NORTH-HOLLAND

Factors Influencing the Adoption of Sustainable Agricultural Technologies
Evidence from the State of Espírito Santo, Brazil

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ABSTRACT

A dynamic econometric framework (duration analysis) is used to analyze the determinants of farmers' decisions on whether or not to adopt low-external-input and sustainable agriculture (LEISA) technology. A wide range of potential determinants (both economic and non-economic) are considered. Our results suggest that the probability of a farmer adopting this technology increased if the farmer was more integrated with farmers' organizations, had contacts with nongovernmental organizations, was aware of the negative effect of chemicals on health and the environment, could rely on family labor, and had a farm located in an area with better soil conditions. On the other hand, the probability of adoption was reduced by increases in farm size. In addition, time-varying economic variables outside farmers' control were found to be significant determinants of adoption and the rate of diffusion. Changes in relative prices were particularly influential. Specifically, the diffusion of sustainable technology accelerated when declining output prices squeezed agricultural profit and many farmers faced difficulties in buying external inputs. Similarly, when labor became relatively cheap in periods of economic crisis, low-external-input practices became a more attractive option for family smallholdings. © 1998 Elsevier Science Inc.

Introduction

Concern about the negative environmental impact of modern agricultural practices, agriculture's increasing reliance on non-renewable resources, and the long-term productivity of high external-input agricultural systems has prompted a number of initiatives from both governmental and non-governmental bodies to promote the adoption and diffusion of more sustainable agricultural technologies. For these interventions to be effective, they should be based on an understanding of what induces the producer to

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Technological Forecasting and Social Change 60, 97–112 (1999)

0040-1625/99/$–see front matter
655 Avenue of the Americas, New York, NY 10010
PII S0040-1625(98)00040-7

switch from conventional to alternative agricultural practices. While there is now a burgeoning literature on the determinants of the adoption of sustainable technologies, most of it is partial both in terms of its coverage (often dealing only with relative profitabilities or similar economic determinants), and its methodological treatment (using only a static approach, or lacking statistical rigor, providing only a descriptive narrative of adopters and non-adopters) (e.g., [1–3]).

Logit and probit methods are well-established approaches in the literature on adoption of technology [4]. The empirical analyses conducted using these techniques have dissociated adoption from diffusion. In general, the data used refer to a given point in time, resulting in a static model of adoption. The dependent variable (adoption or non-adoption) does not pick up adoption over time, as it does not allow for firms' different waiting times. Besides, the chosen explanatory variables usually refer only to the point in time when the data were collected.

Another method for investigating the adoption of new technologies is to model the diffusion process by evaluating the cumulative adoption process at the aggregate level [4], which typically generates S-shaped curves that are rationalized as "epidemic" processes described by logistic or other related functional forms [5]. One problem with this aggregate approach is that there is relatively little micro-foundation given for the diffusion process and hence, it is difficult to account for the heterogeneity in the underlying sample of firms.

In this article we adopt an alternative approach. Utilizing data from an under-researched area of Brazil (the State of Espírito Santo), we analyze the relative influence of a wider range of potential determinants (both economic and non-economic) within an appropriate dynamic econometric framework, namely duration analysis, used widely in labor economics. Although this technique has obvious advantages in the analysis of technology adoption there are only a few examples in the technology literature [6–8] and, it would seem, even fewer in the particular context of agricultural technology adoption [9,10]. The major advantage of duration analysis over the preceding methods is that it can deal with both cross-section and time series data. As a result, it can capture both cross-sectional and temporal changes in firms' characteristics, costs of adopting the innovation, output price, environmental characteristics, and other explanatory variables. Adoption and diffusion can, therefore, be investigated together within a dynamic process.

The Study Area

Following the lead of their counterparts in other Brazilian states, most farmers in Espírito Santo were using Green Revolution technologies by the end of the 1970s. However, by the mid-1980s, the number of farmers switching to low-external-input and sustainable agriculture (LEISA) technology had begun to grow. This alternative agricultural system involves specific practices, such as the use of organic fertilization and cheap but more "environmentally friendly" methods of plant protection (see Table 1 [11]. Two factors might have contributed to the increased diffusion of these techniques. First, an economic crisis in the rural areas of the state, precipitated by decreased international coffee prices and leading to lower rural wages (which decreased the use of external inputs and encouraged more labor intensive practices), and second, the extension services provided by NGOs to promote the adoption of alternative technologies by small farmers.[1] What roles these factors and other possible determinants play in influencing the adoption decision of farmers are explored in the empirical analysis reported here.

[1] Notably, FASE (Federačao de Orgãos para Assistência Social e Educacional), a Brazilian NGO, launched the Alternative Agriculture Project (PTA) in 1981 and established a national network of offices in 10 Brazilian

TABLE 1
Examples of LEISA Technologies

Composting. The breakdown of organic material by micro-organisms and soil fauna to give a humus end product. It is an important technique for recycling organic waste from postharvest processing (dung, nightsoil, urine, etc.) and for improving the quality and quantity of organic fertilizer.
Green manure. Trees, shrubs, cover crops, grain legumes, grasses, weeds, ferns, and algae provide an inexpensive source of organic matter and fertility.
Mineral fertilizer. It normally increases the availability of biomass for organic fertilizer and may enhance soil life when applied moderately.
Mulching. A shallow layer at the soil/air interface; its composition usually includes dry grass; crop residuals (straw, leaves, etc.); fresh organic material from trees, bushes, grasses, and weeds; household refuse and live plants (cover crops, green manures). It is an important technique for improving soil microclimate; enhancing soil life, structure and fertility; conserving soil moisture; reducing weed growth; preventing damage by impact from solar radiation and rainfall (erosion control); and reducing the need for tillage.
Intercropping. The growing of two or more crops simultaneously on the same field. It has beneficial effects in terms of better control of insects, diseases, and weeds.
Trap and decoy crops. Various kind of traps can be made to catch insects, rodents, or other creatures which threaten crops or livestock. The most common is the light trap, set up to catch night flying insects. Pests can also be attracted by certain plants. When these are sown in the field or alongside it, insects will gather on them and can thus be easily controlled.
Biological control. Pests are suppressed by their natural enemies, such as birds, spiders, miter, fungi, bacteria, viruses, or plants (e.g., cover crops to control weeds).
Plant-derived pesticides. Numerous plants have defensive or lethal effects on vertebrates, insects, mites, nematodes, fungi, or bacteria. Active components can be extracted from various parts of plants and dispersed over the crop.
Integrated crop-livestock-fish farming. Integrated systems which optimize the use of on-farm and adjacent resources, and encourage habitat conservation and diversity. Such systems are productive and profitable because they utilize waste as inputs in other enterprises within the farm, and because fish are a highly nutritious and valuable traditional food. They use microenvironments within a farm system which add to farm productivity and security.
Minimum tillage. Soil management practices which seek to minimize labor inputs and soil erosion, to maintain soil moisture and to reduce soil disturbance and exposure. Crop stubble is left or mulch is applied to protect soil. Also known as conservation tillage or reduced tillage. In its most extreme form (zero- or no-tillage), seeds are drilled directly into the otherwise undisturbed soil.
Multiple cropping. Growing two or more crops in the same field in a year, at the same time, or one after the other, or a combination of both.
Multistorey cropping. Growing tall crops (often perennials) and shorter crops (often biennials or annuals) simultaneously.

Source: Derived from [11].

This study[2] [12] is based on a survey of 148 farmers spread across 22 municipalities in the state of Espírito Santo. The survey, conducted during August–September 1994, used personal interviews to gather all relevant information on both the adopters and non-adopters of sustainable agricultural technologies. Adopters were selected with the help of experts from APTA (see footnote 1), who were asked to provide the best possible representation of farmers using LEISA technologies in the state. To be classed as an adopter, the farmer had to be using at least one of the practices that support

states. The office in Espírito Santo was set up in 1986; the new regional name of the NGO is Alternative Technology Programs Association (APTA).

[2] The fieldwork and quantitative analysis was carried out by de Souza Filho [12].

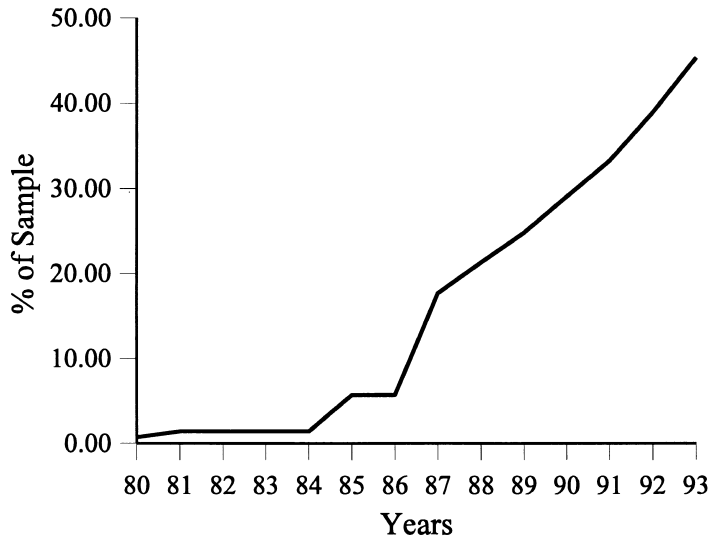

Fig. 1. Cumulative distribution of the number of adopters in a sample of 141 farms, Espírito Santo, Brazil.

sustainability (Table 1). This criterion did not preclude the use of some agro-chemicals. However, as an examination of the detailed production data confirmed, adopters recorded low and decreasing usage of these inputs. In other words, they were seen to be committed to the process of using more sustainable practices.

For each adopter, a nearby conventional farmer was chosen at random.[3] The sampling method could not be based entirely on a random selection for two reasons: (1) the number of adopters in relation to the total number of farmers in the state was expected to be small, which would make it difficult to obtain a satisfactory number of observations from a totally random selection; and (2) a complete list of adopters, from which a sample could be drawn, did not exist. After inspection of the completed questionnaires, seven observations were dropped due to missing data. The final sample consisted of 64 adopters and 77 non-adopters.

Figure 1 shows the cumulative distribution of the number of adopters over time. The duration model described below helps to explain why some years elapsed between the first adoption in 1980 and a more widespread diffusion in the second half of the decade and in the early 1990s.

Crops and pastures occupied three quarters of the total area, and coffee was the main crop for both groups of farmers. Adopters, however, were more diversified with 87% of their crop production value coming from coffee, beans, and horticultural products, covering a variety of fruits and vegetables (mainly coconut, oranges, beetroot, potatoes, carrots, cabbage, green beans, and lettuce). Non-adopters were less diversified as they obtained the same percentage of production value from only three traditional products: coffee, beans, and maize.[4] It was also observed that after adoption of alternative

[3] This sampling technique decreased the interviewers' transport costs, but also reduced the scope for discriminating adopters from non-adopters in terms of their environmental characteristics (soil types, terrain, topography, water supply, and climate).

[4] Data on livestock were not available.

TABLE 2
Definitions of Explanatory Variables

SIZE	Farm size (hectares).
ACCIDENT	Dummy variable indicating farmer's knowledge of the negative effect of chemicals on health and environment. It assumes a value of 1 if the farmer knew of any accident caused by chemicals on the farm or in the region (before adoption, if the farmer was an adopter), and 0 otherwise.
SOCIAL	Dummy variable indicating farmer's social integration. It assumes a value of 1 if the farmer frequently attends meetings of any kind of farmers' organization (cooperatives, rural unions, farmers associations).
ENVIRON	Dummy variable indicating the effect of farm physical characteristics. It assumes a value of 1 if more than 50% of the farm land has flat/undulating topography and there is a stream as a water source, and 0 otherwise. These are characteristics of fertile lands at the bottom of hills.
F-LABOR	Number of family members working on the farm, including the farmer.
EXT-NGO	Dummy variable assuming a value of 1 if the farmer has contact with non-governmental extension service, and 0 otherwise.
NGO_t	Dummy time variable indicating the period of operation of the APTA. It assumes a value of 0 up to 1985, and 1 thereafter.
$R\text{-}TRADE_t$	Time variable indicating the evolution of the annual rate of change in the terms of trade for the agriculture of Espírito Santo. Terms of trade in a year t, T_t, are the IPR (index of prices received by farmers) divided by the IPP (index of prices paid by farmers) in that year. $R\text{-}TRADE_t = (T_t - T_{t-1})/T_{t-1}$.
$WAGE\text{-}CHE_t$	Time variable indicating the evolution of the rural wage in relation to the prices of chemical fertilizers and crop protectors. It is the Getulio Vargas Foundation's index for seasonal-labor rural wage divided by an index of chemical fertilizers and crop protectors prices (average price of 28 types of fertilizers and formulations, and 101 types of crop protectors). 1980 = 1.
EXT-GO	Dummy variable assuming a value of 1 if the farmer has contact with the governmental extension service, and 0 otherwide.
AGE	Farmer's age.
RESIDENCE	Dummy variable assuming a value of 1 if the farmer lives on the farm, and 0 otherwise.
EDUCATION	Years of schooling
OWNERSHIP	Dummy variable assuming a value of 1 if the farmer owns the farm, and 0 otherwise.
OFF-INCOME	Percentage of off-farm income in the farmer's total income.

practices, farmers reduced their production of tomatoes and garlic considered to be economically difficult without the use of chemicals. Only three adopters in the sample were new entrants to agriculture.

The Data

It is hypothesized that both the economic environment and the non-economic characteristics of the farmer and farm enterprise were important to the adoption process. The full list of potential determinants which the data set permitted us to consider is presented in Table 2. Some descriptive statistics of the time-invariant variables are given in Table 3, while the time-paths of the time-varying variables are shown in Figure 2.

There appears to be insufficient variation in the data with respect to the age and education of the sampled farmers to discriminate adopters from non-adopters. The mean age of both groups was in the mid-40s.[5] The average number of years of formal education corresponds to primary schooling, but indicates at least basic mathematics

[5] At the time of adoption, adopters' mean age was 37.5 years with a standard deviation of 13.7 years.

TABLE 3
Descriptive Statistics for the Time Invariant Variables in the Adoption Model

	Adopters		Non-adopters	
Variable name	Mean	S.D.	Mean	S.D.
SIZE (ha)	24.2	29.6	47.9	67.9
ACCIDENT (0,1)	0.7	0.4	0.4	0.5
SOCIAL (0,1)	0.8	0.4	0.4	0.5
ENVIRON (0,1)	0.3	0.5	0.1	0.3
F-LABOR (number)	4.4	3.1	3.5	2.7
EXT-NGO (0,1)	0.7	0.5	0.2	0.4
EXT-GO (0,1)	0.2	0.4	0.4	0.5
AGE (years)	43.5	13.7	45.5	12.8
RESIDENCE (0,1)	0.9	0.3	0.8	0.4
EDUCATION (years)	8.1	2.7	8.1	3.2
OWNERSHIP (0,1)	0.8	0.4	0.8	0.4
OFF-INCOME (%)	17.8	27.8	20.5	32.2
Number of Observations	64		77	

and literacy.[6] Middle-age and low-level education for both groups of farmers would seem to contradict previous findings that younger and better educated farmers are more likely to adopt [2, 13]. Most farmers in the sample live on the farm, are landowners, and rely mainly on on-farm income for their livelihood. However, as shown in Table 3, there appears to be too little variation in the data on RESIDENCE, OWNERSHIP, and OFF-INCOME to clearly distinguish adopters from non-adopters here.

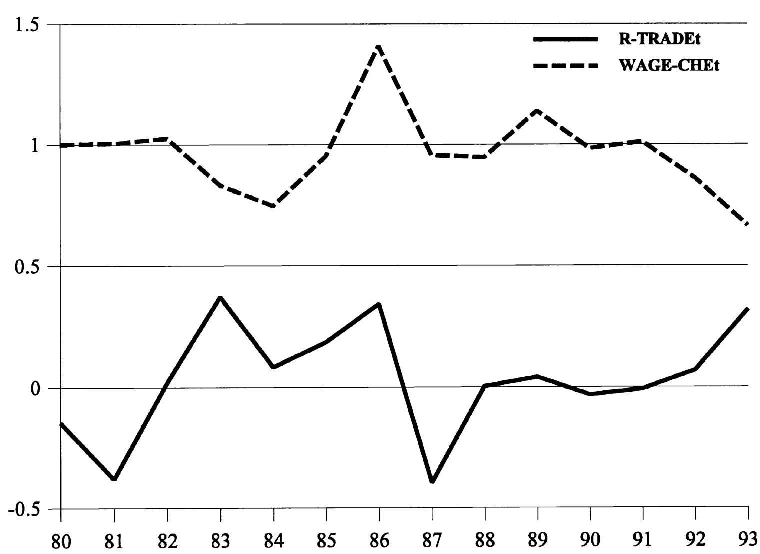

Fig. 2. Values of R-TRADE$_t$ and WAGE-CHE$_t$.

[6] Formal education in Brazil comprises eight years of primary school, three years of secondary school, and four years of undergraduate study. Five adopters and nine non-adopters in the sample were illiterate.

Duration Analysis

Duration analysis has a long history in biometrics and statistical engineering but Lancaster's study on unemployment [14] appears to be the first application of the technique in the social sciences [15, 16].[7] As its name suggests, duration analysis is concerned with explaining the duration of an episode or spell, where a spell starts at the time of entry into a specific state (say, unemployment) and ends at a point when a new state is entered (say, employment).

In the study of technology adoption the start or entrance date can be set either at the time when the first adoption of an innovation took place or, if the firm was created after that, at the time of its creation. The exit data, or the end of a spell, would be the time a firm adopts the innovation. In practical terms the available data for social researchers are usually gathered by cross-section surveys and some spells may not have been completed at the time of data collection. Some people might still be unemployed or some firms may not have adopted the technology by that time. In other words, the ends of some spells are unknown, although they might occur in the future. For these cases the statistical procedure is to right-censor the duration at the end of the observation period, that is at the time when the data were collected.

Probability theory plays a fundamental role in duration analysis. Instead of focusing on the time length of a spell, one can consider the probability of its end, or, as it is the same, the probability of transition to a new state. In a technology adoption study, the pertinent question would be: what is the probability of a firm adopting a certain technology at time t, given it has not adopted by that time? The answers are generated by the hazard function, defined below.

Let $f(t)$ be a continuous probability distribution of a random variable T, where t, a realization of T, is the length of a spell. The corresponding cumulative density is given by

$$F(t) = \int_0^t f(s)\, ds = Prob\ \ (T \leqslant t). \tag{1}$$

Alternatively, the distribution of T can be expressed by

$$S(t) = 1 - F(t) = Prob\ (T \geqslant t), \tag{2}$$

which is the survival function, or the mirror image of the cumulative density. $S(t)$ gives the probability that a spell is, at least, of length t, that is, the probability that the random variable T is equal to or exceeds t. The hazard, which is the probability of a spell being completed at duration t, given that it has lasted until t as defined above, can be expressed by $Prob\ (t \leqslant T \leqslant t + \Delta \mid T \geqslant t)$, where Δ is the next short interval of time following t. The limiting value of this probability divided by Δ, when Δ tends to zero, gives the hazard function

$$\begin{aligned} h(t) &= \lim_{\Delta \to 0} \frac{Prob\ (t \leqslant T \leqslant t+\Delta \mid T \geqslant t)}{\Delta} \\ &= \lim_{\Delta \to 0} \frac{F(t+\Delta) - F(t)}{\Delta\ S(t)} \\ &= \frac{f(t)}{S(t)}. \end{aligned} \tag{3}$$

The hazard function specifies the instantaneous rate of completion of a spell at $T = t$,

[7] Useful reviews of the application of duration analysis in economics can be found in [15, 16].

conditional upon survival up to time t. The cumulative density, survival, and hazard functions are alternative but mathematically related functions through which the distribution of T can be expressed.

The distribution of T can assume any parametric specification in a model of duration analysis. For example, for the exponential and Weibull distributions:

	Exponential	Weibull
Cumulative density, $F(t)$	$1 - \exp(-\lambda t)$	$1 - \exp(-\lambda t^{p})$
Survival function, $S(t)$	$\exp(-\lambda t)$	$\exp(-\lambda t^{p})$
Hazard function, $h(t)$	λ	$\lambda p t^{p-1}$

The parameters λ and p define the scale and shape of the distribution, respectively. The hazard for the exponential distribution is a constant, meaning that the conditional probability of failure, or change of state, in a given short interval does not depend on the duration that has elapsed. For this reason it is called memoryless. To allow for dependence on duration, one has to rely on other distributions, such as the Weibull, in which the hazard increases or decreases monotonically, depending on the value of the parameter p.

Once the parametric distribution of T has been chosen, estimation of parameters follows maximum likelihood procedures. Assuming the duration for each individual, t_i, is independent of the others, the log-likelihood function for completed spells is

$$L(\theta) = \sum_{i=1}^{n} \ln f(t_i,\theta) \tag{4}$$

where $f(t_i,\theta)$ is the density function and θ is the parameter vector, which, say, for the Weibull distribution, would comprise only the parameters λ and p. In cases where censored observations are included, information on their exact durations is not available and, therefore, the density function cannot be applied. However, we know that the duration of these observations is, at least, t_j. In other words, the survival function, $S(t_j,\theta)$, is available. Thus, the likelihood function becomes

$$L(\theta) = \sum_{i=1}^{n} d_i \ln f(t_i,\theta) + \sum_{i=1}^{n} (1-d_i) \ln S(t_i,\theta), \tag{5}$$

or

$$L(\theta) = \sum_{i=1}^{n} d_i \ln h(t,\theta) + \sum_{i=1}^{n} ln\ S(t,\theta) \tag{6}$$

where $d_i = 1$ if the ith spell is not censored and $d_i = 0$ if censored. Maximum likelihood procedures can be used to estimate the θ parameters.

Explanatory variables, or covariates, can be introduced to alter the distribution of durations. These may be time invariant, as in the case of gender and race, for example, or may be assumed to be so, in the absence of information on the time paths of some variables (e.g., farm size). We also may wish to consider time-varying covariates, such as the cost of an innovation, which do not follow a continuous time path, but rather are step-functions over time. Finally, there are other variables, such as age and time itself, which change continuously as a function of time; these are called time-dependent covariates [16, 17].[8]

The hazard function can be re-formulated to allow for the influence of explanatory variables. Let X be a vector of time invariant covariates with a vector of unknown parameters β. The hazard can now be expressed as

$$h(t,X,\theta,\beta) = h_0(t,\theta)\ q(X,\beta), \tag{7}$$

where $h_0(t,\theta)$, which is known as the baseline hazard, denotes the hazard for the individual under "standard" conditions, and the covariates enter the function $q(X,\beta)$. Models with this specification are called proportional hazards since the proportional change in the hazard due to a change in an explanatory variable is not a function of duration. The most widely used and convenient specification for $q(.)$ is

$$q(X,\beta) = \exp(\beta' X). \tag{8}$$

This form guarantees the necessary non-negativity without imposing restrictions on β. Also, log-linearization allows an easy partial-derivative interpretation of parameters. That is,

$$\frac{\partial \ln h(t,X,\theta,\beta)}{\partial X} = \frac{\partial \ln q(X,\beta)}{\partial X} = \beta. \tag{9}$$

As the covariates act multiplicatively on the baseline hazard, the signs of β are interpreted as the direction of the effect that the explanatory variables have on the conditional probability of completing a spell.

Time series variables, such as output and innovation prices, which can influence the adoption decision, may not be employed in logit/probit models, because they usually do not vary from one individual to another. In duration analysis, variation in covariates over time is an alternative to variation between individuals. Thus, this type of information is not lost. Although this is a major advantage of duration analysis, it is not always feasible to obtain complete information on the past behavior of many relevant variables. This is particularly true of variables representing individual characteristics. Sometimes it may be necessary to assume some variables as time invariant and combine them with available time variant covariates. Moreover, the most appropriate way of handling time-varying variables in duration analysis is still the subject of research in econometric theory.

OUR APPROACH

In this study we specify a proportional hazards model with a constant baseline hazard. Specifically, the following relationship between the conditional probability of adoption and explanatory variables is assumed

$$h(t) = h_0 \exp(\beta' X_t), \tag{10}$$

where $h(t)$ is the hazard rate and h_0, the baseline hazard, is assumed to be a constant. The vector X includes the explanatory variables, both time invariant and time varying. This hazard will change when time-varying covariates change over time but it is not a function of duration per se. One reason for choosing this specification is that the time paths of the time-varying covariates used here—NGO_t, R-TRADE_t—are the same for

[8] For a broad classification of covariates, see [16, 17]. Some computer packages are not able to estimate models with either time-varying covariates or time-dependent covariates.

TABLE 4
Estimates of Alternative Specification of Exponential Hazard Functions

	Model 1		Model 2		Model 3	
	Estimate	Prob $\|t\| \geqslant X$	Estimate	Prob $\|t\| \geqslant X$	Estimate	Prob $\|t\| \geqslant X$
h_0	0.009	0.005	0.048	0.029	0.007	0.000
SIZE	−0.012	0.024	−0.010	0.034	−0.009	0.062
ACCIDENT	0.878	0.009	0.801	0.016	0.699	0.021
SOCIAL	0.690	0.050	0.781	0.020	0.652	0.039
ENVIRON	0.579	0.077	0.529	0.082	0.441	0.116
F-LABOR	0.108	0.062	0.130	0.007	0.111	0.016
EXT-NGO	0.858	0.034	0.815	0.021	0.759	0.019
NGO_t	2.280	0.000	2.253	0.000	—	—
R-$TRADE_t$	−1.055	0.140	−1.111	0.104	—	—
WAGE-CHE_t	−3.930	0.009	−3.914	0.005	—	—
EXT-GO	−0.220	0.564	—	—	—	—
AGE	0.014	0.309	—	—	—	—
RESIDENCE	0.446	0.445	—	—	—	—
EDUCATION	0.064	0.242	—	—	—	—
OWNERSHIP	0.337	0.420	—	—	—	—
OFF-INCOME	−0.001	0.804	—	—	—	—
Log-likelihood	−214.987		−217.725		−252.413	

all farms, which makes it difficult to separate the effect of their trend from possible duration dependence [15].

Results

The results from fitting Equation (10) for our sample[9] [18] are presented in Table 4. Three alternative specifications of the model are considered. Each has a different set of explanatory variables and is chosen to allow us to explore the significance of particular covariates and the robustness of parameter estimates when the model specification is altered. Model 1 contains the full set of explanatory variables—both time-invariant and time-varying. Model 2 represents a more parsimonious specification as it excludes those variables which were not statistically significant, on the basis of *t*-values, in Model 1. Given that duration analysis allows the possibility that time-varying covariates influence the adoption decision, it is interesting to assess the significance of these variables in the present context. To facilitate this assessment, we estimate Model 3 which omits NGO_t, $R - TRADE_t$, and WAGE-CHE_t. As noted above, the signs of the estimated parameters in Table 4 indicate the direction of the effect of the respective variables on the conditional probability of adoption.

The likelihood ratio (LR) test was used to evaluate these three specifications of the model. By comparing Models 1 and 2, it is possible to test the hypothesis that the coefficients of EXT-GO, AGE, RESIDENCE, EDUCATION, OWNERSHIP, and OFF-INCOME are jointly zero. Here, the LR test statistic is 5.476. With 6 degrees of freedom, the critical chi-square value at the 5% significance level is 12.59, and so we fail to reject the joint hypothesis. It may be further noted that the estimated coefficients of the retained variables in Model 2 are little different from their values in Model 1. In the same way, a comparison of Models 2 and 3 provides us with a test for the joint hypothesis that the coefficients of time-varying covariates, NGO_t, R-$TRADE_t$, and

[9] All estimation was performed using LIMDEP Version 6.0. See [18].

WAGE-CHE$_t$, are zero. This hypothesis is rejected (LR = 69.376; χ^2 with 3 degrees of freedom is 7.81) confirming the important role that these time-varying variables play in explaining the adoption decision of farmers. As Model 2 is considered to be the preferred specification, the results of that specification are interpreted more closely below.

The sign of the marginal effect of ACCIDENT confirms that adopters are relatively more concerned with health and environment. The farms' physical characteristics (ENVIRON) are also found to be relevant to the adoption decision, while the marginal effects of SIZE and F-LABOR shows that adopters tend to have smaller farms and rely more on family labor than non-adopters.

The positive and significant coefficients of SOCIAL and EXT-NGO indicate that these less conventional institutional means of information diffusion played a fundamental role in promoting the adoption of LEISA technologies. Adopters have been closely integrated in farmers' organizations, the formation of which has been stimulated by other non-governmental organizations.

It is hypothesized that periods of shrinking agricultural profit aggravate farmers' financial constraints and increase, thereby, the probability of adopting LEISA technologies, whereas periods of increasing profits have reduced this probability. The rate of change in the terms of trade, R-TRADE$_t$, is used here as a proxy for the rate of change in agricultural profitability. The index is formed by relating the Getulio Vargas Foundation's IPR (index of prices received by farmers) with the IPP (index of prices paid by farmers) in the way as defined in Table 2. The IPR represents the evolution of farmers' agricultural revenue, while the IPP reflects the same for agricultural cost [19].[10] The coefficient of R-TRADE$_t$ which is significant at the 10% level has a negative sign consistent with the hypothesized relationship between farm profitability and the adoption of LEISA technologies noted above.

The negative sign and significance of WAGE-CHE$_t$ indicate that the conditional probability of adoption increases when rural wages become depressed relative to the price of chemical inputs. This result is not surprising, given the fact that LEISA is labor-intensive. The importance of the availability of labor in the adoption decision is supported by the sign and significance of the coefficient of F-LABOR, which suggest that the availability of family labor, possibly because it has a lower opportunity cost, makes LEISA technologies more attractive.

Finally, the positive and highly significant coefficient of NGO$_t$ shows that the APTA and the other non-governmental organizations that make up the Agroecology Network in the study region had an important role in the diffusion of information about LEISA technologies.

The specification of Model 2 could be improved if information on individual farm profitability, and input and output prices were available. In that case, the use of proxy variables (R-TRADE$_t$ and WAGE-CHE$_t$) which do not change across farms is not needed and the variations in the regressors' time paths across individual farms could be obtained. This would allow us to increase the precision of our estimated coefficients,

[10] The IPP covers the following items of expenditure: seeds (13.97%), fertilizers (28.43%), chemical crop protectors (10.95%), services (14.75%), fuel (14.40%), and labor (17.50%) (see [19]). The main activities included in the IPR are: coffee (45.46%), milk (13.51%), cattle-beef (8.28%), beans (4.17%), maize (4.00%), chicken (3.96%), cocoa (3.66%), bananas (3.62%). Agricultural profitability in Brazil has been affected by inflation and government policies, mainly the PGPM and the rural credit system. R-TRADE$_t$ can reflect the effect of inflation and the PGPM, although it does not allow for the direct effects of rural credit subsidies remaining an important determinant of profitability among privileged farmers. This drawback, however, is not serious in the context of our sample as only a few farmers have been assisted by the rural credit policy.

TABLE 5
Hazard Rate and Adoption Probability for Two Representative Farmers[a]

	Farmer A				Farmer B			
	Model 2		Model 3		Model 2		Model 3	
	Hazard	Adoption probability	Hazard	Adoption probability	Hazard	Adoption probability	Hazard	Adoption probability
1980	0.04	0.04	0.16	0.15	0.00	0.00	0.02	0.02
1981	0.05	0.08	0.16	0.28	0.00	0.01	0.02	0.03
1982	0.03	0.11	0.16	0.38	0.00	0.01	0.02	0.05
1983	0.04	0.15	0.16	0.48	0.00	0.01	0.02	0.06
1984	0.08	0.21	0.16	0.55	0.01	0.02	0.02	0.08
1985	0.03	0.24	0.16	0.62	0.00	0.02	0.02	0.09
1986	0.04	0.27	0.16	0.68	0.00	0.02	0.02	0.11
1987	0.57	0.59	0.16	0.73	0.04	0.06	0.02	0.12
1988	0.38	0.72	0.16	0.77	0.03	0.08	0.02	0.13
1989	0.17	0.76	0.16	0.80	0.01	0.09	0.02	0.15
1990	0.34	0.83	0.16	0.83	0.02	0.11	0.02	0.16
1991	0.30	0.87	0.16	0.86	0.02	0.13	0.02	0.18
1992	0.49	0.92	0.16	0.88	0.03	0.16	0.02	0.19
1993	—	—	—	—	0.05	0.21	0.02	0.20

[a] The hazard rates were calculated using the expression $h_t(t) = \exp(X_t'\beta)$. The probability of adoption by the end of t years is calculated using the expression: $1 - \exp(-\sum_{t=1}^{t}\exp(X_t'\beta))$ and the coefficients of Models 2 and 3 given in Table 4.

and to test other functional forms for representing the baseline hazard. This empirical limitation does not undermine the methodological advantages of duration analysis which has allowed us to highlight the effect of variables that change over time and are external to farmers.

Our results allow us to predict the probability that in a given time period a farmer with a specific set of socioeconomic characteristics will adopt LEISA practices. To illustrate, the hazard rate and the adoption probability for two farmers in the sample are presented in Table 5. Farmer A, observed as an adopter, has a farm size of 28 hectares, has 10 family members working on the farm, and is aware of an accident with agro-chemicals having occurred in the region. In contrast, farmer B, a non-adopter, has 85 hectares, no additional family labor, and has no knowledge of any agro-chemical accidents. Both farms have similar topography and contact with the non-governmental extension service. Farmer A adopted sustainable practices in 1992, when the calculated adoption probabilities were 92% and 88% from Models 2 and 3, respectively. Farmer B was a non-adopter and presented low probabilities of adoption (0.2 or less) throughout the sample period. The hazard rate in Model 3 remains constant over time due to the exponential specification of the baseline hazard and the absence of time-varying covariates. However, when time-varying covariates are included (Model 2), the hazard changes over time and accelerates or decelerates the process of diffusion.

The estimated model can also be used to generate an estimated time to adoption. Where the model includes time-varying covariates, the estimate will depend on the assumed evolution of these covariates, both over the sample period and possibly beyond, but in the case where the hazard is exponential and excludes time-varying covariates (e.g., Model 3), the estimated time to adoption is simply given by the reciprocal of the hazard [15]. So, for example, Model 3 predicts that Farmer A would adopt in 6.25 years (i.e., 1/0.16) and Farmer B would adopt in 50 years (i.e., 1/0.02).

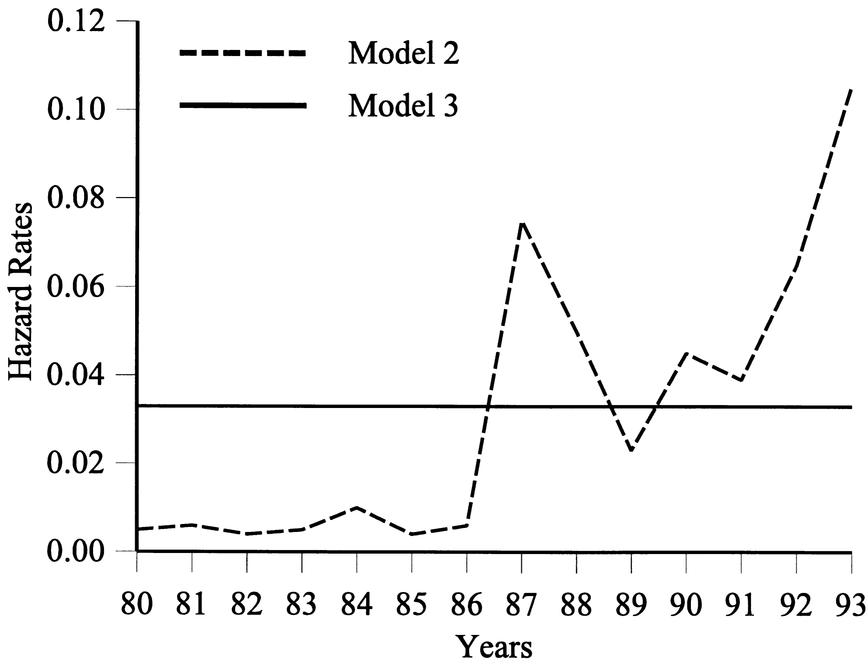

Fig. 3. Hazard rates at mean values of time invariant covariates.

Finally, Figure 3 illustrates the constant hazard of Model 3 and the impact of the time-varying covariates on the estimated hazard of Model 2. There is a substantial increase in the latter after the mid-1980s which can be attributed to the impact of the NGO but with other variables moderating the effect: for example, the sharp increase in 1987 is a result of the decline in both relative rural wages and agricultural terms of trade in that year (Figure 2). The hazards can be used to generate average adoption probabilities for the farmer with mean characteristics (Figure 4). The shift in the hazard translates into a considerable jump in the adoption probabilities, which mirrors the actual adoption time path (see Figure 1).

Concluding Remarks

This article has addressed the question of adoption of sustainable agricultural technology using a modeling framework which is superior to the conventional approaches to the study of adoption and diffusion in that it can accommodate both the heterogeneity of individual farmers and the explicitly dynamic nature of the adoption process. While duration analysis has been extensively used in other areas of economics, the current study appears to be the first published application to agricultural adoption. It has illustrated the technique's capacity to accommodate a wide range of farm-level socioeconomic factors as well as variation in the macroeconomic conditions over the study period.

Our results suggest that in the context of our study area in the state of Espírito Santo, Brazil, the probability of a farmer adopting LEISA technologies increased if the farmer was more integrated with farmers' organizations, had contact with non-governmental organizations, was aware of the negative effect of agro-chemicals on health and the environment, could rely on family labor, and had a farm located in an area of better soil

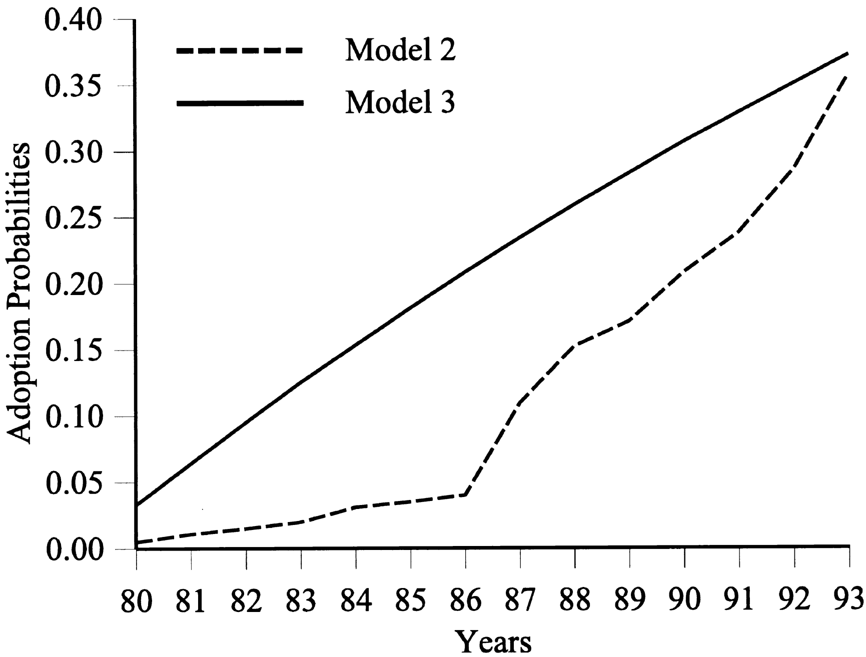

Fig. 4. Adoption probabilities at mean values of time invariant covariates.

conditions. On the other hand, the probability of adoption was reduced by increases in farm size. In addition, time-varying, economic variables outside the farmers' control were found to be significant determinants of adoption and the rate of diffusion. Changes in relative prices were particularly influential. Specifically, the diffusion of sustainable technology accelerated when declining output prices squeezed agricultural profit and many farmers faced difficulties in buying external inputs. On the other hand, when labor became relatively cheap during periods of economic crisis, low-external-input practices became a more attractive option especially for family smallholdings.

Policy interventions in the field of agricultural technology can have far-reaching effects on production, employment, and income distribution as well as on the social, political, and environmental infrastructure. There is, therefore, a danger of overstating the policy relevance of this type of partial analysis of the adoption process. Nevertheless, our results do indicate the broad areas in which policy interventions might prove to be especially promising.

The analysis suggests that any increase in output prices and rural wages relative to the prices of external inputs leads to a decrease in the speed of diffusion of sustainable agricultural technologies. In Espírito Santo, this can happen, for example, when coffee prices increase markedly. During such periods, some adopters can even reverse their adoption decisions and revert to the use of external inputs, including agro-chemicals (our data do not permit us to test this hypothesis but the modeling framework can be adapted to deal with "multiple spells" [20]). To counter this and to promote the diffusion of LEISA practices, although one could suggest policy interventions that penalize high-external-input agriculture, other avenues might equally be explored.

A number of alternative or supplementary measures, such as the creation of technical and administrative capabilities to enforce the current restrictive legislation on chemicals, delimitation of environmentally-sensitive areas, and incentives for R&D and extension on environmental friendly technologies, could be implemented. Diffusion of information could be speeded up by joint efforts of governmental and non-governmental organizations. Although our results suggest that farmers' adoption of LEISA technologies is not influenced by government agencies, the government extension network is nevertheless well placed both to develop new LEISA practices and to encourage their adoption through the provision of credit and input support. Moreover, the mass media, such as television, which has had a major influential role, can be used not only to spread information on sustainable practices, but also to raise public awareness of environment and health issues.

Technological progress, alternative rural credit policies, and premium prices can enhance the relative profitability for farmers adopting sustainable practices and can speed up their diffusion. While Brazil already has some governmental organizations which deal with R&D on sustainable agriculture, further investment in this area and cooperation with non-governmental organizations especially in the extension spheres could have a powerful impact on the diffusion process. The rural credit system would have to be adapted not only to the economic conditions of smallholder agriculture but also to the specific technical/financial requirements of the new practices (e.g., an emphasis on credit resources for payment of labor and other non-chemical inputs, rather than for purchasing agro-chemicals). Special credit conditions for farmers adopting sustainable practices would be one policy option. Government subsidies on prices may be unrealistic in the current Brazilian context, but premium market prices for chemical-free production could be generated if certification schemes were set up. This could be particularly important to Espírito Santo's farmers, since the state is located in a region with a large potential market for certified products, but it would require formal agreement on the range of acceptable practices to qualify for certification.

The research reported here was financially supported by the Federal University of Espírito Santo (UFES) and the National Council for Scientific Development and Technology (CNPq). Fieldwork in Brazil was funded by the WWF.

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Received 21 November 1997; accepted 21 May 1998