

THE INTRA-FIRM DIFFUSION OF NEW PROCESS TECHNOLOGIES

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Abstract: The study of intra firm diffusion has largely been neglected and the limited extant literature overwhelmingly relies upon uncertainty reduction via information spreading or epidemic learning as the main driver. In this paper, an alternative approach is taken whereby the intra firm diffusion of new process technologies reflects the profitability of new technology adoption as proxied by firm characteristics. The approach is tested using data relating to the diffusion of Computer Numerically Controlled Machine tools within firms in the UK engineering and metalworking sectors. The empirical analysis does not reject the hypothesis that profitability considerations are important with a number of firm characteristics being isolated as of special relevance, including firm size and the use of complementary technologies and managerial techniques. However there is little support for the traditional epidemic effect.

Keywords: Intra firm diffusion, technological change, innovation, CNC

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1. INTRODUCTION

Technological change is the main driver of increasing output, productivity and welfare. It is however only as new technology is used that such benefits arise. The analysis of technological diffusion addresses issues relating to the nature and determinants of the time profile of the use of new technologies. This time profile (within an industry or an economy) can conceptually be considered as made up of two parts – the time profile of the number of firms using the technology (inter firm diffusion) and the time profile of the extent of use by individual firms (intra firm diffusion). Battisti 2000 and Battisti and Stoneman (2003) show empirically that the inter firm effect is more important in the early stages, the intra firm effect more important in the later stages of the whole diffusion process. The majority of the extant diffusion literature (see Stoneman, 2001) is concerned solely with inter firm diffusion and intra firm diffusion has been largely ignored, despite its importance. The objective of this paper is to go some way towards redressing that balance² by offering a new approach to modelling intra firm diffusion and testing that approach using a rare data set (a single 1993 cross section) on the intra-firm diffusion of CNC technology in the UK engineering and metalworking industry.

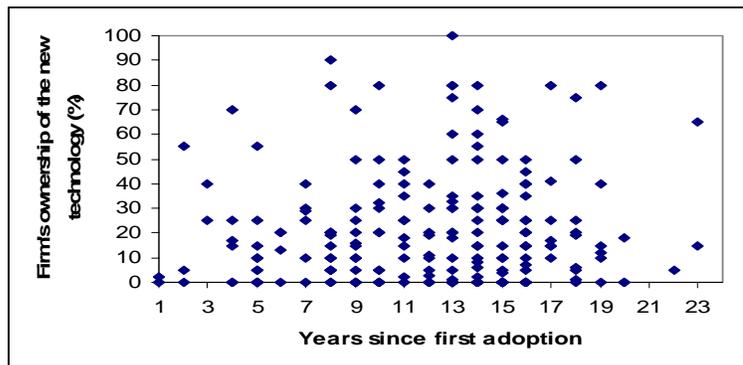
The limited existing literature on intra firm diffusion has largely relied upon learning based models. In the seminal Mansfield (1963a) approach it is assumed that as use of a specific new technology increases, the risk attached to further adoption is reduced through learning, either within or across firms, leading to further increases in use, which as a result follows an S-shaped, logistic, diffusion path over time. Much of the existing empirical work also relies upon learning and/or epidemic frameworks (for example, Mansfield 1963a, Romeo 1975, Nabseth and Ray 1974, Schenk 1974, Globerman 1976, Antonelli 1985 and Levin et. al. 1992). However, as pointed out by Stoneman and Battisti (1997), for some technologies the Mansfield type epidemic explains relatively little of the intra firm diffusion process or, at least, the model is not robust across different technologies.

The Mansfield type epidemic learning model predicts in particular that the extent of use of a

² This paper is developed from a work first published as a Ph.D. thesis from the University of Warwick, (Battisti, 2000). We wish to thank the examiners of that thesis and participants in the 2003 European Association for Research in Industrial Economics (EARIE) conference, the 2002 Royal Statistical Society Annual Conference, the April 2002 One Day Research Workshop at the Technological Innovation Research Unit at Warwick Business School for their useful comments. We also wish to thank two referees of this journal for their useful comments on earlier drafts, but of course all errors that remain are the responsibility of the authors alone.

new technology within the firm will increase with the number of years since first adoption. We plot in Figure 1 the extent of use of CNC in 1993 against years since first adoption for the firms in our sample. Although there is an upward sloping trend to the data, in line with the more formalised study of Stoneman and Battisti (1997), time since adoption alone can only explain a minimal proportion (about 10%) of the total variability of the level of ownership of the new technology. Therefore, it cannot be just learning about the technology that determines the heterogeneity of observed use.

Figure 1. Proportion of CNC ownership by time since first adoption



Source: CURDS data set

More recent theoretical literature also suggests that technology usage may not increase monotonically from the date of first adoption until the end of the diffusion process. In an uncertain world a firm might immediately adopt the optimal level of the new technology (which is not necessarily 100%) or choose a temporary or permanent suspension of the within firm adoption process implying that the intra-firm diffusion pattern, if there is one, can be discontinuous and not necessarily monotonic (see for example Weiss (1994) and Grenadier and Weiss (1997)). Stoneman (1981) constructs a more explicitly decision theoretic, means variance model with Bayesian learning that will generate similar results. These observations and other well known weaknesses of the learning based model (see for example Davies, 1979), indicate that an alternative approach to modelling intra firm diffusion is required. This observation becomes even more pointed when one observes the contrast to the inter-firm literature which has now recognised the importance of, for example, profitability considerations, game theoretic strategies, and technological complementarities to the decision to adopt.

The inter firm literature has been summarised by Karshenas and Stoneman (1993 and 1995) as involving rank, stock, order and epidemic effects. In this paper, we develop a new approach to intra firm diffusion that mirrors such effects within firms rather than across firms by allowing the firm's decision on how much to invest in a 'new' or advanced process technology to be based upon the expected profit gain resulting from cost reductions (as a result of adoption). This approach is also taken in the recent work of Forman, Goldfarb and Greenstein (2003) on the intensity of internet usage (which study also employs a single cross section of data)

In section two we present the new approach in detail. The nature of CNC technology, the data set and sample selection issues are discussed in section three. The application of the model is developed and empirical estimates presented in section four. In section five we discuss the findings and in section six conclude.

2. A PROFIT DRIVEN FRAMEWORK

2.1 Introduction

The essence of a profit driven model of technological diffusion is that technology use in time t will only extend to the point where the marginal expected profit gain from further adoption equals the cost of adoption (appropriately defined) of the new technology. Over time either the marginal gain and/or the cost of adoption may change and as they do so the level of use will change. The key component of the model concerns the determinants of the profit gain from adoption. The inter firm literature indicates three basic approaches in which the profit from adoption is either determined by rank effects, stock effects or order effects (Karshenas and Stoneman, 1993). Carrying this approach over to the intra firm context it is difficult to see relevance for an order effect (any order effects will anyway be internalised) however the rank and stock effects transfer naturally and easily.

The rank effect states basically that firms are different and as such will get different (net or gross) gains from extending use of new technology. For a given cost of acquisition the level of intra firm diffusion may thus differ across firms. The stock effect approach argues that the profit gain to the firm from the use of one extra unit of the new technology in time t is dependent upon the existing level of use by the firm. Given the cost of acquisition at time t , it will then only be profitable for the firm to extend use to a certain point thus

limiting the extent of intra firm diffusion. This is the intra firm equivalent of the Reinganum (1981a\b\c) inter firm model. For the stock model to predict that intra firm diffusion will not be instantaneous it is necessary that the marginal profit gain from increased use of new technology decreases with use.

Formally (for further details see Battisti, 2000), assume a profit maximising, price taking firm with perfect foresight on factor and output prices for whom there are two competing technologies on the market: the standard (or old) technology incorporating the combination of the existing technology/ies used by the firm (with capital stock K_o) and the new technology (with capital stock K_n). Assume that the firm uses only the standard technology until it decides to adopt the advanced technology but at any time t after first adoption the firm can decide to invest in both, neither, or only one of the available technologies. Essentially, at each point in time the firm upgrades its capital stock in line with what is optimal at that time. For this reason, the model belongs to a class of so called equilibrium models as opposed to the class of disequilibrium models typified by the epidemic approach.

Using the subscripts i for firms, j for technology (primarily $j = o$ or n , old or new) k for industry and t for time (but suppressing wherever possible), during the ‘intra-firm’ diffusion process³ i.e. from when the firm owns at least one unit of the new technology until almost the end of the diffusion process when the firm owns only one unit of the old technology the production possibilities of the firm⁴ are summarised by

$$(1) \quad Y_t = A_t L_t^\beta K_{ot}^{\alpha_o} K_{nt}^{\alpha_n}$$

with three inputs, labour (L_t), existing technology capital (K_{ot}) and new technology capital (K_{nt}) producing output Y_t . Assume constant returns to scale i.e. ($\alpha_o + \alpha_n + \beta = 1$).

A useful indicator of the extent of intra firm diffusion (and one that can be measured in the data set explored below) is given by the share of new type capital in the total capital stock.

³ In the pre and post-diffusion periods the firm will operate within a different technological possibilities set represented by the standard two factor production function.

⁴ With this formulation new capital shows declining marginal productivity and thus ceteris paribus, as the stock of new capital increases the marginal profit gain to the firm from extra units of new capital declines. This is a required characteristic of a stock effect based diffusion model.

Pursuing a standard neoclassical model of investment (see Jorgenson, 1963) the extent of intra firm diffusion in time t is given by (2)

$$(2) \quad K_{nt} / (K_{nt} + K_{ot}) = 1 / (1 + (\alpha_o / \alpha_n) (c_{nt} / c_{ot}))$$

where c_{nt} and c_{ot} are the user costs of capital for new and old technologies. As (2) is inherently non linear and thus difficult to handle econometrically, applying a logarithmic transformation and expressing K_j in terms of percentages (k_{jt}) of the total capital stock, so that $k_{nt} + k_{ot} = 100\%$, may be rewritten as:

$$(3) \quad \log[k_{nt} / 100 - k_{nt}] = \log(\alpha_n / \alpha_o) + \log(c_{ot} / c_{nt})$$

where the lhs is the log of the ratio of new to old in the machine tool stock of the firm in time t .

Equation (3) essentially arises from taking a ratio of the demand for the new and old technologies and thus factors that affect both equally have no effect on the intra firm diffusion path. This immediately allows us to argue that, under not too restrictive assumptions, firm specific adjustment costs and firm specific taxes will not affect the diffusion path. Similarly, if output markets and factor markets are not perfectly competitive then the demand for both new and old technologies will be equally affected and thus the diffusion path will be unaffected by the structure of the industry in which the firm is located. It has been suggested to us by commentators that the level of intra firm diffusion could however be affected by the wage rate. This would only be so if the firm pays different wages to workers operating different technologies (which is of course possible if skill requirements are different), otherwise the wage variable drops out when the ratio of the optimal ownership of new to old is considered. Unfortunately our data does not allow us to explore this further.

We also allow the investment decision to be affected by general revenue or market uncertainty a la Bertola (1998) so that profits are expected to grow at a constant mean rate but the realised growth rate is random, normally distributed and independent over time. Within a Dixit and Pindyck (1994) framework such future profits can be approximated by

geometric Brownian motion with drift where the future values are lognormally distributed with a variance that grows linearly with the time horizon i.e.

$$(4) \quad \delta\pi_t = \varpi \pi_t dt + \sigma \pi_t dz$$

where π_t is profit in time t , z is a standard Wiener process equalling $\varepsilon_t (dt)^{1/2}$ and ε_t is a normally distributed random variable with mean zero and a standard deviation of one. (ϖ) is the growth rate, (σ) the standard deviation of profits, and β is the largest root of the Bellman quadratic (differential) equation (6), i.e.

$$(5) \quad \beta = 1/2 - \varpi/\sigma^2 + \sqrt{\{[\varpi/\sigma^2 - 1/2]^2 + 2(\rho + \delta)/\sigma^2\}}$$

With such uncertainty, the firm might find it more profitable to exercise an option to wait before investing in (more) capital goods whereas in the absence of uncertainty ($\sigma = 0$) the standard neo-classical investment rule will still hold. Thus the user cost of capital is defined to include a term in β as in (6).

$$(6) \quad c_{jt} = (r + \delta + 1/2 \sigma^2 \beta) q_{jt} - dq_{jt}$$

where r is the discount rate, δ the rate of depreciation (which could differ across technologies but as we do not have data to pursue this option, is not here allowed to do so), q_{jt} the price of capital good j , and dq_{jt} the one period ahead expectation of the change in q_{jt} .

There is also the possibility of alternative forms of uncertainty, for example, possible technological uncertainty about the timing and the significance of future technological improvements, see Rosenberg (1976), Weiss (1994) and Grenadier and Weiss (1997). With such uncertainty the firm may exercise the 'option' to wait or to terminate the adoption of advanced technology. Consequently it sits well in the real options framework specified above and can be assumed to be covered by that approach. A final type of uncertainty arises due to the lack of knowledge about the performance characteristics of new technologies on the part of potential buyers *a la* Mansfield (1968). As discussed above this type of uncertainty has formed the basis of the epidemic model reasoning. To incorporate such uncertainty and also to have a more encompassing model, we introduce an extra term

in to (3) to reflect epidemic effects or technological uncertainty a la Mansfield. We argue however that as the old technology will have been in existence for some time, its performance characteristics are known. Such uncertainty thus only relates to the new technology. We thus define a variable E (to be empirically specified below) that represents such learning and post multiply the rhs of (3) by a function of E, f(E).

Bringing these arguments together yields the diffusion curve (7)

$$(7) \quad \log[k_{nt}/100-k_{nt}] = \log(\alpha_n / \alpha_o) + \log(c_{ot}/c_{nt}) + \text{Log } f(E)$$

which essentially states that intra firm diffusion at a moment in time will reflect α_n / α_o , the productivity of the old technology with respect to the new (i.e. rank effects), c_{ot}/c_{nt} the relative user costs of the technologies and f(E), an epidemic effect.

3. CNC TECHNOLOGY, DATA SOURCES AND DIFFUSION PATTERNS

Our data is a cross section relating to the use of CNC technology in the UK engineering and metalworking sector in 1993 collected by the Centre for Urban and Regional Studies (CURDS) at the University of Newcastle upon Tyne. CNC first appeared in the early 1970's and by incorporating microcomputer technology into numerically controlled machines provided the capability of automatic and flexible machining. The CURDS data set provides information upon the use of CNC for a sample of 343 establishments (plants in US usage). It also contains information on whether each establishment is a stand-alone organisation (defined in the questionnaire as an *independent firm*) or whether it is part of a multi establishment firm/organisation that, following the practice used in the survey source we label a *group* (although we do not know whether any of the responding establishments belong to the same groups). In order to focus on the capital configuration and the technological constraints of the replacement process we keep the establishment as the unit of analysis but to relate more closely to the existing literature we continue to talk throughout of intra firm and inter firm diffusion. It is also assumed that each establishment is an autonomous decision making unit⁵, which we label the firm, although it might be part

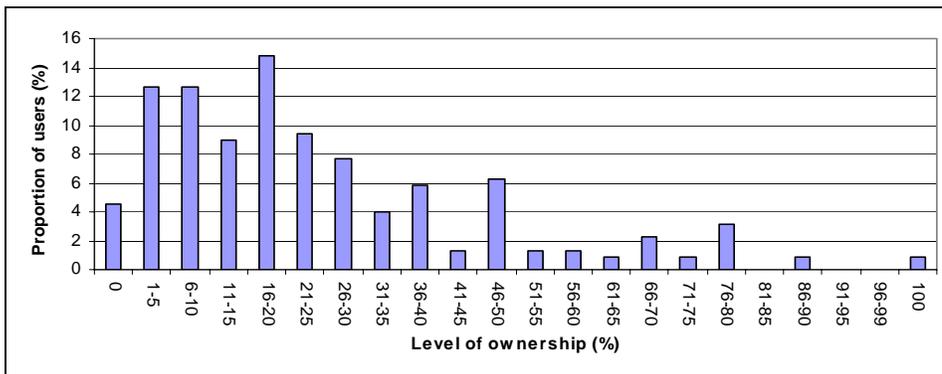
⁵ This is in line with several empirical inter firm studies that have underlined the role played by establishment characteristics in the diffusion of a new technology (Rose and Joskow (1990), Oster (1982), Colombo and Mosconi (1995) Astebro (2002), etc.).

of a group, but later test whether group membership affects the extent of intra firm diffusion.

Although intra firm data is only available for 1993, the CURDS survey was undertaken on the same sample of firms in 1981, 1986 and 1993 and contains information on the inter firm pattern of ownership and use over time of five technologies including CNC machine tools. It contains longitudinal data on establishment characteristics, such as employment in 1970-1975, 1981, 1985 and 1993, year of start-up, financial position, information on R&D, whether the firm is export oriented, as well as on other managerial and technological characteristics of the firm. In particular it contains information on the date at which each firm in the sample first adopted CNC (and the other four technologies). By 1993 the proportion of potential users (excluding 59 of the 343 who consider that the technology is not appropriate to their production activities) that have adopted CNC is about 80%, 222 having adopted CNC at or before 1993, of whom 212 were still users in 1993 (i.e. 10 were no longer users by 1993).

The CURDS survey measures intra firm diffusion by the percentage of the machine tool stock of the firm that in 1993 incorporated CNC. Of the 212 users in 1993, only 1 was using the technology at the 100% level. In Figure 2 we illustrate the full pattern of intra firm diffusion in 1993 by plotting the extent of diffusion (where 0 represents that the firm is no longer a user) against the share of adopters over the 222 adopters. The proportion of the machine tool stock of the establishment that incorporates CNC is less than 20 per cent for 52 per cent of the adopting firms and only 7 per cent have a proportion in excess of 70 per cent.

Figure 2. The intra-firm diffusion of CNC in 1993



Source: CURDS data set

This data shows that (i) even though many of the sample firms have been using CNC for a number of years only a very small proportion have attained intra firm diffusion approaching 100% by 1993; (ii) there are considerable differences across firms in the extent to which the new technology has been diffused by 1993; (iii) despite CNC having been on the market for more than twenty years and about 80% of the firms having already adopted it, in 1993 new users, ex- users and non adopters still co-exist.

The sample that is available to test our model is restricted to the single cross section of firms for whom we have data upon the extent of intra firm diffusion in 1993. Of these the model only applies to the current users defined as those adopters that are currently undertaking the process of intra firm technology transfer, using both new and old technology to some extent at that date, and have thus started but not “completed” the diffusion process. However, to use only that part of our data that relates to such firms can cause bias in the estimates because, (i) for a firm to be involved in intra firm diffusion is conditional on having become an adopter sometimes in the past (in or by 1993), (ii) it would ignore the truncation of the adoption probability distribution in 1993 and, (iii) it would exclude information relating to those adopting firms in the sample that are currently using technology at ‘extreme levels’ 0 or 100%. After experimentation with different model specifications to account for the possible bias generated by truncation, censoring and sample selection, we decided to econometrically eliminate the potential bias by using the two-stage Heckman (1979) procedure but with some modifications (see for further details Battisti, 2000 and 2003). The first stage models the adoption decision and the characteristics of the adopters in or by 1993. The resulting inverse Mills ratio (see Greene, 1993 and Maddala, 1994) is then included to correct for the sample selection bias due to the selection of current users in a second stage model of the extent of firm usage by those firms still diffusing in or by 1993. The two stage model was estimated using for the first stage the whole sample of eligible firms for which data was available (max 149)⁶ and selecting at the second stage only the sample of current users. Clearly, the selection criterion equation is essentially inter firm diffusion modelling while the technology replacement equation in the second step is intra firm diffusion modelling.

⁶ We included among the explanatory variables in the first stage estimates indicators, the firm’s date of adoption, the price of CNC, the share of firms in the industry using CNC, firm size, management characteristics, and characteristics of the firm’s production system. Further details on the first stage modeling are available on the journal’s supplementary material web site: <http://www.mgmt.purdue.edu/centers/ijio/eo/eosup.htm>

4. THE INTRA FIRM DIFFUSION EQUATION

Allowing for sample selection issues the second stage ‘corrected’ intra firm diffusion equation becomes:

$$(8) \quad \log[k_{nt}/100-k_{nt}] = \log(\alpha_{nt} / \alpha_{ot}) + \log(c_{ot}/c_{nt}) + \log f(E_t) + IMR_t + v_{it}$$

where IMR_t is the inverse Mills ratio and v_{it} is a stochastic error. Equation (8) has been estimated using the sample of adopting firms for whom $0 < k_n < 100$ in 1993. In Table 1 we provide the summary definitions of the remaining variables included in the model specification. In Table 2 we present our preferred estimates of the intra firm diffusion equation. Such estimates, including the correction for Logit sample selection have reasonable explanatory power ($R^2 = 0.68$; R^2 corrected = 0.40) and the residuals are well behaved. The sample size, after removing observations with missing data (from both steps of the model) and excluding non adopters and extreme users, comprised 82 firms. In this section we discuss in more detail the variables included in the estimating equation, the coefficients estimates pertaining thereto and their significance.

4. 1 Sample selection

The inverse Mills ratio (IMR_t) has been included to compensate for sample selection bias generated from the selection of the set of current users from the eligible firms. Its effects is not significant and thus although the sample selection correction was important on conceptual grounds it is not found to be of statistical significance. Moreover, as the selection criterion equation was essentially inter firm diffusion modelling, this would suggest that the decision to first adopt a new technology is a necessary but not a sufficient condition for extensively using such technology (see Battisti 2000, 2003 and Battisti and Stoneman 2003).

4.2. User costs of capital

The user cost of capital for technology j may be written as (9).

$$(9) \quad \log(c_{jt}) = \log[(r + \delta + 1/2 \sigma^2 \beta)q_{jt} - dq_{jt}] \quad j = \text{old, new}$$

Taking $(-dq_{jt})$ outside the square bracket⁷ and making use of the approximation $\log(1+x)=x$, this can be rewritten as (10) :

$$(10) \quad \log c_{jt} = \log (-dq_{jt}) + [(r + \delta + 1/2 \sigma^2 \beta)q_{jt}/(-dq_{jt})]$$

Using (10) yields (11)

$$(11) \quad \log (c_{ot}/c_{nt}) = \log (-dq_{ot}) - \log (-dq_{nt}) - (r + \delta + 1/2 \sigma^2 \beta) [q_{nt}/(-dq_{nt}) - q_{ot}/(-dq_{ot})]$$

where q_{jt} is the price of technology j in time t and dq_{jt} is the expected change in the price of technology j between t and $t + 1$. As all firms will face the same capital good prices, cross sectional variation in $\log c_{ot} - \log c_{nt}$ can only arise from differences across firms in r, δ, σ^2 and β (but as we are unable to measure any of these indicators we do not pursue this line of argument) or from differences across firms in dq_{jt} , the expected change in the price of capital good j .

There is no obvious guide as to how to model price expectations formation although there is some presumption that rational expectations are to be preferred. We therefore use a slight modification of the naïve extrapolative expectation models (e.g. Ferber 1953, Maddala, 1992) and test the hypothesis of rationality against the hypothesis of imperfect information assuming that the relationship between expected price (dq_{jt}^e) and observed prices (dq_{jt}) could be written as:

$$(12) \quad dq_{jt}^e = \gamma_j dq_{jt}$$

According to equation (11) $\gamma_j=1$. This means that, at each moment in time, the change in the expected price equals the observed change ($dq_{jt}^e=dq_{jt}$) and that the firm operates under perfect foresight with perfect information about future prices (rational expectations). We leave the empirics to determine whether γ_j is equal to 1 and therefore whether the rational expectation hypothesis can be accepted. In order to introduce some cross sectional variation we assume that expected changes between t and $t+1$ in the price of technology j by the firm i will equal the annual average realised change in the price of technology j since the date of first acquisition by the firm i of the new technology (t_{0i}). It is thus being assumed that price expectations are based upon the firm specific experience of price

⁷ In (14) it is useful to remember that the real price of new technology tends to fall over time and thus as logs

changes since its own first adoption so that earlier adopters have greater experience of past patterns of price changes, while later adopters base decisions upon a shorter observation period. However, to avoid forcing the price effect (in absolute value) to be larger for early adopters than for latecomers, the change in the price has been approximated by the average annual incremental change from the firm's date of first adoption. Although not ideal this is the best approximation one can get from the data available for this study. For such reasons the interpretation of the expectation coefficient should be considered as indicative rather than authoritative. Specifically we assume that for each i:

$$(13) \quad dq_{j1993} = (q_{j1993} - q_{jt0}) / (1993 - t_0)$$

which after substitution enables us to write a parameterised version of (11) as the firm specific (14) where $t = 1993$.

$$(14) \quad \log c^*_{ot} - \log c^*_{nt} = \gamma_1 \log[-(q_{o1993} - q_{ot0})] + \gamma_2 \log[-(q_{n1993} - q_{nt0})] + \gamma_3 \cdot [q_{nt} / (-dq_{nt}) - q_{ot} / (-dq_{ot})]$$

where $\gamma_1=1$, $\gamma_2=-1$ and $\gamma_3 = -(r + \delta + 1/2 \sigma^2 \beta)$. Rather than trying to measure $r + \delta + 1/2 \sigma^2 \beta$ from available data, we treat γ_3 as a parameter yielding an estimate of $-(r + \delta + 1/2 \sigma^2 \beta)$ and then discuss the parameter estimate. The parameter estimate should be negative. Allowing the interest rate to be equal to the yield on Treasury Bills expressed as an annual interest rate (i.e. $r_{1993} = 0.0495$ source: ONS) and that the depreciation rate is about 0.025 per quarter as in Jorgenson (1963) (i.e. 10% per annum)⁸, then approximately $(r + \delta) = 0.15$. If the coefficient estimate of γ_3 in absolute value is significantly different from 0.15 then one may argue that $1/2 \sigma^2 \beta$ is significantly different from zero and there is a business conditions uncertainty effect in the data.

The price of CNC is measured by the *real quality adjusted price at the factory gate*. Price data on CNC machine tools was supplied by the ONS but unfortunately for a number of years the data for CNC and NC (its previous non-computerised version) were not separately distinguished. The adjustment for quality has been carried out using a modified version of the hedonic price approach whereby, given that data upon CNC generations are not available, the quality change was approximated by the trend in the quality

are being taken the negative of the price change is the most convenient variable to include.

improvements of computers outsourced from the study of Triplett (1989) and Stoneman et al. (1992). Further details can be found in Battisti, 2000. The price of old technology, here defined as the set of all non-CNC technologies in use by the firm, is measured by the real price index of Gross Domestic Fixed Capital Formation sourced from the National Accounts. Both prices are measured as indices.

Table 1. Determinants of intra-firm technology diffusion: variable definitions and expected sign

DEPENDENT Variable		
$\text{Log}[k_{\text{nit}}/100-k_{\text{nit}}]$	• Log ratio of the percentage of new technology (k_{nit}) over the old technology ($100-k_{\text{nit}}$)	(Expected Sign)
PRICE EFFECTS		
LDQCNC_t	• $\text{Log}[-(q_{01993}-q_{0t})]$. Log of negative of change in real price of CNC between 1993 and date of first adoption.	(-)
LDQTOT_t	• $\text{Log}[-(q_{n1993}-q_{nt0})]$: Log of negative of change in real price of old capital, measured by real price of Gross Domestic Fixed Capital Formation, between 1993 and date of first adoption	(+)
GQCNCOTOT_t	• $q_{nt}/(-dq_{nt})-q_{ot}/(-dq_{ot})$ Difference between inverse growth of prices of CNC and old capital between 1993 and date of first adoption	(-)
RANK EFFECTS		
<u>Employment</u>		
LEMP_z	• Log number of employees times size class dummy, z =small (<50), medium (50 – 200), large (>200) weighted average 1986-1993	(+)
<u>Age</u>		
LAge_t	• Log years from start-up (1993-startup year)	(+/-)
<u>R&D</u>		
R\&D_t	• In House R&D dummy (yes=1, no=0)	(+)
<u>Ownership</u>		
GROUP_t	• Dummy (1 =Group establishment ; 0 = Independent)	(+)
<u>Export</u>		
Ex20/50_t	• Dummies on Exports (1 if >20% of output ; 0=otherwise)	(+/-)
<u>Managerial Innovation</u>		
USERMJ_t	• Dummy (1=Yes; 0= No), user 1993 of managerial innovation J, J=CAPM, JIT,TQM;BS5750-ISO900	(Tech specific)
<u>Complementary and/or substitute technologies</u>		
USERTJ_t	• Dummy for user of technology J (1=Yes ; 0= No) of J=CAD; Microprocessors in products (MProd); Microprocessors in Processes (Micro); CoT; NC; etc in/by 1993-1	(Tech specific)
<u>Production System Characteristics</u>		
USERPSI_i	• Dummy for Firm Prod. System (Yes=1; 0= otherwise) $i = 1$ (Engineering to order); 2 (Make to order), 3 (Make to stock), 4 (Job shop), 5 (Mixed)	(+/-)
LBATCH	• Log average batch size	(Tech specific)
EPIDEMIC EFFECTS		
LTIME_t	• Log years from firm first adoption of CNC up to 1993 (*93-date of first adoption)	(+)
LSH_i	• Log Within Industry i ($i=1,2,\dots$) share of adopters at time of the firm first adoption	(+/-)
SAMPLE SELECTION FACTOR		
IMR	• Inverse Mills ratio	

Astebro (1995 and 2000) argues that in some cases these “hardware” prices are not the most relevant. He shows that in the case of soft technologies such as spreadsheets it is the

⁸ This figure is also very similar to that used by Shapiro (1986) in his empirical study on investment and the cost of capital. Specifically he uses an average depreciation rate of 0.024 a quarter.

employees' opportunity cost of switching, rather than the acquisition cost that is important. In his inter firm study on the adoption of CNC and CAD specifically separates out capital and non capital costs of adoption. We are in some sympathy with that approach however our data does not allow us to pursue it. We would also argue that for some technologies (such as CNC) the non-capital costs can be seen as switching costs that the firm has to face at the time of first adoption but do not necessarily impact upon the decision to further invest in a new technology and are thus not especially relevant to intra firm diffusion.

Table 2. The intra firm diffusion equation

Variable	Coefficient	Standard Error	t-test	P-value
LDQCNC	-1.5935	0.6713	-2.374	0.0176
LDQTOT	0.3684	0.8300	0.444	0.6571
GQCNC TOT	-0.4567	0.1366	-3.342	0.0008
LEMP SMALL	0.4536	0.2075	2.186	0.0288
LEMP MEDIUM	0.3215	0.1267	2.538	0.0112
LEMP LARGE	0.2496	0.1081	2.308	0.0210
LAGE	-0.1926	0.2624	-0.734	0.4629
R&D	1.1135	0.3525	3.159	0.0016
EX20	-0.6674	0.2908	-2.295	0.0218
GROUP	0.6042	0.2295	2.632	0.0085
USERCAPM	0.0657	0.2681	0.245	0.8064
USERJIT	-0.1989	0.2612	-0.762	0.4462
USERTQM	0.0765	0.2850	0.269	0.7883
USERBS5750	0.3260	0.2702	1.206	0.2278
USERCAD	1.1337	0.2996	3.784	0.0002
USERMPROD	-0.8521	0.2825	-3.017	0.0026
USERMICRO	0.6343	0.3214	1.973	0.0485
USERCOT	-0.2497	0.3938	-0.634	0.5261
USERNC	0.1512	0.3360	0.450	0.6526
LBATCH	0.0418	0.0665	0.628	0.5297
USERPS5	0.9882	1.002	0.987	0.3238
USERPS2	0.4958	0.3008	1.648	0.0993
USERPS3	-0.4394	0.4039	-1.088	0.2766
USERPS4	0.6153	0.5144	1.196	0.2317
LTIME	-0.0698	0.6677	-0.104	0.9168
LSH2	-1.8426	2.8232	-0.653	0.5140
LSH3	3.4411	5.9581	0.578	0.5636
LSH5	1.5143	1.5149	1.000	0.3175
LSH678	-3.3421	2.0936	-1.596	0.1104
LSH10	3.4941	2.3016	1.518	0.1290
LSH12	-2.4173	4.1918	-0.577	0.5642
LSHGROUP	-1.7018	2.3578	-0.722	0.4704
IMR	0.5972	0.6184	0.966	0.3341

Number of Observations = 82
Degr of freedom = 49
R-squared = 0.68
Adjusted R-squared = 0.40
F[32,49] = 2.48 ; Prob value = 0.002
Log-L = -74.11 ; Restr. Log-L = -134.72
Amemiya Pr. Crt.= 0.84 ;
Akaike Info. Crt.=2.61
Standard error corrected for selection 0.69

The results indicate that the expected change in the price of CNC ($LDQCNC = \log [-(q_{o1993}-q_{o0})]$) as predicted, carries a significant and negative coefficient. However, the expected change in the price of old technologies ($LDQTOT = \log [-(q_{n1993}-q_{nt0})]$) although carrying a coefficient of the expected positive sign is not significant. Measuring this variable by the price of GDFCF is not ideal and thus we also experimented using the price index of Plant and Machinery, but the results did not change significantly. The model predicts that the coefficients on these variables should be plus and minus unity respectively, and Wald tests do not reject these hypotheses at 5% significance ($\chi^2_{LDQTOT} = 0.57903$; $p=0.45$; $\chi^2_{LDQCNC} = 0.781758$; $p=0.38$).

The third price variable ($GQCNCCTOT = q_{nt}/(-dq_{nt})-q_{ot}/(-dq_{ot})$) measures the differences in the inverse growth rates of the prices of new and old technology and is expected to carry a negative coefficient equal to $-(r + \delta + 1/2 \sigma^2 \beta)$. The estimated coefficient is negative as expected and also significant. We have argued that if the coefficient differs in value from -0.15 then there may be a quantitatively significant impact of revenue uncertainty upon intra firm diffusion. The coefficient estimate is -0.457 which is more than two standard errors different from -0.15 ($t_{GQCNCCTOT} = -2.244$ see also the Wald test $\chi^2_{GQCNCCTOT} = 5.0355$; $p= 0.029$) and thus one may safely conclude that revenue uncertainty has slowed the intra firm diffusion of CNC machine tools.

4.3. Rank effects

In the diffusion equation the term in $\log (\alpha_n/\alpha_o)$ captures differences in the “productivity” of new and old technologies across firms i.e. rank effects, and may be considered as firm and (old) technology specific. As our data is a single cross section sample such rank effects are of the essence in the empirical analysis. The choice of variables that we include as determinants of (α_n/α_o) is largely based on the findings in the literature on inter firm diffusion, but also partly by a priori reasoning and partly by data availability.

Early work of Mansfield (1968), as well as Hannah and MacDowell (1984), Karshenas and Stoneman (1993), Saloner and Shephard (1995), Noteboom (1993), Colombo and Mosconi (1995), Oster (1982) and more recently Astebro (2002) finds that size of the establishment shows a significant and usually positive impact upon inter-firm technology adoption. After experimentation, in order to account for possible non-linearities we include firm size represented by a set of size class specific variables ($LEMP_{small}$, $LEMP_{medium}$, $LEMP_{large}$). Moreover, to account for possible endogeneity we define

them as the log of the weighted smoothing average number of employees between 1986 and 1993 if the firm is in the size class (i.e. small medium or large) and zero otherwise. The three size variables all carry positive coefficients and are significant. The coefficients decline with size ($\beta_{LEMP_{small}} = 0.454$; $\beta_{LEMP_{medium}} = 0.321$, $\beta_{LEMP_{large}} = 0.250$) therefore the elasticity is lower the larger the firm, but it should be noted that these variables are defined as firm size (in log number of employees) times a size class dummy. Thus the estimates indicate that that within each size class, diffusion is greater for larger firms (diffusion increases with firm size in a size class). Therefore, using the data on the average firm size in the sample for each size class (0.4377, 1.4977 and 2.7538) at these averages the predicted contributions to the dependent variables are 0.198, 0.48 and 0.688 for small medium and large firms and thus on average larger firms will diffuse faster.

The Schumpeterian hypothesis that formalised R&D exerts a positive impact upon the use of a technology is in line with a later study by Cohen and Levinthal (1989) who illustrate that firms which spend upon R&D are more easily able to assimilate new technology. Due to the high number of missing values in the data set on the R&D spending, this variable is introduced as a dummy that takes the value 1 if in 1993 firms do in house R&D and zero otherwise It is found that doing R&D in house impacts positively and significantly on intra firm diffusion ($\beta_{R\&D}=1.11$).

The age of the establishment in logs (LAGE) is also included on the basis that older firms generally have accumulated knowledge that allows them to assess new technologies better than younger firms do. However, the opposite might also be true. Earlier studies of inter firm effects of age are Baldwin et al. (1998), Dunne (1994), Little and Triest (1996) and Noteboom (1993). We find that (LAGE) is not significant as a determinant of intra firm diffusion.

In addition we consider variables that reflect: (i) whether in 1993 the firm is export intensive, i.e. exports >20% of its output (EX20) and find that Export intensity carries a negative coefficient indicating that those firms exporting more than 20% of their output use CNC less extensively than those exporting less ($\beta_{EX20}= -0.667$); (ii) whether the firm, as an establishment, belongs to an industrial group in 1993 (dummy: GROUP) reflecting the possible impact of both internally sourced information relating to technology performance and technological competencies (and will also pick up whether there are

different degrees of autonomy for firms that are independent as opposed to being part of a group) (see Cainarca et al., 1990), Dunne 1994, and Astebro, 2002): the estimated coefficient is positive and significant.

Characteristics of the production system may also affect the adoption of a new technology. For example, Colombo and Mosconi (1995), suggest that plants with no job shop are more likely to pioneer adoption of flexible manufacturing and assembling systems, while plants with a job shop will perform better as regards the introduction of NC or CNC and also computer aided and engineering equipment. Data on the type of production organisation available in the CURDS data set has been specified as a series of dummy variables such as: engineer to order (USERPS1), make to order (USERPS2), make to stock (USERPS3), job shop (USERPS4), and mixed (USERPS5). The log of average batch size (LBATCH) is also included as an explanatory variable.

Interdependencies and complementarities between technologies are also believed to play a relevant role in diffusion, based upon the principle that the firm's capabilities reflect its stock of knowledge and technical and managerial skills, all of which are enhanced by the use of previous technologies (Baldwin et al., 1998, Astebro, 2002, Stoneman and Toivanen, 1997, Stoneman and Kwon, 1994, Colombo and Mosconi, 1995). Consequently, a series of dummy variables sourced from the CURDS data set is here used to indicate previous adoption of complementary and substitute technologies such as numerical control (USERNC), carbide tools (USERCOT), microprocessors in processes (USERMICRO), computer aided design (USERCAD), and microprocessors incorporated in products (USERMPROD).

As emphasised by the managerial literature, managerial as well as organisational innovation can generate complementarities from the use of other existing technologies and speed up the use of the advanced technology (see for example Jaikumar, 1986, Colombo and Mariotti 1987, Cainarca et al. 1990, Colombo and Mosconi 1995, Caroli and Van Reenen, 2001 for empirical evidence in support of this hypothesis). This is tested via the inclusion of dummy variables indicating whether, by 1993, the firm has adopted: Computer Aided Production Management systems (USERCAPM); Total Quality Management principles (USERTQM) and Just in Time principles (USERJIT) and whether the firm has been awarded the BS5750/ISO9000 accreditation (USERBS5750). Of these variables representing use of other advanced technologies and managerial innovations, the

use of CAD ($\beta_{\text{USERCAD}}=1.134$), Microprocessors in products and in processes ($\beta_{\text{USERMPROD}}=-0.852$ and $\beta_{\text{USERMICRO}}=0.634$), all have significant measured impacts and all but $\beta_{\text{USERMPROD}}$ are positive. Of the production system characteristics (USERPS1 – USERPS4) only USERPS2 has a slightly significant impact ($\beta_{\text{USERPS2}}=0.495$) suggesting that a make to order system encourages diffusion of CNC. However, this result is not robust to different model specifications.

Finally the responsive of technology adoption to each of the specified variables can best be indicated by estimates of elasticities. For the independent variables that are continuous and specified in logs the coefficient estimates are also the elasticities. For the only continuous variable not specified in logs, (GQNCCTOT), at the sample mean the elasticity is 0.15. For the dummy variables, being discrete, firm level elasticities do not exist, however one may calculate sample wide elasticities (reflecting the average impact across the whole sample) as the coefficient times the value of the sample mean of the dummy variable. Using this approach, and considering only variables significant at 5%, the largest elasticities are for LDQCNC (-2.89), LEMPlarge(0.69) and the R&D (0.86) and USERCAD (0.84) dummies. All other elasticities relating to significant variables are in the range from 0.20 to 1. One may thus argue that where we have statistical significance, diffusion is also quantitatively responsive to the variable.

4.4. Epidemic effects

We follow the epidemic tradition by modelling $f(E)$ as a function of two variables (i) the (log of) the proportion of firms in the industry⁹ to which the firm belongs that were adopters at the date of adoption (LSH_k) and (ii) the (log of) the number of years between the date of first adoption by the firm and 1993 ($LTIME=1993-t_0$). All should carry positive and significant coefficients if the epidemic effect is to be playing a role. However, none of these variables turns out to be significant. During the estimating process we sometimes found that LSH_{10} was significant. We also experimented testing for the existence of within industry effects specifying separate industry dummies (D_j where $j=1\dots 15$) and combining the within industry share of users into one aggregate variable (Lindshare). The results are shown in Table 3 Column 2. The Lindshare variable is not

⁹ For each firm the data set reports the SIC classification up to three digits for 11 industries: (1=MLH331, 2=MLH332, 3=MLH333, 4=MLH336, 5=MLH337, 9=MLH 341, 10=MLH361, 11=MLH390, 12=MLH349, 13=subcontractors and 14=other mechanical engineering). For one industry it provides the classification up to four digits (6=MLH3393/4, 7=MLH3391/2/5/6/7/8 and 8=MLH3399).

significant and of the industry dummy variables only that for industry 10 shows significance. As it is possible that epidemic effects are insignificant because their true impact is captured by other time-based variables, a previous commentator suggested that we might include both industry specific effects and industry specific epidemic effects.

Table 3. The intra firm diffusion equation, further estimates

	(1)	(2)	(3)
	Coefficient (s.e.)	Coefficient (s.e.)	Coefficient (s.e.)
LDQCNC	-2.213 (0.648)	-1.668 (0.708)	-1.655 (0.698)
LDQTOT	0.741 (0.798)	0.443 (0.895)	-
QCNCTOT	-0.497 (0.130)	-0.458 (0.142)	-0.369 (0.149)
LEMPsmall	0.561 (0.213)	0.426 (0.222)	0.421 (0.188)
LEMPMEDIUM	0.246 (0.132)	0.306 (0.129)	0.350 (0.127)
LEMPLARGE	0.185 (0.128)	0.234 (0.111)	0.248 (0.107)
LAGE	-0.032 (0.266)	-0.109 (0.293)	-
R&D	1.551 (0.362)	1.255 (0.366)	1.095 (0.319)
EX20	-0.711 (0.292)	-0.667 (0.318)	-0.607 (0.276)
GROUP	0.577 (0.262)	0.568 (0.236)	0.314 (0.228)
USERCAPM	0.160 (0.270)	0.058 (0.294)	-
USERJIT	-0.196 (0.318)	-0.094 (0.285)	-
USERTQM	0.348 (0.316)	-0.010 (0.302)	-
USERBS5750	0.663 (0.333)	0.259 (.295)	-
USERCAD	1.319 (0.310)	1.087 (0.320)	0.845 (0.294)
USERMPROD	-0.707 (0.295)	-0.829 (0.285)	-1.026 (0.249)
USERMICRO	0.732 (0.354)	0.635 (0.322)	0.605 (0.274)
USERCOT	-0.597 (0.451)	-0.258 (0.462)	-
USERNC	-0.069 (0.359)	0.252 (0.379)	-
LBATCH	0.007 (0.072)	0.040 (0.070)	-
USERPS5	0.236 (0.982)	0.858 (1.017)	-
USERPS2	0.859 (0.316)	0.445 (0.307)	-
USERPS3	-0.404 (0.399)	-0.452 (0.412)	-
USERPS4	0.621 (0.545)	0.644 (0.529)	-
LTIME	0.070 (0.651)	0.063 (0.709)	-
LSH2	-0.618 (3.007)	-	-
LSH3	3.923 (6.494)	-	-
LSH5	1.082 (1.466)	-	-
LSH678	-2.098 (2.255)	-	-
LSH10	5.843 (2.268)	-	-
LSH12	-6.405 (4.251)	-	-
LSHGROUP	-0.815 (2.357)	-	-
LAVGRT	-0.0637(0.191)	-	-
USERROBOT	0.838 (0.482)	-	-
D1	-	-0.359 (0.222)	-
D2	-	-0.190 (0.668)	-
D3	-	-0.680 (0.910)	-
D5	-	-1.137 (1.966)	-
D6	-	0.331 (0.847)	-
D7	-	-0.301 (0.670)	-
D8	-	0.118 (0.562)	-
D9	-	-0.486 (0.960)	-
D10	-	-1.168 (0.562)	-
D11	-	-0.329 (0.708)	-
D13	-	-0.717 (1.217)	-
D15	-	-0.683 (1.379)	-
LIndshare	-	0.394 (6.779)	-
IMR	-0.205 (0.647)	0.673 (0.670)	0.188 (0.549)
Observations	68	82	101
Degr of freedom	33	43	89
R-squared	0.71	0.63	0.52
Adj. R-squared	0.41	0.30	0.40
F,[Prob value]	2.37 [0.007]	1.91 [0.020]	3.05 [0.001]
Log-L	-46.74	-67.72	-121.4
Restr. Log-L	-113.38	-134.72	-159.79
Amemiya Pr. Crt.	0.722	0.859	1.087
Akaike Info. Crt.	2.404	2.603	2.915
S.e.corrected for selection	0.69	0.79	0.95

We thus estimated the model with separate industry dummies and a variable accounting for the within industry shares of users in aggregate. While the latter variable was never significant, one of the industry dummies was significant (all the other estimates remaining significantly unchanged). Despite the industry samples being small, this provides little evidence that there exist within industry effects or within industry epidemic effect. Overall these results suggest to us that there are no significant epidemic effects a la Mansfield.

We also experimented with the inclusion of a number of other variables available in the CURDS dataset . We report one such estimate in Table 3 column 1 where the information on the real firm average turnover (AVGTURN= Log weighted average of real turnover 1990-93 per employee) as well as the adoption status of Robots (USEROBOT) have been included. However, AVGTURN, similar to the other financial indicators did not work at all well. Moreover, AVGTURN (as well as ROBOT) was characterised by a high number of missing values that further reduced the sample size to 68. These findings have led us to omit further discussion of such results. Finally, we observe that our initial estimates have a smaller small sample size than we would wish, due to the high number of missing values. To overcome this to some degree and to check the robustness of our parameters estimates, we have generated some more parsimonious estimates with a smaller range of independent variables and as a result a larger sample size. The parsimonious version of model (9) is reported in table 4 column 3. In the reduced model the sample size increases to 101 however the parameter estimates do not change significantly. We have preferred to focus our presentation on the unrestricted model, it being more informative than its reduced version.

5. DISCUSSION

A prime objective of this paper has been to develop and test an approach to modelling intra firm diffusion based upon differences across firms (and potentially) changes over time in the profitability of adoption. This approach indicates that rank effects will be important in determining the use of technology at a point in time. The modelling explicitly incorporates uncertainty (about future innovations as well as future financial and market conditions) and attempts have been made to introduce some price effects. To be encompassing an epidemic effect has also been introduced. The findings generally support a profitability based model of intra firm diffusion.

The inverse Mills ratio has been included in the intra firm diffusion equation to compensate for sample selection effects but is not significant and thus although the sample selection correction was important on conceptual grounds it is not found to be of statistical significance. One cannot therefore accept the hypothesis that the decision to become an adopter directly affects the current level of use of the new technology.

This equilibrium approach is also further supported by the lack of significance of epidemic effects. We included variables to represent the traditional Mansfield type epidemic effects but these are not significant. Of course, it may be that we have not captured the essence of the epidemic model in these variables or that learning is not undertaken in the way that the epidemic model suggests. For example, learning may involve active search rather than the passive information acquisition process which is the foundation of the epidemic approach. If the findings are to be believed however, they suggest that there is little variance across firms in their information capital relating to the new technology and thus such differences cannot explain different patterns of intra firm diffusion. This suggests that epidemic learning is not the major factor in the intra firm diffusion process or at least not for a “hard”, rather standard, process technology such as CNC. We are inclined to argue instead that information is important but it is the capability to decode, assimilate and process information and of making it operative that is crucial and is different from firm to firm (see for example Battisti and Pietrobelli, 2000). These differences in turn will reflect differences across firms in general skills accumulated over time by the use of other technologies, their history, their production characteristics, their managerial capabilities, etc.

Although the sample relates only to a single cross section in 1993 we have introduced some variance in the user cost of capital by allowing that expectations of firms as to the cost of acquiring new technology (relative to the old) is related to the average reduction per annum in the cost of that technology since first adoption. It is found that the parameters relating to this variable are of the correct sign, generally significant and of the correct size. The results on the impact of prices are important evidence in suggesting that epidemic models cannot tell the whole intra firm diffusion story and profitability effects as modelled here may also matter. In fact if the three price variables are removed from the model the goodness of fit reduces from 0.68 to 0.51. Although the expectations formation hypothesis might be criticised the results are encouraging. In addition, our finding that the parameter on the difference between inverse growth rates of the prices of new and old technology carries a significant coefficient that in absolute value is significantly greater than would be

expected if revenue uncertainty did not impact upon intra firm diffusion, indicates that such uncertainty does play a role in the intra firm diffusion process. It has long been hypothesised that uncertainty affects the diffusion process but rarely is the effect explicitly incorporated as here and even more rarely is the effect quantified.

The profitability based approach indicates that the firm characteristics (rank effects) will impact upon intra firm diffusion. The importance of rank effects is a common property of the recent inter firm literature. Firm size matters and export intensity also impacts significantly, albeit negatively (although there is always the danger that there are problems with directions of causality in such findings). If the firm does R&D it is also likely to have higher levels of intra firm diffusion. This suggests that a faster diffusing firm may be innovative in several dimensions. This is perhaps reinforced by the findings that the adoption of several other technologies and management techniques also impacts positively, in most cases when significant, on the diffusion process. This effect may reflect technological complementarities but is just as likely to suggest again that innovative firms are innovative in all dimensions and not just some, and that the higher are the core competencies (and not just the knowledge about the new technologies) of the firm in processing information and in making it operative, the faster diffusion will be.

6. CONCLUSION

In the overall diffusion of new technology intra firm diffusion is as important as inter firm diffusion. We have illustrated above that the intra firm process of technology transfer is a long one, with new and old technologies co- existing for a long period of time and very heterogeneous across the sample. However, the study of intra firm diffusion has been relatively ignored in the past and the literature that does exist tends to over rely upon information spreading or epidemic type models.

In this paper an alternative profitability based approach to modelling intra firm diffusion is proposed and tested upon data relating to the intra firm diffusion of CNC machine tools in the UK engineering and manufacturing sector. The model predicts that for an individual firm the replacement process of an old with a new technology is driven by the relative (new vs. old) user costs of capital (allowing for price expectations and uncertainty) with differences across firms reflecting their characteristics (rank effects), know-how and firm specific skills in efficiently combining and using their production inputs. An epidemic

element has also been incorporated to both enable model comparison and to test whether epidemic learning as suggested by Mansfield still has a role to play.

The empirical analysis, accounting for sample selection bias, truncation and censoring, does not reject the hypothesis that different user costs are a driving force or that rank effects matter. A number of firm characteristics are isolated as of special importance including whether R&D is undertaken, firm size, export intensity and the use of complimentary technologies and managerial techniques. It is apparent that generally firms that are innovative in other directions also diffuse faster. There is little support for any additional epidemic effects as specified by the Mansfield model.

There is further need to analyse intra firm diffusion as it has been much neglected. A basic reason for this neglect is data availability. Here for example we have used a single 1993 cross section. Panel data would be much preferred and would enable much more realistic testing of price effects. However, in any analysis of new data sets, the results here suggest that the epidemic model should no longer be considered the natural approach. A greater emphasis upon profitability, its changes over time and differences across firms would seem more appropriate.

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