Effects of Crop Insurance on Farm Disinvestment and Exit Decisions

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Abstract

Over the last two decades, the U.S. federal crop insurance program expanded rapidly. Despite growing importance of crop insurance programs, little is known about the relationship between crop insurance and disinvestment and exit decisions of farms. Using a farm-level panel dataset, we parametrically and semi-parametrically estimate the effects of crop insurance on the likelihood of farm disinvestment and farm exits with carefully developed identification strategies. Our estimation results from a dynamic panel model and from the Cox proportional hazard model with propensity score matching indicate that a) crop insurance lowers the likelihood of farm disinvestment and b) reduces the likelihood of farm exits. The positive and significant effects of crop insurance on farm survival remain robust across different specifications.

Key words: Crop insurance, disinvestment, farm exit, dynamic panel model, propensity score matching, survival analysis

JEL classification: Q12, Q18

1. Introduction

Producers face various risks in their revenues due to unexpected changes in prices and quantities caused by exogenous factors such as adverse weather, crop pests or diseases, and unpredictable changes in demand. With the initiation of agricultural insurance markets in Europe over 200 years ago, there has been a rapid expansion in the range of agricultural insurance products, especially in the last 50 years (Smith and Glauber, 2012). The U.S. crop insurance program, the world's largest in volumes of premiums and liabilities, expanded rapidly over the past 20 years with liabilities in excess of $100 billion (RMA, 2015). Also, in many developing countries, governments and development agencies have been increasingly involved in the support of crop insurance in recent years to protect their agricultural sectors against 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 disinvestment and exit decisions of farms using a farm-level dataset from Kansas Farm Management Association (KFMA). As a leading U.S. producer of arable crops, Kansas produced about 20% and 50% of total wheat and grain sorghum in the U.S. in 2010 (Guesmi et al., 2015). By exploring a farm-level panel dataset, we provide empirical evidence on significant impacts of crop insurance on farm disinvestment and exit decisions from parametric and semi-parametric estimations.

Crop insurance expanded with substantial increases in premium subsidies and product developments (Glauber, 2013). Several legislative changes over the last two decades have increased premium subsidy rates and have stimulated the developments of crop insurance products. For example, the Crop Insurance Reform Act of 1994 and the Agricultural Risk Protection Act of 2000 increased the premium subsidy rate for 65% coverage rate from 30% to almost 60% (O'Donoghue, 2014). Also, newer crop insurance products such as revenue-based products and area-based index products have been introduced and marketed to the U.S. farms.

A real option theory, pioneered by Dixit (1989), provides two important implications on the effects of crop insurance on farm disinvestment and exit decisions. First, assuming that farms face stochastic revenue streams, the theoretical framework of Dixit (1989) implies that if the revenue becomes less volatile then disinvestment or an exit would occur at higher revenue thresholds. Second, if the expected value of the revenue increases then the disinvestment or the exit would occur at lower revenue. Subsidized crop insurance reduces variabilities of farm revenues but also increases the expected values of farm revenues by providing premium subsidies which eventually translated to the increased expected farm revenues. Therefore, the empirical assessments of whether subsidized crop insurance deters farm disinvestment and exit decisions would provide important economic insights.[1]

The changes in credit uses and farm leverages as responses to the availability of subsidized crop insurance affect the likelihoods of farm disinvestment and farm exits. Risk-balancing theory implies that the risk-reducing government policies would increase the debt financing and farm leverages (Gabriel and Baker, 1980; Collins, 1985; Featherstone et al., 1988). Subsidized crop insurance, therefore, is expected to have positive effects on farm debt uses and leverages. Ifft et al. (2015) provide the empirical evidence of this risk-balancing theory. Yet, how the increases in farm debt uses and leverages affect the likelihoods of farm disinvestment and farm exits is to be determined by empirical analyses.

We next describe how we contribute to the existing literature on farm disinvestment and exit. We then illustrate our empirical approaches, data and variables we use. Next, we present our estimation results followed by the description of our sensitivity analyses and the implications. Finally, we conclude with the insights from our empirical findings.

[1]By investigating the European Common Agricultural Policy, Sckokai and Moro (2009) find that an increase in intervention price positively affects farm investment from their simulation results. From the dataset of German farms, Hüttel et al. (2010) provide empirical evidence on the joint effect of imperfect capital market, irreversibility and uncertainty on farm investment behavior.

2. How crop insurance affects farm disinvestment and exit decision

Several previous researches have found that the probabilities of farm disinvestment and exits are lower in the presence of the decoupled subsidies (e.g., Kazukauskas et al., 2013; Serra et al., 2009; Key and Roberts, 2006) while others find that relying on government subsidies lead to the faster rate of exits (e.g. Goetz and Debertin, 2001) or find the government subsidies induce increased debt uses and higher finance risk (e.g., Gabriel and Baker, 1980; Collins, 1985; Featherstone et al., 1988). Although both subsidized crop insurance and decouple government subsidies are risk-reducing policies and the lessons from the decoupled government subsidies are insightful for analyzing the effects of subsidized crop insurance, there are important differences, such as sign-up processes and the degrees of risk reduction, and thus, it demands more rigorous analyses on the effects of subsidized crop insurance.

Crop insurance can lengthen farm survival by providing indemnity payments when farms have financial shocks from declines in crop prices or yields.[2] This argument is supported by previous studies that find the positive effects of financial constraints or distress on the probability of firm exits (e.g., Vartia, 2004; Bridges and Guariglia, 2008; Musso and Schiavo, 2008; Holmes et al., 2010). Musso and Schiavo (2008) find that financial constraints, a synthetic index incorporating seven different variables such as 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. For the firms in the United Kingdom, Bridges and Guariglia (2008) show that lower collateral and higher leverage increase the probability of firm failure and Holmes et al. (2010) find lower interest rates lengthen firm survivals.

However, the prediction from the real option theory is ambiguous. The framework of Dixit (1989) indicates that reducing the variability of a stochastic revenue stream would increase the exit or disinvestment thresholds and increasing the expected value of a stochastic revenue would lower the exit or disinvestment thresholds. From the experimental data, Musshoff et al. (2012) find supporting empirical evidence of the real option theory. Thus, the rigorous empirical assessment on the effects of crop insurance on disinvestment and exits of farms is necessary.

Also, the availability of crop insurance may have little impact on farm survivability since there are other existing risk management tools besides crop insurance. For example, the government offers disaster assistance to help producers recover financially from natural disaster

[2]Previous studies also have established conceptual frameworks for the role of risk management tools. Risk management can assist in reducing costs (e.g., financial distress where a firm is unable to repay debt) by providing a producer with stable internal cash flows which could allow them can take advantage of lower costs of external financing (Froot et al., 1993). Cornaggia (2013) argues that risk management could positively affect the value of a firm through improved productivity.

events. The continuation of ad hoc disaster assistance has prevented the need for crop insurance adoption (Harwood and Novak, 2001) and this is consistent with Innes (2003), which argues ex ante crop insurance deters ex post disaster relief. Additionally, producers have other means to manage risk, such as contracts, diversification, government programs, off-farm income, savings, and storage.

There have been several studies that have explored other factors that influence farm survival. These factors include farm characteristics (e.g., Kimhi and Bollman, 1999; Weiss, 1999; Glauben et al., 2006; Breustedt and Glauben, 2007), subsidy decoupling (Kazukauskas et al., 2013), marketing strategies (Foltz, 2004), state aid (Heim et al., 2017), cooperative extension (Goetz and Davlasheridze, 2017), and government payments (Ahearn et al., 2005; Key and Roberts, 2006). However, little is known how crop insurance affects survival of individual farms. This article contributes to this literature as it is the first to assess the effect of crop insurance on the likelihood of disinvestment and farm survivability.

3. Empirical approaches

For our empirical analysis, we focus on two outcomes: a) the likelihood of disinvestment, and b) farm survival rates. We conduct two separate analyses for each outcome with different empirical strategies. For analyzing the impact of crop insurance on the likelihood of disinvestment, we utilize a dynamic panel model to incorporate the dynamic nature of disinvestment and to control for farm-level unobservables. We use duration models to investigate the impact of crop insurance on farm survival. The results from the two analyses complement each other.

3.1. Dynamic panel model

We specify the dynamic panel model as

$$y_{it} = \beta_0 + \sum_{k=1}^{5} \delta_{it-k} y_{it-k} + \beta_1 CI_{it} + BX_{it} + u_i + \varepsilon_{it} \tag{1}$$

where y_{it} is the disinvestment status for farm i in year t, CI_{it} is a measure of crop insurance for farm i in year t, and X_{it} is a vector of control variables.

For farm i in year t, we define disinvestment as

$$y_{it} = \begin{cases} 1 \; if \; Asset_t < Asset_{t-1} \\ 0 \; otherwise \end{cases} \tag{2}$$

where *Asset* is defined as the value of non-current assets such as buildings, machinery, land, or other farm-related properties.

For the crop insurance variable, we consider three different measures: a) insured in the year before, i.e. $CI_{it} = 1$ if farm i was insured in year t and $CI_{it} = 0$ otherwise, b) the number of years insured during the last three years, and c) the number of years insured during the last five years. We also control for other possible factors affecting farm disinvestment. The vector of controls,

X, includes the age of the operator, years operated, lags of the ratio of labor dedicated to crop production over labor dedicated to livestock production, the ratio of owned land over total land, non-farm income, log of total crop acres, and debt-to-asset ratio.

If farm-specific unobservables that are correlated with crop insurance decisions affect the farm disinvestment, then the estimates would be inconsistent. The panel fixed-effect approach can mitigate the endogeneity.[3] However, with small numbers of time periods, the fixed-effect estimates of equation (1) in levels would be biased and inconsistent since the lagged dependent variable becomes endogenous, i.e. Nickell bias (Nickell, 1981). Thus, similar to Bernard and Jensen (2004), we estimate the equation (1) with the first-difference model by Generalized Method of Moments (GMM) of Arellano and Bond (1991). The GMM estimator of Arellano and Bond (1991) uses moment conditions formed from the first-differenced errors and the instruments, which are the lagged levels of the dependent variable.

Finally, we test for reverse causality by estimating

$$CI_{it} = \alpha_0 + \alpha_1 y_{it-1} + AX_{it-1} + v_i + \varepsilon_{it} \tag{3}$$

for all three different measures of CI_{it}. If we fail to reject the null of $\alpha_1 = 0$, it is unlikely that the reverse causality is driving the estimation results of equation (1).

3.2. Duration model

In order to estimate the impact of crop insurance on farm survival, we utilize duration models, a nonparametric model, Kaplan-Meier survival curve, and a semi-parametric model, Cox proportional hazard model. For survival analysis, we restrict our samples to the farms who were observed at least in years 1995 and 1996 and use the year 1996 as the base year.

We chose the year 1996 as the base year since there has been a significant policy change between 1995 and 1996. The Crop Insurance Reform Act of 1994 required farms to participate in the federal crop insurance program in order to be eligible for 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 subsequent years. We investigate survival rates for farms that instantly opted out from the federal crop insurance program in 1996 and subsequent years versus farms that continuously participated.

Cox proportional hazard model (Cox, 1972) mitigates the standard right censoring problem, i.e. we do not observe the exit of farms those who did not exit at the end of the time frame.[4]

[3] For the binary dependent variable, one can argue that nonlinear models are more appropriate. However, it is challenging to incorporate the fixed effects in the nonlinear models due to the incidental parameter problems and even more complicated when the dynamics are being considered. Also, note that in the context of estimating average marginal effects, the difference between the nonlinear and the linear models is limited (Angrist and Pischke, 2008).

[4] We also mitigate the left truncation problem by including the length of survival from the initial year of our dataset, which is 1973, as a control variable in the Cox proportional hazard model. Note that the data we used (Kansas Farm Management Association) are not available prior to 1973.

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:

$$h(t;D_i,X_i) = h_0(t)\exp(\gamma D_i + \Gamma X_i) \tag{4}$$

where $h_0(t)$ is the baseline hazard function, D_i is a variable equal to one if farm i is in the treatment group and equal to zero otherwise, X_i is a vector of control variables. We define treatment (control) in the following three ways: 1) if farm i had purchased (not purchased) crop insurance for every (any) year since 1996, 2) if farm i had purchased (not purchased) crop insurance consecutively for five years since 1996, and 3) if farm i had purchased (not purchased) crop insurance consecutively for three years since 1996. Note that the Cox proportional hazard model is a semi-parametric model consisting of both nonparametric, $h_0(t)$, and parametric components, $\exp(\gamma D_i + \Gamma X_i)$.

There exists an identification challenge since treatments 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) find 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. To control for the possible 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 is to use the Propensity Score Matching (PSM) methods. We utilize both approaches in this analysis.

For the PSM, we match treated farms to similar control farms based on the similarities of the selected farm characteristics. We use a set of explanatory variables in 1995 to estimate the propensity scores since the decision whether to purchase crop insurance in the year 1996 or subsequent years is likely to depend on the charateristics of the year 1995. 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, Z, (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:

$$y_0, y_1 \perp D|Z \Longrightarrow y_0, y_1 \perp D|p(Z) \tag{5}$$

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

The propensity score, $p(Z)$, 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:

$$p(Z) = Prob(D = 1|Z) = E(D|Z). \quad (6)$$

which is the propensity score is the conditional probability of purchasing crop insurance given pre-treatment characteristics Z.[5]

The nearest neighbor matching algorithm is employed and we use one-to-one matching and sampling with replacement. 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 a researcher to match observations with more similar characteristics (Bellemare and Novak, 2016). Three different caliper sizes used in this study include: 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).

Using the propensity score, $Prob(D = 1|Z)$, the impact of crop insurance on survival year can be estimated. The estimated impact of the treatments on farm survival rates, which is estimated by the Cox proportional hazard model after matching, is analogous to the average treatment effect on the treated (ATT) and it is interpreted as the average causal effect of crop insurance treatment per the propensity score theorem and CIA (equation (5)).

Because the outcomes of pre-treated are identical to those of post-treatment in survival analyses, it is not feasible to check the parallel trend of the post-matching data. Thus, we conduct a placebo test using data from a different period by creating pseudo-treatment and pseudo-control groups to check the robustness of our results. For the placebo test, we use data from 1982 to 2001.[6] Although we do not have a crop insurance variable in 1982, the crop insurance participation rate was extremely low due to limited availability and a low subsidy (Glauber, 2013). We mimic our main analysis using 1982 data by creating a pseudo-treatment group and a pseudo-control group. If we find statistically significant differences in farm survival rates between the pseudo-treatment and the pseudo-control, our estimated impact of crop insurance is in fact caused by the systematic differences in unobservables because the pseudo-treatment and the pseudo-control do not received different crop insurance treatments.[7]

To create the pseudo-treatment and the pseudo-control group, we first obtain propensity scores of being treated for each farm in 1982 using the estimated coefficients from the estimation of equation (6) with 1996 data. Based on the propensity scores in 1982, we match

[5]Similar to Sherrick et al. (2004), six input variables are used in estimating equation (6): crop acres, operator's age, the ratio of crop labor input over livestock labor input (crop labor percentage), debt-to-asset ratio, a ratio of owned acres to total acres operated, and non-farm income.

[6]This is the beginning year of KFMA collecting crop labor percentage data. We picked the period 1982 - 2001 to mimic our main analysis which is looking at 20 years from the starting year.

[7]Both pseudo-treatment and pseudo-control groups include farms who participated in crop insurance programs in the later years. Note that the placebo test hinges on the fact that majority of both groups did not have crop insurance in the beginning period of the test since our focus is on whether having crop insurance continuously from the beginning year of the analysis affects farm survivability or not.

these farms with the treatment group and the control group in 1996, respectively. Therefore, farms in 1982 with similar propensity scores as the treatment group in 1996 are defined as the pseudo-treatment group and the farms in 1982 with similar propensity scores as the control group in 1996 are defined as the pseudo-control group.

4. Data and variable descriptions

A farm-level panel dataset from the Kansas Farm Management Association (KFMA) is used in this analysis. KFMA collects detailed accounting and production information from its members such as farm characteristics, crop and livestock production, farm income expenses, depreciation, assets and liabilities, and non-farm income, and expenses, non-farm assets and assets and liabilities.[8]

Table (1) reports the descriptive statistics for the key variables from 1993 through 2015. Note the year 1993 is the first year that KFMA reports the crop insurance expenditure data. Approximately three-quarters of farm-year combinations reduce non-current asset from last year and about 70% of the farm-year combinations were insured throughout the sample period. The average number of insured years within the last 3 and 5 years are 2.4 and 4 years. Figure 1 presents numbers of non-insured and insured farms over the period. The proportion of farms who were insured generally increases over time, while the total number of farms gradually declines over time.

[Table 1 about here.]

[Figure 1 about here.]

The definition of farm exit is crucial in farm survival analyses. Key and Roberts (2006) use Census of Agriculture data that included all U.S. farms. They define a surviving year as how long the farming operation has been operating before the farming operation no longer appeared in the Census data. Using data from the French Administrative Direction of Statistics (INSEE), Bontemps et al. (2012) define 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 (2) presents how long a farm consecutively left the KFMA and comes back 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

[8] KFMA farms may not be representative of all farms across the United States. Kuethe et al. (2014) examine the distribution of farm financial and demographic characteristics for KFMA and the greater population of U.S. 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.

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 about here.]

Table (3) illustrates how farm exits are defined in this study. 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. 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 about here.]

To test whether exits from the dataset can be a good proxy for farm exits, we check the correlation between farm disinvestment and the exits from the dataset. Kazukauskas et al. (2013) state that capital disinvestment is a sign that a farm has started the gradual process of the exit by reducing its capital stock and the level of production, which leads them to use farm disinvestment as a proxy for farm exit. Therefore, we can conclude that exits in the dataset is a proxy for farm exits if exits in the dataset are correlated with farm disinvestment.

Table 4 reports the result from the fixed-effects regression with the binary indicator of whether a farm exited from the dataset after year t as the dependent variable and the current and the lags of the indicator variable of non-current asset reduction. There is a statistically significant relationship between the exits from the dataset and the likelihood of asset reduction, i.e. disinvestment. The result strengthens our assumption that the exits in the dataset can be treated as farm exits.

[Table 4 about here.]

5. Estimation results

5.1. Impacts on farm disinvestment and years survived after being treated

Figure 2 plots the variation of the non-current asset reduction and the ratio of farms that purchased crop insurance over time. While the pattern is not obvious, it reflects a negative relationship between the fraction of farms that reduce non-current asset from the last year, which declines over time, and the ratio of farms purchasing crop insurance, which gradually increases over time.

[Figure 2 about here.]

Table (5) reports estimation results of impact of crop insurance on farm disinvestment described in equation (1) using the data from 1993 - 2015. Column (1) reports the estimation results where the variable of interest is a binary variable indicating whether a farm was insured in the last year. Column (2) and (3) report the estimation results where the variable of interest is the number of insured years during the last 3 and 5 years.

For all measures of crop insurance status, the results suggest that the crop insurance reduces the probability of a farm reducing non-current asset. The insignificant effect when crop insurance is measured as whether a farm was insured in the last year or not is suspect to be due to the lack of variations and the variations are getting smaller as year goes. When the crop insurance is measured as the number of insured years during the last 3 or 5 years, we find statistically significant impacts of crop insurance on the likelihood of farm disinvestment. This finding is consistent with the literature that finds the negative effect of risk-reducing government policies on the likelihood of farm disinvestment.

[Table 5 about here.]

As described in the section 3.1, we test for the reverse causality, for example, a possibility of farms who are likely to reduce assets tend not to purchase crop insurance by estimating equation (3). Table (6) shows the result. Column (1) reports the estimation results where the dependent variable is a binary variable indicating whether a farm is insured in the next year. Column (2) and (3) report the estimation results where the dependent variable is the number of insured years during the next 3 or 5 years. Table (6) shows that none of the coefficients on non-current asset reduction are statistically significant or have magnitudes that are large enough to be economically important.[9]

[Table 6 about here.]

5.2. Survival rates

We begin this section by presenting systematic differences between treatment and control group. Table (7) presents summary statistics of selected farm characteristics used in the duration model for the two groups: 1) farms with crop insurance (treatment), and 2) farms without crop insurance (control) across three different definitions of treatment in 1996. Across all definitions, farms with crop insurance are more likely to stay in business longer. In addition,

[9] Including more lags of the non-current asset reduction variable do not change the conclusion.

farms with crop insurance have larger total crop acres, younger operators, higher percentage of labor devoted to crops, lower ratio of owned acres to total acres operated (tenure), and higher debt-to-asset ratio. If these variables, which are correlated with the crop insurance purchasing decision, are affecting farm survival rates, it will lead to a biased estimate of the effect of crop insurance on farm survival.

[Table 7 about here.]

Table (8) reports the results of the logit estimation of equation (6). Across all three different definitions of treatment, farms with larger total crop acres are more likely to purchase crop insurance. As producers specialized in crop production, they tend to purchase crop insurance. In addition, farmers with higher financial leverage are more likely to purchase crop insurance.

[Table 8 about here.]

With the definition of farm exit in the section 4, figure 3 provides nonparametric estimation results (Kaplan-Meier survival curves) when D_i is equal to one if farm i had purchased crop insurance every year since 1996 (Treatment 1). Farm survival probability is estimated for the treatment group and the control group for the 20-year window using the unmatched samples (top panel) and the matched samples (bottom panel). If crop insurance purchase decision is positively (negatively) correlated with other factors that increase farm survival rates, the top panel, which is the survival curves from the unmatched sample, may overestimate (underestimate) the impact of crop insurance. We observe that the farms in the treatment group have higher survival rates for the both top and bottom panels. The bottom panel shows that 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.

[Figure 3 about here.]

Table (9) reports results from the Cox proportional hazard model for three different definitions of treatment. Each column reports the effect of crop insurance on the hazard rates for different specifications. The first and second column of table (9) correspond to the model using the unmatched sample without and with covariates. In Columns (3), (4), and (5), we match the sample with three different caliper sizes. Each row presents the impact of crop insurance on farm exit under different periods of treatment. The estimates of crop insurance can be interpreted as the effect of crop insurance on a conditional probability of farm exit.

The first row in table (9), treatment 1, presents the effect of crop insurance on farm exits by comparing farms that had purchased crop insurance every year since 1996 with farms that had not purchased crop insurance any year since 1996. 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 a farm with crop insurance is 44.3% (1 −

$exp(-0.584) = 0.443$) less likely to exit than a farm without crop insurance. After matching, the point estimates increase and these estimates suggest that farms with crop insurance reduces the rate of farm exit by 61.7% to 63.0%. The results suggest that estimation with unmatched sample underestimates the impact of crop insurance.

We also investigate the role of crop insurance on farm survival for several different periods of treatment. We do this by changing the definition of treatment: treatment 2, $D_i = 1$ ($D_i = 0$) if farm i had purchased (not purchased) crop insurance consecutively for five years since 1996, and treatment 3, $D_i = 1$ ($D_i = 0$) if farm i had purchased (not purchased) crop insurance consecutively for three years since 1996. We find smaller impacts of treatment with these two definitions. This implies that the crop insurance effect on farm exit is magnified by the length of insured years.

[Table 9 about here.]

Table (10) reports the result of the placebo test with the first definition of treatment (Treatment 1). We find no statistically significant differences between the pseudo-treatment and the pseudo-control (Columns 1 and 2). We also find none of our matching schemes derives the estimates to become statistically significant (Columns 3–5). While there are some remaining limitations of this exercise, the result of our placebo test supports the reliability of our results and interpretations.

[Table 10 about here.]

6. Conclusion

Although crop insurance programs have grown substantially over the past two decades, the role crop insurance has, if any, on farm disinvestment and exit decision is rarely known. This article investigates the impact of crop insurance on farm disinvestment and exit decisions using the Kansas Farm Management Association (KFMA) farm-level panel dataset.

Our results support the positive and significant effect of crop insurance on farm survival. We find that crop insurance lowers the likelihood of farm disinvestment. The dynamic panel model captures the dynamics of farm investment and controls for farm-specific unobservables and provides reliable estimates of the impact of crop insurance on farm disinvestment. Since farm disinvestment has been widely used as a proxy for farm exit, our results indicate the positive effect of crop insurance on farm survival. The results from the Cox proportional hazard model with Propensity Score Matching find that crop insurance has a negative and significant impact on farm exit. We also test for the possibility of reverse causality and conduct sensitivity analysis and find that our results remain robust.

Our findings indicate that the subsidized crop insurance program deters farm disinvestment and farm exits. Future research that explores the heterogeneous impacts of crop insurance on farm survival varies can inform policy-makers and have better understanding of the economic consequences of the U.S. federal crop insurance program and other crop insurance programs.

References

Ahearn, M. C., Yee, J. and Korb, P. (2005). Effects of differing farm policies on farm structure and dynamics. *American Journal of Agricultural Economics* 87: 1182–1189.

Angrist, J. D. and Pischke, J.-S. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *The Review of Economic Studies* 58: 277–297.

Bellemare, M. F. and Novak, L. (2016). Contract farming and food security. *American Journal of Agricultural Economics* 99: 357–378.

Bernard, A. B. and Jensen, J. B. (2004). Why some firms export. *Review of Economics and Statistics* 86: 561–569.

Bontemps, C., Bouamra-Mechemache, Z. and Simioni, M. (2012). Quality labels and firm survival: some first empirical evidence. *European Review of Agricultural Economics* 40: 413–439.

Breustedt, G. and Glauben, T. (2007). Driving forces behind exiting from farming in western europe. *Journal of Agricultural Economics* 58: 115–127.

Bridges, S. and Guariglia, A. (2008). Financial constraints, global engagement, and firm survival in the united kingdom: evidence from micro data. *Scottish Journal of Political Economy* 55: 444–464.

Collins, R. A. (1985). Expected utility, debt-equity structure, and risk balancing. *American Journal of Agricultural Economics* 67: 627–629.

Cornaggia, J. (2013). Does risk management matter? evidence from the us agricultural industry. *Journal of Financial Economics* 109: 419–440.

Cox, D. R. (1972). Regression models and life-tables (with discussion). *Journal of the Royal Statistical Society. Series B (Methodological)* 34: 187–220.

Dixit, A. (1989). Entry and exit decisions under uncertainty. *Journal of Political Economy* 97: 620–638.

Featherstone, A. M., Moss, C. B., Baker, T. G. and Preckel, P. V. (1988). The theoretical effects of farm policies on optimal leverage and the probability of equity losses. *American Journal of Agricultural Economics* 70: 572–579.

Foltz, J. D. (2004). Entry, exit, and farm size: assessing an experiment in dairy price policy. *American Journal of Agricultural Economics* 86: 594–604.

Froot, K. A., Scharfstein, D. S. and Stein, J. C. (1993). Risk management: Coordinating corporate investment and financing policies. *Journal of Finance* 48: 1629–1658.

Gabriel, S. C. and Baker, C. B. (1980). Concepts of business and financial risk. *American Journal of Agricultural Economics* 62: 560–564.

Glauben, T., Tietje, H. and Weiss, C. (2006). Agriculture on the move: Exploring regional differences in farm exit rates in western germany. *Review of Regional Research* 26: 103–118.

Glauber, J. W. (2013). The growth of the federal crop insurance program, 1990–2011. *American Journal of Agricultural Economics* 95: 482–488.

Goetz, S. J. and Davlasheridze, M. (2017). State-level cooperative extension spending and farmer exits. *Applied Economic Perspectives and Policy* 39: 65–86.

Goetz, S. J. and Debertin, D. L. (2001). Why farmers quit: A county-level analysis. *American Journal of Agricultural Economics* 83: 1010–1023.

Guesmi, B., Serra, T. and Featherstone, A. (2015). Technical efficiency of kansas arable crop farms: a local maximum likelihood approach. *Agricultural Economics* 46: 703–713.

Harwood, J. and Novak, U. J. L. (2001). Crop insurance and disaster assistance. *The 2002 Farm Bill* .

Heim, S., Hüschelrath, K., Schmidt-Dengler, P. and Strazzeri, M. (2017). The impact of state aid on the survival and financial viability of aided firms. *European Economic Review* 100: 193–214.

Holmes, P., Hunt, A. and Stone, I. (2010). An analysis of new firm survival using a hazard function. *Applied Economics* 42: 185–195.

Hüttel, S., Mußhoff, O. and Odening, M. (2010). Investment reluctance: irreversibility or imperfect capital markets? *European Review of Agricultural Economics* 37: 51–76.

Ifft, J. E., Kuethe, T. and Morehart, M. (2015). Does federal crop insurance lead to higher farm debt use? evidence from the Agricultural Resource Management Survey (ARMS). *Agricultural Finance Review* 75: 349–367.

Innes, R. (2003). Crop insurance in a political economy: an alternative perspective on agricultural policy. *American Journal of Agricultural Economics* 85: 318–335.

Kazukauskas, A., Newman, C., Clancy, D. and Sauer, J. (2013). Disinvestment, farm size, and gradual farm exit: the impact of subsidy decoupling in a european context. *American Journal of Agricultural Economics* 95: 1068–1087.

Key, N. and Roberts, M. J. (2006). Government payments and farm business survival. *American Journal of Agricultural Economics* 88: 382–392.

Kimhi, A. and Bollman, R. (1999). Family farm dynamics in canada and israel: the case of farm exits. *Agricultural Economics* 21: 69–79.

Kuethe, T. H., Briggeman, B., Paulson, N. D. and Katchova, A. L. (2014). A comparison of data collected through farm management associations and the agricultural resource management survey. *Agricultural Finance Review* 74: 492–500.

Mahul, O. and Stutley, C. J. (2010). *Government support to agricultural insurance: challenges and options for developing countries*. World Bank Publications.

Musshoff, O., Odening, M., Schade, C., Maart-Noelck, S. C. and Sandri, S. (2012). Inertia in disinvestment decisions: experimental evidence. *European Review of Agricultural Economics*

40: 463–485.

Musso, P. and Schiavo, S. (2008). The impact of financial constraints on firm survival and growth. *Journal of Evolutionary Economics* 18: 135–149.

Nickell, S. (1981). Biases in dynamic models with fixed effects. *Econometrica: Journal of the Econometric Society* : 1417–1426.

O'Donoghue, E. (2014). The effects of premium subsidies on demand for crop insurance. *USDA-ERS Economic Research Report* .

RMA (2015). Summary of business. http://www.rma.usda.gov/data/sob.html.

Rosenbaum, P. R. and Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika* 70: 41–55.

Sckokai, P. and Moro, D. (2009). Modelling the impact of the CAP single farm payment on farm investment and output. *European Review of Agricultural Economics* 36: 395–423.

Serra, T., Stefanou, S., Gil, J. M. and Featherstone, A. (2009). Investment rigidity and policy measures. *European Review of Agricultural Economics* 36: 103–120.

Sherrick, B. J., Barry, P. J., Ellinger, P. N. and Schnitkey, G. D. (2004). Factors influencing farmers' crop insurance decisions. *American Journal of Agricultural Economics* 86: 103–114.

Smith, V. H. and Glauber, J. W. (2012). Agricultural insurance in developed countries: where have we been and where are we going? *Applied Economic Perspectives and Policy* 34: 363–390.

Vartia, L. (2004). Assessing plant entry and exit dynamics and survival–does firms' financial status matter? *Mimeograph, European University Institute* .

Weiss, C. R. (1999). Farm growth and survival: econometric evidence for individual farms in upper austria. *American Journal of Agricultural Economics* 81: 103–116.

Tables

Table 1. Descriptive statistics of key variables (1993 - 2015)

VARIABLES	(1) N	(2) mean	(3) sd
Total crop acres	41,340	1,212	1,109
Operator age	41,340	53.92	21.08
Years operated	41,340	15.72	10.64
(Labor input, crop)/(Labor input, livestock)	41,340	0.755	0.275
Non-farm income	41,340	25,322	68,549
Debt-to-asset ratio	41,332	0.371	1.492
Owned land/total land	40,385	0.377	0.345
Non-current asset reduction	34,966	0.359	0.480
Insured in the last year	34,966	0.769	0.422
Number of insured years within the last 3 years	26,341	2.366	1.065
Number of insured years within the last 5 years	20,232	3.982	1.678

Table 2. 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 3. Definition of farm exits

Farm	2012	2013	2014	2015	Type
Farm	Observed	Observed	Observed	Observed	Stayer
Farm	Observed	Observed	Observed	Not Observed	Stayer
Farm	Observed	Observed	Not Observed	Not Observed	Stayer
Farm	Observed	Not Observed	Not Observed	Not Observed	Exitor
Farm	Not Observed	Not Observed	Not Observed	Not Observed	Exitor

Table 4. Panel Fixed-Effects estimation: Exits from data are likely to be real exits

VARIABLES	(1) Last year observed
Non-current asset reduction	0.0163***
	(0.00311)
Lag(1) Non-current asset reduction	0.00413
	(0.00304)
Lag (2) Non-current asset reduction	0.00589*
	(0.00305)
Constant	0.0465***
	(0.00208)
Observations	26,341
Number of farm	2,905

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

Table 5. Arellano-Bond GMM estimation: Impacts of crop insurance on farm disinvestment

	(1)	(2)	(3)
VARIABLES	Non-current asset reduction		
Insured in the last year	-0.0337		
	(0.0213)		
Number of insured years within the last 3 years		-0.0319**	
		(0.0133)	
Number of insured years within the last 5 years			-0.0240**
			(0.0118)
Lag(1) Non-current asset reduction	-0.0667***	-0.0665***	-0.0664***
	(0.0133)	(0.0133)	(0.0133)
Lag(2) Non-current asset reduction	-0.0600***	-0.0596***	-0.0595***
	(0.0117)	(0.0117)	(0.0117)
Lag(3) Non-current asset reduction	-0.0738***	-0.0733***	-0.0735***
	(0.0111)	(0.0111)	(0.0111)
Lag(4) Non-current asset reduction	-0.0497***	-0.0494***	-0.0494***
	(0.0103)	(0.0103)	(0.0103)
Lag(5) Non-current asset reduction	-0.00361	-0.00350	-0.00328
	(0.00963)	(0.00963)	(0.00964)
Operator age	0.00293	0.00291	0.00295
	(0.00201)	(0.00201)	(0.00201)
Years operated	-0.00524**	-0.00483*	-0.00466*
	(0.00265)	(0.00265)	(0.00267)
Lag(1) (Labor input, crop)/(Labor input, livestock)	-0.143***	-0.143***	-0.145***
	(0.0511)	(0.0510)	(0.0511)
Lag(1) Owned land/total land	0.183***	0.184***	0.184***
	(0.0563)	(0.0562)	(0.0562)
Lag(1) Non-farm income	1.13e-07	1.12e-07	1.12e-07
	(1.22e-07)	(1.21e-07)	(1.21e-07)
Lag(1) ln(total crop acres)	0.0226	0.0226	0.0223
	(0.0240)	(0.0240)	(0.0240)
Lag(1) Debt-to-asset ratio	0.0501	0.0497	0.0490
	(0.0480)	(0.0482)	(0.0482)
Constant	0.278	0.320*	0.337*
	(0.183)	(0.184)	(0.186)
Observations	15,315	15,315	15,315
Number of farm	1,899	1,899	1,899

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

Table 6. Panel Fixed-Effects estimation: Testing for reverse causality

VARIABLES	(1) Insured in the next year	(2) Number of insured years during the next 3 years	(3) Number of insured years during the next 5 years
Non-current asset reduction	0.000557	-0.00491	-0.00815
	(0.00361)	(0.00760)	(0.0106)
Operator age	-0.00118**	-0.00406**	-0.00557*
	(0.000597)	(0.00183)	(0.00297)
Years operated	0.00588***	0.0215***	0.0341***
	(0.000875)	(0.00294)	(0.00519)
(Labor input, crop)/(Labor input, livestock)	0.0385**	0.102*	0.135
	(0.0195)	(0.0567)	(0.0991)
Owned land/total land	-0.0223	-0.0739	-0.0405
	(0.0182)	(0.0554)	(0.116)
Non-farm income	-1.96e-08	-8.59e-08	-5.90e-08
	(2.91e-08)	(9.09e-08)	(1.65e-07)
ln(total crop acres)	0.0480***	0.0954***	0.159***
	(0.00925)	(0.0290)	(0.0528)
Debt-to-asset ratio	0.0107	0.0851**	0.0788
	(0.00859)	(0.0396)	(0.0632)
Constant	0.430***	1.593***	2.669***
	(0.0686)	(0.214)	(0.391)
Observations	29,721	22,742	17,498
R-squared	0.014	0.031	0.042
Number of farm	3,249	2,589	2,088

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

Table 7. Descriptive statistics by group (1996)

	Mean/Share					
	Treatment 1 (always insured vs never insured)		Treatment 2 (Insured for 5 years vs not insured for 5 years)		Treatment 3 (Insured for 3 years vs not insured for 3 years)	
Variable	Treatment	Control	Treatment	Control	Treatment	Control
Survival year	12.3	8.5	12.7	11.0	12.7	11.5
	(7.0)	(6.8)	(6.7)	(7.1)	(6.6)	(7.0)
Total crop acres	1,255	440	1,221	532	1,204	592
	(894)	(473)	(874)	(522)	(868)	(583)
Operator's age	50.2	54.5	50.0	53.3	49.9	53.1
	(13.2)	(14.9)	(13.0)	(14.1)	(13.0)	(14.0)
(Labor input, crop)/(Labor input, livestock)	0.802	0.530	0.790	0.559	0.786	0.566
	(0.224)	(0.333)	(0.228)	(0.328)	(0.232)	(0.321)
Owned land/total land (%)	0.325	0.539	0.329	0.494	0.330	0.470
	(0.307)	(0.392)	(0.306)	(0.377)	(0.306)	(0.372)
Non-farm income ($)	15,655	19,681	15,904	17,712	15,674	16,660
	(22,796)	(23,174)	(22,255)	(21,722)	(22,326)	(20,950)
Debt-to-asset ratio	0.487	0.326	0.480	0.337	0.473	0.334
	(1.405)	(0.309)	(1.305)	(0.306)	(1.258)	(0.308)
Number of observation	964	182	1,132	266	1,224	314

Note: Standard deviations are in parentheses.

Table 8. Propensity score estimation (Logit Model)

Variables	Treatment 1 (always insured vs never insured)	Treatment 2 (Insured for 5 years vs not insured for 5 years)	Treatment 3 (Insured for 3 years vs not insured for 3 years)
Constant	-0.992*	-0.963**	-0.826**
	(0.528)	(0.418)	(0.385)
Total crop acre	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)
Operator's age	-0.012	-0.009	-0.0105*
	(0.008)	(0.006)	(0.006)
(Labor input, crop)/(Labor input, livestock)	2.380***	2.050***	2.107***
	(0.352)	(0.282)	(0.272)
Owned land/total land	-0.237	-0.135	-0.009
	(0.298)	(0.242)	(0.228)
Nonfarm income	0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Debt-to-asset ratio	0.607**	0.650**	0.712***
	(0.345)	(0.266)	(0.249)
Number of observation	1,146	1,398	1,538
Log likelihood	-345.490	-528.139	-634.364
Pseudo R-squared	0.311	0.224	0.185

Note: Robust standard errors appear in parentheses. Asterisks ***,**, and * denotes significance at the 0.01, 0.05, and 0.10 level, respectively.

Table 9. Cox proportional hazard model estimation: Impact of crop insurance on farm survival rates

	(1)	(2)	(3)	(4)	(5)
Cox Proportional Hazard (Dependent Variable: Hazard Rate)					
Treatment 1 (always insured vs never insured)					
Treated	-0.584***	-0.648***	-0.994***	-0.994***	-0.959***
	(0.086)	(0.109)	(0.051)	(0.051)	(0.066)
Number of observation	1,146	1,146	2,072	2,072	1,364
Treatment 2 (Insured for 5 years vs not insured for 5 years)					
Treated	-0.265***	-0.277***	-0.158***	-0.158***	-0.108**
	(0.076)	(0.087)	(0.045)	(0.045)	(0.051)
Number of observation	1,398	1,398	2,584	2,584	2,030
Treatment 3 (Insured for 3 years vs not insured for 3 years)					
Treated	-0.203***	-0.202***	-0.128***	-0.128***	-0.105**
	(0.070)	(0.077)	(0.042)	(0.042)	(0.046)
Number of observation	1,538	1,538	2,954	2,954	2,432

Note: Robust standard errors appear in parentheses. Asterisks ***,**, and * denotes significance at the 0.01, 0.05, and 0.10 level, respectively. In specification (1) the result with unmatched sample is presented, specification (2) presents the result with unmatched sample with covariates, and specification (3), (4), and (5) represents the results with matched sample with three different caliper sizes of 0.25, 0.1, 0.01, respectively.

Table 10. Cox proportional hazard model estimation: Pseudo-treatment and pseudo-control

	(1)	(2)	(3)	(4)	(5)
Cox Proportional Hazard (Dependent Variable: Hazard Rate)					
Treatment 1 (always insured vs never insured)					
Treated	-0.099	-0.135	0.019	0.019	0.010
	(0.094)	(0.107)	(0.053)	(0.053)	(0.025)
Number of observation	1,146	1,146	2,014	2,014	1,402

Note: Robust standard errors appear in parentheses. Asterisks ***,**, and * denotes significance at the 0.01, 0.05, and 0.10 level, respectively. In specification (1) the result with unmatched sample is presented, specification (2) presents the result with unmatched sample with covariates, and specification (3), (4), and (5) represents the results with matched sample with three different caliper sizes of 0.25, 0.1, 0.01, respectively.

Figures

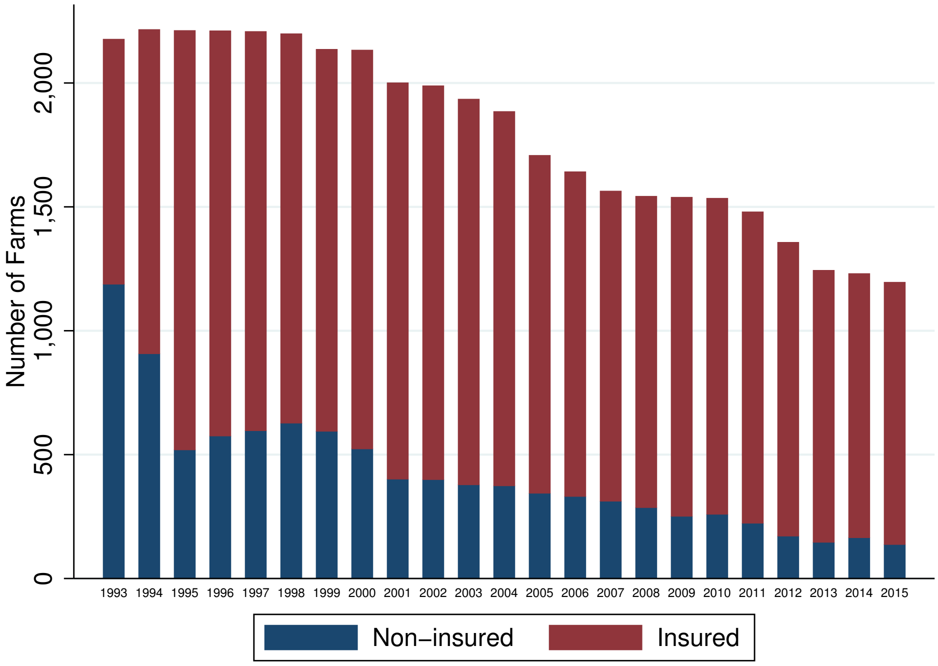

Figure 1. Numbers of non-insured and insured farms (1993 - 2015)

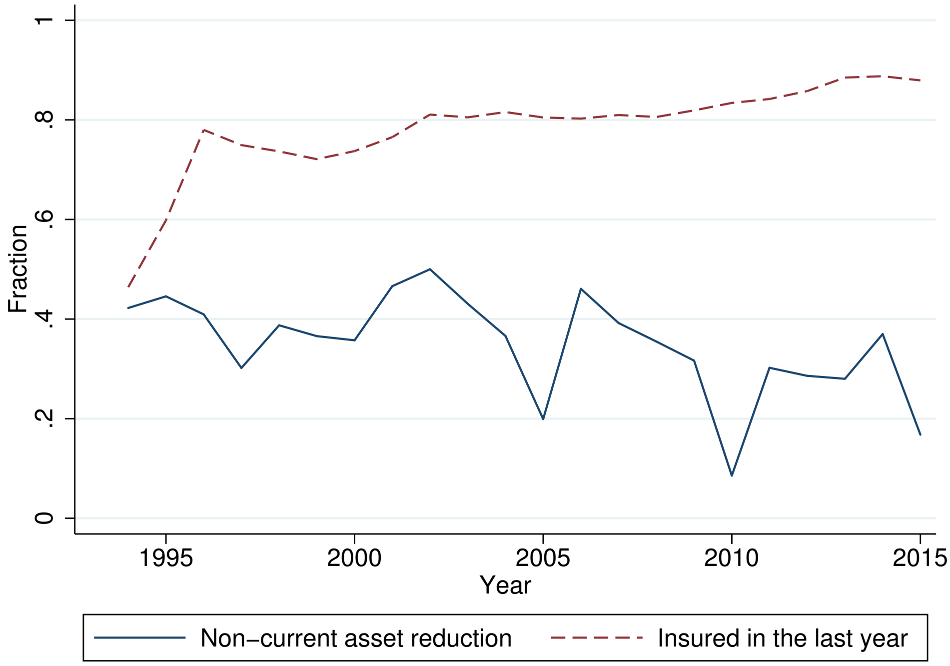

Figure 2. Fractions of farms insured and farms disinvested (1993 - 2015)

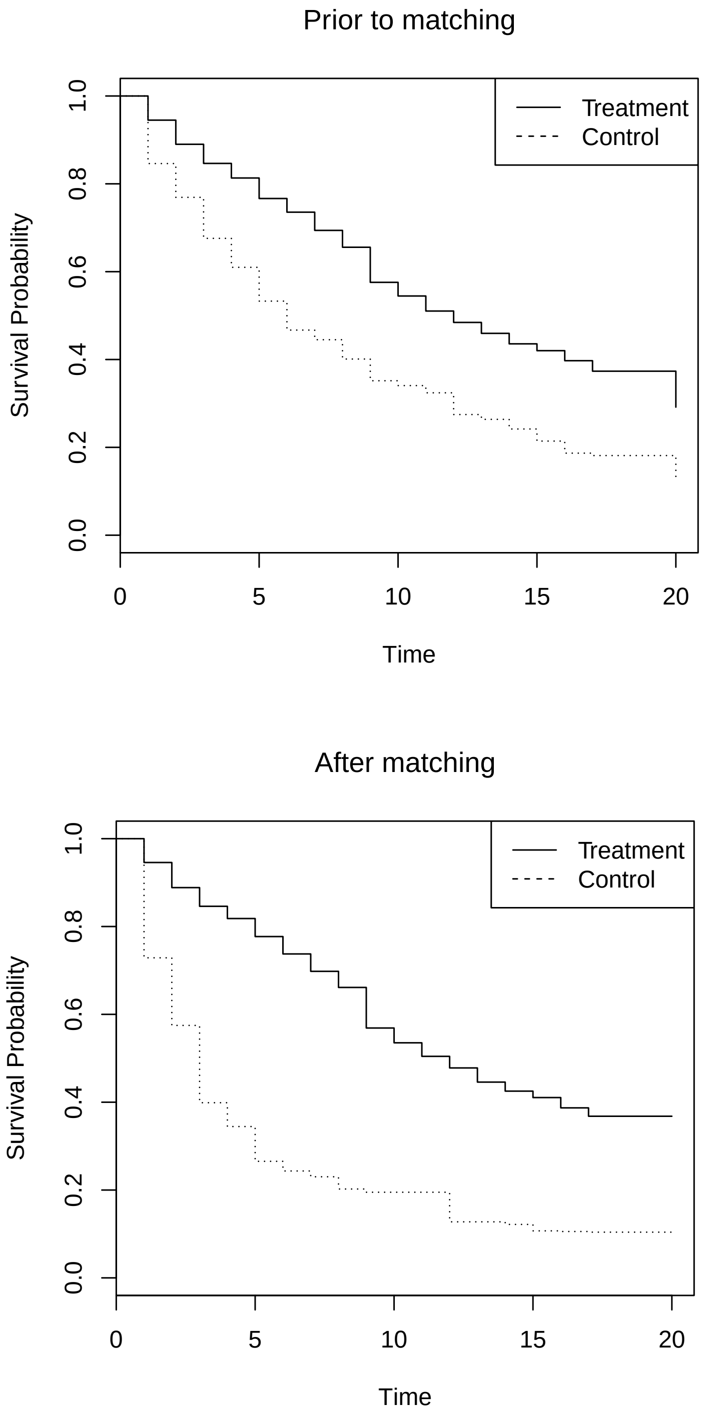

Figure 3. Kaplan-Meier survival curves by treatment status (Treatment 1)