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Modelling the adoption of organic horticultural technology in the UK using Duration Analysis

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Duration Analysis, which allows the timing of an event to be explored in a dynamic framework, is used to model the adoption of organic horticultural technology in the UK. The influence of a range of economic and non-economic determinants is explored using discrete time models. The empirical results highlight the importance of gender, attitudes to the environment and information networks, as well as systematic effects that influence the adoption decision over the lifetime of the producer and over the survey period.

1. Introduction

Organic farming is perceived by many to offer some solutions to the problems of environmental degradation, depletion of non-renewable resources, food safety and other problems associated with conventional agricultural practices in industrial countries (Lampkin and Padel 1994). Indeed, a number of governments, including that of the UK, have been actively encouraging farmers to adopt organic practices. The present study aims to identify the factors which prompt farmers to adopt these alternative farming practices and to assess their relative importance in that decision. It is hoped thereby to provide the basis for better informed policy interventions in this area. An additional aim is to highlight a relatively new use of Duration Analysis, a research method which by focusing on the timing of

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the adoption decision, has, in our view, particular advantages in the study of the take-up of new technologies.

To put the study in context, it is part of a larger project, covering also Brazil and Spain, on the determinants of the adoption of 'sustainable' agricultural technologies. Organic farming was chosen as the basis of the empirical analysis, because of the close association between organic production and the concept of agricultural sustainability (for more discussion of this association, see Rigby and Cáceres 2001). The organic tradition is one of the oldest approaches to agricultural production, pre-dating all other environmentally-aware approaches (Scofield 1986), and as Lampkin (1994) notes, 'sustainability lies at the heart of organic farming and is one of the major factors determining the acceptability or otherwise of specific production practices'. The organic sector was beginning to grow rapidly in the UK at the time of the empirical work reported here and this growth has continued and accelerated in the period thereafter. The area of organically managed land in the UK accounted for 3.3% of agricultural land in 2002, compared to 0.5% in 1998 and 0.2% in 1993. The retail value of UK organic produce has grown from £93 million in 1992 to £920 million in 2002. A focus on the organic sector was also advantageous in the present study in that organic production is regulated and inspected and it exists as an international movement with continuing attempts to further coordinate national standards (Tate 1994). Furthermore, organic registration bodies hold detailed membership lists which facilitate the necessary fieldwork. The present research project focuses on horticultural producers, because significant numbers of adopters of alternative technologies can be found in this sector.

There have been two main statistical approaches to investigating the use of new agricultural technology: adoption studies that employ bivariate analysis at the farm level, with adoption measured at a point in time, or diffusion studies that model the cumulative adoption rate at the aggregate level (Feder *et al.* 1985; Thirtle and Ruttan 1987; Feder and Umali 1993). However, as has been noted elsewhere (Mohr 1982), the dichotomy between diffusion as a process and adoption due to individual heterogeneity is an artificial one, in that the diffusion curve is simply the aggregate of the individual adoption decisions. Thus adoption studies fail to allow for the timing of the adoption event, and the impact that time-varying factors may have on it, while it is inevitable that diffusion studies do not address the issue of why particular firms adopt earlier than others (Davies 1979).

An alternative approach, explored here using Duration Analysis, is to model explicitly the time to adoption of a technology for individual producers, thereby including both adoption and diffusion components of the problem. Duration analysis has been used widely in labour economics, with some examples in technology literature (Hannan and MacDowell 1984, 1987; Levin *et al.* 1987) and even fewer in agricultural economics (exceptions are de Souza Filho 1997; Caletto *et al.* 1999; Fuglie and Kascak 2001). The dearth of applications to agricultural adoption is rather surprising as the great advantage of Duration Analysis is that it deals with both cross-section and time series data. Firms' characteristics, the price of the new technology, output price, environmental characteristics and other potential determinants of the adoption decision may change not only from one economic agent to another, but also over time. Duration Analysis allows information on both these types of change to be included; adoption and diffusion are investigated together. As we note in Section 4, under some circumstances Duration Analysis is equivalent to the traditional bivariate analysis of adopters/non-adopters, but in many cases, in particular where there are time-varying determinants of adoption (e.g., prices, or policy), conventional approaches are either misspecified or would require prohibitively complex statistical techniques.

In the empirical study reported here, an analysis is made of a wide range of potential determinants of the adoption decision, both economic and non-economic. Specifically, we attempt to explain the time it will take a producer, from first starting to manage the farm, to adopt organic practices on the holding. As explained below, an important feature of the approach is that one can estimate the probability that a farmer with given attributes will adopt organic practices in a particular year, given that adoption had not occurred by that time.

The paper is set out as follows. In the next section, we consider a number of factors which may influence the adoption decision. There then follows (Section 3) a description of the data set. In Section 4, the use of the duration model in modelling the process of adoption is described in some detail. The results of applying the model are presented and discussed in Section 5. Section 6, in which some policy implications are drawn, concludes the paper.

2. Determinants of adoption of alternative agricultural technologies

There have been a number of theoretical models explaining the time to adoption, based on learning, information acquisition and prior beliefs of the profitability of the innovation (e.g., Lindner *et al.* 1979; Lindner 1980; Feder and O'Mara 1982; Jensen 1982, 1983; Feder and Slade 1984; Bhattacharya *et al.* 1986; Fischer *et al.* 1996) and these provide the basis for empirical work. Much of the empirical work which has been undertaken has focused on the economic potential and risk associated with alternative technologies, the characteristics of the farmer (representing human capital assets), and farm assets (which link to factor costs, capital costs and risk aversion) (see, e.g. Feder *et al.* 1985). However, other factors are potentially relevant, particularly in the context of a study of sustainable agricultural technologies.

Colman (1994) has argued that the motives for economic behaviour can not be reduced simply to profit maximisation, rather they '… may be complex, of benefit to a third party, to serve political or religious cause or reflect other motives than satisfaction in personal consumption or ownership' (p. 304). A number of studies provide evidence that attitudes are indeed important in the choice of agricultural practices, particularly in regard to conservation/sustainable technology (e.g., Bultena and Hoiberg 1983; Beus and Dunlap 1994; Comer *et al.* 1999). Padel and Lampkin (1994) and Padel (1994) reviewed the evidence on the motivations of organic farmers, and identified the most common factors among organic producers as concerns about their family's health, concerns about husbandry (e.g., soil degradation, animal welfare), lifestyle choice (ideological, philosophical, religious) and financial considerations. Recent changes in agricultural policy, the economics of conventional farming and increasing consumer concerns regarding food safety, animal welfare and other related issues are likely to have led to some changes in the pattern of these motivations since the reviews were undertaken. A note of caution worth adding here is that care is required when interpreting results on attitudes and motivation because, without relying on recall data, it is difficult to discern whether attitudes expressed at the time of data collection were held at the time of adoption (and so may have been a significant factor in the choice of technology) or whether they have evolved over time (and so are irrelevant to the adoption decision).

The differences in attitude or belief of many farmers involved in 'alternative' agricultural systems such as organic farming are likely to be related to the farmer and farm characteristics noted above as featuring in much empirical work. Hence, there have been a variety of studies, most often in the USA and Europe, finding systematic differences in the demographic profile of organic producers compared to their conventional counterparts (recent examples include Lockeretz 1995; OFRF 1997; Lipson 1999; Burton *et al.* 1999). Although there have been variations in the precise findings regarding these differences in demographic profile, Rigby *et al.* (2001), upon reviewing the published literature, conclude that past evidence has indicated that 'organic producers (i) were motivated significantly by non-economic factors in converting to organic production, and (ii) had different characteristics in terms of demographics, economic situation and attitudes' (p. 609).

Information is also viewed as a critical factor in the adoption process, particularly in terms of awareness and evaluation of alternative technologies (e.g., Nowak 1987). Low-input systems have been described as 'information intensive' and the availability of information is particularly important for a 'knowledge-based' innovation such as organic farming (Padel 2001).

However, some sources may be viewed as more reliable and credible than others in providing information on alternative technologies. To take a specific example in the context of the present study, the Agricultural Development and Advisory Service (ADAS),[1] the principal extension agency in the UK, appeared, at least until relatively recently, little interested in promoting anything other than high-input, modern technology and so producers, considering alternatives to conventional methods, may have sought other information sources. Nevertheless, it is again difficult to be certain that the principal information sources cited *ex post* by survey respondents were indeed those used *ex ante* in making the adoption decision.

Finally, networks of farmer interactions represent the social capital assets of the farm household and may influence, through the process of learning, the time to adoption.

3. Survey data

The present study is based on a cross-sectional survey of 237 farms in the UK, comprising 86 organic farmers (the 'adopters') and 151 conventional farmers (the 'non-adopters').[2] An adopter is a farmer who uses organic practices on all or part of the farm; the date of adoption is identified by the farmer as the year they began to use organic practices.

In this context, the duration of interest is the length of time it takes a producer to adopt the innovation (in this case organic production techniques). In the analysis of duration data for an innovation, the date for the start of the duration for each individual is usually clearly defined: it is either the date at which the innovation is first made available, or the date at which the firm first existed, whichever is latest. In the present case, there is no clearly defined date for the innovation: organic production techniques have always been 'available' to farms. Our approach is to calculate the duration from the date at which the farmer started to manage the holding[3]. Our earliest

[1] ADAS, originally part of the Ministry of Agriculture, Fisheries and Food, was privatised in April 1997.

[2] The survey data have been lodged at and are available from The Data Archive, University of Essex, Wivenhoe Park, Colchester, Essex, CO4 3SQ email: archive@essex.ac.uk Study Number: 3900.

[3] This is not strictly true for five farmers in the sample, who started to manage in the period 1939–1948, whom we have assumed started to manage in 1953. This was because in the earlier period certain agricultural techniques will have been proscribed due to wartime. The date of 1953 was selected as it was the initial management date for the farmer in our sample who first adopted organic techniques. It has been found that deleting these 5 'censored' farms from the data set does not affect the results significantly.

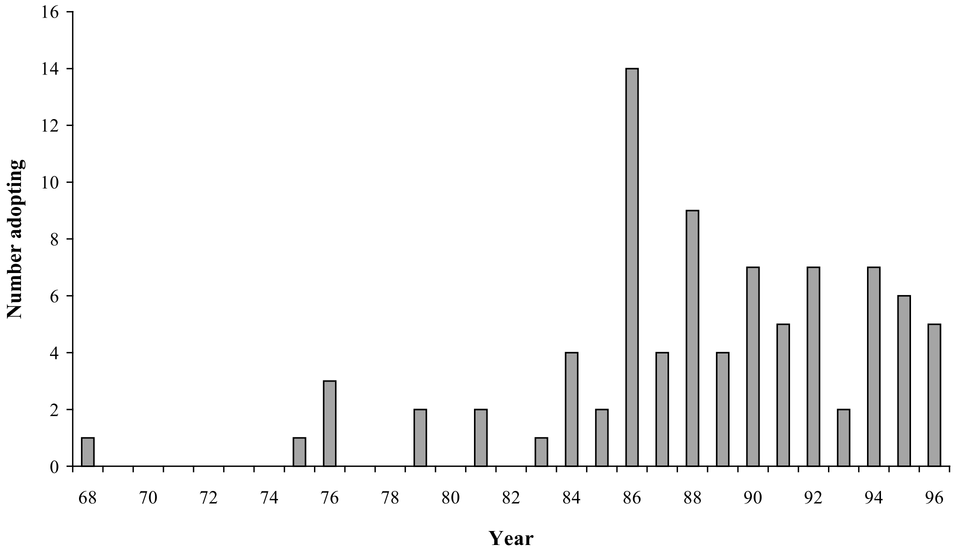

Figure 1 Adoption of organic farming in sample, 1968–1996

calendar date is given as 1953 and the maximum duration is 44 years, i.e. there are some farmers who entered at 1953 and have not adopted by 1996, the survey date. However, the average duration for all farmers in the data set is much lower (14 years). Figure 1 shows the number of adopters and the timing of adoption in our sample.

The survey was conducted in 1996, using a structured questionnaire completed during face-to-face interviews.[4] The survey questionnaire covers: (a) the physical characteristics of the farm (e.g., area, number of sites, soil type); (b) the characteristics of the farmer (e.g., age, gender, experience, education); (c) cropping patterns (e.g., areas of each crop, irrigation, tillage methods, soil analysis); (d) input use (e.g., pest control, fertilisers, weed control); (e) economics of the farm enterprise (e.g., farm sales, other income sources, capital assets); (f) sources of information (e.g., advisory bodies, buyers/merchants) and contact with other groups (e.g., membership of producer groups, co-operatives); and (g) attitudes to environmental issues such as the sustainability of conventional agriculture, and awareness of aid to organic producers, market opportunities, etc. Regrettably, it has proved

[4] The relatively small number of organic farmers in the UK meant that random sampling would not have generated a large enough set of adopters for the empirical analysis. Organic producers were therefore contacted from the membership lists of the various registration bodies in the UK. Conventional interviewees were selected from lists purchased from the National Farmers Union and supplied by small horticultural producer groups.

Table 1 Functional forms for the exponential and Weibull models

	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	$\lambda p t^{p-1}$

Table 2 Descriptive statistics for the sample (237 farms)

	Organic sample (86)		Conventional sample (151)	
Variable	Mean	SD	Mean	SD
HHSZE (no.)	3.70	1.94	3.19	1.65
AGE (years)	45.71	11.62	48.36	11.31
GEN (0,1)	0.23	0.42	0.05	0.21
HEFE (0,1)	0.57	0.50	0.55	0.50
YAGRIC (0,1)	0.59	0.49	0.85	0.36
TOTHA (ha.)	35.60	73.00	110.60	207.00
INFBUY (0,1)	0.26	0.44	0.60	0.49
INFFMRS (0,1)	0.73	0.45	0.44	0.50
INFADAS (0,1)	0.13	0.34	0.40	0.49
INFPSS (0,1)	0.39	0.49	0.64	0.48
MEMPGA (0,1)	0.20	0.40	0.46	0.50
MEMENV (0,1)	0.50	0.50	0.34	0.47
CONINDEF (0,1)	0.05	0.21	0.63	0.48
ORGFF (0,1)	0.73	0.45	0.13	0.33
ORGENV (0,1)	0.97	0.18	0.75	0.49
ENVISS (0,1)	0.97	0.18	0.74	0.44
FSV (0,1)	0.80	0.40	0.54	0.50
MAXCON (0,1)	0.93	0.26	0.67	0.47

SD, Standard deviation. Definitions of abbreviations can be found in Appendix 1.

impossible to identify appropriate time series of product prices and costs associated with organic horticultural production. Appendix 1 and Table 2 report definitions and summary statistics for a number of the variables in the data set, split by adopters and non adopters.

4. Modelling the process of adoption

4.1 Duration Analysis

Duration Analysis has a long history in biometrics and statistical engineering but Lancaster's study on unemployment appears to be the first application of the technique in the social sciences (Lancaster 1972). The purpose of Duration Analysis is to statistically identify those factors which have a significant effect (both positive and negative) on the length of a spell. A spell starts at the time of entry into a specific state and ends at a point when a new state is entered. This approach has been used to study a wide range of phenomena: one may be analysing the duration of a spell which begins when a person becomes unemployed and ends when they find a job, or the duration of a spell between major surgery and eventual death. In each case the aim is to identify the sign and magnitude of the effects of explanatory variables on the length of the spell. Hence in the unemployment example, the person's age, gender and educational status are likely to be included as explanatory variables in the study, while in the medical example the patient's age, gender and post-operative treatment will feature in the analysis. Reviews of the use of Duration Analysis in economics are to be found in Lancaster (1990) and Kiefer (1988) among others.

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 date, or the end of a spell, is the time a firm adopts the innovation. In practice the available data for social researchers are usually gathered by cross-sectional surveys and some spells may not have been completed at the time of data collection, i.e. some firms may not have adopted the technology by that time. For these firms the ends of their 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 (i.e. at the time when the data were collected), indicating that for these cases the process is ongoing. Estimation must take account of the censored nature of the data.

Probability theory plays a fundamental role in duration analysis. Instead of focusing on the 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 very shortly after time t, given it has not adopted by that time?

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

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

Equivalently, the distribution of T can be expressed by

$$S(t) = 1 - F(t) = \Pr(T > t) \tag{2}$$

which is the survivor function.[5] $S(t)$ gives the probability that a spell is of length at least t, that is, the probability that the random variable T exceeds t. The hazard function specifies the instantaneous rate of completion of a spell at $T = t$, conditional upon survival to time t. It is formally defined as:

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

The hazard function can be thought of as the continuous time version of a sequence of conditional probabilities (in this case, conditional probabilities of adoption). The cumulative distribution, survivor and hazard functions are equivalent ways of expressing the distribution of T. To see this, note that $S(t) = \exp\left(-\int_0^t h(s)ds\right)$, when it is assumed that, $\int_0^t h(s)ds$ diverges as t $\to \infty$, so that the distribution of T is non-degenerate and so the spell must eventually end, that is, adoption must eventually occur.[6] For an individual, $1-S(t)$ gives the probability that an individual will have adopted the innovation by time t, but if one considers a population of individuals, all of whom are present at the date of the innovation, it will also represent the expected diffusion of the innovation through that population, that is, the share of the population that has adopted the technology.

4.2 Parametric models

There are many suitable parametric specifications for the distribution of T. Table 1 reports the relevant functional forms for the exponential and

[5] The terms used in Duration Analysis are drawn from the biometric literature, hence the use of the terms 'survivor' function and 'hazard' function, referring to the analysis of the length of time between medical intervention and subsequent death.

[6] It is possible to specify a 'defective' distribution which permits some spells never to be completed (i.e., some farmers never adopt) (Lancaster 1990) but at the expense of more complex estimation procedures, at least in the continuous time models. The approach relies on estimates of the hazard at the higher duration levels which tend to be imprecise because of the small number of observations. This, together with the conflating problem of death or retirement at older ages, has prompted us to retain the assumption of non-degeneracy and so we simply interpret exceptionally long durations as equivalent to non-adoption.

Weibull distributions, which we use in the present study. 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 duration. For this reason it is called 'memoryless', that is, the passage of time does not affect its value. The Weibull distribution allows the hazard to vary monotonically as the duration proceeds; with 'positive duration dependence', the hazard rises and with 'negative duration dependence', the hazard decreases over the duration. The exponential is nested in the Weibull distribution when $p = 1$. An alternative approach, which we also explore, is to specify piece-wise constant hazards, which allow the hazard to shift, in steps, over the duration (the limiting specification is the Cox proportional hazard, which identifies a different baseline hazard (defined below) at every t, and essentially avoids imposing a parametric form on the baseline hazard: see Kalbfleisch and Prentice 1980).

Once the parametric distribution of T has been chosen, estimation of parameters follows maximum likelihood procedures. Assuming independently observed durations, t_i^*, and that all firms adopt within the data period (i.e. all spells are complete), the log-likelihood function 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. In cases where censored observations are included, information on their exact durations is not available. However, we know that the duration of these observations is at least z_i, where z_i is the censoring time for individual i. Thus, the likelihood function becomes

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

or

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

where $t_i = \min(t_i^*,z_i)$ 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 (Kalbfleisch and Prentice 1980; Lancaster 1990). The simplest covariates to include are those which do not change over time, such as gender and race, or which, in the absence of appropriate data, may be assumed to be time invariant, such as farm size. We also may wish to consider time-varying covariates, such as the price of an innovation, which do not follow a continuous time path, but are step-functions over time.

Finally, there are other variables, such as age and time itself, which change continuously as a function of time.

The hazard function can be reformulated to allow for the influence of explanatory variables. Let X be a vector of time invariant covariates and β a vector of associated unknown parameters. The hazard may then be expressed as

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

In this formulation there is a common function of time, $h_0(t,\theta)$, known as the baseline hazard, which is independent of the covariates X. The covariates enter via $q(X,\beta)$ and act multiplicatively on the baseline hazard. Models with this specification are called proportional hazards, and are used in the present study. The most widely used specification of $q(.)$ is

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

which guarantees that the hazard function, h, is non-negative, as required by definition, without imposing restrictions on β. Rather than report the underlying parameters, it is common to report the exponential of the parameters: $\exp(\beta_j)$, as this represents the ratio of two hazards, different only by a unit value of variable j:

$$\frac{h_0(t,\theta)\exp(\beta_{j\sim}X_{j\sim} + \beta_j(X_j + 1))}{h_0(t,\theta)\exp(\beta_{j\sim}X_{j\sim} + \beta_j X_j)} = \exp(\beta_j) \tag{9}$$

where $j^{\sim}$ is the complement of j. A value of 1 implies no impact of the variable on the hazard; a value greater than 1 implies an increased hazard and hence a negative relationship between the variable and the length of time to adoption, and the converse for a value less than 1.

4.3 Discrete time duration models

Thus far we have assumed that the durations have been drawn from a continuous time distribution (i.e., t can take any, possibly non-integer, value). However, for many cases in economics the data collection process will generate grouped data (i.e. an event may occur during a time interval, but its precise timing within the interval is unknown), or the process under consideration is genuinely discrete. As a result, observed durations are clustered at mass points, and estimation should take account of this. A specification of the model which accommodates such data has been suggested by Prentice and Gloeckler (1978). Following Meyer (1990) the log-likelihood function for this specification is given by:

$$L = \sum_{i=1}^{N}\left[d_i \log(1 - \exp\{-\exp(\gamma(t_i) + \beta' X(t_i))\}) - \sum_{j=1}^{t_i - 1}\exp(\gamma(j) + \beta' X(j))\right] \quad (10)$$

where $\gamma(t) = \ln\left\{\int_t^{t+1} h_0(s)ds\right\}$.

An appropriate parameterisation for the baseline hazard then yields 'Weibull', 'exponential' or 'piece-wise constant' discrete-time models. In fact, the baseline hazard can be estimated as any general function.

Note that the discrete-time specification will, in general, lead to different estimates of the hazard and effects of covariates as compared to its continuous-time counterpart, although the estimates of the two models will converge as the size of the grouping interval tends to zero. We would suggest that in the case of agricultural adoption studies, such as this, where the times to adoption will most naturally be reported as integer years and where duration times are relatively small, the discrete-time model is appropriate. Consequently only results using discrete-time models are reported here (a number of alternative continuous-time specifications are given in Burton *et al.* 1997).

The mathematical relationships between hazard and survival functions presented above are true whether the covariates that affect the hazard are time-varying or time invariant. However, the statistical implications of the two alternatives are profound. The inclusion of time-varying covariates in the hazard means that the survival function will not fall within one of the well-known distributional families. Hence there may be no closed form representation of the survival function, and in some cases, the survival function may not exist at all. The pragmatic implication of this is that the traditional bivariate analysis of factors that determine adoption based on a categorisation of individuals as adopters or non-adopters at a point in time will either be prohibitively complex, or even impossible, in cases where time-varying covariates, such as prices or changing policy regimes, are hypothesised to affect the adoption decision. Appendix 2 contains a simple mathematical example to support this contention. In the following section we present the results from an application of the hazard function approach.

5. Duration Analysis results

When analysing a set of duration data, it is usual to consider first some summary of the survival times of all the individuals in the sample. If the data contain censored observations, the Kaplan-Meier estimate of the survivor function is commonly used. This is a non-parametric approach,

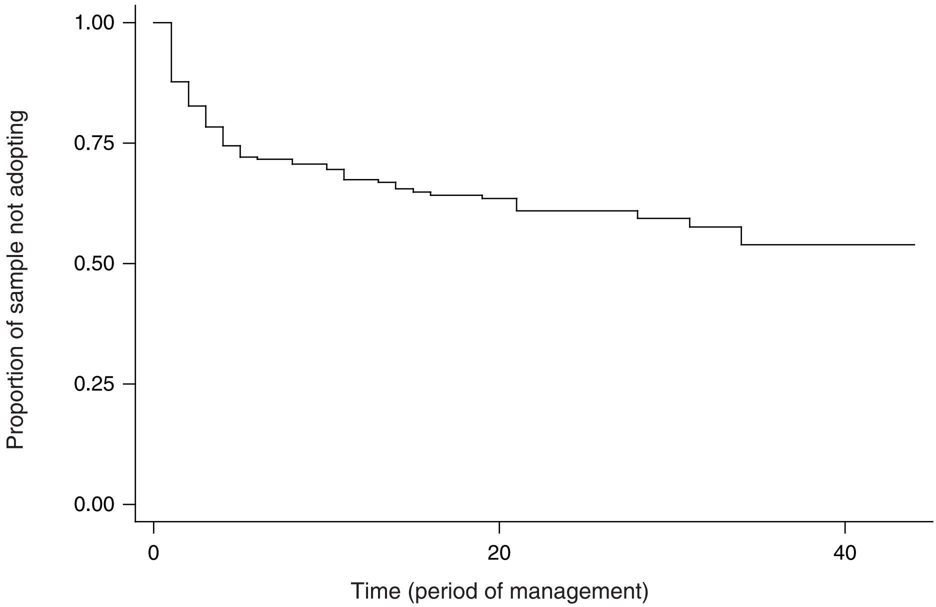

Figure 2 Kaplan-Meier survival estimates

making no assumptions regarding the underlying distribution of survival times. It involves dividing the period of observation into a series of intervals, each containing one or more adoptions at its beginning. The function can only be identified at times when adoption occurs. The estimated survivor function between t_r and t_{r+1} is estimated as the number of producers who have not adopted at time t_r, divided by the number of producers 'at risk' of adopting at time t_r. This estimate is unchanged until the next producer(s) adopt at time t_{r+1}.

The Kaplan-Meier estimate of the survivor function is plotted in Figure 2, giving a step function. It should be noted that the horizontal axis is scaled in 'artificial time', from 0 to 44, representing the 44 years between the first 'at risk' date (1953) and the year of survey (1996). Furthermore, all cases enter at $t = 0$, regardless of which point in calendar time they begin to be observed. At $t = 0$, the value of the function is 1, since all farms are initially considered to be conventional. The value of the function falls sharply in the first interval, since 29 of the farmers (88% of the sample) adopt in their first year of management. There are adopters in each of the subsequent 5 years giving an evenly spaced step, but there are long periods thereafter where there are no adoptions and hence the Kaplan-Meier survivor function does not change. The last change in the value of the function occurs when the last of the 86 adoptions occurs, at $t = 34$.

Turning to the parametric approach, we specify a flexible functional form for the baseline hazard which nests the two commonly used specifications identified in Table 1:

$$h_0(t) = \lambda p t^{p-1} + \exp\left(\sum_{t=1}^{5} \alpha_t\right) \tag{11}$$

The α_t parameters are introduced to permit the baseline hazard to shift from period to period over the duration (Jenkins 1995). For present purposes, these parameters appear only in the first 5 periods of the duration.[7] If $\alpha_t = 0$ ($t = 1, \dots, 5$) then the hazard reduces to the standard Weibull form. If $p = 1$ then it is a piece-wise constant specification, with variation in the hazard over the first 5 periods but constancy thereafter. If $p = 1$ and $\alpha_t = 0$ (t = 1, … , 5) then the baseline hazard collapses to an exponential form.

It is the hazard function that determines the expected rate of adoption, and at the aggregate level, the diffusion path. Higher vales for λ will imply a higher instantaneous probability of adoption, and hence a faster diffusion of the innovation through the population. If the α_i are positive, it implies a greater propensity to adopt early in the life of the individual, and hence cause the cumulative diffusion path to rise more quickly than otherwise. A time-varying covariate in the proportional hazard may reduce the hazard for time periods beyond a certain date, and hence cause the diffusion pattern (either for any individual who has not adopted, or for the remaining population as a whole) to become flatter than it would be otherwise.

In Table 3, Model 1 reports the results for the most general model, with parameters reported as hazard ratios.[8] The significance of the hazard ratio is reported in parentheses, where the significance level is with respect to the null of no impact, i.e., the hazard ratio equals one. A hazard ratio greater (less) than one denotes that the variable has a positive (negative) impact on the likelihood of the spell ending, that is, on adoption. So, for example, the reported hazard ratio for the variable denoting gender, **gen**, (2.49) indicates that female farmers have a conditional probability of adoption which is almost two and half times that of their male counterparts.

In terms of the other time-invariant covariates, concern about environmental issues (**enviss**) and the belief that organic farming is better for the environment (**orgenv**) have a strong positive impact on the hazard, whereas those farmers who believe that conventional agriculture can sustain productivity (**conindef**) have a much lower hazard. Similarly, farmers whose

[7] Experiments including dummy variables for durations greater than 5 did not lead to any significant impacts being identified.

[8] All estimation has employed STATA, Release 5 (Statacorp 1997).

Table 3 General and restricted duration models of adoption

	Model 1	Model 2	Model 3
hhsze	1.10 (0.201)		
gen	2.49 (0.003)	2.34 (0.003)	2.24 (0.006)
cage	0.98 (0.103)		
hefe	0.61 (0.064)	0.66 (0.081)	0.68 (0.100)
totha	1.00 (0.239)		
maxcon	1.60 (0.274)		
yagric	0.84 (0.483)		
orgff	1.47 (0.224)		1.68 (0.075)
orgenv	3.20 (0.070)	4.29 (0.015)	3.47 (0.041)
fsv	0.57 (0.085)		
enviss	4.05 (0.031)	4.71 (0.012)	3.78 (0.031)
conindef	0.07 (0.000)	0.07 (0.000)	0.08 (0.000)
memenv	1.50 (0.103)		
mempga	0.72 (0.271)		
infpss	0.78 (0.314)		
infbuy	0.45 (0.004)	0.41 (0.001)	0.46 (0.004)
inffmrs	1.62 (0.070)	1.93 (0.009)	1.71 (0.037)
infadas	0.46 (0.027)	0.38 (0.004)	0.43 (0.013)
oas	4.42 (0.001)	4.12 (0.002)	3.72 (0.003)
yrrge1	1.13 (0.020)	1.13 (0.018)	1.13 (0.018)
yrrge2	0.91 (0.035)	0.90 (0.014)	0.92 (0.053)
$\alpha 1$	6.08 (0.166)	6.65 (0.000)	
$\alpha 2$	3.74 (0.188)	4.39 (0.000)	
$\alpha 3$	4.42 (0.086)	5.00 (0.000)	
$\alpha 4$	5.00 (0.024)	5.75 (0.000)	
$\alpha 5$	3.97 (0.047)	4.41 (0.003)	
p	0.86 (0.279)		0.37 (0.000)
Log Likelihood	–222.97	–231.49	–233.89

All coefficients, apart from p, are reported as hazard ratios (i.e., $\exp(\beta_i)$). Significance levels reported in parentheses are for the null that the hazard ratio, and p, equals unity. See Appendix 1 for definitions of abbreviations.

principal source of information regarding farming issues is buyers/merchants (**infbuy**) or the agricultural advisory service ADAS, (**infadas)**, have a lower probability of adoption than those who cite other farmers (**inffmrs**) as their main information source. A number of variables one might have expected, on the basis of past studies (Harris *et al.* 1980; Dalecki and Bealer 1984; Beus and Dunlop 1994; Allen and Bernhardt 1995; Lockeretz 1995) to be significant in the model are found not to be so. The experience of further/higher education (**hefe**) is found to have a negative, but marginally insignificant, impact on the hazard. The effects of income from agriculture being the household's main source of income (**yagric**), the physical size of the holding (**totha**) and the opinion that larger farm sizes are bad for the environment (**fsv**) are all found to be insignificant.

Model 1 also includes a number of time-varying covariates. A dummy variable, **oas**, denoting the period over which the Organic Advisory Service (OAS) has been operating (since 1986), allows for an epoch shift and is found to have a strong positive impact on the hazard. The variables **yrrge1** and **yrrge2** represent a split time trend, based on the calendar year. The variable **yrrge1** runs from 1953 to 1985, with an initial value of −33, increasing by one in each period, and taking a value of zero in 1985 and all periods thereafter. **yrrge2** takes a value of zero for all periods prior to 1986 and then increases by one thereafter; it allows for the marginal effect of calendar time to differ before and after 1986. The inclusion of these three variables is an attempt to capture systematic changes in the economic conditions facing farmers, which may be affecting their decisions to adopt. As noted, the absence of appropriate time series data on product prices and input costs has necessitated their exclusion from the analysis; however, the scope of duration analysis to incorporate time-series data is a great advantage over traditional, static bivariate adoption techniques.

Taking the most general specification (Model 1 in Table 3) as a baseline, we test for permissible restrictions of the baseline hazard. A Likelihood Ratio test for $p = 1$, while maintaining $\alpha_t \neq 0$, (generating Model 2 in Table 1) gives a $\chi^2(1)$ statistic of 0.08. The corresponding test of the significance of $\alpha_t = 0$, while maintaining $p \neq 1$, (generating Model 3 in Table 1) gives a $\chi^2(5)$ statistic of 7.74. Thus, in this generalised model, either set of restrictions could be accepted. Using an Akaike information criteria provided little guidance to model choice as the divergences between them were very small. We have therefore proceeded with both alternative specifications of the baseline hazard, one employing the piece-wise continuous specification (Model 2), and the second the 'Weibull' (Model 3). Both models imply a very rapid decline in the hazard after the initial periods of the duration, although the exact time path is clearly different.

Table 3 reports the results after a general-to-specific specification search over all the other variables, for both of the two baseline specifications, excluding those variables that are not significant. The size and significance of the other variables seem to be largely invariant to the specification of the baseline hazard, which is reassuring.

In terms of behaviour, the results of these models indicate the importance of attitudes to the environment and sources of information in the adoption decision. Those with strong environmental concerns and communication links with other farmer groups have a higher conditional probability of adopting. It is tempting to rationalise the significance of farmers as a source of information by appealing to some notion of the costs of acquiring information in this way, or the quality of that information, and hence linking these results back to the theoretical models discussed earlier, but without more detailed information on the nature of the information being obtained through the different channels, this interpretation has to be viewed with caution.

There is also the possibility, noted earlier, that the survey records attitudes and communication links which have developed after adoption has taken place and which therefore did not determine the adoption decision. Given that in most cases the changing of opinions and attitudes and of information sources is a gradual process, then identifying the precise timing of the change is difficult. Many farmers prior to conversion, when still evaluating organic production, may seek out and consult other organic producers in the area. That is, the change in information sources is likely to be ongoing through the process of considering adoption, deciding to adopt and adoption itself. Again without more information than the survey provides, we cannot state categorically the extent of this problem. However, when the attitudes and information sources of recent adopters in the sample (1994–1996) were compared with those who had converted in the period 1968–1993, they were found to be remarkably similar. This suggests that the experience of adoption itself is not solely altering these attitudes and information sources, and that it is likely that they were established prior to adoption itself. We would argue, therefore, that while an element of caution is required because of the *ex post* nature of the data in studies of this type, these non-economic factors are quite robust indicators of adoption behaviour.

Of the personal characteristics of the farmer, gender stands out as being a particularly strong predictor of adoption: being female more than doubles the conditional probability. This gender effect is a relatively unusual finding; Padel (2001) notes that in this regard 'empirical evidence on gender issues is scarce' (p. 44). The split time trend indicates a steady increase in the propensity to adopt, but with a fourfold jump in the hazard in 1986, after which the external impacts on the hazard decline. A rationalisation of the 1986 epoch effect could be that with the establishment of the OAS information on organic techniques is more readily available, although very few (20%) of adopters indicated that contact with the OAS increased the likelihood of conversion. Hence we would argue that the significance of this epoch effect is the growing interest in environmental issues related to agricultural sector occurring at this time, something of which the establishment of the OAS was itself symptomatic. Perhaps more noteworthy, given the theoretical results of Lindner *et al.* (1979) and Fischer *et al.* (1996), and previous empirical findings, are the variables that are not significant: age and education, farm size and non-farm income. It is interesting that in a binomial analysis of the adoption process using this data, Burton *et al.* (1999) found age and farm size to be significant. However, if the 'true' data generating process is the one specified here, the bivariate model will be misspecified (the cumulative probability $F(t)$ will be a function of the integral of the time dependent variables). This suggests that in modelling adoption using a 'one shot', static process, the dynamic aspects may have been captured by these variables, both of which have a strong temporal component. Whether this is also true for other bivariate studies that employ these variables is impossible to say.

5.1 Diagnostics

An implicit assumption being made in estimating the model is that the functional form selected is correct and that the explanatory variables account fully for differences across individuals in the sample. If the model specification is incomplete and there are unobserved differences in the sample (known as unobserved heterogeneity), inference based on the estimated model may be misleading. An analysis of residuals provides some insight as to whether the sample is homogeneous or unobserved heterogeneity is present. The investigation conducted here used a non-parametric approach (Lancaster 1990) and parametric tests for unobserved heterogeneity.[9] Bearing in mind the frailty of the tests for neglected heterogeneity (Orme 1998), in both cases the results suggest that unobserved heterogeneity does not represent a serious problem here.

6. Concluding Remarks

Many governmental and non-governmental agencies regard the adoption of organic agricultural techniques as an important aspect of the movement towards a more sustainable agriculture (Lampkin and Padel 1994). In this context, an understanding of the factors that lead farmers to adopt such techniques is a key component of policy design. The present paper has examined the determinants of adoption of organic agricultural practices in the UK horticultural sector and although it cannot be claimed that a fully comprehensive set of factors has been explored, a number of interesting and pertinent findings have emerged. Moreover, this is one of the first agricultural adoption studies to have employed Duration Analysis, an approach which has strengths in relation to several of the shortcomings of the more conventional bivariate or aggregate diffusion approaches.

In circumstances where adoption of an innovation involves accumulation of information, technical skills or physical capital, the act of adoption will

[9] We follow Meyer (1990) in assuming that unobserved heterogeneity, if present, takes a multiplicative form with a gamma distribution and we use an estimation procedure suggested by Jenkins (1995, 1997). Details of both parametric and non-parametric tests are available on request from the authors.

be conditioned by more than the economic or social circumstances that exist at the time of adoption, but the accumulation of experience over the prior period. Conventional bivariate statistical techniques are not able to capture these effects; either the intertemporal nature of the adoption process is explicitly ignored, or an attempt is made to capture it indirectly by including alternative 'time' related variables (such as age of the respondent). In these circumstances, the use of duration models is clearly superior to the analysis of adoption at a point in time. However, that advantage brings with it a stringent requirement for more data, and, in particular, the values of critical variables over the time period. For some variables this may be straightforward (e.g. published series on prices) but where one requires on-farm, demographic or other information, then this information may be unavailable, or unreliable if based on recall over long time periods. In the current study, while data unavailability has limited the range of such variables considered in the present study, the use of farmer's age, time trends and epoch effect variables has highlighted the potential of the approach.

We identify a very strong negative duration dependence, with the conditional probability of adoption falling to low levels after 5 years. Indeed, for some combinations of exogenous variables commonly found in the conventional farming sub-sample, farmers are predicted to have times to adoption that exceed their working lifespans i.e., the adoption distribution is in effect, degenerate. This would yield a long tail of 'laggards' in the adoption process, which Fischer *et al.* (1996) have identified as a common feature of agricultural adoption processes. We also observe that there are important external factors that may come to bear on the decision; in particular, there appears to be an epoch effect associated with the establishment of the OAS in 1986.

In terms of farm specific variables, the gender of the farmer is found to be of paramount importance. In addition, there are a number of attitudinal variables which consistently indicate that those who have concerns about the environment and the sustainability of the food system are more likely to adopt. This confirms the importance of non-economic factors in the adoption decision and suggests that analysis of the organic sector which confines itself to farm-level financial measurement may ignore significant determinants of the adoption decision.

The present study also generated a number of interesting 'negative' results, i.e., some variables, such as education, farm size, household size and reliance on agricultural sources of income, were found not to affect the time taken to adoption, whereas these have been found to be significant in earlier studies of the adoption of organic farming. As we note earlier, this may be due to differences in country and commodity coverage (e.g., none of the previous studies has been in the UK). It may be a consequence of using Duration Analysis, as opposed to bivariate or simple descriptive statistics of adopters and non-adopters. As we have argued previously, *a priori* Duration Analysis has significant advantages in the analysis of technology adoption, but establishing the formal statistical relationship between the duration/bivariate approaches is an area that would benefit from further research, especially where the bivariate approach is seen as misspecified.

The present study provides a number of insights into the adoption process which are of value for those who wish to increase the growth of organic agriculture in the UK. Rogers (1995) suggests that identifying 'opinion leaders' within the community, who provide a contact and dissemination source for new ideas, and encouraging their adoption may be a cost effective means of increasing overall adoption. Our results reveal that organic farmers have a different information network to their conventional colleagues, relying on other farmers and the OAS rather than ADAS and market-led information sources. This suggests that the information networks of the two types of farms are segmented and that the diffusion of organic farming within one group may not 'spill over' into the other. Second, if it is felt that it would be beneficial for extension services to target potential early adopters (van den Ban and Hawkins 1996), our results suggest that information on farm size, education and the degree to which agriculture is the main source of income do not provide any useful guidelines on identifying this group. Most importantly, the results from the estimation process suggest that farmers tend to become 'locked in' to conventional production systems. The causes of this are worth further analysis. It may be that the longer the producer continues as a non-organic farmer, the greater are the costs associated with conversion to an organic system, however, an assessment of whether these increased costs are physical, psychological or both is beyond the scope of the present study.

An inevitable question is whether the findings of a study based on 1996 data can be extrapolated to the present day. Experience in the late 1990s in the UK suggest that possibly we have entered a new epoch. The collapse of producer returns and farm incomes and a series of food scares (salmonella, E-coli, BSE etc.) has created a situation in which consumer demand for organic foodstuffs has risen dramatically and significant numbers of farmers are looking for alternative strategies in order to stay farming. The UK government has also stepped up its support for the sector with increased support for the organic sector with the establishment of the Organic Conversion Information Service in 1996 and increased conversion incentives in 1998. These changes have led to the surge in the area of land under organic management and the values of organic sales referred to in Section 1 (see Rigby *et al.* 2001 for more on these changes).

These changes indicate the need to investigate the adoption decision using both farmer- and farm-specific information alongside changes over time beyond the farm gate. Investigations of this nature are, we would argue, something to which Duration Analysis seems rather well suited.

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Appendix 1

Definition of farmer and farm characteristics

hhsze	the size of the farm household (no.),
totha	the size of the farm (ha),
age	the age of the farmer at the date of the survey (years),
gen	the gender of the farmer (=1 for female; =0 for male),
hefe	if the farmer has had further or higher education =1, =0 otherwise,
yagric	if income from agriculture is the main source of household income =1, =0 otherwise.
maxcon	If the farmer tries to maximise the proportion of own consumption which is supplied from his/her own farm =1, 0 otherwise.
infbuy	if a farmer's primary information source is buyers/merchants, =1; =0 otherwise,
infpss	if main information source is the press =1, =0 otherwise,
inffmrs	if main information source is other farmers =1, =0 otherwise,
infadas	if main information source is ADAS =1,=0 otherwise,
mempga	if the farmer is a member of a producers' group =1, =0 otherwise,

memenv if a member of a countryside or environmental organisation =1, =0 otherwise,
conindef if the farmer believes that 'current practices in conventional farming will sustain farm productivity indefinitely' =1, =0 otherwise,
orgff if the farmer believes that organic farming alone can 'satisfy society's needs for food and fibre' =1, =0 otherwise,
orgenv if the farmer believes that organic agriculture is better for the environment =1, 0 otherwise,
enviss if the farmer is concerned about local, national or global environmental issues =1, =0 otherwise,
fsv if the farmer believes that the trend to larger farm sizes is detrimental to the environment, =1, =0 otherwise.

Time varying covariates
cage The age of the farmer
oas Dummy variable, =0 prior to 1986, 1 from 1986 onwards
yrrge1 Calendar year time trend, taking a value of −33 in 1953, with increments of one until 1985 and 0 thereafter.
yrrge2 Calendar year time trend =0 from 1953–1985, 1 in 1986 and increments of one thereafter.

Appendix 2

Implications of time varying covariates for the survival function

In the following example, a specific distribution (log normal) is employed, as it leads to a well known survival function. However, the implications of this appendix will hold for any distribution.

If $h(t)$ is the hazard function (the conditional probability that an item will fail at time t, conditional on it not failing earlier), then the survival function (unconditional probability that it will not have failed by t) is given by:

$$S(t) = \exp\left\{ -\int_0^t h(s)ds \right\}. \quad \text{(A.1)}$$

If one assumes that the hazard follows a log normal distribution:

$$h(t) = \frac{\phi(x)}{\sigma t(1 - \Phi(x))} \quad \text{(A.2)}$$

where

$$x = \frac{\ln(t) - \mu(X)}{\sigma} \quad \text{(A.3)}$$

one gets the survival function:

$$S(t) = 1 - \Phi(x). \tag{A.4}$$

Thus, the traditional analysis of adoption based on a probit model which uses log of time and individual covariates (X) is underpinned by a hazard function of the form (A.2), as long as the covariates are time-invariant. Analysis of an adoption data set based on either the hazard or the survival representation will give equivalent results, and given the convenience of the probit model, one would suggest this approach is to be preferred. However, consider the case where X contains time-varying covariates, e.g.

$$x = \frac{\ln(t) - (\alpha + \beta P_t)}{\sigma}. \tag{A.5}$$

Integration of the hazard to identify the survival is now more complex, and there may be no closed form. If the price P_t is piece-wise constant over the periods 0–t_1, t_1–t_2, etc., then it is the case that

$$\ln(S(t)) = -\int_0^{t_1} h(s,P_{t_1})ds - \int_0^{t_2} h(s,P_{t_2})ds - \ldots \tag{A.6}$$

and the survival function is

$$S(t) = \exp\{\ln[1 - \Phi(x(t_1,P_{t_1}))] + \ln[1 - \Phi(x(t_2,P_{t_2}))] - \ln[1 - \Phi(x(t_1,P_{t_2}))] \ldots\}. \tag{A.7}$$

This collapses to the standard form if there is only one interval. Thus, the determinants of the adoption process could be identified by a binary model, but the survival function will have a large number of elements, and if the time-varying covariate is different for each individual, it will become very complex (there will be a different number of arguments to the likelihood for each individual). Note that this transfer from simple probit model to high complexity has occurred purely as a result of the introduction of a time-varying covariate. Analysis of the survival function which ignores the time path of the time-varying covariates on the transition from one state to another will lead to incorrect inferences regarding the impact of these covariates.[10]

The position is made more complex if P_t is an 'internal' covariate i.e., it is only observed when the individual is in the initial state. For example, this may be the level of profit using the initial technology, which by definition will not be observed once adoption has occurred. Duration Analysis can still proceed, as the analysis of the hazard is based only on the periods at

[10] Simulation results that show this are available on request.

risk, during which P_t is observed. However, analysis of the survival function is conditional on the time varying covariate path to date and by definition, internal covariates cannot be identified for the whole period. As Lancaster (1990) notes: '... these conclusions serve to emphasise how much more fundamental is the hazard function than the density function in modelling duration data.' (p. 31).