_2}$$

where A_1 and A_2 are constants and β_1 and β_2 are the solutions of the differential equation. Similarly, $V_1(R)$, the expected net present value of farming in the active state $(s = 1)$ is

(3) $$V_1(R) = B_1 R^{\beta_1} + B_2 R^{\beta_2} + \frac{R}{(\rho-\alpha)} - \frac{C}{\rho}$$

where B_1 and B_2 are constants, ρ is the discount rate, and C is the variable cost. The farm pays the transaction cost for a farm to exit, E, to transit from the active state to the idle state. The exit threshold that triggers a farm exit, R_L, should satisfy a pair of conditions, the value matching condition

(4) $V_0(R_L) = V_1(R_L) - E$

and the smooth-pasting condition

(5) $V_1'(R_L) = V_0'(R_L)$.

The value-matching condition (equation (4)) states that R_L is determined at the point where the expected net present value of the farm in the idle state coincides with the expected net present value of the farm in the active state minus the transaction cost for a farm exit (E). The smooth-pasting condition (equation (5)) shows that the expected net present value of the farm in the idle state should be smoothly tangent to the expected net present value of the farm in the active state at the point R_L.

Solving these simultaneous equations (equation (4) and (5)), equation (6) provides the analytical solution of R_L.[2]

(6) $R_L = (\frac{\beta_2}{\beta_2 - 1})(\rho - \alpha)(\frac{C}{\rho} - E)$

Now we compare the derived exit thresholds of farming for 1) a farm without crop insurance, and 2) a farm with crop insurance. For a farm with crop insurance, the revenue flow has a smaller variance due to crop insurance indemnity payments. Also, because the U.S. crop insurance program is highly subsidized, it also increases the expected profit.[3]

Similar to Dixit (1989), we can show that 1) R_L increases as σ decreases, and 2) R_L

decreases as α increases from equation (6).[4] In our context, the above findings can be interpreted as that crop insurance reduces the variance of the revenue process (i.e., decreases in σ) and it leads to a higher R_L while crop insurance increases expected profit (i.e., increases in α) and it leads to a lower R_L.

Figure 1 illustrates the revenue flows and the exit thresholds of a farm without crop insurance and a farm with crop insurance. The solid line represents the revenue of the farm without crop insurance. The farm without crop insurance would exit if the revenue falls below the exit threshold, R_L. Suppose crop insurance increases the drift parameter and decreases the variance of the revenue flow (represented by the dash-dotted line in figure 1). The exit threshold may decrease ($R_{L,CI\ 1}$) or increase ($R_{L,CI\ 2}$). The change in the exit threshold depends on the degrees of changes in the drift parameter and the variance caused by crop insurance participation.

Under this illustrative conceptual framework, farms exit if the revenue falls below the exit threshold and the effect of crop insurance on the exit threshold is ambiguous. The probability of the revenue falling below the exit threshold would be lower for the farm with crop insurance unless the exit threshold increases by a large degree. Although the illustrative conceptual framework suggests that crop insurance is less likely to trigger the exit threshold, empirical investigation is necessary to test this hypothesis.

Data and Descriptive Statistics

We use a farm-level panel dataset from the Kansas Farm Management Association (KFMA). KFMA collects detailed accounting and production information from its members such as farm characteristics, crop production, livestock production, farm income, farm expense, depreciation, farm assets and liabilities, non-farm income and expense, and non-farm assets and liabilities.[5]

A panel of 1,016 farms for the period 1996 to 2015[6] is used and compare two groups of farms: 1) farms who opted out from the federal crop insurance program after the 1996 repeal of the mandatory provision in the 1994 Act, and 2) farms who continued to participate in the federal crop insurance program after the 1996 repeal. In 1996, 893 farms reported purchasing crop insurance while the remaining 123 farms did not report purchasing any crop insurance products. The focus of this study is on how long the farms we observed in 1996 survived throughout our sample period.

The definition of farm exit is crucial in farm survival analyses. Key and Roberts (2006) used Census of Agriculture data that includes all U.S. farms. They defined a surviving year as how long the farm has been operating before the farm no longer appeared in the Census data. Using data from the French Administrative Direction of Statistics (INSEE), Bontemps et al. (2013) defines a cheese firm as out-of-business if it is no longer observed in the dataset. The underlying assumption of these papers is that if firms no longer respond to the government survey then they are considered out-of-business.

Producers who participate in KFMA may not renew their annual membership, for unknown reasons, but continue to operate their farm. Table 1 presents how long a farm consecutively left the KFMA for each different starting year from 1995 to 1999. If a farm left the dataset more than two times, we count the longest consecutive missing years. The average length of consecutive missing years was between 2.44 to 2.74. This suggests that if a producer does not renew their membership (i.e., disappeared from the KFMA dataset) for more than two years from the last analysis year, 2015, it is more likely that the farm has exited the business rather than temporarily left the KFMA.

Therefore, this study defines farm exit as a farm not actively participating in KFMA for more than two years from the last year in the analysis, 2015, to take into account the temporary absence of some farms in our data. In other words, we assume a farm has survived even though the farm has not been observed in the KFMA dataset after 2013.

Table 2 illustrates how farm exits are defined in this study. The time periods evaluated are measured in years, over the period of 1996 – 2015. An exitor and a stayer are defined based on the years of absence from the last participation year, 2015, in KFMA. Farms 1-3 are considered a stayer since Farm 1 did participate in KFMA all years, Farm 2 and Farm 3 did not participate in KFMA for one and two years, respectively, from the last participation year, 2015 (Table 2). Farm 2 and Farm 3 are likely to reappear in the KFMA dataset rather than exiting farming since participating KFMA members temporarily left the dataset for two years on average. On the other hand, Farm 4 and Farm 5 are treated as an exitor as they did not participate in KFMA for three and four years from the last participation year, 2015, respectively. We assume those farms exited the business.

Table 3 presents summary statistics of selected farm characteristics for 1996, 2015, the first and last year of the analysis, respectively, and overall time period 1996-2015. Among 1,016 farms operating in 1996, 278 (27.7%) farms were in business in 2015.[7] Farms that survived in 2015 are likely to have higher total crop acres, higher crop labor percentage, higher tenure, higher non-farm income and lower debt-to-asset ratio compared to farms operating in 1996. If these variables are also correlated with the crop insurance purchasing decision, it will lead to a biased estimate of crop insurance. In the following section, we introduce several ways to have an unbiased estimate of crop insurance.

Estimation Framework

To estimate effects of crop insurance on farm survival, two estimation models are employed: 1) Ordinary Least Squares (OLS), and 2) Cox Proportional Hazard Model. In this section, these two models are first described followed by a discussion concerning a potential endogeneity problem. We then discuss how the endogeneity problem is mitigated by discussing the Propensity Score Matching (PSM) methods.

Econometric Models

The estimation equation of the first model, OLS, is defined by

(7) $$y_i = \beta_0 + \beta_1 D_i + B'X_i + \varepsilon_i$$

where y_i is the length of farm survival for farm i, D_i is a dummy variable that equals to one if farm i had crop insurance in 1996 and equals to zero otherwise, X_i is a vector of control variables, and ε_i is an error term.

The length of farm survival for farm i, y_i, is computed by subtracting the initial analysis year, 1996, from the last year the farm i appears in the dataset. For some farms that disappeared for one or two years from the last analysis year, t, the length of farm survival is 20 years (2015 – 1996), since those farms are considered a stayer (table 2).

If D_i is exogenous to the length of farm survival, the estimated coefficient of D_i (β_1) in equation (7) would be the average treatment effect of crop insurance on farm survival and can be interpreted as a causal relationship. However, crop insurance participation, D_i, is not randomly assigned and it is determined by other farm characteristics that affect farm survival. The potential endogeneity issue and our identification strategy used to address this are described in a later section.

The survival lengths are left-truncated since a producer must survive to a sufficient year since we begin observing businesses in 1995. For example, if a farm was initiated in 1985 and is observed in the KFMA dataset in 1995, this observation is left-truncated at ten years. By accounting for left truncation in the estimated likelihood function associated with the Cox proportional hazard model, we can mitigate the problem of length-biased sampling. In addition to left truncation, an observation is terminated before all farms' survival are realized (right censoring). If a farm did not exit at the end of the study's time frame, 2015, we can no longer follow up with those farms. Both left truncation and right censoring problems are taken into consideration with the Cox proportional hazard model (Cox 1972).

The Cox proportional hazard model is used to estimate the effect of crop insurance on the probability of a farm exit. For a farm that survived until time t, the conditional probability of exiting after time t is called a hazard function and is displayed as follows

$$h(t; D_i, X_i) = h_0(t) \exp(\gamma D_i + \Gamma X_i) \quad (8)$$

where $h_0(t)$ is the baseline hazard function. The Cox proportional hazard model is a semi-parametric model consisting of both nonparametric $h_0(t)$ and parametric components $exp(\gamma D_i + \Gamma X_i)$. Again, the crop insurance participation variable, D_i, is potentially endogenous to the conditional probability of a farm exit.

Endogeneity

Crop insurance purchase decisions are not randomly assigned. Farm characteristics such as crop acreage, non-farm income, and debt-to-asset ratio may affect both farm survival and crop insurance purchase. For example, Sherrick et al. (2004) found that the likelihood of purchasing crop insurance is likely to be higher for farms that have larger crop acreage and more highly leveraged and older producers with less tenure.

Table 4 presents descriptive statistics of selected farm characteristics for the two groups: 1) farms with crop insurance in 1996, and 2) farms without crop insurance in 1996. It shows that the treatment group and control group for the covariates are statistically different except for nonfarm income. Farms that purchased crop insurance in 1996 have larger total crop acreage, younger operators, higher percentage of labor devoted to crops, lower ratio of owned acres to total acres operated (Tenure), and a higher debt-to-asset ratio.

Table 5 indicates that crop insurance purchases are correlated with farm characteristics, crop labor percentage, and total acres operated. As producers specialize in crop production and have more total crop acreage, they tend to purchase crop insurance. This clearly shows that these variables are correlated with both crop insurance purchasing decisions.

To control for the systematic differences between farms that purchased crop insurance and those that did not purchase crop insurance, farm characteristics can be used as control variables. An alternative approach to mitigating the endogeneity problem is using the PSM methods. Both approaches, OLS with control variables and PSM, are used in this analysis and the results are presented below.

Propensity Score Matching

We match farms that purchased crop insurance to similar farms that did not purchase crop insurance based on the similarities of the selected farm characteristics by employing the PSM method.[8] The propensity score is the probability of being assigned into a treatment group given pre-treatment characteristics. According to Rosenbaum and Rubin (1983), if a potential outcome is independent of a treatment conditional on a vector of covariates x (CIA: conditional independence assumption), the outcome is independent of the treatment conditional on the propensity score, the probability of receiving treatment. It can be expressed as

(9) $y_0, y_1 \perp D|x \Longrightarrow y_0, y_1 \perp D|p(x)$

where y_0 is outcome for the treatment group, y_1 is outcome for the control group, $p(x)$ is the propensity score, x represents observable characteristics, and D denotes treatment.

After matching the two groups, the potential endogeneity bias is mitigated since the matching equalizes the observable farm characteristics. Recall, the treatment group (D = 1) denotes farms that purchase crop insurance and control group (D = 0) is those farms that that did not purchase crop insurance.

The propensity score, $p(x)$, can be estimated by a logit model for the likelihood of being assigned into the treatment group with a set of explanatory variables that may affect the likelihood (equation (10)). That is, the propensity score is the conditional probability of purchasing crop insurance given pre-treatment characteristics x: crop acres, operator's age, crop labor percentage, debt-to-asset ratio, ratio owned acres to total acres operated, and non-farm income.

(10) $p(x) = Prob(D = 1|x) = E(D|x)$

Following Sherrick et al. (2004), six input variables are used in estimating equation (10): crop acres, operator's age, crop labor percentage, debt-to-asset ratio, a ratio owned acres to total acres operated, and non-farm income. The same variables, except livestock income, are used as the previous study to derive the propensity score. Instead of the livestock income variable, this study uses crop labor percentage, an index of the farm's diversification.

The nearest neighbor matching algorithm is employed and used one-to-one matching method. A caliper is the distance which is acceptable for any match. If an observation is outside of the caliper, it is dropped from the sample. Even though a large number of observations are likely to be dropped from the sample as the caliper gets small, the small caliper allows one to match observations with more similar characteristics. Three different caliper sizes used in this study include: 1) a caliper size of 0.25 times standard deviation (PSM 1), 2) a caliper size of 0.01 times standard deviation (PSM 2), and 3) a caliper size of 0.01 times standard deviation (PSM 3).

Using the propensity score, $Prob(D = 1|x)$, where x is pre-treatment control variables and D is a dummy variable for the treatment, the impact of crop insurance on survival year can be measured as the average treatment effect on the treated (ATT). ATT is obtained by averaging the impact of crop insurance of the treatment conditioning on the treated, farms that purchase crop insurance. ATT have a causal inference and it is interpreted as the average causal effect of crop insurance purchasing because crop insurance purchasing is randomly assigned conditional on the propensity score. In this study, ATT implies how much longer the insured farms survived as a consequence of purchasing crop insurance. Per the propensity score theorem and CIA (equation (9)), we estimate the conditional average treatment effect on treated.

Results

Table 6 presents the comparison results between the treatment and control groups of key farm characteristics. After matching, the differences in mean between the treatment and control groups are prone to get smaller across all farm characteristics variable, except non-farm income and debt-to-asset ratio.[9]

Figures 2 and 3 present the Kaplan-Meier estimation results. Farm survival probability is estimated for the treatment group and the control group for the 20-year window using both the unmatched samples and matched samples. Figure 2 displays the estimated Kaplan-Meier survival curves for farms that purchase crop insurance and for farms that did not purchase crop insurance from the unmatched sample. Survival rates are higher for farms that purchase crop insurance; however, the difference in survival rates could be attributed to other farm characteristics. If crop insurance purchase decision is positively (negatively) correlated with other factors that increase farm survival rates, figure 2 may overestimate (underestimate) the impact of crop insurance.

To account for the possibility of these other farm characteristics impacting farm survival rates, Kaplan-Meier survival curves were estimated for both groups from the matched sample. Figure 3 shows there is an increase in probability of surviving between the two groups after matching. The results suggest there is a positive effect of crop insurance on farm survival.

Table 7 presents the results of the OLS estimation under five different specifications. In the first two columns, we present the OLS results with the unmatched sample. While the first specification employs only a crop insurance variable, D_i, the second specification employs not only a crop insurance variable, D_i, but other control variables. In the last three columns, OLS results are presented using the matched sample with three different caliper specifications: 1) a caliper size of 0.25 standard deviation (PSM 1), 2) a caliper size of 0.1 standard deviation (PSM 2), and 3) a caliper size of 0.01 standard deviation (PSM 3).

The results in the first column shows that the treatment group tends to survive about three years longer than the control group. Notice that this result cannot be interpreted as causal. By incorporating additional variables in the OLS estimation, we can control for observed confounding factors that may be correlated with crop insurance purchasing decision and survival time. The coefficient on crop insurance in the second column was slightly higher than the first column which suggests that the estimate without control variables was biased downward.

The estimated coefficients of the crop insurance variable have more than doubled using the PSM method. The OLS estimates from the matched sample indicate that the treatment group is likely to survive about seven to eight years longer than the control group. Although OLS with control variables and OLS with matched samples from the PSM method has the same motivation, the OLS result with the matched sample is different from the OLS result using the unmatched sample with covariates. One possible explanation is that the PSM may control unobserved confounding factors that are correlated with observed control covariates while it is impossible to control unobserved heterogeneity by employing control variables. Importantly, similar to the nonparametric evidence, both approaches suggest that ignoring the endogeneity problem leads to the underestimation of the effect of crop insurance on farm survival.

Table 8 reports the results from the Cox proportional hazard model. The estimates of crop insurance can be interpreted as the effect of crop insurance on a conditional probability of farm exit. These results are consistent with the OLS estimation results. The coefficient in the first column was obtained by estimating the Cox model with the unmatched sample and employing only a single variable, crop insurance. It suggests that the estimated hazard ratio (relative risk) of farm exit for farms that purchased crop insurance relative to farms that did not purchase crop insurance is 0.608 indicating crop insurance lower hazard rate by 38.2%.

As shown in the second column, after employing control variables, the coefficient was higher and indicates that the likelihood of farm exit decreases by 43.4% if a farm purchases crop insurance. Consistent with the OLS results, this coefficient estimate falls between the coefficient estimate with the unmatched sample employing no control variables and the PSM coefficient estimates. After matching, the point estimates sharply increased and these estimates suggest that farms with crop insurance reduces the rate of farm exit by 72.2% to 74.1%. Again, this result strengthens our finding that farms purchasing crop insurance is not randomly assigned and it underestimates the impact of crop insurance.

Sensitivity Analysis

For the sensitivity analysis, we first consider different types of crop insurance products, Catastrophic Risk Protection (CAT) and Buy-up Plan. In the Crop Insurance Reform Act of 1994, CAT program was created and initially protected 50% of the historical yield at 60% of projected market price. Producers could purchase coverage levels that were higher than CAT, also referred to as a buy-up plan. The premium for CAT was fully subsidized by the federal government; however, producers paid an administrative fee of $50 per crop per county, but not to exceed $200 per producer per county.

Although the KFMA dataset does not report the type of crop insurance that farms purchased, it does report how much farms paid for the crop insurance purchase. Thus, we define producers that had crop insurance expenses that were less than $200 as CAT participants and producers that paid more than $200 in crop insurance expenses as Buy-up participants. Among 893 farms that reported purchasing crop insurance in 1996, 62 farms purchased only CAT and 831 farms purchased a buy-up plan. We matched farms that purchased a buy-up plan to farms that purchased CAT or did not purchase crop insurance.

Column 1 and 2 in Table 9 present the results of OLS and Cox estimation when treatment group indicates farms that purchased buy-up plan while control group indicates farms that did not. The result shows that the buy-up plan increases the length of survival by about four years compared to the farms without crop insurance or only with CAT. The effect of crop insurance, in terms of the length year, gets smaller since we compare farms that purchased buy-up plan with farms that purchased CAT or did not purchased any, rather than comparing crop insurance participants with crop insurance nonparticipants. On the other hand, in terms of the rate of farm exit, the effect of crop insurance does not get smaller. The Cox estimation results suggests that buy-up lowers exit rate by 70.1% which is similar to the previous result.

To control for sample heterogeneity across the different crop categories, an indicator variable for the crop category was added into a set of observable characteristics in matching. Farms were classified into the five main Kansas crops categories: corn, grain sorghum, wheat, soybeans, and other crops. A farm is classified as a crop based on the largest crop income source. If none of these crops' income exceed zero, they were classified as "other crops". The results from this model were robust to the addition of an indicator variable for the crop category. Column 3 and 4 in Table 9 indicate that crop insurance is associated with an increase of approximately seven years in survival and a decrease of about 69.3% in the rate of farm exit for those farms that purchase crop insurance.

Conclusions

Although crop insurance programs have grown substantially over the past two decades, the role crop insurance has, if any, on farm survival is unknown. This study investigates the impact of crop insurance on farm survival using Kansas Farm Management Association

(KFMA) data for 1995-2015. The impact of crop insurance on farm survival is likely to be plagued by severe selection bias. To overcome selection bias, this study matches farms that purchased crop insurance in 1996 to a similar farm that did not based on the similarities of the selected farm characteristics by employing the PSM method. This conjecture is corroborated in the OLS results with an unmatched sample across different specifications. The results indicate that ignoring endogeneity problem leads to downward biased estimates of the impact of crop insurance on farm survival.

Our results indicate that crop insurance has a positive and significant impact on farm survival using several different specifications. The results of the OLS represent that farms that purchased crop insurance are prone to survive about three to seven years longer than farms that did not purchase crop insurance. Consistently, the results of the Cox estimation support the hypothesis that crop insurance is positively associated with farm survival by decreasing the rate of farm exit by 72.2% to 74.1%. The results are robust to different specifications.

This study captures the average impact of crop insurance for the entire farm even though it is probable that its impact is heterogeneous for farm size. Future research should explore how the impact of crop insurance on farm survival varies across the size of farms.

Footnotes

[1] Of course, crop insurance participation is a part of production decision and thus, endogenous to farm exit. We describe how we mitigate this issue in our empirical framework section.

[2] The derivation is illustrated in Appendix A.

[3] For the illustrative purpose, we define revenue of a farm with crop insurance as the sum of crop revenue and indemnity payments minus the subsidized premium. With this definition, farms without crop insurance and farms with crop insurance have same cost, C. Thus, we can simply compare the revenue streams and the revenue thresholds for farm exit of the two farms.

[4] The derivation can be found in Appendix A.

[5] KFMA farms may not be representative of all farms across the United States. Kuethe at al. (2014) examined the distribution of farm financial and demographic characteristics for KFMA and the greater population of farms, ARMS. They found that KFMA farms are prone to be larger, tend to have a greater share of crop, and younger producers than ARMS.

[6] The number of total farms operating in 1996 was 1,333. In the estimation, farms who reported zero total crop acres are excluded.

[7] This rate is similar to Key and Roberts (2006), where 22.5% of farms survived from 1982 to 1997.

[8] We compare farms that purchased crop insurance in 1996 with farms that did not purchase crop insurance in 1996. We use a set of explanatory variables in 1995 for the PSM of these two groups since a producer's decision whether to purchase crop insurance is based on the previous year's farm characteristics.

[9] To check whether the difference in these two variables affects the estimate of the variable of interest, we also match farms based on the only these two variables as a sensitivity analysis. The results are reported in Appendix B.

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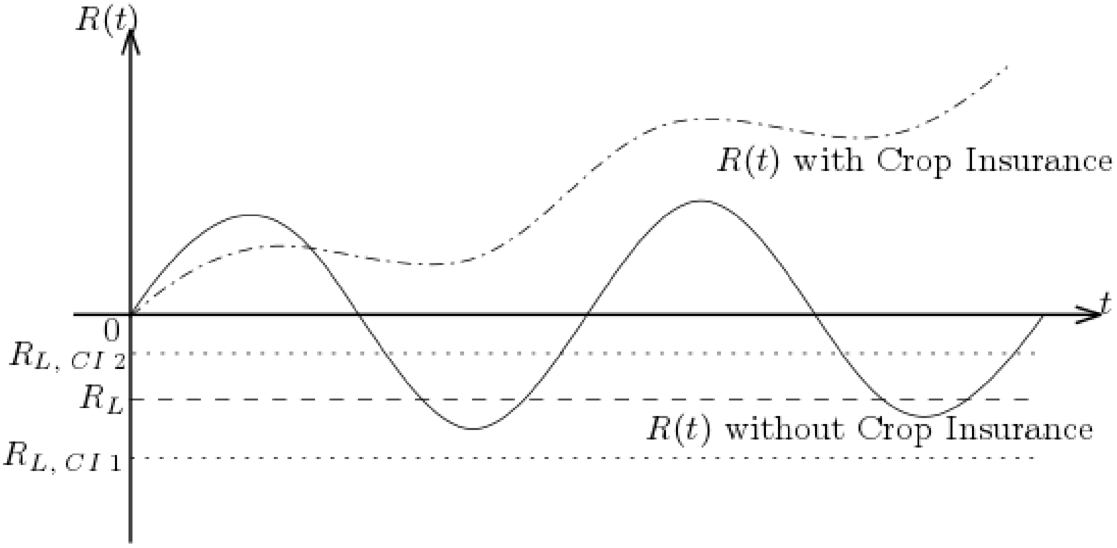

Figure 1. Revenue flows and the exit thresholds of the farm without crop insurance and with crop insurance

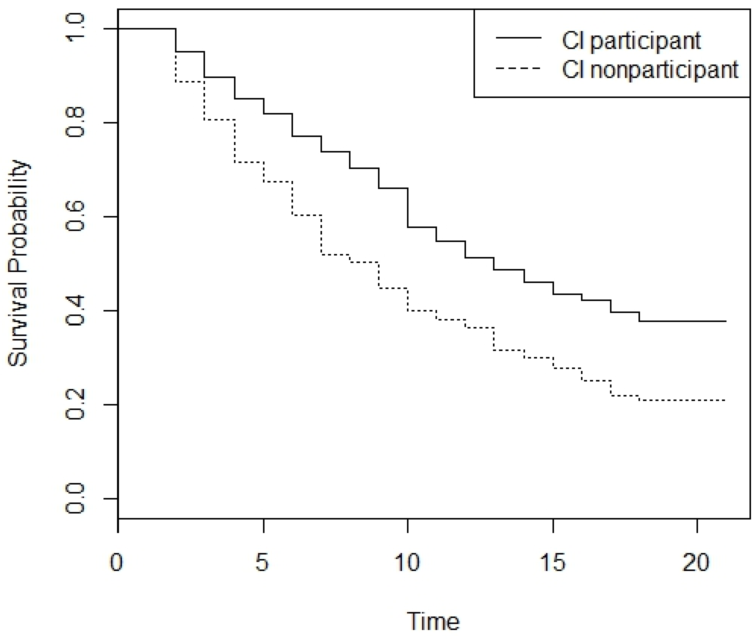

Figure 2. Kaplan-Meier survival curves of crop insurance (CI) with unmatched data

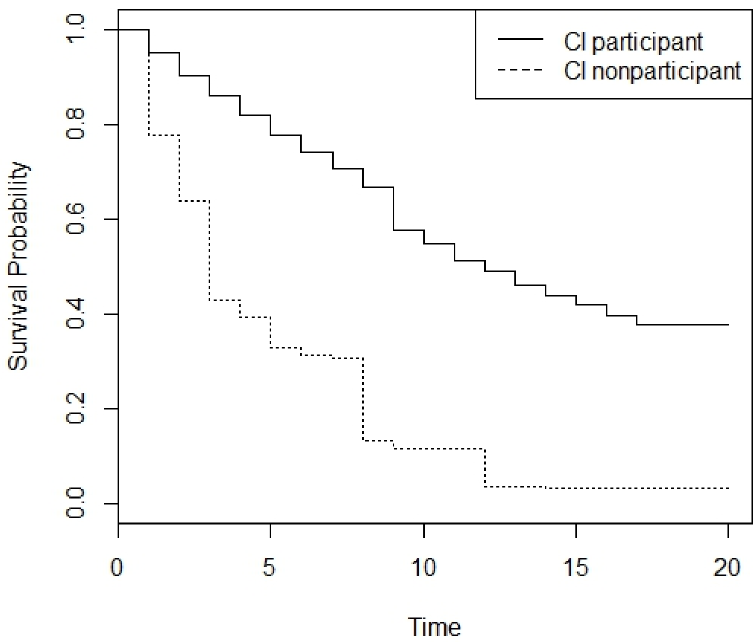

Figure 3. Kaplan-Meier survival curves of crop insurance (CI) with matched data

Table 1. Average Length of the Consecutive Missing Years

Initial Year	Missing Years	Number of observation
1995	2.66	1,247
1996	2.74	1,333
1997	2.73	1,408
1998	2.50	1,413
1999	2.44	1,416

Note: If a farm disappeared from the dataset more than once, the longest consecutive missing years are counted.

Table 2. Definition of Farm Exit

Farm	2012	2013	2014	2015	Type
Farm 1	Observed	Observed	Observed	Observed	Stayer
Farm 2	Observed	Observed	Observed	Not Observed	Stayer
Farm 3	Observed	Observed	Not Observed	Not Observed	Stayer
Farm 4	Observed	Not Observed	Not Observed	Not Observed	Exitor
Farm 5	Not Observed	Not Observed	Not Observed	Not Observed	Exitor

Table 3. Summary Statistics on Selected Farm Characteristics

	Mean/Share		
	1996	2015	Overall
Total crop acres	1,114	1,492	1,295
	(843)	(1,135)	(988)
Operator's age	50.8	64.6	56.8
	(13.0)	(8.80)	(12.3)
Crop labor percentage	0.762	0.851	0.812
	(0.261)	(0.189)	(0.236)
Tenure (%)	0.351	0.408	0.369
	(0.327)	(0.307)	(0.320)
Non-farm income ($)	15,918	29,760	25,830
	(22,782)	(50,527)	(64,672)
Debt-to-asset ratio	0.472	0.190	0.335
	(1.371)	(0.210)	(0.310)
Corn (%)	0.158	0.252	0.198
	(0.365)	(0.435)	(0.399)
Grain sorghum (%)	0.096	0.126	0.083
	(0.295)	(0.332)	(0.275)
Wheat (%)	0.475	0.302	0.439
	(0.500)	(0.460)	(0.496)
Soybeans (%)	0.211	0.288	0.222
	(0.401)	(0.454)	(0.415)
Others (%)	0.059	0.032	0.058
	(0.236)	(0.177)	(0.235)
Number of observation	1,016	278	11,192

Notes: Standard errors appear in parentheses.

Table 4. Comparison of Treatment and Control Characteristics with Unmatched Sample

Variables	CI participants	CI nonparticipants	P-value
Total crop acre	1,219	355	0.000
Operator age	50.4	53.6	0.016
Crop labor percentage	0.805	0.449	0.000
Tenure (%)	0.324	0.547	0.000
Nonfarm income ($)	15,649	17,872	0.268
Debt-to-asset ratio	0.490	0.340	0.008
Number of observation	893	123	-

Note: CI indicates crop insurance.

Table 5. Estimated Coefficients for Crop Insurance Participation (Logit Model)

Variables	Coefficients
Constant	-1.842**
	(0.669)
Total crop acre	0.0030***
	(0.000)
Operator age	-0.005
	(0.010)
Crop labor percentage	3.157***
	(0.450)
Tenure	-0.133
	(0.372)
Nonfarm income	0.000
	(0.000)
Debt-to-asset ratio	0.578
	(0.445)
Number of observations	1,016
Log likelihood	-226.39
Pseudo R-squared	0.396

Note: Standard errors appear in parentheses. Asterisks ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 6. Comparison of Treatment and Control Characteristics with Matched Sample

Variables		CI participants	CI nonparticipants	P-value
Total crop acre	PSM 1[a]	1,218.7	1,204.8	0.343
	PSM 2[b]	1,221.4	1,206.7	0.316
	PSM 3[c]	1,579.4	1,502.2	0.371
Operator age	PSM 1	50.4	49.6	0.183
	PSM 2	50.3	49.7	0.214
	PSM 3	50.2	50.5	0.688
Crop labor percentage	PSM 1	0.805	0.895	0.000
	PSM 2	0.805	0.897	0.000
	PSM 3	0.839	0.929	0.000
Tenure	PSM 1	0.324	0.321	0.852
	PSM 2	0.322	0.321	0.906
	PSM 3	0.297	0.262	0.044
Nonfarm income	PSM 1	15,649	12,748	0.003
	PSM 2	15,634	12,789	0.004
	PSM 3	16,179	16,270	0.954
Debt-to-asset ratio	PSM 1	0.490	0.382	0.035
	PSM 2	0.490	0.382	0.034
	PSM 3	0.552	0.326	0.020
Number of observation	PSM 1	1,074	1,074	-
	PSM 2	1,071	1,071	-
	PSM 3	617	617	-

Note: CI indicates crop insurance.

[a] Nearest neighbor matching with 0.25 caliper is shown.

[b] Nearest neighbor matching with 0.1 caliper is shown.

[c] Nearest neighbor matching with 0.01 caliper is shown.

Table 7. Effects of Crop Insurance on Farm Survival: OLS Estimation

Variables	(1) OLS with unmatched sample	(2) OLS with unmatched sample with covariates	(3) OLS with Matched Sample (PSM1[a])	(4) OLS with Matched Sample (PSM2[b])	(5) OLS with Matched Sample (PSM3[c])
Crop insurance	3.048***	3.283***	7.073***	7.067***	7.738***
	(0.669)	(0.750)	(1.595)	(1.595)	(0.864)
Total Crop acre		0.000			
		(0.000)			
Operator's age		-0.106***			
		(0.017)			
Crop labor percentage		-2.879**			
		(0.942)			
Tenure		-0.564			
		(0.738)			
Non-farm income		-0.000			
		(0.000)			
Debt-to-asset ratio		-0.380*			
		(0.157)			
Constant		17.75***			
		(1.129)			
Number of observations	1,016	1,016	2,148	2,142	1,234
R-squared	0.019	0.075	-	-	-

Note: Standard errors appear in parentheses. Asterisks ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

[a] Nearest neighbor matching with 0.25 caliper is shown.

[b] Nearest neighbor matching with 0.1 caliper is shown.

[c] Nearest neighbor matching with 0.01 caliper is shown.

Table 8. Effects of Crop Insurance on Farm Survival: Cox Proportional Hazard Model Estimates

Variables	(1) Cox with unmatched sample	(2) Cox with unmatched sample with covariates	(3) Cox with Matched Sample (PSM1[a])	(4) Cox with Matched Sample (PSM2[b])	(5) Cox with Matched Sample (PSM3[c])
Crop insurance	-0.497*** (0.110)	-0.569*** (0.140)	-1.283*** (0.053)	-1.281*** (0.054)	-1.349*** (0.074)
Total Crop acre		0.000 (0.000)			
Operator's age		0.027*** (0.000)			
Crop labor percentage		0.654*** (0.186)			
Tenure		0.125 (0.137)			
Non-farm income		0.000 (0.000)			
Debt-to-asset ratio		0.084*** (0.027)			
Number of observations	1,016	1,016	2,148	2,142	1,234

Note: Standard errors appear in parentheses. Asterisks ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

[a] Nearest neighbor matching with 0.25 caliper is shown.

[b] Nearest neighbor matching with 0.1 caliper is shown.

[c] Nearest neighbor matching with 0.01 caliper is shown.

Table 9. Sensitivity of Results to Different Specifications

Variables	Treatment: Purchasing Buy-up plan		Crop category was added in matching	
	(1) OLS	(2) Cox	(3) OLS	(4) Cox
Crop insurance	4.199*** (0.951)	-1.208*** (0.066)	7.491*** (1.507)	-1.180*** (0.056)
Number of observations	1,840	1,840	1,944	1,944

Note: Standard errors appear in parentheses. Asterisks ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

Appendix A: Derivation of the revenue threshold that triggers farm exit

Appendix A provides derivations of the exit revenue threshold that triggers farm exit, R_L, and the comparative statistics that are discussed in the article. Suppose $V(R)$ is the expected net present value of farming. A stochastic dynamic programming problem can be written in the form of Bellman's equation

(A1) $\rho V(R)dt = (R - C) + E[dV(R)]$

where R is the revenue that follows a Brownian motion described by equation (1), C is the variable cost and ρ is the discount rate.

When a farm is idle, a producer will not expect any profit from farming and thus, the farm has zero profit. If we expand equation (A1) for $V_0(R)$ and use Ito's lemma, then we have the following

(A2) $\frac{1}{2}\sigma^2 R^2 V_0''(R) + \alpha R V_0'(R) - \rho V_0(R) = 0.$

The general solution of equation (A2) can be written as

(A3) $V_0(R) = A_1 R^{\beta_1} + A_2 R^{\beta_2}$

where A_1 and A_2 are constants and β_1 and β_2 are the solutions of the differential equation.

The solutions of the differential equation, β_1 and β_2 can be expressed as

(A4) $\beta_1 = \frac{1}{2} - \frac{\alpha}{\sigma^2} + \sqrt{\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2\rho}{\sigma^2}} > 1$, and

(A5) $\beta_2 = \frac{1}{2} - \frac{\alpha}{\sigma^2} - \sqrt{\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2\rho}{\sigma^2}} < 0.$

The expected net present value of for a farm in an active state, $V_1(R)$, can be derived from the same procedures as above while we incorporate $\pi = R - C$ since a producer can expect revenue after it activates farming:

(A6) $V_1(R) = B_1R^{\beta_1} + B_2R^{\beta_2} + \frac{R}{(\rho-\alpha)} - \frac{C}{\rho}$.

We set $A_2 = 0$ since the probability of investing in farming is very small if R is very small. Similarly, $B_1 = 0$ since the probability of not farming is very small if R is very high. In addition, if sunk investment cost k, the firm pays to transit from idle state to active state, goes to infinity, the entry option becomes worthless and A_1 goes to zero (Dixit 1989).

Thus, $V_0(R)$ and $V_1(R)$ can be rewritten as

(A7) $V_0(R) = 0$, and

(A8) $V_1(R) = B_2R^{\beta_2} + \frac{R}{(\rho-\alpha)} - \frac{C}{\rho}$.

The value matching condition and the smooth-pasting condition are

(A9) $V_1(R_L) = V_0(R_L) - E$, and

(A10) $V_1'(R_L) = V_0'(R_L)$.

If we substitue $V_0(R)$ and $V_1(R)$ (equations (A7) and (A8)) and their derivatives into equations (A9) and (A10), the value matching condition and the smooth-pasting condition become

(A11) $B_1{R_L}^{\beta_2} + \frac{R_L}{(\rho-\alpha)} - \frac{C}{\rho} = -E$, and

(A12) $\beta_2B_1{R_L}^{\beta_2-1} + \frac{1}{(\rho-\alpha)} = 0$.

If we solve equation (A11) and (A12), we have

(A13) $R_L = (\frac{\beta_2}{\beta_2-1})(\rho - \alpha)(\frac{C}{\rho} - E).$

Now, consider how the exit threshold, R_L, of a farm changes with respect to the drift parameter or the variance of revenue flow. Here, we first consider the derivative of R_L with respect to α

(A14) $\frac{\partial R_L}{\partial \alpha} = \left(\frac{C}{\rho} - E\right)\left[-\left(\frac{\beta_2}{\beta_2-1}\right) - (\alpha - \rho)\left(\frac{1}{(\beta_2-1)^2}\right)\left(\frac{\partial \beta_2}{\partial \alpha}\right)\right].$

This can be rewritten as

(A15) $\frac{\partial R_L}{\partial \alpha} = -\left(\frac{\beta_2}{\beta_2-1}\right)\left(\frac{C}{\rho} - E\right)\left[1 + (\rho - \alpha)\left(\frac{1}{\beta_2(\beta_2-1)}\right)\left(\frac{\partial \beta_2}{\partial \alpha}\right)\right]$

where $\frac{\partial \beta_2}{\partial \alpha} = -\frac{1}{\sigma^2}\left[1 + \left(\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2\rho}{\sigma^2}\right)^{-0.5}\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)\right].$

Since β_2 is negative, and $\left(\frac{C}{\rho} - E\right)$ is positive, $1 + (\rho - \alpha)\left(\frac{1}{\beta_2(\beta_2-1)}\right)\left(\frac{\partial \beta_2}{\partial \alpha}\right)$ determines the sign of $\frac{\partial R_L}{\partial \alpha}$.

From equation (A5), we have

(A16) $\sqrt{\left(\frac{\alpha}{\sigma^2} - \frac{1}{2}\right)^2 + \frac{2\rho}{\sigma^2}} = \frac{1}{2} - \frac{\alpha}{\sigma^2} - \beta_2.$

Then,

(A17) $\frac{\partial \beta_2}{\partial \alpha} = -\frac{1}{\sigma^2}\left(\frac{-\beta_2}{\frac{1}{2} - \frac{\alpha}{\sigma^2} - \beta_2}\right) = \frac{\beta_2}{\frac{\sigma^2}{2} - \alpha - \sigma^2\beta_2}.$

Thus, we can simply equation (A15) to the following

(A18) $\frac{\partial R_L}{\partial \alpha} = -\left(\frac{\beta_2}{\beta_2-1}\right)\left(\frac{C}{\rho} - E\right)\left[1 + \left(\frac{\rho - \alpha}{(\beta_2-1)(\frac{\sigma^2}{2} - \alpha - \sigma^2\beta_2)}\right)\right]$

since $\left(\frac{\beta_2}{\beta_2-1}\right)$ is positive and $\left(\frac{C}{\rho}-E\right)$ is positive, $\frac{\partial R_L}{\partial \alpha}$ is negative if

$$\text{(A19)} \quad 1+\left(\frac{\rho-\alpha}{(\beta_2-1)(\frac{\sigma^2}{2}-\alpha-\sigma^2\beta_2)}\right) \geq 0.$$

This equation is equivalent to the following if we plug β_2 into

$$\text{(A20)} \quad -\alpha < \rho + \left(\frac{\sigma^2}{2}+\alpha\right)\left(\left(\frac{\alpha}{\sigma^2}-\frac{1}{2}\right)^2+\frac{2\rho}{\sigma^2}\right)^{0.5}+\sigma^2\left(\frac{\alpha}{\sigma^2}-\frac{1}{2}\right)^2$$

since α, ρ and σ^2 are all positive, this condition is always satisfied. Thus, $\frac{\partial R_L}{\partial \alpha}$ is negative.

Next, we consider the derivative of R_L with respect to σ^2.

$$\text{(A21)} \quad \frac{\partial R_L}{\partial \sigma^2} = -\left(\frac{C}{\rho}-E\right)(\rho-\alpha)\left(\frac{1}{(\beta_2-1)^2}\right)\left(\frac{\partial \beta_2}{\partial \sigma^2}\right)$$

where $\frac{\partial \beta_2}{\partial \sigma^2} = \alpha(\sigma^2)^{-2} - \frac{1}{2}\left(\left(\frac{\alpha}{\sigma^2}-\frac{1}{2}\right)^2+\frac{2\rho}{\sigma^2}\right)^{-0.5}(-2\alpha^2(\sigma^2)^{-3}+\alpha(\sigma^2)^{-2}-2\rho(\sigma^2)^{-2})$.

The derivative, $\frac{\partial \beta_2}{\partial \sigma^2}$, determines the sign of $\frac{\partial R_L}{\partial \sigma^2}$, since the convergence condition requires $\rho > \alpha$. The derivative, $\frac{\partial \beta_2}{\partial \sigma^2}$, can be rewritten as

$$\text{(A22)} \quad \frac{\partial \beta_2}{\partial \sigma^2} = 2\alpha^2(\sigma^2)^3 + (2\rho-\alpha)(\sigma^2)^{-2} + \sqrt{\frac{\alpha^2(4\alpha^2+(\sigma^2)^2+4\sigma^2(2\rho-\alpha))}{(\sigma^2)^6}}.$$

Thus, $\frac{\partial \beta_2}{\partial \sigma^2}$ is positive and, eventually, $\frac{\partial R_L}{\partial \sigma^2}$ is negative.

Therefore, we find that 1) R_L decreases as α increases, and 2) R_L decreases as σ^2 increases. Recall, that crop insurance is likely to increase α and to decrease σ^2.

Appendix B: Sensitivity analysis with different covariates for the propensity score matching method

In Appendix B, we check whether non-farm income and debt-to-asset ratio cause the systematic difference between the treatment and control groups.

We show the results of the balancing tests that compares the mean of non-farm income and debt-to-asset ratio across three different specifications: 1) a caliper size of 0.25 standard deviation (PSM 4), 2) a caliper size of 0.1 standard deviation (PSM 5), and 3) a caliper size of 0.01 standard deviation (PSM 6). Table B.1 shows that no statistically differences for the mean of non-farm income and debt-to-asset ratio between treatment and control groups across all specifications.

Table B.2 presents that the results of the OLS estimation with the unmatched sample and three matched samples which are matched based on the similarities of non-farm income and debt-to-asset ratio. The estimates of crop insurance for the PSM ranges from 3.3 to 4.4 years. These estimates are slightly higher after matching, but the results between the unmatched and matched samples are similar. Since the results with matched sample for two variables are not quite different from the unmatched sample, we conclude that the two variables do not play an important role in finding the causal impact of crop insurance on farm survival. Also, note that these two variables are insignificant in the logit regression for the propensity score construction (table 5).

Table B.1. Comparison of Treatment and Control Characteristics with Matched Sample

Variables		CI participants	CI nonparticipants	P-value
Nonfarm income	PSM 4[a]	14,786	14,073	0.351
	PSM 5[b]	14,814	13,987	0.292
	PSM 6[c]	14,883	15,438	0.611
Debt-to-asset ratio	PSM 4	0.432	0.429	0.250
	PSM 5	0.403	0.399	0.258
	PSM 6	0.352	0.355	0.622
Number of observation	PSM 4	974	974	-
	PSM 5	933	933	-
	PSM 6	511	511	-

Note: CI indicates crop insurance.

[a] Nearest neighbor matching with 0.25 caliper is shown.

[b] Nearest neighbor matching with 0.1 caliper is shown.

[c] Nearest neighbor matching with 0.01 caliper is shown.

Table B.2. Effects of Crop Insurance on Farm Survival: OLS Estimation

Variables	(1) OLS with unmatched sample	(2) OLS with Matched Sample (PSM4[a])	(3) OLS with Matched Sample (PSM5[b])	(4) OLS with Matched Sample (PSM6[c])
Crop insurance	3.048***	4.490***	4.423***	3.261***
	(0.669)	(0.829)	(0.773)	(0.380)
Number of observations	1016	1948	1866	1022
R-squared	0.019			

Note: Standard errors appear in parentheses. Asterisks ***, **, and * denote significance at the 0.01, 0.05, and 0.10 level, respectively.

[a] Nearest neighbor matching with 0.25 caliper is shown.

[b] Nearest neighbor matching with 0.1 caliper is shown.

[c] Nearest neighbor matching with 0.01 caliper is shown.