RANK, STOCK, ORDER AND EPIDEMIC EFFECTS IN THE DIFFUSION OF NEW PROCESS TECHNOLOGIES: AN EMPIRICAL MODEL

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Abstract

In this paper we set up a general duration model of technology adoption which incorporates the main factors discussed in the different demand side theories of diffusion of new process technologies. The model is applied to the data on diffusion of CNC in the UK engineering industry. It is found that while there is strong evidence for the rank and endogenous learning effects, there seems to be little evidence in support of the stock and order effects, as characterized by the game theoretic models.

Keywords: Technology Diffusion, Survival Analysis, CNC

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1. Introduction

The literature on technological diffusion i.e., the process by which the use of new technology spreads, has grown apace in recent years (for surveys see Stoneman 1983, 1986 and 1987). There have been a number of significant theoretical advances made in this literature, however it is still fair to state that the majority of the empirical work on this topic has not yet caught up with the theory. In this paper we attempt to construct an empirical model of the diffusion process (which we then apply to data on the spread of Computer Numerically Controlled Machine Tools (CNC) in the UK) in order to gain some insight into the extent to which the various theoretical frameworks have some empirical validity. This work is part of an ongoing project funded by the Economic and Social Research Council and the Department of Trade and Industry in the UK, some other results of which are available in Karshenas and Stoneman (1990).

Early work on the diffusion of new technology tended to concentrate upon epidemic theories of diffusion which in their crude form considered that potential adopters would acquire new technology upon receipt of information relating to its existence. Some refinement of this approach (see for example, Mansfield 1968) has improved the conceptual basis of such models but the reliance on information spreading remains. This approach has been particularly prevalent in empirical work (see, e.g., the latest piece by Mansfield 1989). In contrast a major aspect of recent theoretical developments has been the increasing emphasis placed on the explicit treatment of a firm's or consumer's decision to adopt, with very little, if any, account being taken of information spreading or other epidemic type forces.

The essential prediction of a theory of diffusion is that potential adopters of a new technology should have different (preferred) adoption dates. In the recent theoretical literature three different mechanisms have been suggested that would yield such an outcome.

a) *Rank effects.* These effects arise from assuming that potential adopters of a technology will obtain (due to different inherent characteristics such as firm size) different returns from the use of new technology. This allows one to specify a distribution of reservation prices across potential adopters. Diffusion proceeds as the cost of acquisition of the new technology falls over time, firms adopt as prices fall below reservation prices, and the benefit distribution is mapped out as a diffusion path. This strand of the literature, generally known as probit models, is exemplified by the work of David (1969), Davies(1979), and Ireland and Stoneman(1986).

b) *Stock effects*. As the use of a new technology expands and costs of production of users fall, industry price will fall and output will expand. These changes will in turn affect the return to the adoption of new technology. On the assumption that as use expands the return to adoption falls, at any given cost of acquisition there will be a number of adopters beyond which adoption is not profitable. By assuming that this number actually adopt, a diffusion path can be generated as the cost of adoption falls over time. This 'game theoretic' approach is best exemplified by the work of Reinganum(1981) and Quirmbach(1986).

c) *Order Effects*. Fudenberg and Tirole (1985) extend the stock effects model by reasoning that in that model earlier adopters get the greatest returns and thus there will be a battle to be first. Such 'order effects' can be considered more generally however. Early adopters could obtain prime geographic sites, pre-empt the pool of skilled labour or build up first mover advantages more generally defined. A general model where such effects are considered is to be found in Ireland and Stoneman(1985). Basically, a firm in deciding whether to adopt in a time period or whether to wait takes account of the effect on profits of its moving down the adoption order as a result of waiting. This yields an adoption date as a function of the cost of acquisition, and as this cost falls so diffusion proceeds.

These three effects, the rank, stock and order effects, summarise the recent theoretical advances in diffusion analysis. In section 2 of this paper we build a decision theoretic model that incorporates all three effects and which may be used empirically to assess their applicability. However, one should not ignore the epidemic effects previously discussed. Thus in the first two parts of section 2 the modelling of the decision to adopt is *conditional upon awareness*. In the third part of section 2 we introduce the epidemic effect to reflect awareness and uncertainty factors and thus generate a model that incorporates all four of the basic approaches to diffusion analysis. The resulting model is applied to data on the diffusion of CNC in the UK. In section 3 we discuss the data and the implications of the sample design for the specification of the estimating model. Estimation and results are discussed in section 4, and the main conclusions of the paper are reviewed in section 5.

2. An Empirical Model

The basic empirical approach taken here derives from the work of Hannan and McDowell (H&M) (1987) who 'use as a guide, the presumption that an innovation will appear more attractive to a potential adopter the greater the positive differential between expected profits with and without the innovation and the less the uncertainty or risk associated with the innovation'. Defining X(t) as a vector of relevant explanatory variables that determine the difference in expected profits and uncertainty, they assume that h(t), the hazard rate, or the conditional probability that firm i adopts in time t (given that it has not adopted by {t-1}), is given by (1)

$$h_i(t) = \exp\{X'_t\beta\} \tag{1}$$

where β is a vector of coefficients. In their work H&M include as the main components of X, the wage, market growth, concentration, firm size, time and usage to date. Our approach is similar to that of H&M in that we model the adoption duration, however in doing so we have cause to extend the list of relevant explanatory variables and assume a more general functional form for the hazard rate.

A Deterministic Model

Assume for present that there is complete information and that there is no uncertainty. Define the function g(.) as determining in a given industry the benefits obtained by a firm from use of a new technology per period of use. The arguments of g(.) will reflect the rank, stock and order effects discussed above. For the rank effect assume a vector of characteristics for the firm, C_i, that determine its rank in the distribution of benefits. For the stock effects define K(t) as the number of firms in the industry using the new technology in time period t. For order effects define S(t) as the number of previous adopters in the industry at time t (this being done purely for expositional reasons it being obvious that $S(t)\equiv K(t)$). Abstracting completely from the level of use of a technology by the firm (which is done throughout the paper, thus in effect making its main interest inter firm rather than intra firm diffusion), we may then state that for the ith firm adopting a new technology at time t, its per period or annual benefits from adoption at time $\tau\geq t$ will be

$$g_i(\tau) = g(C_i, S(t), K(\tau)), \qquad \tau \geq t,\ g_2<0,\ g_3<0 \tag{2}$$

Defining r as the discount rate/interest rate, assuming no depreciation we may write the present value of the increase in gross profits arising from adoption at time t ($G_i(t)$) to be:

$$G_i(t) = \int_t^{\infty} g(C_i, S(t), K(\tau)) \exp\{-r(\tau-t)\}\, d\tau \tag{3}$$

The acquisition decision, or the choice of an optimal t, t^*, will be determined by two conditions (of which H&M seem to only consider the first), the profitability condition and the arbitrage condition. The first we may interpret as that acquisition must yield positive profits, the second condition requires that the net benefit of acquisition is not increasing over time. Let P(t) be the cost of acquisition at time t, and $Z_i(t)$ be the net present value of acquisition at time t, then for acquisition to be profitable at time t it is necessary that

$$Z_i(t) = -P(t) + G_i(t) \geq 0 \tag{4}$$

For it not to be more profitable to wait before acquisition it is necessary that

$$y_i(t) \equiv \frac{d(Z_i(t).\exp\{-rt\})}{dt} \leq 0 \tag{5}$$

where $Z_i(t)$ is discounted to ensure a common time basis of evaluation. Assuming profit maximizing behaviour by the firm, while the profitability condition determines the set of potential adopters, it is the arbitrage condition which actually governs optimal adoption time, t^* for each potential adopter. We may then specify that the optimal adoption date for firm i, t^*_i is given by:

$$y_i(t^*_i) \leq 0 \tag{6}$$

where the inequality sign allows for the possibility of corner solutions, e.g., when it is optimal to adopt the technology immediately on the first date of its introduction[1]. Assuming Cournot conjectures, using

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[1] To prove the existence of an optimum value for $Z_i(t)$ at some $t<\infty$, we first note the conditions under which $Z_i(t)$ is bounded. Assuming an upper bound **g** for per period benefits g(.), and a lower bound for the price of technology $\underline{P}$, it would be clear from equations (3) and (4) that:

$$\begin{aligned} Z_i(t) &\leq -\underline{P} + \int_t^{\infty} \mathbf{g} \exp\{-r(\tau-t)\} d\tau \\ &\leq -\underline{P} + \mathbf{g}/r \end{aligned}$$

and $Z_i(t)$ is bounded from above. We may then show that if each member i of the population is a potential adopter there exists an optimum time $t_i^*<\infty$ where net benefits of adoption are maximized. Note that for a firm to be a potential adopter there must exist

(3) and (5) we may rewrite $y_i(t)$ as in (7)

$$y_i(t) = rP(t) - p(t) + \int_t^{\infty} g_2(C_i, S(t), K(\tau))\, s(t) \exp\{-r(\tau-t)\}\, d\tau - g(C_i, S(t), K(t)) \qquad (7)$$

where, using lower case letters for derivatives with respect to time, s(t) and p(t) represent expected changes respectively in the number of users and the price of technology in the small time interval {t, t+dt}. One might note at this stage that given complete myopia where $p(t)=s(t)=0$ and $K(\tau)=K(t)$ for all $\tau>t$, the condition $y_i(t)=0$ yields a t^*_i that would be the same as that implied by $Z_i(t)=0$, and thus under myopia the arbitrage and the profitability conditions coincide.

In equation (7), $g_2(C_i,S(t),K(\tau))$ represents the marginal change in benefits from adoption for all $\tau \geq t$ resulting from a change in firm i's order of adoption at time t. It is plausible to make the simplifying assumption that such marginal benefit changes resulting from moving down the order of adopters at time t are independent of the level of future stock of adopters $K(\tau)$ for $\tau>t$[2]. Under this assumption equation (7) can be simplified to:

$$y_i(t) = rP(t) - p(t) + g_2(C_i, S(t), K(t))\, s(t)/r - g(C_i, S(t), K(t)) \qquad (8)$$

A Stochastic Model

Under the assumption of perfect foresight equations 6 and 8 above give the exact date of adoption t_i for the individual firm i. The model as specified above, however, abstracts from various real life factors which though they may be known with certainty to the individual adopters cannot be incorporated into the model. These factors are introduced through a stochastic error term ε in the model. Assuming that

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a price $P_t \geq \underline{P}$ where net benefits of adoption ($Z_i(t)$) are non-negative. Under these conditions, taking the limit of $Z_i(t)$ as time goes to infinity we will have:

$$\lim_{t\to\infty} Z_i(t) = \lim_{t\to\infty} \left[-\underline{P} + \int_t^{\infty} g \exp\{-r(\tau-t)\}\, d\tau \right]$$

$$= -\underline{P} < 0$$

But since we assumed each firm to be a potential adopter, i.e., $Z_i(t) \geq 0$ for all i, it follows that $Z_i(t)$ must achieve its maximum at some $t<\infty$. This also means that for a potential adopter the arbitrage condition dominates the profitability condition, and thus in what follows we need only consider the arbitrage condition.

[2] This can be obtained for example if we assume an additive benefit function of the form $g(C_i,S(t),K(\tau)) = g^1(C_i,S(t)) + g^2(C_i,K(\tau))$.

the distribution of ε remains invariant across the firms over time, the adoption condition as specified in equation 6 now becomes:

$$y_i(t) + \varepsilon \leq 0 \qquad (9)$$

Assuming ε is distributed independent of y with a distribution function $V(\varepsilon)$, the probability of adoption in the small time interval {t, t+dt} for a firm which has not adopted the technology by time t, i.e., h(t) the hazard rate, becomes:

$$h_i(t) = \text{Prob}\{y_i(t)+\varepsilon \leq 0\} = V(-y_i(t)) \qquad (10)$$

From (8) we may observe that $y_i(t)$ is a positive function of r(t)P(t), S(t) and K(t), through the first and last terms, and also a function of C_i with sign to be determined[3]. The second and third terms in (8) imply also that $y_i(t)$ is negatively related to the expected change in the cost of acquisition p(t), and given $g_2<0$, negatively related to the expected change in the number of uses of new technology s(t). Given that V is a decreasing function in y, and that K(t)=S(t), we may then write (10) as (11):

$$h_i(t) = J(r(t)P(t), K(t), C_i, p(t), k(t)/r(t)) \qquad (11)$$

where $J_1<0$, $J_2<0$, $J_3 \gtrless 0$, $J_4>0$, and $J_5>0$. It should be noted that, as is clearly evident from equation (8), $g_2(.)$ is a variable function of C_i and K(t). This signifies the fact that marginal changes in benefits resulting from moving down the order of adoptions depends on factors such as characteristics of the firm, market conditions and level of adoptions to the date. We can allow for these effects, assuming a linear functional form for $g_2(.)$, by introducing cross product variables between k(t) on the one hand and C_i and K(t) on the other. The hazard function incorporating these cross product terms then becomes:

$$h_i(t) = J\{r(t)P(t), K(t), C_i, p(t), (a_0+a_1C_i+a_2K(t))\, k(t)/r(t)\} \qquad (12)$$

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[3] In the empirical model discussed above we assumed a fixed discount rate r for ease of exposition. It is however straightforward to show that the same results are obtained under a variable discount rate r(t), if we substitute a time varying discount factor $\rho_t = \exp\{-\int_{0,t} \upsilon \, d\upsilon\}$, for r in the model. In the estimating model therefore we treat r(t) as a time varying covariate. The first two terms on the right hand side of equation (8) could be written as P(t)[r(t)-p(t)/P(t)] where the expression within the square brackets is the familiar user cost of capital formula. We have, however, preferred to incorporate r(t)P(t) and p(t) as separate terms in the estimating equation as this allows a more explicit discussion of the mis-specification error in myopic type models in the subsequent sections of the paper.

where the hypothesis regarding the existence of order effects could be tested by considering the joint significance of coefficients a_0, a_1, and a_2.

At this point it is useful to address two specific conceptual issues.

1- The first issue arises from the inclusion of both rank and stock effects in one framework. The most common rank effect in the literature is due to the hypothesis that benefits from adoption vary with firm size, due, basically, to scale effects. Firm size is then used as an exogenous explanatory variable in the diffusion study. We will be doing this below, firm size being one of the few firm specific characteristics on which we have data. However, in the stock effect models firm size is endogenous and determined by adoption dates. In principle this could be accommodated in the model by treating SIZE, an element of vector C_i, as a time varying endogenous covariate. At the estimation stage we could then model $SIZE_t$ in terms of adoption time, K(t) and other exogenous variables, and consistent estimates of the coefficients of interest of the model can be made by using a two stage estimation method (as for example discussed in Lee, 1981). This is not however possible as the data available to us provides information on the size of the firm only at a point in time. We also have our doubts as to whether adoption or not of any one particular technology will have a significant impact on firm size. Given the availability of data a useful approach is to allow for the scale (rank) effects by using firm size, proxied by the number of employees, as an exogenous variable, and letting the stock effects to be introduced through the effect of K(t) on the hazard rate.

2- Throughout the above discussion little attention has been given to what it is that the g(.) function measures. It was described as the annual benefit from adoption of new technology. It is informative however to consider three different types of investment decisions. Define π as the quasi rents p.a. on new technology and π^* as the quasi rents on an old technology, and concentrate on the profitability condition assuming myopia. We may then state that for a firm to replace old technology with new it is necessary that

$$\pi-\pi^* \geq rP$$

For a new firm considering investing in new or old technology or for a firm expanding capacity, new technology will be bought if

$$\pi - rP \geq \pi^* - rP^*$$

where P^* is the price of the old technology. This latter rule would also apply when old technology is physically obsolescent. Thus it is clear that, ceteris paribus, new firms, firms with worn out equipment or those expanding capacity are more likely to adopt earlier than other firms. An attempt is made to cater for this in the empirical work by introducing an explanatory variable reflecting output growth rates, and another reflecting the date of establishment of the firm.

Epidemic and Learning Effects

In the absence of a specific functional form, at least for the g(.) function, we cannot be precise as to the functional form of J(.) in equation (12). A common approach in the econometric literature has been to introduce the explanatory variables in the hazard function in exponential form, which has the advantage of ensuring a positive hazard without the need to impose any further restrictions on the parameters of the model. More specifically, a common practice has been to adopt some version of the general class of proportional hazard functions suggested by Cox(1972), where the explanatory variables act multiplicatively on the hazard rate (or additively on log hazard). We too shall be assuming a proportional hazard form, and letting the data decide the appropriateness of this assumption at the empirical stage. Here we are concerned with the restrictions which economic theory may impose on the baseline hazard and on the other parameters of interest in the model. We shall thus begin with the general form of the proportional hazard function:

$$h(t|X,\beta) = h_0(t) \exp\{X'\beta\} \qquad (13)$$

where X is a vector of explanatory variables incorporating all the variables discussed under rank, stock and order effects above, β is a vector of parameters, and $h_0(t)$ is the baseline hazard. If the variables included under the rank, stock and order effects provide an adequate explanation of the diffusion process the baseline hazard $h_0(t)$ would be expected to remain constant over time. This leads to the exponential hazard function, as estimated, for example, by Hannan and McDowell(1987), of the following form:

$$h(t|X,\beta) = \exp\{X'\beta\} \quad (14)$$

where h_0, the baseline hazard, is absorbed in the constant term in vector X.

Our next step is to extend the above model by introducing epidemic effects, or endogenous learning processes, to the model. Thus far this has been ignored, but its importance in the past literature suggests that it ought to be incorporated. The exogenous learning processes - related for example to the R&D expenditure of the firm, its size, corporate affiliation etc. - will be incorporated in the model through the rank effect discussed above. The epidemic effects refer to endogenous learning as a process of self propagation of information about the new technology which grow with the spread of the technology. The endogenous learning effects could be introduced by specifying the hazard function as:

$$h(t|X,\beta,\theta) = h_0(t) \exp\{X'\beta\} \; \psi(t;\theta) \quad (15)$$

where ψ incorporates the endogenous learning effects and θ is a vector of parameters. There have been different parameterizations of the function ψ in the literature (see e.g., Karshenas and Stoneman, 1990, and the references quoted there). The simplest and most commonly used form is based on the logistic function. We shall therefore begin by considering the specific functional form of ψ in the logistic case. As we shall argue below, the behaviour of ψ remains invariant under a wide range of specification of the underlying endogenous diffusion curves.

The behavioural justification for the use of the logistic in characterizing the endogenous learning effects in the diffusion process is often made by analogy to the spread of epidemics as discussed in biological sciences. Consider a community with a number of persons susceptible to a new infection, N, a number of already infected people S, and a constant rate of infection θ_1 (i.e., θ_1 = probability of contracting the infection after a contact is made). Under the assumption of a homogeneously mixing population, it is plausible to assume that the probability for a susceptible to meet an infected person and contract the diseases in a small time interval dt is $\theta_1(S/N)dt$. In a population of (N-S) susceptibles the average number of infections in a small time interval dt would therefore be:

$$dS = \theta_1 \, (S/N) \, (N-S)dt \quad (16)$$

Integrating this equation gives the simple logistic curve for the spread of the epidemic as a single valued function of time:

$$S = N / (1+\exp\{-\theta_0-\theta_1 t\}) \quad (17)$$

where θ_0 is the constant of integration. The analogy often made between the spread of epidemics and the diffusion of a new technology or product is either based on the learning processes involved in the use of new technology and its transmission through human contact, with the 'infection' being information, or based on pressure of social emulation and competition, or reductions in uncertainty resulting from extensions of use.

By simple manipulation of equations (16) and (17) we can derive the epidemic hazard function, i.e., the conditional probability for a firm which has not adopted the technology by time t to 'get informed' about the technology and adopt in the small interval {t, t+dt}:

$$\psi(t;\theta) = (dS/dt)/(N-S) = (\theta_1 \exp\{\theta_0+\theta_1 t\}) / (1+\exp\{\theta_0+\theta_1 t\}) \quad (18)$$

It follows that:

$$d\psi/dt = \theta_1^2 \exp\{\theta_0+\theta_1 t\} / (1+\exp\{\theta_0+\theta_1 t\})^2 \quad (19)$$

which is greater than zero. In other words, epidemic diffusion as characterized by the simple logistic growth curve implies a hazard rate which increases with the elapsed duration. This result could be shown to hold under a variety of functional forms put forward in the epidemic based literature[4]. As there is not a unique parametric specification of the epidemic effect we assume a non-parametric epidemic hazard with the proviso that $d\psi/dt>0$, i.e., the hazard rate should be increasing. Equation 15 therefore could be written as:

$$h(t|X,\beta) = h_0(t) \exp\{X'\beta\} \psi(t) \quad (20)$$

This is a general model which incorporates the rank, stock, and order effects, as well as the epidemic influences. However, as is immediately apparent from (20), it is not possible to separately identify the baseline hazard from the epidemic hazard in this equation. We thus absorb the epidemic hazard into the

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[4] Under the general functional form $dS/dt = H(S(t))$, it could be easily seen that a sufficient condition for $d\psi/dt>0$ is that $dS/dt>0$ and $dH/dS>0$ - which is generally true with the epidemic type diffusion curves in the literature.

baseline hazard and test for the time dependence of the baseline hazard. Specifically the estimated model is of the form:

$$h(t|X,\beta) = h_0(t)\exp\{X'\beta\} \tag{20}$$

where X incorporates rP(t), K(t), C_i, p(t), k(t), and the cross product terms in (12). Strictly speaking in the pure game theoretic and probit models, after full account is taken of the relevant explanatory variables in the model, the baseline hazard should remain constant. In fact, if anything the omission of some of the explanatory variables due to lack of data or information, is expected to lead to a negative bias in the time dependence of the estimated baseline hazard (for a proof see, for example, Heckman and Singer, 1984). Thus if our estimates suggest a positive duration dependence then this is indicative of the existence of epidemic effects in the diffusion process.

Moreover, given (8) and (12), the following restrictions on the coefficients of the model are suggested by theory. The coefficient, including cross product terms, on k(t) (reflecting $g_2(.)$) is indicative of the order effect. In the presence of an order effect this coefficient should be significantly greater than zero. The coefficient on K(t) reflects both the stock and order effects. If both exist then the coefficient on K(t) should be significantly less than zero. We thus consider that if the coefficient on k(t) is significantly greater than zero and the coefficient on K(t) is significantly less than zero then the hypothesis that there are both stock and order effects cannot be rejected. If the coefficient on k(t) is not significantly greater than zero, but the coefficient on K(t) is significantly less than zero then the hypothesis of there being an order effect can be rejected, but the hypothesis that there is a stock effect cannot be rejected. Finally, if the coefficient on k(t) is significantly greater than zero, but the coefficient on K(t) is not significantly less than zero, then the hypothesis of there being an stock effect cannot be accepted, but the hypothesis that there is an order effect cannot be rejected. We view this latter situation as providing weak support for the order hypothesis. In addition, if the expectation terms p(t) and k(t) do carry significant positive coefficients then the hypothesis that acquisition decisions are myopic (a la Hannan and McDowell, 1984, 1987) cannot be accepted. Similarly, if the elements of C_i do not carry significant coefficients then the hypothesis of rank effect cannot be accepted.

The variables included in the rank effect have thus far been implicitly referred to as the vector C_i. We need to be more specific about these variables at this stage. There are of course numerous firm-specific factors influencing the adoption decision, some of which may not be even observable or quantifiable. The factors which will be considered below are those which in the literature are believed to exert a systematic influence on the adoption decision - the unsystematic random factors being absorbed in the residual, that is, the base line hazard.

The factors related to the rank effect which we have been able to include in the model are the following:

Size of the firm (SIZE), reflecting possible economies of scale associated with the new technology which makes adoption more profitable for larger firms. Size may be also taken as an indicator of the differences in relative risks faced by different sized firms in adopting the new technology. Such arguments imply a positive sign for the coefficient of SIZE in the model. There are however counterbalancing influences associated with size; e.g., larger firms may be less flexible in their managerial and labour relations which could impede fast adoption. The existing empirical evidence, however, indicates a positive sign between size and the speed of adoption (see, e.g., Davies, 1979, Alderman, Davies, Thwaites, 1988).

Growth of Output (GY), as an indicator of the increase in possibilities for new investment which as argued above are expected to have a positive influence on the speed of adoption. Periods of rapid market expansion create opportunities for new investment, as well as easing the financial constraints on firms and reducing the recoupment period for the machinery incorporating the new technology. A positive sign is expected for the output growth variable.

Research and Development Expenditure (R&D), proxied by the number of full time employees in the R&D department of the establishment. It takes the value of zero where no R&D department exists. This may be taken as an indicator of the ability of the firm to process information about the latest technologies arriving in the market, as well as reducing risks associated with the adoption of a new technology (see, e.g., Cohen and Levinthal, 1989). It could be interpreted as part of the exogenous learning in the adoption process. The sign of the coefficient associated with this variable is therefore expected to be positive.

Date of Establishment (DAT), is supposed to pick up the effect of new entries on the speed of diffusion. As we argued earlier new investment free from the cost of scrapping old capital is expected to lead to faster adoption of the new technology. New firms may also have the added advantage of not being encumbered by organizational restructuring that the adoption of a new technology may entail. This variable is expected to be positively correlated with the speed of adoption.

Corporate Status of the establishment (STATUS), is a dummy variable which indicates whether the establishment is an independent unit or whether it is part of a larger corporate unit. The expected effect of this variable on the speed of adoption is ambiguous. On the one hand independent units may be better positioned with regard to speed of implementation once the decision to adopt is taken. On the other hand establishments which are part of a larger corporation may be better informed and bear less risk in adopting a new technology.

3. The Data and Sampling Distribution of the Model

To estimate the above model we ideally need a data set on complete life histories of the population of potential adopters, as well as the characteristics of a well defined new technology over a sufficiently long period of time beginning with the appearance of the technology in the market. Such ideal data sets are seldom available, and in particular, disaggregated data on the adoption of new technologies is scarce. We have been, however, fortunate to get access to results of a technology adoption survey conducted by the Centre for Urban and Regional Development Studies (CURDS) at the University of Newcastle, which meets most of the requirements for our work[5]. In this section we give a brief description of the data and investigate the likely implications of the sample design for the specification of our estimating equation.

The CURDS survey was conducted in 1981 and it covered all identified establishments in UK manufacturing within nine Minimum List Headings in engineering and metalworking industries[6]. The

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[5] We are grateful to Alfred Thwaites and Neil Alderman for making this data available to us. We are particularly indebted to Neil Alderman who has given generously of his time to extract the data set from the original survey data.

[6] The survey covered the following Minimum List Headings (based on 1968 SIC): MLH 331, MLH 332, MLH 333, MLH 336, MLH 337, MLH 339, MLH 341, MLH 361, and MLH 390. The sample of 1127 establishments comprised all establishments in these MLH groups together with Subcontractors (65 establishments) and a number of establishments (29) in other mechanical engineering.

questionnaire enquired the date of adoption of a number of new technologies for the period up to and including 1980, of which the Computerized Numerically Controlled Machine Tools (CNC) was selected for the present study. The survey also provides information on all establishment-specific variables included in the model. Data on price of technology and on industry-specific variables have been compiled from other sources[7]. The first recorded adoption of CNC in the UK engineering industry was in 1968, which is taken as the base year for measuring the duration of adoption. After purging the data set of the establishments which reported incomplete information or because of the nature of their activities were unlikely to be potential adopters[8], there remained 1056 observations in the data set which were used in the estimation of the model.

Before proceeding to the estimation stage, however, it is necessary to address two issues related to the coverage of the survey and the implications of the sample design for the stochastic specification of the estimating model. The first issue relates to the fact that the data refers to establishment as the unit of adoption, while most of the theory of diffusion is addressed to the firm as the decision making unit. In using this data for estimation therefore we are implicitly assuming that the decision to adopt is an establishment level decision. Empirical evidence suggests that this may not be an unreasonable assumption, specially for small technological changes such as the adoption of CNC[9]. We have nevertheless included a dummy variable in the estimating model which captures possible differences in the hazard rates between the independent establishments and those with corporate affiliation.

The second issue relates to the possible effect of sample design on the sampling distribution of the model. As we noted above the CURDS survey records the adoption time of the 'stock' of establishments existing in 1980. Although the survey is exhaustive in the sense that it covers the entire population of establishments in the selected industries, there may still exist a selection bias due to sample attrition. In

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[7] Price series for CNC over the period 1968-86 were provided by the Machine Tool Trades Association. We are grateful to Geoff Noon for sending us the price series for earlier years. Industry level data on outputs, prices, and concentration indices are based on the Census of Production.

[8] We thus purged from the sample establishments which did not have any metal working activities, which reduced the sample to 1069. The rest of the purges were due to defective questionnaire response.

[9] See, Alderman, Davies, Thwaits (1988). Evidence from interview surveys conducted at CURDS suggests that, `although the parent company in many cases will impose investment criteria on the establishment, the decision to adopt, if these criteria can be met, will very often be left to plant level management'(*ibid*, page 8).

other words the establishments which close down or exit during the period 1968-80 have zero probability of being selected by our sampling procedure. In constructing the likelihood function for estimation, therefore, it would be necessary to allow for the fact that the sample is conditional on survival of the establishment beyond 1980. As we show in the Appendix, for the sampling plan to be ignorable the probability of exit should be independent of the adoption time; otherwise the sampling plan is not ignorable and in constructing the sample likelihood different observations have to be weighted according to the selection probabilities in order to counteract the bias introduced by sample attrition.

Sampling from the stock at one point of time does not generate the information necessary for testing the state dependence of the exit rate of establishments. It may be possible to argue on theoretical grounds that small technological changes, such as the adoption of CNC, may not exert a significant influence on the survival of the establishment and therefore the possible bias due to sample attrition may be negligible, however there exists a follow up survey by CURDS of the original sample of establishments conducted in 1986 which can be used to make inferences about the state dependence of the exit rates during the 1981-86 period. Though this follow up survey is not as complete as the original survey in terms of questionnaire details, it does provide a complete list of the establishments which were closed down during the intervening period. We have utilized this information to test the hypothesis of state dependence of the exit probabilities and the results are reported in the Appendix at the end of the paper. We show there that the hypothesis of state dependence of exit probabilities is rejected and thus in constructing the likelihood function for estimation we may treat the sampling plan as ignorable.

4. Estimation and Results

The hazard function $h(t;X,\beta)$ specified in equation 20 uniquely determines the density function $f(t;X,\beta)$ and the distribution function $F(t;X,\beta)$ for adoption time by each individual establishment. Time is measured from 1968 (the date of first recorded adoption of CNC) for plants which were established before 1968, and from the date of establishment for the plants which entered after that date. If we allow the variable t to represent the time of adoption for establishments which adopted the technology before 1981, and the time of censoring for non-adopters, we can set up the likelihood function for the parameters of interest of the model as:

$$L(\beta) = \prod_{1,n} f(t;X,\beta)^{\sigma} (1-F(t;X,\beta))^{1-\sigma} \qquad (21)$$

where σ is an indicator variable which takes the value of 1 for adopters and 0 for the establishments which had not yet adopted the technology by the time of the survey[10].

Maximum likelihood estimates of the parameters of the model were obtained by considering two possible versions of the model. First, we concentrate on the rank, order and stock effects with the exclusion of epidemic effects, which gives rise to a hazard function with constant baseline hazard of the form:

$$h(t;X(t),\beta) = \exp\{X'(t)\beta\}$$

where the time subscript of X is indicative of the fact that some of our explanatory variables are time dependent. Secondly we allow for possible epidemic effects by introducing a more general, duration dependent, baseline hazard. Assuming a Weibull distribution of adoption times, the hazard function for this second model takes the form:

$$h(t;X(t),\beta,\alpha) = \alpha\, t^{(\alpha-1)} \exp\{X'(t)\beta\}$$

With $\alpha=1$ this model reverts to the first model with constant hazard, i.e., exponential distribution of adoption time. With $\alpha>1$ the model suggests positive duration dependence of adoption time which as we discussed above is indicative of the existence of epidemic effects.

The model was estimated for the above two hazard rate specifications in continuous time, where the integral of the time varying explanatory variables was evaluated by a Simpson approximation[11]. We first estimated the model by treating all the observations in the sample as belonging to one industry, i.e., the engineering industry. This means that the industry specific variables such as cumulative adoptions refer to the whole sample in this run. In a subsequent run we distinguished between the nine MLH groups in the sample by introducing industry specific dependent variables. Most notably, the stock of previous

[10] It should be noted that since the date of entry varies amongst the firms, the censoring scheme is a case of random censoring as discussed, for example, by Kalbfleisch and Prentice (1980). To derive the above likelihood function we thus implicitly assume that entry dates are independent from the parameters of interest of the model. In that case the inclusion of the variable EDATE (date of entry) as an exogenous explanatory variable would capture the possible effect of the variation in entry date on the adoption probability, as suggested by Cox and Oakes (1985).

[11] The model was estimated by the use of MLPACK on the Cambridge University IBM3084 computer (see, Hughes and Guilfoyle, 1986). We would like to thank Gordon A. Hughes for making the package accessible to us, which substantially facilitated the task of estimation.

adopters in the second run is industry specific. We refer to the results of the first run as the aggregate industry results, and to those of the latter as disaggregated industry results.

A list of explanatory variables included in the model is shown in Table 1, and Table 2 provides a number of summary statistics related to these variables for the aggregate industry model. The discount rate is proxied by the yield on treasury bills expressed as p.a. rate of interest. The expectation variables p_t and k_t are set to their actual forward values. Since P_t was monotonically decreasing and K_t was monotonically increasing over the observation period, the use of other expectation formation assumptions may not have substantially changed the results - especially given that both the variables are time varying covariates where their entire path affects parameter estimates.

The aggregate industry results for the Exponential and Weibull models are shown in Table 3. As can be seen the estimates of the parameter vector β between the two models do not vary substantially, but the likelihood ratio test for the significance of epidemic effects rejects the Exponential model in favour of the Weibull model. Furthermore, the coefficient α in the Weibull model is significantly greater than one, suggesting strong positive duration dependence of adoption probabilities. Given that measurement errors and the omission of other possible explanatory variables are expected to lead to a negative estimated duration dependence, this may be taken as strong evidence for the existence of epidemic learning effects.

A notable aspect of the results is that the coefficient K_t though statistically significant has the opposite sign to that predicted by the game theoretic models. The coefficient of k_t reflecting the order effect, on the other hand though having the correct sign does not seem to be significant. There seems to be, however, significant interactions between the order effect and other variables of the model. As the likelihood ratio test for the existence of order effect shows, inclusive of the interaction terms there is evidence of significant order effects in the diffusion process. It should be noted that with the inclusion of the interaction terms, the sign of the order effect coefficient (i.e., $g_2(.)=a_0+a_1C_i+a_2K_t$ as in equations 8 and 12) varies between establishments and over time. Evaluated for the Weibull model, and at values prevailing at the adoption time/censoring time for the time varying covariates, this coefficient turned out to be positive for 85 per cent of the establishments but negative for the remaining 15 per cent, with a mean value of +0.049.

Table 1

Definitions of Explanatory Variables

P_t	= Price of new technology at time t.
p_t	= Expected change of the price of new technology measured by $(P_{t+1}-P_t)$.
K_t	= Cumulative number of owners of the technology up to and including time t.
k_t	= Expected change in the cumulative number of adopters in the interval {t, t+1}, measured by $(K_{t+1}-K_t)$.
SIZE	= Size of the establishment, measured by total number of employees.
GY_t	= Expected growth of industry output measured by $(\log(O_{t+1}/O_t))$, where O_t is real industry output. The data only allowed a distinction to be made between electrical engineering and other engineering industries.
STATUS	= The corporate status of the establishment; a dummy variable taking the value of 0 for independent establishments and 1 for others.
R&D	= Intensity of R&D activity of the establishment as measured by the number of full time employees in their R&D department. It takes the value of 0 for establishments without an R&D department.
EDATE	= Date of establishment of new entrants since the appearance of the new technology; takes the value of zero for those established before the appearance of the technology in the market, and a value ranging between 68 to 80 for other establishments.
CRATIO	= Concentration ratio in the industry (3 digit SIC) to which the establishment belongs. Measured by the percentage share of gross output belonging to the 5 largest firms in the industry.
r_t	= Discount rate, measured by yield on Treasury Bills expressed as annual interest rates.

Table 2

Mean and Standard Deviation of the Variables (Aggregate Industry Model)

Variable	Units	Mean[a]	Standard Deviation[a]
Constant	---	1.00	0.00
K_t	(units)	243.69	65.04
k_t/r_t	$[(K_{t+1}-K_t)/r_t]$	25.67	5.39
SIZE	(100 employees)	2.20	4.17
GY_t	(% growth rate)	-8.86	3.54
r_tP_t	(1975=100.0)	174.88	26.87
p_t	$(P_{t+1}-P_t)$	-11.03	5.22
R&D	(no. of employees)	5.28	18.16
EDATE	(date,68-80 or 0)	19.01	31.6
STATUS	(dummy variable)	0.56	0.49
Cross Product Terms[b]			
k_t/r_t Multiplied by:			
Kt		61.79	14.23
SIZE		0.59	1.25
GY_t		-2.21	.82
R&D		1.47	6.51
EDATE		4.90	8.36
STATUS		0.15	0.14
Number of Observations		1056	
Number of Adoptions		267	
Number of Censored Observations		789	

(a) For the time-varying covariates they refer to the values prevailing at the time of adoption or censoring.

(b) All cross product terms are divided by 100.

TABLE 3

Maximum Likelihood Estimates of the Aggregate Industry Model

Coefficient	Variable	Exponential Model		Weibull Model	
α_1	TIME	---		3.8117	(0.3653)**
β_0	CONSTANT	-0.4813	(1.3557)	-5.3956	(1.5625)**
β_1	K_t	0.0419	(0.0077)**	0.0296	(0.0090)**
β_2	k_t/r_t	0.0770	(0.0300)*	0.0468	(0.0384)
β_3	SIZE	0.0762	(0.0238)*	0.0622	(0.036)*
β_4	GY_t	0.5616	(0.0652)**	0.6950	(0.0611)**
β_5	r_tP_t	-0.0367	(0.0071)**	-0.0304	(0.0076)**
β_6	p_t	0.1135	(0.0133)**	0.1053	(0.01364)**
β_7	R&D	0.0048	(0.0069)	0.0082	(0.0068)
β_8	EDATE	0.0005	(0.0103)	-0.0063	(0.0111)
β_9	STATUS	0.3931	(0.5122)	0.3691	(0.5944)
Cross Product Terms					
β_{10}	$K_t . [k_t/r_t]$	-0.0950	(0.0288)**	-0.0829	(0.0338)*
β_{11}	SIZE . $[k_t/r_t]$	-0.0955	(0.0975)	-0.0623	(0.0977)
β_{12}	$GY_t . [k_t/r_t]$	-1.8612	(0.3246)**	-2.2875	(0.3065)**
β_{13}	R&D . $[k_t/r_t]$	-0.01936	(0.0245)	-0.0267	(0.0241)
β_{14}	EDATE . $[k_t/r_t]$	-0.0598	(0.0358)	0.0319	(0.0429)
β_{15}	STATUS . $[k_t/r_t]$	-0.0553	(1.8282)	-0.0639	(2.2861)
Log Likelihood		-758.9		-733.3	
No. of Observations		1056		1056	
Likelihood ratio test for the significance of epidemic effect (α_1=0)		51.2 ($\chi^2_{.99}(1)$=6.6)			
Likelihood Ratio Test for the existence of order effects ($\beta_2,\beta_{10},\beta_{11},\beta_{12},\beta_{13},\beta_{14},\beta_{15} = 0$)		74.6 ($\chi^2_{.99}(7)$=18.5)		78.0 ($\chi^2_{.99}(7)$=18.5)	

Figures in parentheses refer to the asymptotic standard error of coefficient estimates.
* Significant at the 0.05 level.
** Significant at the 0.01 level.

Size of establishment which has traditionally played an important role in the probit type or rank oriented models has a significant and positive effect on the adoption probability, in conformity with the a priori predictions of theory and with other empirical studies. A further important result is the positive and significant coefficient of output growth, suggesting that periods of market expansion correspond to faster rates of adoption of new technology.

The coefficient of the technology price variable is also significant and has the correct sign. The highly significant and positive coefficient of the expected change in price variable (p_t), which is also in conformity with the predictions of theory, suggest that the myopic type models, as for example used by Hannan and McDowell (1987), may be seriously mis-specified. A formal comparison between the present model with the myopic one is made at the end of this section. The rest of the establishment-specific characteristics such as R&D, corporate STATUS, and date of establishment of the plant (EDATE) do not seem to exert a significant influence on the speed of adoption.

In terms of the rank, stock, order, and epidemic effects it appears that the pattern of CNC adoption in the UK indicates the existence of rank and epidemic effects, but provides weak support for the order effect and does not support the stock effect suggested by the game theoretic models. One objection which may be raised against these results is that stock effects are the result of strategic behaviour by competing firms within narrowly defined markets, and hence the industrial heterogeneity of the sample may have obscured these effects. In other words, adoption precedence variables such as K_t and k_t should refer to more narrowly defined industries composed of competing firms in the final product market. To allow for this within the limits set by the available data, we have re-estimated the model at a disaggregated industry level which distinguishes between 9 MLH groups in incorporating industry specific variables. This also allows the introduction of other industry specific variables into the model - e.g., market structure as measured by the concentration ratio.

The mean and standard deviation of the variables of the disaggregated industry model are shown in Table 4 and the coefficient estimates are reported in Table 5. As can be seen these results are generally in line with the aggregate industry results, with the exception of the coefficient on k_t which, inclusive of the cross product terms, now shows a negative sign for the majority of establishments. The sign of the coefficient of k_t/r_t in the Weibull model is negative for 70 per cent of the establishments with a mean of -

<u>Table 4</u>

<u>Mean and Standard Deviation of the Variables (Disaggregate Model)</u>

Variable	Units	Mean[(a)]	Standard Deviation[(a)]
Constant	---	1.00	0.00
K_t	(units)	20.68	12.04
k_t/r_t	$[(K_{t+1}-K_t)/rt]$	2.84	5.40
SIZE	(100 employees)	2.20	4.17
GY_t	(% growth rate)	-8.86	3.54
r_tP_t	(1975=100.0)	174.88	26.87
p_t	$(P_{t+1}-P_t)$	-11.03	5.22
R&D	(no. of employees)	5.28	18.16
EDATE	(date,68-80 or 0)	19.01	31.6
STATUS	(dummy variable)	0.56	0.49
CRATIO	(% share)	30.40	13.70
Cross Product Terms[(b)]			
<u>k_t/r_t Multiplied by:</u>			
Kt		6.1	6.81
SIZE		0.63	1.62
GY_t		-2.38	2.11
R&D		1.43	6.49
EDATE		5.20	11.5
STATUS		0.16	0.22
CRATIO		8.39	7.56
Number of Observations		1056	
Number of Adoptions		267	
Number of Censored Observations		789	

(a) For the time-varying covariates they refer to the values prevailing at the time of adoption or censoring.

(b) All cross product terms are divided by 10.

TABLE 5

Maximum Likelihood Estimates of the Disaggregated Industry Model

Coefficient	Variable	Exponential Model		Weibull Model	
α_1	TIME	---		5.0805	(0.2237)**
β_0	CONSTANT	-0.5609	(0.6400)	-8.1802	(0.8865)**
β_1	K_t	0.1280	(0.0101)**	0.0670	(0.0111)**
β_2	k_t/r_t	0.3123	(0.1088)*	0.0810	(0.1303)
β_3	SIZE	0.0967	(0.0149)**	0.0872	(0.0189)**
β_4	GY_t	0.0680	(0.0337)*	0.2319	(0.0360)**
β_5	r_tP_t	-0.0282	(0.0042)**	-0.0181	(0.0050)**
β_6	p_t	0.0807	(0.0088)**	0.0581	(0.0092)**
β_7	R&D	-0.0052	(0.0030)	-0.0013	(0.0044)
β_8	EDATE	-0.0141	(0.0041)**	-0.0003	(0.0046)
β_9	STATUS	0.5604	(0.2581)*	0.3924	(0.2837)
β_{10}	CRATIO	0.00450	(0.0083)	-0.0081	(0.0087)
Cross Product Terms					
β_{11}	$K_t . [k_t/r_t]$	-0.0850	(0.0348)*	-0.0404	(0.0368)
β_{12}	SIZE . $[k_t/r_t]$	-0.0666	(0.0580)	-0.0951	(0.0772)
β_{13}	$GY_t . [k_t/r_t]$	0.0327	(0.1099)	0.0722	(0.1121)
β_{14}	R&D . $[k_t/r_t]$	-0.0068	(0.0131)	-0.0218	(0.0140)
β_{15}	EDATE . $[k_t/r_t]$	0.0072	(0.0102)	0.0261	(0.0125)*
β_{16}	STATUS . $[k_t/r_t]$	-0.3300	(0.7652)	0.1123	(0.8680)
β_{17}	CRATIO . $[k_t/r_t]$	-0.0228	(0.0288)	-0.0043	(0.0324)
Log Likelihood		-849.5		-746.4	
No. of Observations		1056		1056	
Likelihood ratio test for the significance of epidemic effect (α_1=0)		206.1 ($\chi^2_{.99}(1)=6.6$)			
Likelihood Ratio Test for the existence of order effects ($\beta_2,\beta_{10},\beta_{11},\beta_{12},\beta_{13},\beta_{14},\beta_{15} = 0$)		37.8 ($\chi^2_{.99}(7)=18.5$)		48.6 ($\chi^2_{.99}(7)=18.5$)	

Figures in parentheses refer to the asymptotic standard error of coefficient estimates.
* Significant at the 0.05 level.
** Significant at the 0.01 level.

0.056 for the whole sample. These results thus suggest that we cannot accept the two hypotheses of there being order and stock effects, but we cannot reject the hypotheses that there are epidemic and rank effects.

The variable CRATIO (concentration ratio) in the disaggregated industry model is meant to capture the effect of market structure on the speed of adoption. This variable is measured as the share of the five largest firms in total output for each of the nine MLH industry groups. In the theoretical literature the effect of market power on the diffusion path is ambiguous. In part of the literature greater market power in the user industry is said to lead to faster diffusion of process technologies (Reinganum, 1981). The reason being that in more concentrated user industries greater profits accrue to the individual users from the cost reductions resulting from the adoption of the new technology, and hence the greater are the incentives to adopt. Quirmbach (1986) on the other hand sets up a model where collusive action between a small number of users in a more concentrated industry retards the pace of diffusion. This results from cooperative behaviour amongst users aimed at protecting profit flows from the existing equipment. According to our empirical results, the concentration ratio appears to have no significant effect on the probability of adoption. This may of course be partly due to the fact that the five firm concentration ratio measure may not provide an adequate representation of market power within the industries concerned.

The above results have been obtained under specific parametric assumptions about the baseline hazard. The similarity of the parameter β estimates for the Exponential and Weibull models, however, appear to suggest that the results are robust in relation to the specific underlying baseline hazard assumptions. To further check this proposition we re-estimated the model assuming a Log-logistic baseline hazard. The results for β coefficient estimates were very close to the above two models and it also confirmed the positive duration dependence of the estimated hazard[12]. Given the closeness of the results under the three baseline hazard assumptions, which have widely diverging properties, the results seem to be fairly robust

[12] For economy of space we do not report these results here. The Log-logistic baseline hazard is of the form:

$$h_0 = (\lambda\alpha(\lambda t)^{(\alpha-1)}) / (1+(\lambda t)^{\alpha})$$

which is decreasing for $\alpha<1$, and for $\alpha>1$ is first increasing and then decreasing, achieving its unique maximum at $t=(\alpha-1)^{1/\alpha}/\lambda$. Our coefficient estimates for α were 4.61 and 6.04 for the aggregate and the disaggregated industry models respectively - thus confirming the positive time dependence of hazard suggested by the Weibull model.

in relation to the assumed underlying baseline hazard. It is, nevertheless, still important to check the adequacy of the proportional hazard assumption.

To consider the appropriateness of the proportional hazard model for our data we examine the residuals of the model. Following Cox and Snell (1968) we may define the generalized residuals of the model as:

$$e_i = \int_0^T h(t;\underline{\alpha},\underline{\beta},X_i) = -\text{Log } S(t;\underline{\alpha},\underline{\beta},X_i)$$

where $\underline{\alpha}$ and $\underline{\beta}$ are the maximum likelihood estimates of the parameters of the model and S(.) is the survivor function (S(.)=1-F(.) as defined in equation 21). If the model is appropriate the residuals are expected to behave like a random sample from a unit exponential distribution. This follows from the general idea that the survivor function S(.) should have a uniform {0, 1} distribution, and thus -Log S(.) should be unit exponential. Goodness of fit checks are normally conducted by plotting the residuals against an ordered random sample from a unit exponential distribution or against -Log of the product limit estimate of their own survival function (see, e.g., Kalbfleisch and Prentice, 1980, Lawless 1982, Cox and Oakes 1985). Since our data were heavily censored we decided to check the goodness of fit of the model directly, by considering how well the residuals fit a unit exponential distribution with censoring. Assuming an exponential distribution with parameter γ for the residuals ($g(e_i)= \gamma \exp(-\gamma e_i)$), we tested the null hypothesis H_0: $\gamma=1$, against the alternative H_1: $\gamma \neq 1$[13]. The maximum likelihood estimates of γ for the Weibull model residuals are reported in Table 6. As can be seen for both the aggregate and the disaggregated industry models the hypothesis that $\gamma=1$ is not rejected.

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[13] A more rigorous approach would be to test the null hypothesis of exponentially distributed errors against a class of alternative distributions, e.g., Laguerre alternatives as suggested by Kiefer (1985).

Table 6

Maximum Likelihood Estimates of γ

Model	Parameter Estimate	Asymptotic Standard Error	95% Confidence Interval
Aggregate	0.981	0.085	0.81 - 1.15
Disaggregate	0.977	0.075	0.83 - 1.12

Finally we compare the results with those of the myopic model. As mentioned in section 2, the adoption decision in myopic type models is based on the profitability condition rather than the arbitrage condition. The myopic model is thus a special case of the model developed here, which will be attained if we restrict all the coefficients of the expectation terms (i.e., p_t, k_t and the cross product terms) to be zero. The coefficient estimates of the myopic model for both the aggregate and disaggregated industry cases for the Weibull model are shown in Table 7. As expected in both cases the likelihood ratio statistic rejects the myopic model in favour of the model with expectation terms. While the coefficient estimates for variables such as SIZE, K_t, P_t and GY_t, do not differ substantially between the two types of models, the myopic model shows significant coefficient estimates for STATUS, R&D and EDATE, with signs contrary to a priori expectations based on theory for the last two variables.

6. Concluding Remarks

In this paper we have set up a general empirical model which incorporates the main demand side effects discussed in the literature on diffusion of new technologies. The model was applied to the data on the diffusion of CNC machine tools in the UK engineering industry for the period 1968-80. It was found that while the rank and endogenous learning effects, as discussed in the probit and epidemic type models respectively, seemed to play an important role in the diffusion process, there was little support for the stock and order effects as characterized by the game theoretic models.

Apart from the comparison of the existing demand side models the paper also reports results which may be of interest in themselves. It was found that growth of output in the user industry had a significant positive impact on the diffusion speed, while user industry concentration did not seem to have a

TABLE 7

Maximum Likelihood Estimates of the Myopic Model

Coefficient	Variable	Aggregate Industry Weibull Model		Disaggregated Industry Weibull Model	
α_1	TIME	2.3720	(0.2454)**	4.4240	(0.2145)**
β_0	CONSTANT	-3.7731	(0.6731)**	-8.5102	(0.6061)**
β_1	K_t	0.01411	(0.0014)**	0.04938	(0.0073)**
β_3	SIZE	0.0386	(0.0146)*	0.04483	(0.0127)**
β_4	GY_t	0.1856	(0.02540)**	0.2510	(0.0261)**
β_5	r_tP_t	-0.0377	(0.0034)**	-0.02140	(0.0032)**
β_7	R&D	-0.0071	(0.0027)*	-0.0068	(0.0023)*
β_8	EDATE	0.0031	(0.0036)	-0.0096	(0.0032)*
β_9	STATUS	0.4581	(0.1767)*	0.4456	(0.1836)*
β_{10}	CRATIO	---	---	-0.0114	(0.0059)
Log Likelihood		-783.7		-780.1	
No. of Observations		1056		1056	
Likelihood Ratio Test for the myopic model (β_2=0, β_6=0, β_{11}-β_{15} = 0).		100.8 ($\chi^2_{.99}(8)$=20.1)		67.4 ($\chi^2_{.99}(8)$=20.1)	

Figures in parentheses refer to the asymptotic standard error of coefficient estimates.
* Significant at the 0.05 level.
** Significant at the 0.01 level.

significant influence on the speed of diffusion. It was further noted that static or myopic models of diffusion which concentrate on profitability of adoption in one period models may suffer from serious mis-specification error.

Empirical research on the diffusion of new technologies has been in the past severely handicapped by lack of data. The relatively high cost of compiling panel data on complete life histories of individual adopters may have been a prohibitive factor. However, as we have seen, sampling the stock of adopters at a point in time can be adequate. In particular, as we have shown the problem of sample attrition in the case of small technological changes may be ignorable. Even for major technological innovations sampling at two points of time can produce the necessary information for correcting the possible selection bias arising from sample attrition. The availability of data sets, similar to the one used here, on other new process technologies is essential for extending the research to cover supply side factors, i.e., factors related to the heterogeniety of the new technologies, in the diffusion process. We would consider that the absence of any such supply side effects (see Stoneman, 1983) from this paper is its major omission, but our future research plans do encompass this.

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APPENDIX

The Effect of Sample Attrition on the Sampling Distribution of the Model

The possible life histories of the establishments over the observation period, 1968-80, are depicted in Figure 1. Time is measured along the horizontal axis. The solid lines represent establishments which have not yet adopted the technology and dotted lines represent establishments after adoption. The figure shows 6 establishment types A1 to A6, classified according to their adoption behaviour and entry and exit times during the 1968-80 period. Establishment type A1 exists before the appearance of the new technology (1968) and survives beyond 1980 without adopting the technology. A2 has the same life history as A1 with the difference that it adopts the technology at calendar time D_1. Plant type A3 enters at time D_2, after the appearance of the technology, and survives beyond 1980 without adopting. A4 enters at time D_3, adopts the technology at time D_4 (which may equal D_3) and survives beyond 1980. Establishment types A5 (adopter) and A6 (nonadopter) exit at dates X_1 and X_2 respectively, and are therefore excluded from the sample observed in 1980.

In an unbiased sample or for the population as a whole the contributions of establishments A1 to A4 to the likelihood function are uniquely determined on the basis of the hazard function discussed in the previous section. Let f(t) and F(t) be respectively the density and distribution functions corresponding to the population hazard function h(t), where t (time of adoption or time of censoring for nonadopters) is measured from the base year 1968, or from the entry date for new entries during 1968-80 period[1]. Clearly in an unbiased sample the contribution of establishments such as A2 and A4 (adopters) to the likelihood function is f(t), and that of A1 or A3 (nonadopters) is [1-F(t)]. The systematic exclusion of establishments such as A5 and A6, however, may introduce a selection bias in the sampling distribution of the model. To account for this the likelihood function must be made conditional on survival of the establishments beyond 1980, i.e., the time of the survey. The probability of adoption at time t,

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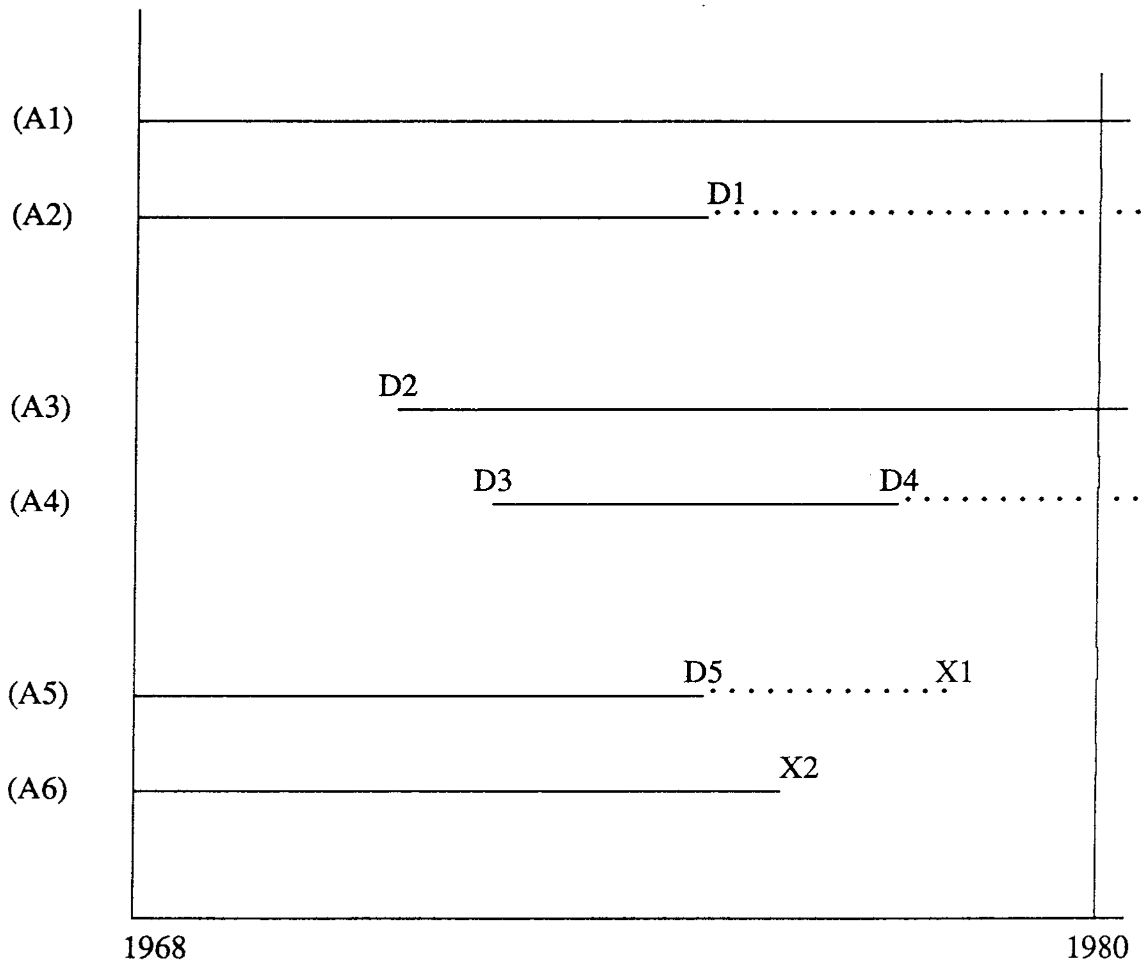
[1] For ease of exposition here we have dropped the explanatory variables and the related parameters of interest from the hazard function. Their inclusion would not change the above conclusions if we maintain the assumption of ancilarity of the explanatory variables and variables such as entry and exit times for the parameters of interest.

Figure 1

Establishment Life Histories



conditional on the exit time x being greater than x* (x*=min{12, (entry date-1980)}) could be written as:

$$f(t/x>x^*) = \frac{f(t)\int_{x^*}^{\infty} g(x/t)\,dx}{\int_{x^*}^{\infty}\int_{0}^{\infty} g(x/t)\,f(t)\,dt\,dx}$$

where g(x/t) is the conditional density of exit time given the adoption time. Clearly for the sampling plan to be ignorable the probability density of exit time should be independent of that of adoption time. In that case the right hand side of the above equation becomes equal to f(t) and the sample likelihood equals the population likelihood. If this condition is not satisfied then the sampling plan is not ignorable and different observations have to be weighted according to the selection probabilities in order to counteract the bias introduced by sample attrition (see, e.g., Hoem, 1985).

As pointed out in the text, here we utilize the results of the follow up survey by CURDS of the original sample of establishments conducted in 1986 to make inferences about the state dependence of the exit rates during the 1981-86 period. Though this follow up survey is not as complete as the original survey in terms of questionnaire details, it does provide a complete list of the establishments which were closed down during the intervening period. We have stratified the original sample according to adoption date and calculated the conditional frequencies of exit during the 1981-86 period for each adoption time interval, which is reported in Appendix Table 1. As can be seen there seems to be no systematic variation in exit frequencies given the adoption time. To test this proposition statistically we have to set up a probability model of the exit time. If we assume that exit time follows an exponential distribution, its hazard rate conditional on the adoption time can be written as:

$$h(x/t,\lambda) = \exp\{\lambda_0+\lambda_1 t\}$$

where t and x are the adoption and exit times as defined above. If $\Omega(x)$ is the distribution function of the exit time, then probability of exit between times x_1 and x_2 given survival up to x_1 is $[(\Omega(x_2)-\Omega(x_1))/(1-\Omega(x_1)]$, and the probability of survival beyond x_2 given survival up to x_1 is $[(1-\Omega(x_2))/(1-\Omega(x_1))]$. If we take x_1 and x_2 to represent exit times corresponding to 1981 and 1986 respectively, the likelihood function for the exit probabilities of the sample of 267 establishments which adopted the technology

Appendix Table 1

Relative Frequency of Exits Conditional on Adoption Time: 1981-86

Adoption time (in years, 1968=0)	0-2	3-4	5-6	7-8	9-10	11-12	12<	All
Number of adopters	6	11	16	55	72	107	789	1056
Number of Exits	2	3	3	9	17	17	228	279
Exit Frequency	0.33	0.27	0.19	0.16	0.24	0.16	0.29	0.26

Appendix Table 2

Maximum Likelihood Estimates of the Parameters of the Conditional Exit Model

λ_0	-2.84 (-5.86)*
λ_1	-0.055 (-1.06)
Log likelihood	-129.7
Number of observations	267
Likelihood ratio test for the significance of adoption time variable	1.0 ($\chi^2_{.90}(1)$=2.7)

Notes:
* Figures in parentheses refer to the ratios of estimated coefficients to their asymptotic standard error.

before 1981 and survived beyond 1980 can be written as:

$$L = \prod_{n=1,267} [1-\exp\{-(x_2-x_1)\exp(\lambda_0+\lambda_1 t)\}]^{\delta} [\exp\{-(x_2-x_1)\exp(\lambda_0+\lambda_1 t)\}]^{(1-\delta)}$$

where δ is an indicator variable taking the value of 1 for establishments which exit during 1981-86 and the value of 0 for the censored observations, i.e., those which survive beyond 1986. The maximum likelihood estimates of λ_0 and λ_1 are reported in Appendix Table 2. Since λ_1 is not significantly different from 0 we may reject the hypothesis of state dependence of exit time and thus regard the sample design as ignorable for estimation purposes.

References

Alderman, N., Davies, S. and Thwaites, A. (1988), *Patterns of Innovation Diffusion,* Technical Report, Centre for Urban and Regional Development Studies, University of Newcastle upon Tyne.

Cohen, W.M. and Levinthal, D.A. (1989), 'Innovation and Learning: The Two Faces of R&D', *The Economic Journal,* 99, pp.569-596.

Cox, D.R. (1972), 'Regression Models and Life Tables (with discussion), *Journal of the Royal Statistical Society,* Series B, 34, pp.187-220.

Cox, D.R. and Oakes, D. (1985), *Analysis of Survival Data,* Chapman & Hall: London.

Cox, D.R. and Snell, E.J. (1968), A General Definition of Residuals (with discussion), *Journal of Royal Statistical Society,* Series B, 30, pp.248-275.

David, P. (1969), *A Contribution to the Theory of Diffusion,* Stanford Centre for Research in Economic Growth, Memorandum no. 71, Stanford University.

Davies, S. (1979), *The Diffusion of Process Innovations,* Cambridge University Press: Cambridge.

Fudenberg, D. and Tirole J. (1985), 'Pre-emption and Rent Equalization in the Adoption of New Technology', *Review of Economic Studies',* 52, pp.383-401.

Hannan, T.H. and McDowell, J.M. (1984), 'The Determinants of Technology Adoption: The Case of the Banking Firm', *Rand Journal of Economics,* 15, No.3, pp.328-335.

Hannan, T.H. and McDowell, J.M. (1987), 'Rival Precedence and the Dynamics of Technology Adoption: An Empirical Analysis', *Economica,* 54, pp.155-171.

Heckman, J.J., and Singer, B.L. (1984), 'Econometric Duration Analysis', *Journal of Econometrics,* 24, 63-132.

Hoem, J.M. (1985), 'Weighting, misclassification, and other issues in the analysis of survey samples of life histories', in J.J. Heckman and B. Singer, *Longitudinal Analysis of Labour Market Data, pp.249-293,* Cambridge University Press:Cambridge.

Ireland, N. and Stoneman, P. (1986), 'Technology Diffusion, Expectations and Welfare', *Oxford Economic Papers,* 38, pp.283-304.

Ireland, N. and Stoneman, P. (1985), 'Order Effects, Perfect Foresight and Intertemporal Price Discrimination', *Recherches economiques de Louvain,* 51, 7-20.

Kalbfleisch, J.D. and Prentice, R.L. (1980), *The Statistical Analysis of Failure Time Data,* John Wiley & Sons:New York.

Karshenas, M. and Stoneman, P. (1990), 'The Role of Exogenous and Endogenous Learning and Economic Factors in the Diffusion of New Technology: An Epidemic Based Study of the Spread of Colour Television Ownership in the UK', *mimeo,* Department of Economics, University of Warwick.

Kiefer, N.M. (1985), 'Specification Diagnostics Based on Laguerre Alternatives for Econometric Models of Duration', *Journal of Econometrics,* 28, pp.134-154.

Lancaster, T. (1985), 'Generalized Residuals and Heterogeneous Duration Models, with Application to the Weibull Model', *Journal of Econometrics,* 28, pp. 155-169.

Lawless, J.F. (1982), *Statistical Models and Methods of Lifetime Data,* John Wiley & Sons: New York.

Lee, L.F. (1981), 'Simultaneous equations models with discrete and censored variables', in C.F. Manski and D. McFadden, (eds), *Structural Analysis of discrete Data with Econometric Applications*, The MIT Press: Cambridge.

Mansfield, E. (1968), *Industrial Research and Technological Innovation*, W.W. Norton: New York.

----- (1989), 'The diffusion of industrial robots in Japan and the United States', *Research Policy*, 18, pp.183-192.

Quirmbach, H.C. (1986), 'The diffusion of new technology and the market for an innovation', *Rand Journal of Economics*, vol.17, no.1, pp.33-47.

Reinganum, J.F. (1981), 'Market Structure and the Diffusion of New Technology', *Bell Journal of Economics*, 12, pp.618-624.

Stoneman, P. (1983), *The Economic Analysis of Technological Change*, Oxford University Press: Oxford

----- (1986), 'Technological Diffusion: The Viewpoint of Economic Theory', *Ricerche Economiche*, 4, 1986, pp.585-606.

----- (1987), *The Economic Analysis of Technology Policy*, Clarendon Press: Oxford.