Computers and Electronics in Agriculture 138 (2017) 11–19

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Original papers

Factors influencing the adoption of Farm Management Information Systems (FMIS) by Brazilian citrus farmers

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ARTICLE INFO

Article history:
Received 19 May 2016
Received in revised form 3 April 2017
Accepted 5 April 2017

Keywords:
Technology adoption
Farm Management Information Systems (FMIS)
Computers
Citrus farms

ABSTRACT

This paper examined the determining factors in decisions of citrus farmers on adoption of computers and Farm Management Information Systems (FMIS). Primary data were collected from a random representative sample of 98 citrus farmers from the state of São Paulo, Brazil. The data was analyzed using logit and count data (Poisson regression) models, which enabled testing hypotheses on the effect of ten variables on the decisions of farmers. The results of the logit model showed that education and production size had a positive and statistically significant effect on the adoption of computers, while experience had a negative effect. The adoption and intensity of use of FMIS were influenced positively by overconfidence in management, production size and use of technical assistance. Contract adjustments and farmers' experience have a negative impact on the adoption of FMIS. The results confirmed the main hypotheses and can contribute to the development of new strategies for greater diffusion of FMIS in Brazilian citrus industry, which is relevant to increasing farm efficiency.

1. Introduction

Brazil is the world's largest orange producer with 19,077,572 tons produced in 2013 (FAO, 2013). The country also has large orange juice processing companies (Cutrale and Citrovita-Citrosuco), in addition to being a major producer and international exporter of orange juice. Despite the importance of this agrifood chain for the Brazilian economy, since the mid-2000s, the citrus industry has been subject to high price volatility, a shift toward industrial concentration of juice processing companies and problems related to increased pests and diseases in the orchards. These issues have increased the pressure for efficiency gains in citrus production, which has ultimately resulted in the departure of thousands of farmers from the activity. In fact, the number of citrus farmers fell from 15,000 in 2001 to 10,100 in 2013, and area planted with oranges dropped by an average rate of 1.25% per year in the same period (Conab, 2013; FAO, 2013).

The economic sustainability of citrus farms in tough market conditions (low output prices, commercial conflicts and increasing institutional pressures for quality and environmental sustainability) is strongly dependent on their efficiency and productivity levels. Differences in the adoption of new production and management technologies are among the main factors that explain differences in the efficiency and productivity of citrus farms in Brazil. Citrus farmers who operate their farms with high total productivity of the factors and positive profitability are characterized by more intense adoption of new production and management technologies (Carrer et al., 2015).

Carrer et al. (2015) used stochastic frontier analysis (SFA) to estimate farms' efficiency indexes and the effects of FMIS adoption on these indexes. Data from 98 citrus farms of the state of São Paulo were used in their econometric analysis. They found that the adoption of Farm Management Information Systems (FMIS) had a positive and statistically significant effect on the technical efficiency of farms. The core argument of the study was that these technologies reduce informational problems and improve decisions related to planning, control and coordination of production processes, resulting in better use of production factors and higher technical efficiency levels. The authors also suggested a future investigation into personal, social and economic variables that explain the adoption of FMIS by Brazilian citrus farmers.

This paper aims to identify the determining factors in decisions of citrus farmers on adoption of computers and Farm Management Information Systems (FMIS) using the same database of Carrer et al. (2015). Different from them, the determinants of adoption of computers and FMIS are analyzed in this paper; instead of reproduce their analysis of the determinants of farms' technical

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http://dx.doi.org/10.1016/j.compag.2017.04.004
0168-1699/

efficiency. Their dependent variable was a proxy for "efficiency", and the set of explanatory variables includes adoption of FMIS. In this paper, the dependent variable is adoption of FMIS, while personal, social and economic characteristics are explanatory variables. The econometric models are also different. To our knowledge, this is the first study to consider factors affecting farmers' adoption of FMIS in Brazilian citrus industry. More generally, there are still few studies on the adoption of FMIS for Brazilian agriculture, which reinforces the importance and innovative character of this paper.

The data were collected by means of personal interviews with owners and managers of 98 citrus farms in the state of São Paulo, where 74% of Brazilian orange production takes place. São Paulo Research Foundation provided financial resources for this survey. Logit and count data (Poisson regression) models were estimated. In the logit model, the value of the dependent variable is 0 (non-adoption) or 1 (adoption), which enables identification of the determining factors of the likelihood of adoption of computers for improve decision-making process by citrus farmers. In the count data model, the value of the dependent variable ranges from 0 to 7, enabling identification of the determining factors for adoption and intensity of use of FMIS.

The contribution of this paper is twofold: it provides empirical evidence on the role of personal, social and economic determinants of adoption of FMIS; and explain the low diffusion and heterogeneity in the adoption of FMIS by rural properties in Brazil. Furthermore, few studies have examined the adoption and diffusion of computers and FMIS in Brazilian agriculture.

Section 2 of the paper contains a literature review on the adoption of management technologies in agriculture. Section 3 presents the analytical framework, the description of the sample and the variables used in the econometric analysis. The fourth section presents and discusses the results of the econometric analyses of the determinants of adoption of computers and FMIS. Finally, Section 5 contains final remarks.

2. Literature review

Analysis of the factors that affect decisions of farmers in the adoption of new technologies is recurrent and widely revisited in agricultural economics literature (Feder et al., 1985; Souza Filho et al., 2011). Pioneering initiatives of the farmers for the adoption of new technologies can foster competitive advantages (e.g., higher total factor productivity – TFP) in relation to those who do not adopt them (non-adopters) or those who only adopt them later (latecomers). Therefore, technology adoption is a process characterized by a certain level of heterogeneity, where it is highly useful to understand the variables/factors that affect the process (Foster and Rosenzweig, 2010).

The advances in Information Technology (IT) observed since the 1990s have encouraged empirical studies on the determining factors for adoption of technologies applied to production management[1] by farmers in different countries. These studies generally use primary data from farms and qualitative choice (e.g., logit and probit) or censured variables econometric models (e.g., tobit and count data) to identify the factors that affect the decision of adoption and intensity in the use of different management technologies by farmers. Table 1 presents a literature review on some of these studies.

[1] Such as the use of computers, precision agriculture technologies, integrated management practices, decision-making information systems and certification of inputs/products. We define management technologies as any technology that affects information organization (collecting, processing, storing, and disseminating) and the decision-making process on farms. These technologies generally also affect the organizational structure of the farms. These technologies are referred to as FMIS.

In Brazilian agribusiness, farm management is still heterogeneous, which is considered one of the main barriers to greater competitiveness for this sector (Mendes et al., 2014). According to data from the Agricultural Census (2006), only 4.54% of farms in Brazil had computers and 1.87% of Brazilian farmers accessed the Internet on their farms during that period. Unfortunately, there is no updated census data on this point. However, it is known that this situation has not improved significantly in recent years. Furthermore, access to IT by Brazilian farmers tends to occur primarily on large farms. Since these technologies are increasingly important for improving information access and generating efficiency gains in agriculture, this situation tends to accentuate the economic and social differences between Brazilian farmers (Souza Filho et al., 2011).

Despite the importance of greater diffusion of IT, there are very few studies on the factors that explain the adoption of these tools by Brazilian farmers. In this regard, it is relevant to better understand the variables that affect decisions by Brazilian farmers to adopt computers and FMIS. Identification of the heterogeneity factors in the technology adoption process is essential for formulating public policies and private strategies aimed at greater diffusion of management technologies (Feder et al., 1985).

3. Materials and methods

3.1. Analytical framework

Neoclassical microeconomic theory postulates that the adoption of production and management technologies is a result of individual decision-making processes, in which the marginal benefits of the technologies are expected to exceed their marginal costs (Foster and Rosenzweig, 2010). Therefore, in deciding to adopt a technology, farmers seek to maximize its expected utility. The decision to adopt a new technology occurs when the expected utility of adoption (U_a) exceeds the expected utility of non-adoption (U_n), i.e., $U_a > U_n$. The parameters of this decision are generally not observed, but can be defined by a latent variable, U_i.

According to revised empirical studies, this latent variable (U_i) is a function of a set of personal (e.g., education and access to information), behavioral (e.g., risk aversion and overconfidence in management) and social (e.g., participation in information networks) factors related to the farmers, as well as characteristics of the technology (e.g., ease of use and profitability), of the farms (e.g., production size and crop diversification) and of the institutional environment (e.g., access to extension policies and rural credit). This set of factors has the potential to affect the perception of farmers regarding the expected utility of a technology, consequently modifying the farmer's likelihood of adopting the technology. Mathematically, this is represented as follows:

$$U_i^* = \beta X_i + e_I \quad i = 1, 2, \ldots, N \tag{1}$$

where β is a parameter vector that shows the effect of the aforementioned X_i factors on the likelihood of adoption of the technology or technologies and e_i is the error term of the equation. Empirical studies use different econometric methods to estimate the β parameters of Eq. (1). The present study used two econometric models to estimate the impact of a set of personal, social, behavioral, structural and institutional factors on the probability of Brazilian citrus farmers adopting management technologies: logit and count data (Poisson regression model). The logit model – whose dependent variable has a value of 0 (non-adoption) or 1 (adoption) – enables identification of the effects of the X_i variables on the likelihood of adoption of computers for management decision-making by citrus farmers. The count data model – whose dependent variable is the sum of the adoption of seven management tools (the closer to

Table 1
Summary of literature review on determinants of FMIS adoption.

Reference	Sample	FMIS analyzed	Determinants of FMIS adoption
Woodburn et al. (1994)	199 South African farmers	Computers as decision-aids in farm management	Farmer's education (+), size of business (+), proportion of farmland rented (+), self-rating of management skills (+), off-farm employment (+), age of farmer (−), beef enterprise (−)
Gloy and Akridge (2000)	1742 U.S. farmers	Computers and internet	Education (+), age (−), farm size (+), nonfamily employees (+), use of written management plans (+), participation in physical labor on farm (−), maximize profitability goal (+)
Adrian et al. (2005)	85 U.S. farmers	Precision agriculture technologies	Perceived net benefit (+), farm size (+), farmer education (+), attitudes of confidence toward technology (+)
Alvarez and Nuthall (2006)	100 dairy farmers in New Zealand and Uruguay	Computer based information systems	Farm size (+), age (−), education (+), information skills (+), time spent on management work (+), adviser time used (+), learning style
Isgin et al. (2008)	491 U.S. farmers	Precision farming technologies	Farm size (+), soil quality (+), computer use (+), indebtedness of farmer (+), urban influences (+)
Souza Monteiro and Caswell (2009)	138 Portuguese pear producers	EurepGAP traceability system	Membership in producer organizations (+), farm productivity (+), full time farmer (+), producing under a protected designation of origin (+), age (−), education (+)
Tiffin and Balcombe (2011)	2366 U.K. farmers	Computers	Number of workers (+), presence of organic enterprises (+), farm type: dairy farm (+), age of farmer (−), education (+), farm size (+)
D'Antoni et al. (2012)	469 U.S. cotton farmers	GPS guidance systems	Perceived importance of technology (+), perceived importance of input cost savings (+), use of computers (+), age of farmer (−), farm size (+)
Dill et al. (2015)	73 Brazilian beef cattle farmers	Economic management practices (organizing economic data, preparing annual plans, and using electronic cash-flow statements).	Internet access (+), association membership (+), use of technical assistance (+), production diversification (−), farm area (−), number of cows (+), weaning rate (+)
Vinholis et al. (2016)	84 Brazilian beef cattle farmers	SISBOV traceability system	Previous experience with technologies (+), access to up-date information (+), diversified life experience (+), participation in relationship networks (+)

Note: The signs show the direction of the effect of each variable on the probability of adopting FMIS.

seven, the higher the intensity of adoption) – enables investigation of the effect of the X_i variables on the intensity of adoption of a set of FMIS. Following is a description of the two econometric models.

3.1.1. Logit models

After obtaining information about the farmers' choices, the standard observed in the adoption of computers for management decision-making can be represented by a dummy variable (*yi*), where:

yi = 1 if *Ua* > *Un*
yi = 0 if not.

The likelihood of adoption of the technology can be defined as follows:

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

where F is a function of cumulative distribution and the β parameters can be estimated through maximum likelihood procedures. The qualitative choice models frequently used in technological adoption studies (logit and probit) differ only in the choice of the cumulative distribution function (F). The logit model assumes a logistical functional form and can be used to estimate the effect of the X_i variables on the likelihood of adoption of computers for decision-making by citrus farmers. In its specific form, the logit model can be expressed as (Greene, 2003):

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

After estimating the β parameters, which only show the effect (positive or negative) of the x_i variables on the adoption of computers, the marginal effects of each variable on the likelihood of adoption can also be calculated. That is, the effect of small changes (usually interpreted as unitary changes) in a specific x_i variable on the likelihood of adoption of computers, *ceteris paribus*:

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

3.1.2. Data count models

In addition to examining the adoption of a single technology (computers for decision-making), the present study also seeks to understand the determinants of adopting a FMIS package. This variable can be considered a proxy for technological intensity in farm management.

Data count models have been used to analyze the adoption of technology packages by farmers (Isgin et al., 2008). In the present study, the dependent variable of the model (y) is the sum of the total number of FMIS that the farmer uses in his/her farm. Consequently, a Poisson probability distribution is more appropriate than a normal (used in the probit model) or logistic distribution (used in the logit model). With Y for the random Poisson variable, the probability density function can be represented as:

$$f(y_i|x_i) = P(Y_i = y_i) = \frac{e^{\lambda}\lambda^{y}}{y!}, \quad y = 0, 1, 2, \ldots \tag{5}$$

where y_i is the number of FMIS adopted by the farmer and x_i are the variables that determine the adoption of FMIS. The expected mean parameter (λ) of this probability function is defined as:

$$E(y_i|x_i) = \lambda_i = \exp(x_i'\beta) \tag{6}$$

Eq. (6) represents the Poisson data count regression model where the β parameters can be estimated through maximum likelihood procedures. This procedure is done through maximizing the following logarithmic likelihood function:

$$\begin{aligned} lnL(\beta) &= \ln\left[\frac{e^{\lambda}\lambda^{y}}{y!}\right] = -\lambda + y_i \ln(\lambda) - \ln(y_i!) \\ &= -\exp(x_i'\beta) + y_i(x_i'\beta) - \ln(y_i!) \end{aligned} \tag{7}$$

The Poisson model assumes that the data has the same dispersion, i.e., the mean and variance of the dependent variable are equal: $E(y_i) = var(y_i) = \lambda$. However, this assumption can be violated depending on the characteristics of the variables analyzed. Thus, overdispersion can occur when the variance is higher than the mean, or underdispersion when the variance is lower than the mean. This results in overestimation or underestimation of standard errors, leading to biased and inconsistent Poisson regression parameters.

In most cases, the count data has a larger variance than mean (Greene, 2003). The negative binomial model, where variance is based on the mean, can be used to deal with the problem of overdispersion. The variance function for the negative binomial model is as follows:

$$var(y_i) = \lambda_i + \alpha\lambda_i^2 \quad (8)$$

where α is the dispersion parameter to be estimated. The negative binomial model is reduced to the Poisson model if α is equal to zero. Therefore, the maximum likelihood ratio test can be performed to test the existence or absence of overdispersion in the data. In this study, the test indicated the absence of overdispersion which, in turn, led to the choice of the Poisson regression model.[2] Thus, for purpose of simplification, the characteristics of the negative binomial model will not be presented here.

3.2. Sample, variables and hypotheses

All the farms in the sample are located in the central, southern and northern regions of the citrus belt of the state of São Paulo (Fig. 1). This state is responsible for 74% of Brazilian orange production (14.117 million tons in 2013). The regions studied have a total of 9370 citrus farms and account for approximately 50% of this state's total orange production. These regions are the most traditional of the citrus belt (Lupa, 2007). To calculate sample size, simple random sampling was used. With a sampling error of 10% and confidence level of 95%, a sample with 98 farms was obtained (47 located in the southern, 31 in the central and 20 in the northern region of the citrus belt). The data collection was carried out from March to September 2014, referring to the crop year 2013/14 (cross section). The interviewers applied a structured questionnaire that was divided into three blocks: (a) personal, social and behavioral characteristics of the farmers; (b) structural characteristics of production (use of factors, production and technology); and (c) aspects of the decision-making process.

Table 2 provides a description of the variables used in the econometric models and the expected signs for each estimated parameter of the independent variables in the models.[3] The first two lines contain a description of the dependent variables of the logit and Poisson models, respectively. The independent variables of the models can be divided into five categories: (i) personal aspects: experience and education; (ii) behavioral aspects: overconfidence in management and risk aversion; (iii) social aspects: participation in technical and management information networks; (iv) structural aspects of farms: production revenue, use of technical and/or management assistance and technology intensity; and (v) institutional environment: access to rural credit and occurrence of contractual adjustments.

Among the personal variables, a positive relationship would be expected between education and the adoption of management technologies. Level of education has potential to increase the ability of farmers to process information, make decisions and procure new management technologies (Feder et al., 1985). The skills obtained through education also facilitate the use of computers and FMIS by farmers (Woodburn et al., 1994; Alvarez and Nuthall, 2006). In terms of production experience, there are two possible effects, in opposite directions. On the one hand, more experience can result in more accumulated knowledge and greater facility in understanding the benefits associated with a new technology (Souza Filho et al., 2011). On the other hand, greater experience can indicate that the farmer is more conservative and less trained in the use of computers and FMIS (Gloy and Akridge, 2000; D'Antoni et al., 2012). Thus, there is no hypothesis for this variable.

Regarding the behavioral aspects of farmers, one would expect overconfidence in management to be positively related to adoption of the technologies analyzed. The behavioral finance literature shows that overconfidence in management leads individuals to overestimate their skills in relation to others, resulting in excessive optimism in terms of expected results from decisions made. These characteristics tend to result in overinvestment by these individuals (Malmendier and Tate, 2005). Furthermore, a potential user of a new technology who is confident about learning and using the technology is more likely to adopt the technology (Adrian et al., 2005). It can be hypothesized that overconfidence of farmers enhances the likelihood of adoption of computers and FMIS.

The hypothesis for the relationship between risk aversion and adoption of management technologies is not so clear.[4] On the one hand, individuals with higher risk aversion tend to be more hesitant to adopt new technologies, since every technology adoption process is characterized by the existence of risks (Aker et al., 2005). On the other, most of the technologies examined in this study (e.g., use of computers to monitor the market and decision-making support systems) tend to increase production predictability and reduce the midterm risk of farmers, which increases the likelihood of adoption by individuals with higher risk aversion.

The only variable related to the social aspects of the farmers is the number of social networks with information sharing potential in which they participate. Participation in social networks is important for sharing information and experiences among farmers and between farmers and other agents in the agroindustrial chain. This sharing of information and experiences generates more learning about the characteristics of new technologies, increasing the likelihood that farmers will adopt them (Souza Monteiro and Caswell, 2009; Dill et al., 2015).

The three farm structural variables (farm size, use of technical assistance and technology intensity in production) tend to have a positive impact on the likelihood of adopting computers and FMIS. On large farms, the coordination of production processes tends to be more complex than on small farms, increasing the need and potential marginal benefits of using computers and FMIS (Woodburn et al., 1994). In addition, since the adoption of certain technologies is usually characterized by representative fixed costs, it is natural that large farms have advantages of scale compared to smaller ones (Feder et al., 1985; Isgin et al., 2008).

The use of technical assistance on farms is important for providing farmers and their employees with new information (Aker et al., 2005). Farm visits by specialists reduce the risk of incorrect

[2] The table chi-square exceeded the chi-square calculated with 1% significance. Thus, the null hypothesis was accepted that α = 0 and, therefore, that there is no overdispersion in the Poisson model.

[3] The correlation matrix between the independent variables was calculated to check the risks of multicollinearity, which were very low. All estimated correlation coefficients for the explanatory variables were lower than 0.7 (in absolute values), a critical value for multicollinearity. Actually, the highest coefficient was 0.52, found between "Production revenue" and "Access to credit" (Appendix A).

[4] There are different ways to measure the risk aversion level of farmers. In the present study, the adoption of long-term sales contracts with predetermined prices and quantity (hedge) was used as a proxy. The behavioral finance literature shows that the use of these contracts has a positive relationship with risk aversion of farmers (Franken et al., 2014).

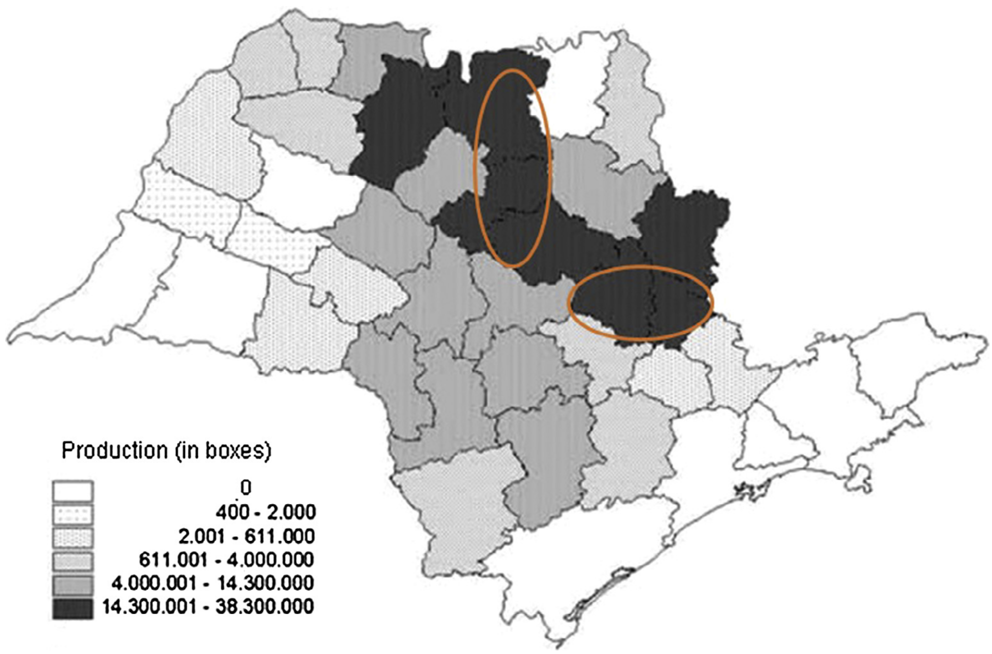

Fig. 1. Citrus map of the state of São Paulo and regions selected for the study sample (in ellipses). Source: Lupa (2007).

adoption and expand the knowledge of farmers and their employees about the characteristics of the technologies, thereby increasing likelihood of adoption (Alvarez and Nuthall, 2006; Dill et al., 2015). Finally, a complementary relationship would be expected between technology intensity in production and farm management. Properties with greater technology intensity in the production process (as measured by the existence of irrigation systems) also tend to require modern management tools for decision-making. The adoption of these technologies can even occur jointly.[5]

The institutional variables (access to credit and contractual adjustments) are related to the influence of the institutional environment on the decision-making process of farmers, thus establishing a link between the institutions and microeconomic agents (Zezza and Llambí, 2002). Rural credit is the main instrument used in agricultural policy in Brazil, which is offered at interest rates subsidized by the federal government and significantly lower than those prevailing on the free market. The amount of official rural credit in Brazil is limited per farmer, which ends up not meeting the optimal demands of all farmers. However, some farmers who represent a lower risk for financial institutions can access larger amounts of official funding (Carrer et al., 2013). Greater access to rural credit tends to reduce the budget constraints of farmers and facilitates investment in new production and management technologies (Souza Filho et al., 2011).

The occurrence of contractual adjustments is related to asymmetric bargaining power in the Brazilian citrus market, whose structure is that of an oligopsony. Since the end of the 2000s, farmers and their representative associations have raised complaints about subsequent contractual adjustments (such as renegotiation of prices and delays in payment of contracts) by juice processing companies, which reduce the profitability of citrus production. Williamson (1996) argues that the occurrence of sequential contractual adjustments tends to reduce incentives for firms to adopt technologies, ultimately leading to their departure from the market. In this regard, it would be expected that farmers who have been affected by a larger number of contractual adjustments have less incentive to adopt new technologies.

Table 3 presents the descriptive statistics for the variables used in the analyzes. The average length of experience of the citrus farmers was 23.9 years and 51% of the farmers had a university degree, which indicates a high level of education in the sample. The index for overconfidence in management averaged 3.76, from a minimum of 1 to a maximum of 5. Among the 98 farmers, 37 used long-term contracts to sell their production from the 2013/14 harvest and were classified as risk-averse in their behavior. The sample mean for participation in social networks was 1.41, within a maximum of 3. Mean orange production revenue in the 2013/14 harvest was USD 248,915.94 and 51% of the farmers from the sample received technical assistance in their farms. There were irrigation systems on 34% of the farms, and the mean volume of official rural credit accessed by farmers was USD 125,963.72. Last, from a maximum of six types of contractual arrangements, in the sample mean the citrus farmers were affected by 1.43 in the 2011/12, 2012/13 and 2013/14 harvests. In terms of dependent variables, computers for management decision-making were used by 64% of the sample of 98 farmers. The FMIS index was 3.18, indicating that in the sample mean citrus farmers used 3.18 of the seven FMIS surveyed. Table 4 shows the frequency of adoption of each tool considered in the FMIS index.

4. Results and discussion

Table 5 presents the results of the logit and Poisson econometric models. In addition to estimated parameters, the marginal effects of each independent variable on the dependent variable of the respective model are also presented. These effects show the variation in the dependent variable as a response to small variations in an independent variable, *ceteris paribus*. In both estimated models, the maximum likelihood ratio test rejects the null hypothesis that all the coefficients are statistically equal to zero. Furthermore, as mentioned in Section 3.1.2, the hypothesis of overdispersion in the data for the Poisson model was tested and subsequently rejected with a statistical significance of 1%. It can be concluded that the estimated models are adequate for identifying the

[5] There are some methods in the literature that enable measuring complementarity in the adoption of different technologies. Since this type of analysis is beyond the scope of the present study, these methods will not be discussed here.

Table 2
Description of the variables used in the econometric analysis of determinants of the adoption of computers and FMIS.

Variable and expected sign	Description
Adoption of computers (y: logit model)	Dummy variable with a value of 1 if the farmer uses computers for making management decisions and 0 if not
FMIS (y: Poisson model)	Index of discrete values ranging from 0 to 7, where FMIS is the summation of seven dummy (0,1) variables for the adoption of seven FMIS management tools: (i) electronic cost control spreadsheets; (ii) electronic records of input stock; (iii) electronic records of production, productivity and incidence of pests per plot of land; (iv) use of integrated decision support systems (DSSs); (v) use of Internet to access market information; (vi) adoption of precision agriculture techniques; and (vii) traceability and quality certifications. FMIS index assumes value 0 if the farmer i adopted none of these technologies and 7 if he or she adopted all of them)
Experience (x_1): ±	Years of experience of the farmer in agriculture
Education (x_2): +	Dummy variable with a value of 1 if the farmer has a university degree and 0 if not
Overconfidence in management (x_3): +	Assumes discrete values ranging from 1 – fully disagree to 5 – fully agree with the following statement: "The management of my farm is better than the average of other farmers in my region"
Risk aversion (x_4): ±	Dummy variable with a value of 1 if the farmer uses long-term contracts for selling production and 0 if not. Proxy variable for risk aversion of the farmer
Social networks (x_5): +	Variable with a value of 0–3 that measures the farmer's participation in three types of social networks: (i) agricultural cooperatives; (ii) farmers' associations and (iii) informal pools for selling products and inputs
Production revenue (x_6): +	Total income (in USD*) obtained from the sale of oranges in the 2013/14 harvest. Proxy variable for production size
Technical assistance (x_7): +	Variable dummy with a value of 1 if the farm received technical and management visits from specialists (agronomists, economists, etc.) in the 2013/14 harvest and 0 if not
Irrigation (x_8): +	Dummy variable with a value of 1 if the farmer has an irrigation system for citrus growing and 0 if not. Proxy for technological intensity in citrus production
Access to credit (x_9): +	Total volume (in USD*) of funds received from official lines of rural credit in the 2013/14 harvest
Contractual adjustments (x_{10}): −	Index with values from 0 to 6 that measures the occurrence of six different types of contractual adjustments in the sale of oranges in the 2011/12, 2012/13 and 2013/14 crop-years: (i) reduction in the agreed price; (ii) delay in receipt of the fruit; (iii) extension of the payment deadline; (iv) reduction of the contracted amount; (v) non-purchase; (vi) other adjustments that generated considerable financial loss to the farmer

* Note: the average exchange rate (Brazilian Real/US dollar) of 2.34 was used for conversions. According to the IPEA (2014), this was the average exchange rate for the period of this study.

variables that affect the adoption and intensity of use of the technologies examined.

Among the ten variables used to identify the determinants of adoption of computers in the logit model, three had statistical significance: experience of the farmers, education and production revenue. The experience of the farmers had a statistical significance level of 5% and a negative effect on the likelihood of adoption of computers. This result is explained by the fact that more experienced farmers are generally older and less trained in the use of computers. These farmers possibly went to school at a time when it was not common to use computers. As mentioned in Section 2, the use of computers to assist in decision-making in Brazilian agriculture is a relatively recent phenomenon and is in the early stages of diffusion. The result of the present study indicate that younger farmers with less experience in agriculture are more likely to adopt computers on their farms.

The education of the farmers had a statistical significance level of 10% and a positive effect on the likelihood of adoption of computers.[6] As expected, farmers with higher education manifest greater demand for information and stronger ability to evaluate the benefits of using computers as a tool to support management decision-making. These individuals are also more adept at using computers for administrative tasks, which tends to increase the marginal yield of the technology. The estimated marginal effect for the variable indicates that the likelihood of adoption of computers increases by 20% among citrus growers who have a university degree, *ceteris paribus*.

Production revenue, a proxy for farm size, had a positive effect and statistical significance level of 10% on the likelihood of adoption of computers, confirming the hypothesis established for this variable. Larger farms are more complex to manage, which increases the need for and benefits from the use of computers and other FMIS to organize management information and coordinate production processes (planting, pruning, fertilizer applications, pesticide applications, etc.). In addition, the fixed investment in computers and FMIS is not proportionally high for farms with large-scale production, demonstrating the advantage of scale for adoption of these technologies. The coefficients and marginal effects of "Production revenue" are low because this variable assumes high values (mean value is 248,915). For instance, USD 1 increase in production revenue would increase 0.0000023% the probability of computers adoption, assuming all other variables at their mean values. Following the same logic, USD 1,000,000 increase would increase 23% this probability. The coefficients and marginal effects of "Access to credit" are low for the same reason.

In the Poisson model, five variables were statistically significant in explaining the adoption and intensity of use of FMIS: experience of the farmers, overconfidence in management, production revenue, technical assistance and contractual adjustments. The effects of the experience and production revenue variables were the same as those for adoption of computers (logit model). The explanation for the results of these variables in the model for adoption and intensity of use of FMIS is similar to the one presented for the model of adoption of computers.

The positive and statistically significant (at 1% level) effect of the overconfidence in management on FMIS adoption confirms the hypothesis based on the behavioral finance literature: farmers with greater overconfidence are more likely to make investments and tend to overestimate the expected results of their decisions. These factors, in turn, increase the likelihood of adoption and use of new management technologies.

The use of technical assistance exerts a positive and statistically significant (at 5% level) impact on the adoption and intensity in the use of FMIS. Technical assistance is an important information transfer tool that increases the knowledge of farmers and their employees about the availability of new production and management technologies. Farm visits by specialists increase the likelihood of correct use of the technologies already present, boosting the trust of farmers in adopting new technologies. Furthermore, the specialists can assist farmers and their employees in the proper handling of new technologies. The estimated marginal effect of the variable, calculated at the sample mean, shows that the use of

[6] The significance level of 10% is considered in the analysis, as in most empirical studies on technological adoption in agriculture. However, parameters of variables with 1% significance are the most important to explain adoption.

Table 3
Descriptive statistics of the variables used in the econometric analyses.

Variable	Mean	Standard deviation	Minimum	Maximum
Adoption of computers (y)	0.64	0.48	0	1
FMIS (y)	3.18	2.04	0	7
Experience (x_1)	23.90	11.63	4	58
Education (x_2)	0.51	0.50	0	1
Overconfidence in management (x_3)	3.76	1.05	1	5
Risk aversion (x_4)	0.38	0.49	0	1
Social networks (x_5)	1.41	0.91	0	3
Production revenue (x_6)	248,915.94	402,232.31	2,350.43	2,136,752.14
Technical assistance (x_7)	0.51	0.50	0	1
Irrigation (x_8)	0.34	0.47	0	1
Access to credit (x_9)	125,963.72	198,037.86	0	1,111,111.11
Contractual adjustments (x_{10})	1.43	1.68	0	6

Table 4
Frequency of adoption of FMIS management tools in a sample of 98 citrus farmers.

Management tools	Frequency of adoption
1. Electronic cost control spreadsheets	51%
2. Electronic records of input stock	64%
3. Electronic records of production and incidence of pests	64%
4. Integrated decision support systems	23%
5. Internet to access market information	64%
6. Precision agriculture techniques	13%
7. Traceability and quality certifications	4%

technical assistance increases in 25.8% the likelihood of adoption and intensity of use of the FMIS examined, *ceteris paribus*.

The occurrence of contractual adjustments, in turn, had a negative and statistically significant effect (at 1% level) on the adoption and use of FMIS. Subsequent contractual adjustments reduce the market incentives for farmers and create unfavorable expectations about the future of commercial relations, leading to lower investments in new technologies. This result is aligned with the theoretical model of Williamson (1996) and shows that tensions in commercial relationships between economic agents can affect the diffusion of technologies in agroindustrial chains.

Finally, the variables "risk aversion", "social networks", "irrigation" and "access to credit" did not have a statistical significance level of 10% in the estimated econometric models. However, except for the access to credit variable, the signs of the other three were consistent with the hypotheses established in Section 3.2.

5. Conclusions

Despite the increasing diffusion of IT since the 1990s, Brazilian agriculture is still characterized by low adoption of computers and decision-making support systems (IBGE, 2006; Mendes et al., 2014). Greater diffusion of these technologies is important for generating production efficiency gains and improving the income of farmers (Souza Filho et al., 2011; Carrer et al., 2015). The objective of the present study was to examine the determinants of adoption of computers and FMIS by Brazilian citrus farms. It was found that education and production revenue had a positive effect on the adoption of computers, whereas production experience of farmer adversely affected adoption. In the case of FMIS adoption and intensity of use, the significant variables and their respective effects were: experience (−), overconfidence in management (+), production revenue (+), technical assistance (+) and contractual adjustments (−). Based on these results, the following suggestions can increase the diffusion of these management technologies in Brazilian citrus industry:

(I) Training of farmers and rural extension agents and dissemination of information about technologies

In the short term, it is not possible to increase the educational level of farmers so that they can adequately understand the benefits and use different technologies. However, it is possible to increase the availability of courses and short-term training and encourage the dissemination of these courses and training

Table 5
Results of the logit and Poisson models: determinants of adoption of computers and FMIS by citrus farmers.

Variable	Logit (y = computers)		Poisson (y = FMIS)	
	β	Marginal effect	β	Marginal effect
Intercept	−0.495	–	0.748**	–
Experience (x_1)	−0.059**	−0.009	−0.011*	−0.034
Education (x_2)	1.197**	0.203	0.044	0.138
Overconfidence in management (x_3)	0.246	0.038	0.156***	0.494
Risk aversion (x_4)	−0.235	−0.037	−0.126	−0.396
Social networks (x_5)	0.142	0.022	0.032	0.101
Production revenue (x_6)	0.15×10^{-5}*	0.23×10^{-6}	0.12×10^{-6}	0.40×10^{-6}
Technical assistance (x_7)	0.028	0.004	0.258**	0.802
Irrigation (x_8)	0.742	0.117	0.087	0.279
Access to credit (x_9)	0.44×10^{-6}	0.001	-0.15×10^{-6}	-0.47×10^{-6}
Contract adjustments (x_{10})	0.060	0.009	−0.145***	−0.459
Log-likelihood function	−46.28		−183.00	
Chi squared (10 d.f.)	35.18		43.48	
p-value (significance level)	0.000		0.000	
R^2 McFadden	0.275		0.110	

* Statistically significant at 10%.
** statistically significant at 5%.
*** statistically significant at 1%.

programs through agricultural extension policies. It is also important that these courses reach more experienced farmers (those less likely to adopt technologies), training them in their use and changing their perceptions of the benefits resulting from the adoption of management technologies. Technology diffusion agents also need to be better trained and motivated to further spread technology in Brazilian agriculture. In other words, it is necessary to train human resources in Brazilian agribusiness.

(II) Incentive to use private and/or government technical assistance

The transfer of information about new technologies and assistance in the use of the technologies after adoption is critical for farmers who do not have proper training. In such cases, farm visits by production and management specialists are very important for providing information and helping farmers and their employees. Technical assistance can be obtained through self-employed specialists and specialized firms (private) or rural organizations and agricultural extension departments (public). There are also cases of farmers using the technical assistance offered by their cooperatives and pools at a lower cost than the assistance provided by specialized firms.

(III) Better coordination in commercial relationships between farmers and juice processing companies

Fewer contractual adjustments are important for reducing transaction costs and increasing incentives and expectations for citrus farmers. In this case, given the asymmetrical bargaining power within the citrus chain, it is important to develop new forms of governance that can create an offsetting power for farmers, to rebalance commercial transactions. The creation of a council to establish prices and other negotiation conditions for the sale of oranges could potentially reduce commercial conflicts and enhance the expectations of citrus farmers. In the mid-term, this improvement has the potential to increase technology diffusion and productivity gains in citrus farms.

(IV) Incentives to adopt management technologies on small and medium-sized farms

Although less complicated in terms of production process coordination, small and medium-sized farms can also take advantage of the benefits associated with the use of computers and FMIS. The continuation of these farms in citrus production depends on production efficiency gains that can stem from the adoption of these technologies. Some technologies with high fixed costs could be jointly adopted among small farmers from the same region, lowering the average cost per farmer. For example, the necessary machinery for adopting certain precision agriculture technologies could be jointly purchased by farmers through cooperatives or pools, with the initial investment and fixed costs divided among the members. For use of the equipment, farmers could establish formal or informal rules and organize training in the cooperatives, thereby increasing the probability that it will be used properly. Joint adoption additionally enables the exchange of information and experiences about the technology among the group of farmers.

It should also be noted that the present study was innovative in testing the effect of personal, social, behavioral, structural and institutional variables on the likelihood of FMIS adoption. The results for the overconfidence in management and occurrence of contractual adjustments variables are interesting and rarely studied in other analyses on the adoption of technologies in agriculture. It can be seen that the behavior of farmers and the institutional environment in which they operate their farms are important for determining the decision-making process and consequently the adoption of technologies. In the first case, it is important to incorporate new behavioral finance theory models to measure the behavior of individuals and test the effect of these aspects on decision-making. In the second case, commercial relationships and the regulatory environment in which they occur have an important impact on the decisions of economic agents.

The main limitation of the study is the use of cross-section data for the 2013/14 crop. In addition, the sample is restricted to the traditional citrus belt of the state of São Paulo - Brazil's largest orange producer. Data from farms of other regions, as well as from other harvest years, could broaden the scope of analysis. The adoption of FMIS over time could be investigate by using panel data. Thus, the role of variables that change over time, such as prices of output and inputs, would be revealed. Lack of data collected systematically and the high cost of a survey with personal interviews prevented this analysis.

There is room for further studies on the adoption of management technologies in Brazilian agriculture. Future studies may be able to use panel data and incorporate new variables and econometric models to identify the determinants of adoption of these technologies by farmers in different rural activities.

Appendix A. 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	−0.28	0.01	−0.15	−0.07	0.05	−0.14	−0.19	0.02	−0.18
X_2		1	0.25	0.09	0.08	0.13	0.22	0.05	0.19	0.21
X_3			1	0.07	0.19	0.27	0.07	0.15	0.28	0.11
X_4				1	0.02	0.40	0.30	0.10	0.18	−0.31
X_5					1	0.22	−0.03	0.23	0.29	0.02
X_6						1	0.28	0.20	0.52	−0.17
X_7							1	0.18	0.23	−0.14
X_8								1	0.09	−0.24
X_9									1	−0.04
X_{10}										1

Note: Experience (X_1), Education (X_2), Overconfidence in management (X_3), Risk aversion (X_4), Social networks (X_5), Production revenue (X_6), Technical assistance (X_7), Irrigation (X_8), Access to credit (X_9), Contractual adjustments (X_{10}).

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