

Determinants of agricultural insurance adoption: evidence from farmers in the state of São Paulo, Brazil

Agricultural
insurance
adoption

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Abstract

Purpose – The purpose of this study is to investigate the determinants of agricultural insurance adoption by farmers of the state of São Paulo, Brazil.

Design/methodology/approach – Primary data from the 2015/2016 crop season was collected from a sample of 175 farmers. Logit econometric models were applied to identify the variables that affect the probability of agricultural insurance adoption.

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Findings – The empirical results show that the education level, access to technical assistance, use of management tools and farm size positively affect the probability of adopting agricultural insurance. In addition, farmers who produce soybean and/or corn are more likely to use insurance. On the other hand, the higher the farmers' propensity to take risk the lower the likelihood of using insurance.

Research limitations/implications – The empirical analysis is based on cross-sectional data of a sample of 175 farmers of the state of São Paulo. The use of panel data with a larger sample of farmers, considering a period of years, could provide additional information.

Originality/value – To the best of the knowledge, this is the first empirical analysis about determinants of agricultural insurance adoption by Brazilian farmers, considering behavioral factors. The findings provide useful insights for policymakers in formulating risk management programs in the Brazilian agricultural markets. A better understanding about the determinants of insurance adoption is also relevant for private companies that sell insurance to farmers. Therefore, the paper may contribute with the diffusion of rural insurance as risk management tool in Brazilian agriculture.

Keywords Risk management, Agricultural insurance, Production risk

Paper type Research paper

1. Introduction

Agricultural production is characterized by a set of risks related to production, prices, credit and the environment (OCDE, 2009). Production risk, which is the focus of this article, is primarily associated with exposure to climatic and biological (pests and disease) factors, whose effects on yield can be severe. Weather interruptions, for example, can lead a producer to financial insolvency and a loss of wealth when the returns from farming are insufficient to cover expenses involved in the activity. In this context, the adoption of risk management mechanisms becomes an essential element to at least guarantee a continuation of production.

Various risk management instruments can be used to counteract or mitigate the impact of risk events on the cost and revenue structure of agricultural activity. On one hand, the adoption of technologies (e.g. irrigation and specific seed selection), rural extension programs, human resource training and government policies for disease prevention, among other measures, have the potential to increase yields and prevent potential crop failures or problems with livestock. On the other hand, actions such as rural insurance, crop diversification and off-farm income have the capacity to mitigate the effects of weather or biological events that decrease production (Buainain & Silveira, 2017).

Of the various types of actions used to manage production risk, rural insurance is one of the most important mechanisms. When purchasing insurance, an individual trades unknown future costs and uncertainty (related to damages from a poor crop, which can potentially be very costly) for the anticipated and relatively lower cost of a premium (Ozaki, 2008). By reducing the consequences of adverse climate risks and contributing to the stability of agricultural activity, the contract in question provides rural producers with greater peace of mind and ensures the continuity of their production (Ministério da Agricultura, Pecuária e Abastecimento – MAPA, 2018).

The increasing use of rural insurance has been a central axis in agricultural policy in Brazil. The Rural Insurance Subsidy Program (PSR) – implemented through Law 10,823 on December 19, 2003 by Decree 5,121 on June 30, 2004 – aims to reduce the cost for producers to purchase rural insurance policies and consequently increase the use of this instrument for risk management (Ministério da Agricultura, Pecuária e Abastecimento – MAPA, 2018). The federal government pays a portion of the cost of purchasing rural insurance, thereby reducing the effective cost to the producer and functioning as an incentive to use the insurance market [1].

However, the adoption of rural insurance by Brazilian producers remains very low. Data from the Ministry of Agriculture, Livestock and Supply (Ministério da Agricultura, Pecuária

e Abastecimento – MAPA, 2019) show that in 2018, only 42,376 rural Brazilian producers used insurance to manage production risks. If we consider preliminary data from the Agricultural Census (Instituto Brasileiro de Geografia e Estatística – IBGE, 2017), which indicates the existence of approximately five million rural establishments in Brazil, we find that the portion of establishments using rural insurance is very limited. This low adoption of rural insurance could be explained by various factors, including the availability or continuity of government budget resources for this subsidized program (Medeiros, 2013; Santos, Sousa & Alvarenga, 2013) and high transaction costs due to information asymmetry and problems of adverse selection (Buainain & Vieira, 2011; Ozaki, 2007, 2008, 2010).

The recent studies have evaluated the determinants of production insurance adoption in various countries, exploring how producer and business characteristics influence a producer's decision to use the risk management tool (Fahad et al., 2018; Hill, Hoddinott & Kumar, 2013; Salazar, Jaime, Pinto & Acuña, 2019; Santeramo, 2018; Velandia, Rejesus, Knight & Sherrick, 2009; Was & Kobus, 2018; Zubor-Nemes, Fogarasi, Molnár & Kemény, 2018). Similar studies have been performed in Brazil, with a focus on price risk management tools (Carrer, Silveira and Souza Filho, 2019; Carrer, Silveira, Souza Filho & Vinholis, 2013; Costa, Castro, Callegario, Andrade & Oliveira, 2015; Cruz, Irwin, Marques, Martines Filho and Bacchi, 2011; Silveira, Cruz & Saes, 2012; Silveira, Maia, Cruz & Saes, 2014) and farm operations management (Carrer, Souza Filho & Batalha, 2017; Vinholis, Souza Filho, Carrer & Chaddad, 2016).

In this context, the objective of this study is to identify factors that influence access to the rural insurance market by rural producers in the state of São Paulo. To this end, we use primary data collected from a survey of 175 producers from the 2015/2016 crop year. We use logit models to explore the socioeconomic and behavioral characteristics of the producer (e.g. characteristics of the business) that could influence producer's decision to adopt rural insurance.

This study presents empirical evidence that contributes to the debate on the use of rural insurance as a risk management tool for Brazilian agricultural production. This evaluation is particularly relevant in the face of growing climate uncertainty, which has the potential to directly impact the viability of agricultural activities. In this context, we must remember the importance of agribusiness in the country, which in addition to representing approximately 22% of the gross domestic product (GDP), plays a critical role in terms of exports, job and income generation, land use and food security (Buainain et al., 2019). Thus, on one hand, if higher risk demands more risk management tools, the latter become extremely relevant in a scenario in which agribusiness is fundamental to the economic dynamics of the country.

The results of this study may be useful for policymakers – especially for understanding the factors that determine the adoption of risk management tools by rural producers – and contribute to a more effective dissemination of the use of such tools in agricultural production. In addition, as no research of this type exists in Brazil, our study highlights points of interest to the academic community by analyzing producer decision-making with respect to production risk, including producer behavior characteristics. Such producer characteristics (e.g. risk perception and management confidence) have been incorporated into research that investigates the decision-making of producers in different contexts involving, for example, the adoption of technology (Ward & Singh, 2015) and the use of risk management tools (Carrer et al., 2019; Fahad et al., 2018; Silveira et al., 2014).

2. Literature review

We can classify the risk management tools used in agriculture by three strategies, namely, prevention, mitigation and coping. Focusing our analysis on production risk, while a

preventative strategy seeks to reduce the probability of events that lead to yield loss, a mitigation strategy serves to lessen or neutralize the shock caused by the risk element. Meanwhile, coping is based on *ex post* strategies, after a negative event occurs and seeks to “alleviate the negative effects provoked by the occurrence of events” (Buainain & Silveira, 2017, p. 58). Table 1 provides examples of the three strategies and the different agents involved.

Recent studies have investigated the effect of different production risk management instruments, emphasizing questions related to the prevailing climate change framework. For example, Burney et al. (2014) analyzed how the adoption of technologies and specific actions, such as the use of rural extension, have decreased the exposure of small producers in the Jacuibe Basin (Bahia state) to climate risk. Herwehe & Scott (2018) have also focused on the northeastern region of Brazil, exploring how different adaptive actions such as income diversification and the adoption of irrigation and government programs to combat poverty served to reduce the vulnerability of a sample of rural producers in the state of Pernambuco to weather events. Meanwhile, Pires et al. (2016) found that in Brazil, the adoption of certain varieties of short-maturity soybeans have not only reduced the probability of disease and thereby increased the likelihood for obtaining better soybean prices but have also allowed for the planting a second crop following soybean harvest. However, weather risks in agriculture have increased, particularly due to the uncertainty associated with rainfall volumes. A study by Raucci, Silveira & Capitani (2019) showed that this type of risk can be mitigated by soybean producers in the state of Rio Grande do Sul by adopting rainfall derivatives during the most important growth periods of the plant.

The analyses that exclusively involve rural insurance in Brazil generally discuss the importance of rural insurance (Fornazier, Souza & Ponciano, 2012), the evolution of the different programs adopted, an evaluation of their performance (Macedo, Pacheco & Santo, 2013; Ozaki, 2007, 2008, 2010; Santos et al., 2013) and the potential and challenges present in the rural insurance market (Buainain & Vieira, 2011). Ramos Franca & Angelo (2010) observed the low use rural insurance among producers in the state of São Paulo – only 2.2% of agricultural area was insured in 2007 and 4.6% in 2008. The authors found that in general, the producer (the user of rural insurance) can be characterized by a high level of technology and management of his/her farm.

The recent international literature on rural insurance has focused on analyzing the determinants of the use of insurance as a production risk management instrument. For example, Zubor-Nemes et al. (2018) explored this theme among Hungarian producers. The

Strategy	Farm/community	Institutional level	
		Market	Government
Prevention	Technology choice	Training in risk management techniques	Macroeconomic policies, prevention against natural disasters and animal disease
Mitigation	Production diversification; crop sharing	Weather derivatives, rural insurance, off-farm income	Progressive income tax system, counter-cyclical programs, biosafety measures
Coping	Loan from family, friends and/or community	Sale of assets, bank loan, off-farm income	Social assistance, producer support programs

Table 1.
Production risk management strategies

Source: Adapted from OECD – Organization for Economic Co-Operation and Development (2009)

authors found that the higher the level of education, the size of production and the level of debt, the more likely the use of insurance. Using a sample of Italian producers, [Santeramo \(2018\)](#) found that producer experience using insurance in previous crop years played a key role in the decision to use insurance again. Specifically, the knowledge accumulated with respect to this management mechanism encouraged its continued use. [Was & Kobus \(2018\)](#) confirmed this result using data from Polish producers, highlighting that past losses and experiences using insurance positively affected the decision to adopt insurance. A study by [Li, Liu & Zhang \(2017\)](#) showed that the level of local economic development influences the decision of Chinese producers to use insurance. They found that education and income level also positively impacted the probability of insurance adoption. [Mukhopadhyay, Sinha & Sengupta \(2019\)](#) analyzed the role of gender in the use of rural insurance among rural producers in India, finding that women are most likely to adopt the tool. Finally, using a sample of 1,400 producers in Ethiopia, [Hill et al. \(2013\)](#) used probit models to investigate factors determining the propensity of paying for weather insurance. The study found that male producers – with higher incomes, better access to financial institutions, higher education levels, greater confidence in their capacity to make decisions and a lower aversion to risk – presented a higher propensity to purchase insurance against weather risks. The result of the risk aversion variable presented results that were contrary to what was expected (that producers with greater risk aversion would be more likely to use rural insurance). In addition, the authors found that the insurance premium has a negative effect on the propensity to purchase insurance.

3. Methodology

3.1 Sample

The empirical analyses from this study are based on data obtained from a survey of 175 rural producers in the state of São Paulo, for the crop year 2015/2016 (cross-section). The data were collected by applying a structured survey questionnaire during on-site visits. The producers are from the main agricultural regions of the state of São Paulo, as shown in [Figure 1](#), and produce various agricultural products through varied production systems. The main crops produced on the farms sampled were the following: soybeans (produced on 22.3% of the farms surveyed), corn (35.4%), beef (76%), milk (30.3%), peanuts (4.9%), edible beans (2.9%), eucalyptus (24.6%), sugarcane (14.9%) and fruit and vegetables (16.6%). We collected information regarding the characteristics of the producers, their farms and the management tools adopted in their operation.

3.2 Theoretical model

This study adopts two complementary theories in understanding producer adoption of rural insurance as follows:

- (1) the information asymmetry perspective; and
- (2) the behavioral perspective.

The information asymmetry perspective assumes that the rural insurance market has certain characteristics that differentiate it from other markets. It is based on the existence of information asymmetry between insurers and rural producers ([Ozaki, 2008](#); [Smith & Goodwin, 1996](#)). Specifically, insurers have no way of knowing – at least at a reasonable cost – all relevant information regarding producers and their conduct, neither before or after they sign an insurance policy contract. As a result, screening and monitoring mechanisms are required due to possible failures to enforce insurance contract clauses.

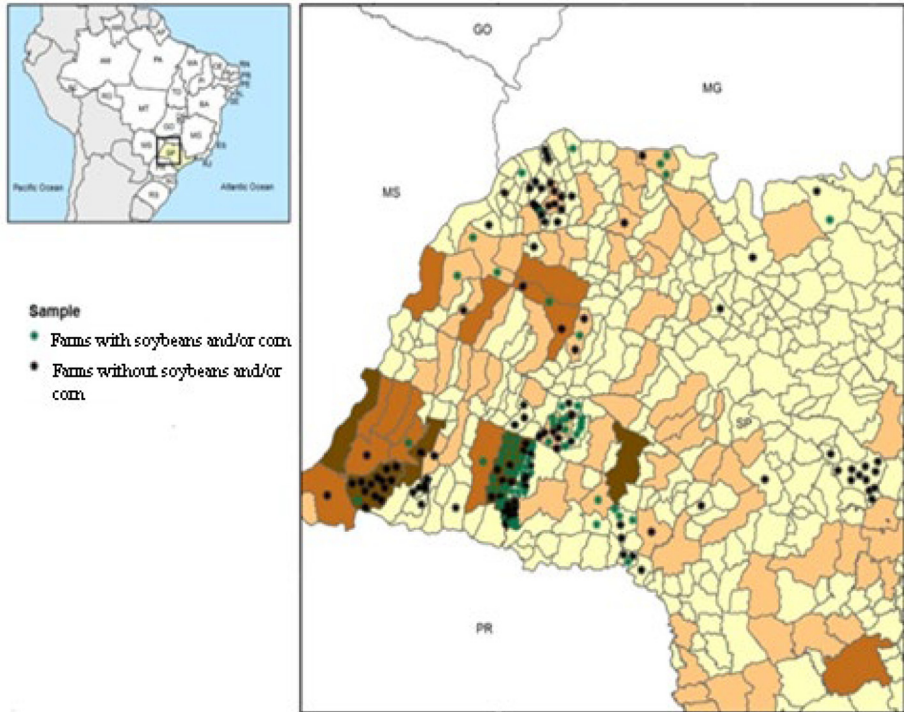


Figure 1.
Geographic
distribution of sample
of farms

The two situations described above, known in the economic literature as adverse selection and moral hazard, imply high costs in rural insurance transactions (Quiggin, Karagiannis & Stanton, 1993). Adverse selection affects agents before the transaction takes place (*ex ante*) and the development of insurer screening mechanisms becomes necessary. In this case, insurers can create favorable conditions for access to rural insurance (e.g. reduce the price of the policy) for wealthier producers or producers with better credit history, for example. Meanwhile, moral hazard affects agents after transactions occur (*ex post*) and can be characterized by a situation in which the producer adopts actions for his/her own benefit, after the contract is written. For example, the rural producers can sub-optimally allocate inputs to benefit from the payment of the insured value, which increases considerably the risks of the operation (Smith & Goodwin, 1996).

To manage the problem of moral risk, insurers must use mechanisms to monitor the conduct of the producer following the purchase of insurance, which, in turn, increases the costs of the transaction. Given this scenario of information asymmetry, the agents offering the insurance can ration access to this mechanism in certain situations, offering insurance only to low-risk producers, which would difficult access to insurance for high-risk producers (Salazar et al., 2019). Likewise, some producers may access more information than others regarding the supply and processes necessary to obtain rural insurance, which would increase the likelihood of their access to insurance (Marr, Winkel, van Asseldonk, Lensink & Bulte, 2016).

In this study, we assume that the rural insurance market is characterized by a high degree of information asymmetry, which can lead to adverse selection and moral hazard and

consequently increase the transaction costs in negotiating this type of financial product. To evaluate the impact of information asymmetry in the adoption of rural insurance, we use proxies with the potential to reduce this asymmetry between producers and insurers. These proxies are the following: education level, production size, use of management tools and access to technical assistance (Fahad et al., 2018; Marr et al., 2016; Salazar et al., 2019). We will elaborate on these points in the next section.

From a behavioral perspective, we assume that the adoption of rural insurance results from an individual decision-making process, in which the marginal expected benefits from its adoption must outweigh their marginal costs. Using an expected utility function (Von Neumann & Morgenstern, 1944), the decision to adopt insurance occurs when the expected utility of adoption (U_a) outweighs the expected utility of non-adoption (U_n) or when $U_a > U_n$. Otherwise, the producer will not adopt the instrument.

The parameters of this decision are not generally observable but can be defined by a latent variable, U_i , which represents the expected utility of producer i in relation to the adoption of rural insurance. This latent variable is a function of a set of personal and behavioral characteristics of the rural producer (e.g. education level, risk propensity, self-confidence in management and confidence in financial institutions). We assume that these characteristics influence the producer perception of the expected utility of insurance adoption and affect the likelihood of adoption (Carrer et al., 2019; Hill et al., 2013; Vergara et al., 2004; Was & Kobus, 2018; Zubor-Nemes et al., 2018). Thus, within this theoretical perspective, risk management strategies are relatively subjective and can vary greatly among producers with differing characteristics (Ozaki, 2008).

3.3 Logit model

The adoption of rural insurance for managing production risk can be represented by a dummy variable (Y_i), such that:

$$Y_i = 1 \text{ if } U_a > U_n \tag{1}$$

$Y_i = 0$ otherwise.

The probability of adopting rural insurance can, therefore, be described as:

$$P[Y_i = 1] = P(e_i > -X_i\beta) = 1 - F(-X_i\beta) = F(X_i\beta) \tag{2}$$

where F is a cumulative distribution function and the parameters β can be estimated by maximum likelihood procedures. The choice of a distribution function for F determines the logit model, while a normal distribution function determines the probit model. In this study, we adopt a logit model, which is expressed by (Greene (2003):

$$P_i = P[Y_i = 1] = \frac{e^{x_i\beta}}{1 + e^{x_i\beta}} \tag{3}$$

The estimation of the parameters β shows the effect (positive or negative) of the variables X_i on the adoption of rural insurance. We can also calculate the marginal effects of each variable X_i (*ceteris paribus*) on the probability of rural insurance adoption:

$$\frac{\Delta p_i}{\Delta x_i} = \frac{\partial p_i}{\partial x_i} = \beta_i \frac{1}{1 + e^{-x_i\beta}} \times \frac{e^{-x_i\beta}}{1 + e^{x_i\beta}} \tag{4}$$

3.4 Variables and hypotheses

The variables used in our empirical analyses are presented in Table 2. As the dependent variable, we use a binary variable that indicates whether or not the producer purchased rural insurance in the 2015/2016 crop year. Among the 175 producers in the sample, only 34 (19.4%) used the rural insurance market for the 2015/2016 crop year. The use of rural insurance among the sample of producers is low, corroborating census statistics. Of the 175 producers, only 62 (35.4%) stated that they were very familiar with the characteristics of rural insurance. The other producers knew of the existence of the rural insurance market but did not have perfect knowledge regarding the operation of a rural insurance transaction, thus demonstrating the high degree of information asymmetry related to this market. This result is in line with the literature review on rural insurance presented by Marr et al. (2016), which showed that a lack of understanding regarding the importance of this tool and a low financial education of producers are the main barriers to accessing the instrument.

Four independent variables in the model refer to personal and behavioral characteristics of the producer. The variable *Edu* is a proxy for the human capital of the producers. It is a binary variable that assumes a value of 1 if the producer has completed a higher education degree, and 0 if not. In general, we assume that producers who have completed a higher education have a greater capacity to access and process market information, thereby

Variable	Description	Average	Standard error
<i>Dependent variable</i>			
<i>Insurance</i> (<i>Y</i>)	Binary variable that assumes 1 for adoption of rural insurance for the 2015/2016 crop year; 0 otherwise	0.194	0.397
<i>Independent variables</i>			
<i>Personal and behavioral characteristics of the producer</i>			
<i>Edu</i> (<i>X</i> ₁)	Binary variable that assumes 1 if completed higher education; 0 otherwise	0.486	0.501
<i>Exp</i> (<i>X</i> ₂)	Years of experience in farm management	18.766	17.428
<i>Conf</i> (<i>X</i> ₃)	Likert scale index (from 1 to 5) of rural producer's self-confidence in his/her management capacity; the closer to 5, the higher the self-confidence	2.823	0.939
<i>Risk</i> (<i>X</i> ₄)	Risk propensity index (from 0.2 to 1); the closer to 1, the higher the risk propensity	0.471	0.189
<i>Farm characteristics</i>			
<i>SoyCorn</i> (<i>X</i> ₅)	Binary variable that assumes 1 if the producer grows soybeans or corn on his/her farm; 0 otherwise	0.429	0.496
<i>Area</i> (<i>X</i> ₆)	Farm size (hectares)	336.20	346.99
<i>Divers</i> (<i>X</i> ₇)	Production revenue diversification index for the 2015/2016 crop year (from 0 to 1); the closer to 1, the higher the revenue diversification of the farm	0.373	0.252
<i>Adoption of management tools and access to information</i>			
<i>MgmtInd</i> (<i>X</i> ₈)	Index of intensity of use of farm management tools (from 0 to 1); the closer to 1, the greater the intensity of use	0.502	0.138
<i>Assist</i> (<i>X</i> ₉)	Binary variable that assumes 1 if the producer received private technical assistance during the 2015/2016 crop year; 0 otherwise	0.526	0.501
<i>Coop</i> (<i>X</i> ₁₀)	Binary variable that assumes 1 if the producer is a member of an agricultural cooperative; 0 otherwise	0.674	0.469

Table 2.
Variables used in the econometric analyses

reducing the information asymmetry for these producers (Fahad et al., 2018). In addition, they tend to better understand both the importance of adopting risk management tools and the means of accessing such tools, which increases the probability of use of rural insurance (Carrer et al., 2019; Hill et al., 2013; Li et al., 2017; Marr et al., 2016; Zubor-Nemes et al., 2018). Therefore, the variable *Edu* is expected to have a positive effect on the likelihood of adopting rural insurance (*H1*).

The variable *Exp* represents the years of experience of the producer in managing farms. Producers with more experience in managing agricultural production tend to accumulate knowledge in the area and therefore have a positive effect on the adoption of risk management tools (Fahad et al., 2018; Santeramo, 2018; Velandia et al., 2009; Was & Kobus, 2018). Therefore, the greater the experience of the producer, the higher the probability of adopting rural production insurance (*H2*).

The variable *Conf* is a proxy to measure the confidence of the producer in his/her management ability. The variable assumes discreet values of 1 (strongly disagree) to 5 (strongly agree) for the affirmation, "I consider my management capacity to be above the average of the producers in the region." On one hand, as discussed in Subsection 3.2, the behavioral literature shows that excess confidence in administration leads individuals to overestimate their abilities, resulting in excessive optimism with regard to the expected results of decisions made (Cruz et al., 2011; Silveira, Maia, Saes & Cruz, 2013). These characteristics tend to reduce the probability that the individual will seek rural insurance. On the other hand, Hill et al. (2013) argued that producers with higher self-confidence were more likely to demand and pay for insurance against weather risks. The variable *Conf* in this study is intended to affect the probability of access to rural insurance, although we cannot establish a priori the meaning of this effect (*H3*).

The variable *Risk* was constructed from two-point Likert scale questions that assessed the extent to which producers disagreed (1 for strongly agree and 5 for strongly disagree) with the statements: "When it comes to my business, I prefer the safest option" and "Whenever possible, I cover production risks using insurance" The responses to these two questions were totaled and then divided by ten. Therefore, the closer to 1, the higher the risk propensity of the rural producer. Behavioral theory shows that rural producers with a greater risk propensity avoid adopting risk management instruments (Carrer et al., 2019). These producers tend to underestimate the risk associated with production and marketing decisions, which decreases their likelihood to seek rural insurance as a form of protection. Therefore, the hypothesis associated with the variable *Risk* is that risk has a negative effect on the probability of using rural insurance (*H4*).

The variables associated with the characteristics of the farm are: *SoyCorn*, *Area* and *Divers*. As the study sample is composed of producers of various agricultural products, we constructed a binary variable to control for the effects of soybean and corn production on the probability of accessing rural insurance. According to data from *Ministério da Agricultura Pecuária e Abastecimento – MAPA (2015, 2016)*, these products represent, on average, approximately 52% of the beneficiaries of subsidized rural insurance contracts and 59% of the total insured area in the state of São Paulo in 2015 and 2016. In fact, the production of these crops is intensive in terms of capital and agri-chemicals, and the crops are highly prone to pests and vulnerable to weather events. As a result, we hypothesize that producers who grow soybeans and/or corn are more likely to demand and use rural insurance (*H5*). Meanwhile, the variable *Area* measures the effect of production scale on the probability of adopting rural insurance. In this case, three considerations should aid in formulating a hypothesis regarding the expected effect of this variable. First, we assume that producers with larger areas own more land and consequently present a lower risk to insurers. Second,

we assume that economies of scale are present in the purchase of insurance as transaction costs are fixed (Salazar et al., 2019). Finally, we assume that larger farms have greater risk, which leads to the use of more complex risk management instruments (Carrer et al., 2019). Therefore, we hypothesize that *Area* has a positive effect on the probability of adopting rural insurance (*H6*).

The variable *Divers* was calculated as a Herfindahl–Hirschman concentration index (HHI), from which the value of 1 is subtracted to obtain a diversification indicator for each producer. We used the total revenue and the revenue from the different agricultural activities of each farm in the calculation. Therefore, the larger the value of *Divers*, the greater the revenue diversification of the farm. *Divers* could demonstrate two possible effects on the probability of a producer adopting rural insurance. On one hand, we could expect that producers who diversify their production are more risk averse and consequently more likely to seek additional risk management instruments (e.g. rural insurance). On the other hand, diversification in production and rural insurance could be considered as a strategic substitutes for risk management and could lead producers to choose to adopt only one measure [2]. Therefore, we expect that diversification affects the probability of accessing rural insurance, without establishing a priori the exact direction of this effect (*H7*).

The three last explanatory variables in the model refer to management characteristics and access to information. The variable *MgmtInd* is an index that incorporates a producer's use (or non-use) of seven management tools as follows: the preventative management of animal health and pests; the use of techniques for traceability in production; the use of financial management instruments; the establishment of annual production plans; the obtaining of environmental and/or quality certificates; the training of employees; and internet access for consulting market information. The index was constructed by summing the positive responses and dividing these by seven. The closer the index to 1, the greater the producer adoption of management tools. We expect the costs of accessing information to be substantially lower for producers with greater use of management tools, which reduce information asymmetry in the insurance market. In such cases, we can assume that if the insurer is aware of the management capacity of the producer, this will create favorable conditions for accessing insurance for producers with a greater use of management tools, given the lower production risk of such producers. Thus, *H8* is as follows: the greater the use of management tools and the likelier the adoption of rural insurance.

The variable *Assist* is a binary variable that measures if the producer received private technical assistance on his/her farm during the 2015/2016 crop year. Technical assistance is important for disseminating information on new production techniques and farm management. Technicians can additionally help producers to better understand risks and ultimately, the importance of insurance as a risk mitigation tool (Carrer et al., 2013). As a result, access to technical assistance is important to reduce information asymmetry for the producer (Fahad et al., 2018). Therefore, we expect that the variable *Assist* has a positive effect on the probability of adopting rural insurance (*H9*).

Finally, the binary variable *Coop* measures indicates whether the producer is a member of a rural production cooperative. Cooperatives are important spaces for sharing information and experiences on production, management and marketing. Therefore, we expect that producers who are members of cooperatives have greater access to information on the rural insurance market, which tends to increase the probability of its use (*H10*). Table 3 presents a preliminary, descriptive and comparative analysis of the independent variables for the producers who adopted and did not adopt rural insurance.

4. Analysis of results

Table 4 presents the estimations of the logit models to identify the factors determining the adoption of rural insurance by the producers in the sample. We estimated two regressions: in the first, we included all independent variables and in the second, we included only the variables that were significant in the first regression. Appendix 1 shows the goodness of fit measures of the models, which proved to be satisfactory. Appendix 2 presents a correlation matrix of the independent variables, which allows us to avoid problems of multicollinearity for the model estimated [3]. The likelihood ratio test allows us to reject the hypothesis that all the coefficients estimated in Models 1 and 2 are equal to zero at the 1% significance level.

	Group 1: Adopted insurance 34 producers		Group 2: Did not adopt insurance 141 producers		p-value
	Average	Standard error	Average	Standard error	
<i>Edu</i> (X_1)	0.529	0.506	0.475	0.501	0.186
<i>Exp</i> (X_2)	22.294	13.697	17.915	18.153	0.061
<i>Conf</i> (X_3)	2.558	0.927	2.886	0.934	0.094
<i>Risk</i> (X_4)	0.338	0.168	0.503	0.179	0.000
<i>SoyCorn</i> (X_5)	0.852	0.359	0.326	0.470	0.000
<i>Area</i> (X_6)	488.38	415.20	299.51	319.42	0.002
<i>Divers</i> (X_7)	0.490	0.238	0.344	0.247	0.001
<i>MgmtInd</i> (X_8)	0.605	0.112	0.477	0.133	0.000
<i>Assist</i> (X_9)	0.706	0.462	0.482	0.501	0.009
<i>Coop</i> (X_{10})	0.794	0.410	0.645	0.480	0.098

Table 3. Descriptive statistics of the independent variables for the two groups of producers

Notes: p-values refer to t-tests to compare the averages (of the continuous variables); and the frequencies (of the binary variables) between the two groups

Variable	Model 1		Model 2	
	Coefficient	Marginal effect	Coefficient	Marginal effect
Constant	-7.5007**	-	-8.2648***	-
<i>Edu</i> (X_1)	1.4512**	0.1196	1.4522***	0.1245
<i>Exp</i> (X_2)	-0.0157	-0.0013	-	-
<i>Conf</i> (X_3)	-0.3160	-0.0265	-	-
<i>Risk</i> (X_4)	-6.7953***	-0.5706	-6.5713***	-0.5662
<i>SoyCorn</i> (X_5)	2.0612***	0.1878	2.0951***	0.1952
<i>LogArea</i> (X_6)	0.7041**	0.0591	0.6903**	0.0595
<i>Divers</i> (X_7)	1.2196	0.1024	-	-
<i>MgmtInd</i> (X_8)	4.9819**	0.4183	5.3848***	0.4639
<i>Assist</i> (X_9)	1.3595**	0.1095	1.3421**	0.1089
<i>Coop</i> (X_{10})	0.1537	0.0128	-	-
Log-likelihood	-47.3266		-48.5614	
χ^2	77.6791		75.2093	
Significance (p-value)	0.0000		0.0000	
Mcfadden's R^2	0.4507		0.4642	
Area below the ROC curve	0.9204		0.9156	
Hosmer-Lemeshow χ^2	4.0961	p-value 0.8483	2.6904	p-value 0.9522
Predicted corrected values	86.86%		85.14%	

Table 4. Factors determining the adoption of rural insurance

Notes: ***Statistically significant at 1%; **statistically significant at 5%; *statistically significant at 10%

Six of the ten explanatory variables in Model 1 are statistically significant: the binary variable for producer education (*Edu*), the risk propensity index (*Risk*), the variable for if the producer grows soybeans or corn on his/her farm (*SoyCorn*), farm size (*Area*), index of intensity of use of farm management tools (*MgmtInd*) and the binary variable for if the producer received on-farm technical assistance in the 2015/2016 crop year (*Assist*). Model 2 corroborates the importance of these variables; whose significance levels were higher.

Two variables representative of producer characteristics were found to be statistically significant. The first, *Edu*, is a binary variable with a value of 1 if the producer completed a higher education and 0 otherwise. The positive coefficient estimated for this variable corroborates *H1*. The marginal effect of the variable, calculated for the sample average, shows that having a higher education increases by roughly 12% the probability of adopting rural insurance, *ceteris paribus*. This result is in line with recent literature on the topic – for instance with studies by [Fahad et al. \(2018\)](#), [Zubor-Nemes et al. \(2018\)](#), [Li et al. \(2017\)](#) and [Velandia et al. \(2009\)](#). When producers have a higher education, they possess a greater capacity for understanding the functioning of the insurance market, the procedures necessary for accessing insurance and the importance of managing production risk. The costs of accessing insurance and of information asymmetry are lower for these producers than for those who do not have a high level of education.

The second variable, *Risk*, seeks to measure the propensity of the producer to assume risk. The parameter estimated for this variable shows a negative effect on the probability of adopting rural insurance, with statistical significance at the 1% level for both models. This result corroborates *H4*, which is based on evidence obtained from the area of behavioral economics ([Marr et al., 2016](#); [Silveira et al., 2012](#)). We note that the variable in question has a high marginal effect, the highest for the variables used in the models. This result underlines the importance of behavioral characteristics of individuals in explaining the decision-making process. Individuals with a higher risk propensity tend to accept higher risk alternatives and underestimate the importance of adopting risk management instruments ([Carrer et al., 2019](#); [Pennings & Leuthold, 2000](#); [Ullah, Jourdain, Shivakoti & Dhakal, 2015](#)).

We note that farm characteristics also proved to be important in understanding the choice to use rural insurance. Producers of soybeans and/or corn proved more likely to purchase rural insurance, confirming *H5*. The results also showed that the larger the farm size, the higher the probability that a producer adopts rural insurance, corroborating *H6*. In fact, large farms have adjusted more quickly to changing technological and managerial paradigms of Brazilian agriculture ([Carrer et al., 2017](#)). The adoption of new technology and new risk management instruments (e.g. rural insurance) occurs more quickly on larger farms. In addition, the larger the production scale, the larger the economy of scale when purchasing insurance (due to the existing fixed costs) and the higher the incentive to adopt risk management instruments (due to the larger potential for loss) ([Salazar et al., 2019](#); [Silveira et al., 2014](#); [Ullah et al., 2015](#); [Zubor-Nemes et al., 2018](#)). In terms of the supply of insurance, a larger production scale can potentially translate into a lower risk of non-compliance of producers to the insurance contract with insurers; in addition to greater guarantees, these producers tend to have a greater economic and financial capacity compared with smaller-scale producers, and therefore, have more favorable conditions for accessing rural insurance.

Finally, [Table 3](#) shows that two of the variables representing business management also proved to be significant. The results show that the greater the use of management tools (including operational and financial instruments and tools for accessing market information), the higher the likelihood of using rural insurance, validating *H8*. We note that this variable had a high marginal effect. On the side of the insurer, producers with a high use

of management tools tend to suggest a low-risk profile – particularly regarding the operations of the given activity (operational risk) – and thus contribute to the fulfillment of the contract. Consequently, such producers have a higher probability of being approved for purchasing rural insurance.

The positive coefficient estimated for the variable *Assist* validates *H9*. The marginal effect estimated for this variable shows that the probability of purchasing insurance increases 10.9% if the producer receives private technical assistance, *ceteris paribus*. Producers who receive more frequent technical assistance have more exposure to information disseminated by the technicians (Carrer et al., 2019). The access to information from reliable sources such as through technical assistance increases the confidence of producers in the decision to adopt new management instruments such as rural insurance. In addition, rural extension technicians contribute to reducing information asymmetry and transaction costs in the transactions between insurance providers (generally financial organizations) and producers.

5. Conclusions

This study investigated the determinants of adopting rural insurance by producers in the state of São Paulo, using primary data from a sample of 175 individuals. Only 19.4% of producers in the sample purchased insurance in the 2015/2016 crop year. Similarly, only 35.4% claimed to be very familiar with the steps involved in purchasing this type of insurance.

We found that characteristics of the producer (education and risk propensity) and the business/the farm (use of technical assistance, management tools, soybean/corn production and farm size) influenced the likelihood of using rural insurance. The variables with the greatest impact on insurance use were producer propensity to assume risk and the use of management tools. These findings support the empirical literature regarding the adoption of risk management tools among rural producers (Carrer et al., 2019; Fahad et al., 2018; Salazar et al., 2019; Santeramo, 2018; Silveira et al., 2012; Velandia et al., 2009; Was & Kobus, 2018; Zubor-Nemes et al., 2018).

We note that the results indicate that the use of insurance is more likely among large producers, producers with higher levels of education, producers who adopt more farm management tools and producers who receive private technical assistance. These producers can more easily access information and present a lower risk to insurers, corroborating the literature on information asymmetry in the insurance market. In addition, our results confirm that aspects related to the risk behavior of the producer are relevant for understanding producer decisions to adopt risk management instruments. Therefore, such factors should be considered in the formulation of public policies aimed at promoting such management tools.

The evidence from this study can assist producers, policymakers and insurers in conducting their respective activities, and additionally underlines the need for more discussion on the topic. Despite the importance of insurance for risk management, no studies in Brazil take a similar approach and the inclusion of variables related to producer behavior in analyzing determinants of adopting this financial product are rare. Therefore, this analysis can contribute to the dissemination of the use of this instrument and to additional studies that seek to investigate other aspects of this market.

This study has certain limitations, such as its cross-sectional data, the concentration of only certain agricultural products in the study and the analysis of insurance adoption based on a binary dependent variable (for example, and not on the percentage of coverage of the insurance purchased). Future work could explore a broader sample of producers from

different regions, and could evaluate production and price risk management decisions jointly and over time. We also suggest an analysis of the determinants of the use of insurance based on the share of production insured and a study of the effect of regional development characteristics on the adoption of this instrument.

Notes

1. Agricultural insurance accounts for the greatest value of the eight types of rural insurance in Brazil. In 2018, 88% of the PSR budget was allocated to agricultural insurance. Three types of agricultural insurance exist in Brazil: that for operating costs, yields and revenue. Insurance for operating costs has a maximum indemnity limit (LOI) calculated from the cost of the insured crop. The LOI of yield insurance is calculated by the guaranteed yield of the insured area multiplied by the producer price at the moment the insurance is purchased. For these two types of insurance, compensation occurs when the yield obtained is lower which is guaranteed in the policy. The LOI for the third type of insurance (revenue) is measured from expected revenue based on expected yield and the futures market price. Compensation occurs when effective revenue is lower than the expected revenue guaranteed by the policy. Two types of contracts exist in Brazil for agricultural insurance: multi-peril, which covers various weather risks and named-peril, which covers only specific risks of interest. Agricultural crop insurance can be purchased on a plot-by-plot basis for a given farm. To purchase insurance, the rural producer must formalize a proposal for rural insurance with an insurer authorized by MAPA. The insurance levels and yields to be guaranteed by the policy are set by each insurer. To participate in PSR, the insurer submits the proposal to MAPA and requests an insurance subsidy. Upon examination and approval of the proposal, the insurer notifies the producer and the approved subsidy amount is deducted from the premium to be paid by the producer ([Ministério da Agricultura, Pecuária e Abastecimento – MAPA, 2015, 2016, 2018, 2019](#)).
2. We can reasonably assume that the effect of this variable depends on the level of risk aversion of each producer. Producers who are very risk averse may consider diversification and insurance as complementary risk management instruments. Producers with low and intermediate levels of risk aversion may consider the two as substitutes.
3. All correlation indices are less than 0.7, the value considered critical for the existence of multicollinearity ([Gujarati, 2009](#)).

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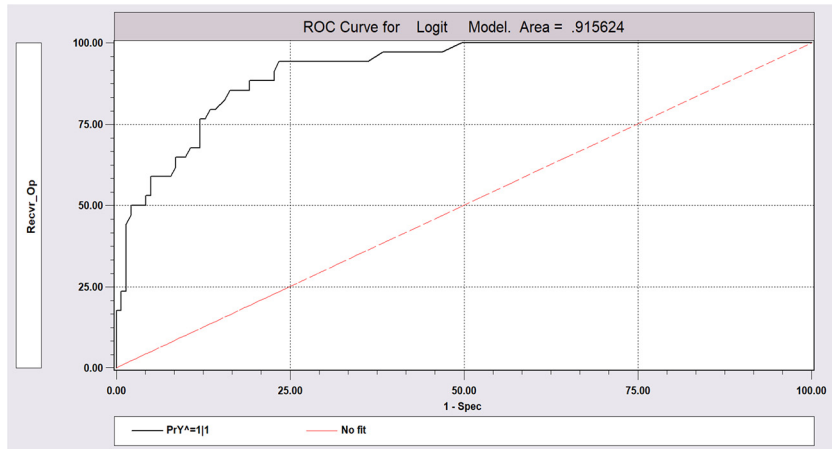
Table A1.
Confusion matrix of
logit model 1

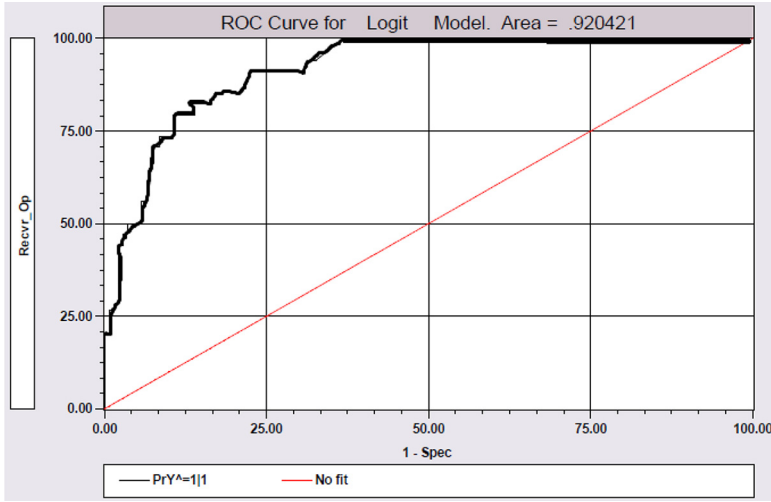
Observed value	Predicted value		Prediction success
	0	1	
0 (non-adopter)	133 (76.0%)	8 (4.6%)	133/141 = 94.33% (% specificity)
1 (adopter)	15 (8.6%)	19 (10.9%)	19/34 = 55.88% (% sensitivity)
	Correct prediction of model		= (133 + 19)/175 = 86.9%

Table A2.
Confusion matrix of
logit model 2

Observed value	Predicted value		Prediction success
	0	1	
0 (non-adopter)	123 (70.3%)	18 (10.3%)	123/141 = 87.23% (% specificity)
1 (adopter)	8 (4.6%)	26 (14.9%)	26/34 = 76.47% (% sensitivity)
	Correct prediction of model		= (123 + 26)/175 = 85.1%

Figure A1.
ROC curve for logit
Model 1





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Figure A2.
ROC curve for logit
Model 2

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Table A3.
Correlation matrix of
independent
variables

	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
X_1	1	-0.37	-0.09	0.23	-0.19	0.13	-0.23	0.01	-0.06	0.19
X_2		1	-0.11	-0.18	0.34	-0.05	0.22	0.11	0.14	-0.06
X_3			1	0.04	-0.07	-0.04	-0.05	-0.09	-0.11	-0.09
X_4				1	-0.16	-0.01	-0.19	-0.04	-0.02	0.02
X_5					1	0.13	0.48	0.54	0.13	0.11
X_6						1	-0.05	0.13	0.06	0.19
X_7							1	0.34	-0.04	0.01
X_8								1	0.09	0.19
X_9									1	0.14
X_{10}										1

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