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Do innovations diffuse faster within geographical clusters?

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Abstract

There is considerable evidence to demonstrate that the diffusion of new technologies is spatially variable. This paper argues that externalities promoting the adoption of new technology are stronger at the regional level and depend positively on the proximity of early users. An empirical model of diffusion is built, including variables related to the regional density of adopters and of technologically close firms. Results support the existence of significant regional learning effects on adoption. These effects seem to be stronger at the early stages of diffusion.

Keywords: Geographical clustering; Technological diffusion; Externalities; Duration models

JEL classification: L10; O30

1. Introduction

There is considerable evidence to demonstrate that the adoption of new technologies varies geographically (see, for example, Hägerstrand, 1967, Thwaites, 1982 and Rees et al. 1984). Alderman and Davies (1990) found that there are significant regional variations in the rates of diffusion of key manufacturing

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technologies. These variations cannot be accounted for exclusively by regional differences in industrial structure and establishment size distributions. The present paper suggests that regional differences in diffusion rates result from the geographical clustering of innovators and early adopters of new technology. Geographical proximity stimulates networking between firms, thereby facilitating imitation and improvement.

It is at the diffusion stage that the greatest impact of technological change upon economic growth is seen to occur. If a region lags behind in the invention or adoption of new technology, it may face industrial decline.

In the present paper, a general model of diffusion is built. The model includes variables representing the regional density of adopters and technologically close firms, in order to examine the effects of the geographical environment on the speed of diffusion. Empirical testing of the model is done using data from the technology adoption survey conducted for the United Kingdom in 1981 by the University of Newcastle's Centre for Urban and Regional Development Studies (CURDS)[1].

2. Background

It has been argued (see Porter, 1990; Feldman, 1994; Baptista, 1998, 1999) and indeed empirically verified (see Glaeser et al. 1992; Audretsch and Feldman, 1996; Baptista and Swann, 1996, 1998) that the geographical concentration of rivals enhances competitiveness and stimulates innovative activity, firm growth and entry. The transmission of new technological knowledge works better within geographical boundaries because this kind of knowledge has a tacit and uncodified nature (Lundvall, 1988). Following such a line of reasoning, one can claim that the diffusion of new technological processes may occur faster in geographical areas where the density of sources of knowledge about such technologies is higher.

Early work on diffusion theory concentrated on epidemic, or learning effects by which potential adopters procure new technology upon receiving information about its existence (see, for instance, Mansfield, 1968). In contrast, more recent theoretical approaches to the subject have emphasised the explicit treatment of a firm's decision to (or not to) adopt a new technology. Different potential adopters should have different preferred adoption dates.

[1] The technology adoption survey conducted by CURDS was funded by the Economic and Social Research Council (ESRC). The author would like to acknowledge Neil Alderman at the University of Newcastle for providing the data on diffusion, and also Paul Stoneman, Otto Toivanen and Peter Swann for providing the data on technology prices.

2.1. The scope of learning effects

The adoption process consists of several stages; adoption is not a simple function of knowledge but requires also evaluation and trial. Much of the information necessary to support the diffusion of an innovation flows through personal contacts. Networks of interpersonal communication that link organisations developing and adopting technological innovations are of considerable importance in the diffusion process.

Debresson and Amesse (1991) argue that networks of innovators have an explicit local dimension. Tassey (1991) proposes that networking is essential for the development of a region's knowledge infrastructure. Pressures from social emulation and a localised competitive environment lead firms to adopt a new technology in order to ''stay in the game''.

Ebadi and Utterback (1984) demonstrated that network cohesiveness is positively correlated to the degree of innovative success. Midgley et al. (1992) found that cohesiveness (defined as direct user-to-user influence) has a positive impact on the diffusion of industrial innovations.

If firms rely on each other to learn about new technology, it can be argued that the diffusion process is characterised by cognitive externalities. The investment in adoption-related R&D should itself increase firms' ability to absorb new technological knowledge, as suggested by Cohen and Levinthal (1989).

Adoption externalities associated with the learning and transfer of new technological knowledge should reduce the costs of taking up technology embodying capital goods and facilitate the assimilation of new technologies into the firms' own value chains. The intensity of such externalities is likely to be stronger at the local level, since new, tacit knowledge flows more easily through interpersonal contacts. Adoption externalities should therefore depend positively on the proximity of early users and of technologically close firms, either acting as competitors, customers, suppliers or service providers.

Given the arguments presented above, it seems reasonable to claim that there are external epidemic or informational effects acting on the diffusion of industrial innovations, and that these effects will be stronger in some regions than in others. Such differences will be associated with the presence of sources of technological information such as, for instance, early adopters.

2.2. Models with perfect information

Epidemic theories of diffusion present a disequilibrium approach resulting from information asymmetries between potential users. Other theories assume that there is perfect information regarding the existence and nature of new technologies. Karshenas and Stoneman (1993) group these other theories into three categories: rank (or probit), stock and order effects. In equilibrium models of diffusion the firm's decision to adopt depends upon the gains from adoption relative to the cost of adoption. As such gains change over time, so does the number of adopters.

In rank or probit models (Davies, 1979), potential users of a new technology differ from each other in some important dimension. As a result of such heterogeneity, some firms will obtain a greater return from the new technology than do others, and will be likely to adopt faster.

The stock effects models (Reinganun, 1981a,b) argue that, as the number of users of a new technology increases, the benefits from adoption decline. Hence, there will be a point in time when the number of accumulated adopters makes adoption by the remaining firms not profitable.

The order effects models (Fudenberg and Tirole, 1985) consider that the firm's position in the adoption order determines its return from the use of the technology, with firms higher in the adoption order obtaining greater returns than firms lower in that order. In this way, if a firm expects the number of future adopters to be high, it will decide to adopt earlier.

Although both the order effects and the stock effects models imply that the profitability of adoption declines as the number of adopter increases, stock effects models focus on the equilibrium number of adopters and the associated lower profitability of adoption, and the stock effect is then a lowering of the probability of adoption. In contrast, the order effects models focus on the anticipation of subsequent adoptions; and hence, the order effect has a positive effect on adoption. The distinction underlies the choice of variables subsequently introduced to capture order effects and stock effects.

3. Variables influencing the adoption decision

The adoption decision is modelled following the work by Karshenas and Stoneman (1993). Appendix A outlines the foundations of the model and the adoption conditions:

– profitability condition – at the optimum adoption time the expected benefits from adoption must be higher than the costs.

– arbitrage condition – adoption at the optimum adoption time must be more profitable than adoption in any subsequent time.

The main adoption cost should be the price of the technology; adoption will depend negatively on the cost of the knowledge-embodying equipment. Moreover, one can predict that expected reductions in the technology price will delay adoption, reflecting the arguments of Rosenberg (1976).

Other variables influencing adoption should incorporate the main firm-specific (rank), stock, order and learning/epidemic effects outlined above. A number of firm and industry-specific variables are deemed to influence the adoption decision. Size of firm is the most frequently used variable in rank or probit models[2] (see Davies, 1979). Many new technologies show positive scale effects. If adoption lowers average costs, bigger firms will have a larger output in which to benefit from it. Early adoption is, therefore, more profitable for larger firms.

There are also effects associated with vintage capital and sunk costs (see Salter, 1960). New entrants, firms with worn-out equipment and firms expanding capacity will be more likely to adopt a new technology. Moreover, new firms will be more flexible to the introduction of new technologies, as argued by Christensen and Rosenbloom (1995). Age of establishment and the expected growth of the industry's output should therefore have an impact on the adoption decision.

The R&D effort at the establishment level provides a measure of the firm's capability of processing new technological information at a minimum cost, as argued by Cohen and Levinthal (1989). The corporate status of the establishment (independent or part of a larger unit) may also have an impact on adoption. On one hand, independent units might be more flexible in terms of implementation speed; on the other hand, establishments that are part of a larger corporation will experience less uncertainty and less financial constraints.

Order effects are assessed by the number of firms expected to adopt in the following period. A high expected number of future users should make firms accelerate adoption, in order to improve their competitive position.

Stock and learning/epidemic effects are included through adoption-precedence variables (regional and national). The accumulation of adopters should have a negative effect on the adoption rate because of the stock effect. However, the epidemic effect acts through a learning-by-contact process, hence the stock of previous adopters will also bring forth a positive effect on adoption. Such an effect will counteract the expected stock and order effects, making the net effect of the variable ambiguous. If learning effects are strong enough to compensate for stock effects, then a positive net effect of the stock of previous adopters should be found. This point is particularly relevant at the regional level, where the learning effect is expected to be stronger.

The inclusion of the regional and national stock of adopters as explanatory variables is bound to produce some degree of collinearity. The problem should be at least partially solved by using the number of previous regional adopters (likely

[2] One should note that, in the stock effects approach (see Reinganun, 1981a,b), firm size is an endogenous variable determined by the adoption time, while it is an exogenous variable in the rank model.

to affect the opportunities for learning) and the national percentage of firms that have adopted (likely to affect competitive pressures and, therefore, to generate stock effects) as explanatory variables[3].

4. Data and methodological issues

The present study uses time to adoption as the dependent variable, following Hannan and McDowell (1984, 1987), Levin et al. (1987), Rose and Joskow (1990), and Karshenas and Stoneman (1993). The 1981 CURDS survey covered all identified UK establishments in the engineering and metalworking industries. Although the survey was repeated in 1986 and 1993, a relatively large number of active firms dropped out, thus generating an incomplete panel. It was therefore decided to use data from the 1981 survey only. The data set covers six three-digit industrial sectors[4]. Establishments are assigned to the ten standard regions of Great Britain as defined by the Central Statistical Office (CSO)[5].

Two technologies were selected for the study: computer numerically controlled (CNC) machine tools and microprocessors. A summary of the adoption data is given in Table 1[6]. CNC machine tools is a relatively complex and expensive technology and its early users were, primarily, large firms. The first recorded adoption in the UK engineering industry occurred in 1968. The data set covers adoption from 1968 to 1980, so no left-censoring bias should be found.

The first microprocessors were introduced in 1971–1972. The survey provides information for the period 1971–1980, so again there should be no left-censoring bias. Microprocessors experienced accelerated development during the period of analysis, leading to quality improvements and notable price reductions.

Fig. 1a and b show the diffusion paths for both technologies. CNC machine tools started diffusing a few years earlier than microprocessors, and the rate of adoption has peaked by the sample date, while microprocessors seem to be just

[3] An alternative specification using the industry output price as a proxy for the stock effect (reflecting cost reductions brought about by technology adoption) was tried. However, results did not improve much, and it is not clear whether or not output price is in fact correlated with adoption.

[4] These are: 320, 321, 322, 325, 328 and 342, according to the 1981 Standard Industrial Classification.

[5] North (N), Yorkshire and Humberside (YH), East Midlands (EM), East Anglia (EA), South East (SE), South West (SW), Wales (WA), West Midlands (WM), Northwest (NW) and Scotland (SC).

[6] The data include 1035 firms of which, by 1980, 284 had adopted CNC machine tools and 120 had adopted microprocessors.

Table 1
Adoption of CNC machine tools[a]

	N	YH	EM	EA	SE	SW	WA	WM	NW	SC	Total
1969	0	1	0	0	0	1	0	0	0	0	2
1970	0	0	0	0	2	0	0	1	0	0	3
1971	0	0	1	0	0	1	0	1	0	0	3
1972	0	1	0	0	1	1	0	0	0	1	4
1973	0	3	0	0	1	0	1	1	0	1	5
1974	4	1	1	1	1	1	0	1	3	3	18
1975	2	3	3	1	2	1	1	7	1	4	23
1976	5	1	1	1	7	4	0	3	1	5	29
1977	5	4	4	5	9	7	1	5	6	3	51
1978	6	2	2	4	11	13	3	12	7	5	65
1979	4	4	4	3	13	10	2	4	7	4	57
1980	2	1	1	3	5	6	0	1	0	3	24
Total	28	26	17	18	52	45	8	36	25	29	284

Adoption of microprocessors

	N	YH	EM	EA	SE	SW	WA	WM	NW	SC	Total
1972	0	0	0	1	0	0	0	0	0	0	1
1973	0	0	0	0	0	0	0	0	0	1	1
1974	0	0	0	0	0	0	0	0	0	0	0
1975	0	0	1	0	0	0	0	2	0	4	7
1976	0	1	0	0	0	0	0	3	0	0	4
1977	1	3	0	1	3	4	0	1	1	0	14
1978	4	2	2	2	3	2	0	1	1	3	20
1979	3	3	4	2	11	2	1	3	5	7	41
1980	4	4	2	0	6	5	0	3	5	3	32
Total	12	13	9	6	23	13	1	13	12	18	120

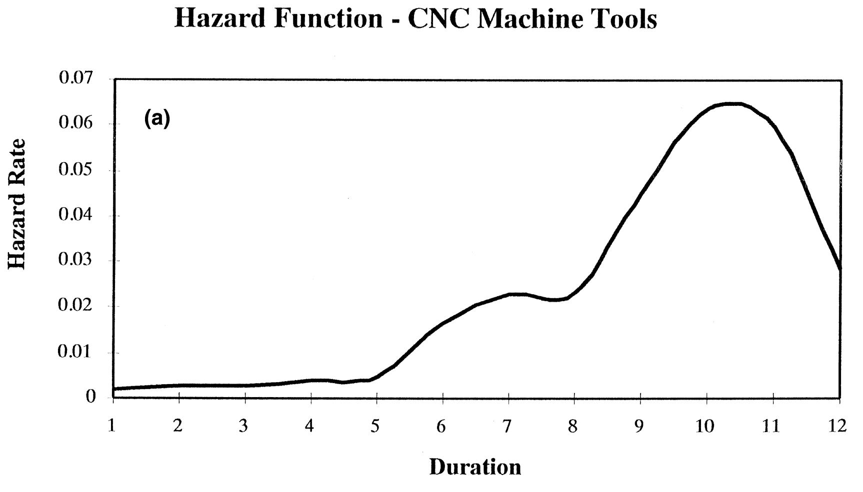
[a] Annual adoption is assigned to the ten CSO Regions: North (N), Yorkshire and Humberside (YH), East Midlands (EM), East Anglia (EA), South East (SE), South West (SW), Wales (WA), West Midlands (WM), Northwest (NW) and Scotland (SC).

starting to take-off. The observation suggests that the two technologies were on different stages of their life-cycles by the sampling date.

The data refer to the establishment as the adoption unit. Although most literature on diffusion treats the firm as the decision-making unit, any external effects acting at the regional level should be primarily reflected on the establishment, and not on the corporation as a whole.

The CURDS survey provides information on all the firm-specific variables included in the model with regard to its final year (1980). None of the establishments changed its location to a different CSO region during the period of analysis.

Time series data on industry outputs and prices were calculated from the census



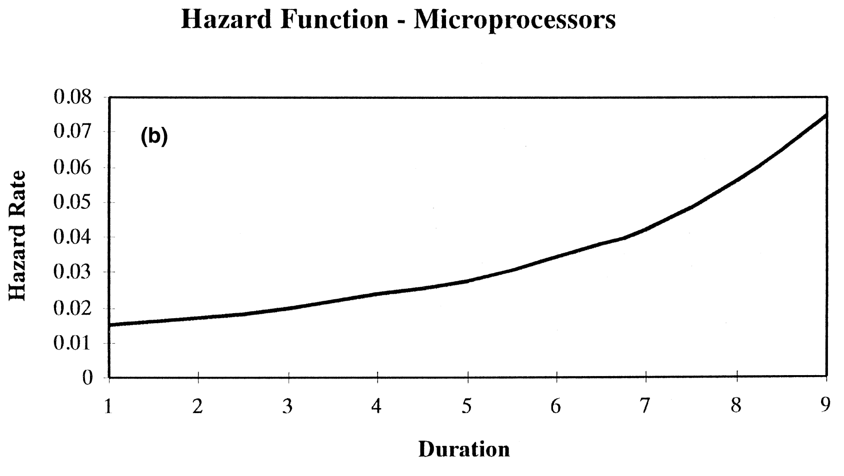


Fig. 1. Hazard functions for CNC machine tools and microprocessors. The hazard functions depicted show the rate at which diffusion happens after each duration t. For instance, in the case of CNC machine tools (Table 1, corresponding to Fig. 1), 2 firms out of 1035 adopt in 1969 ($t=1$), yielding a hazard rate of about 0.002. In 1974 ($t=6$), 18 firms adopt out of 1018 (17 firms had adopted before 1974), hence the hazard rate goes up to 0.017, and so on.

of production. Data on the prices of CNC machine tools are those used by Karshenas and Stoneman (1993) while the price series for microprocessors was generated from data in Swann (1985)[7].

[7] Hedonic prices were obtained by regressing the log-prices of 60 different models of microprocessors on a set of 11 major product characteristics.

Perfect foresight was assumed when determining values for the expectations variables. The inclusion of variables such as the expected price, expected change in output and expected number of adopters raises a question of endogeneity bias and serial correlation. However, both technologies were mainly supplied through imports, so it is unlikely that individual firms' decisions would affect prices. Furthermore, both technology prices and industry output declined monotonically over the observation period, so the use of any expectation rule would not change the results considerably.

One final question relates to sampling design. Data proceed from a survey conducted on a stock of existing establishments, which means that observations are only available for the set of establishments that existed at the time of the survey (1980). There is then a sample selection bias via the exclusion of firms that exited before the time of the survey, but were active during the period between first adoption of the technology and the time of the survey. For the sampling bias to be possible to ignore, the present study assumes that the probability of exit is uncorrelated with the explanatory variables included[8].

5. Econometric estimation

A duration, or failure time model (see Heckman and Singer, 1984a; Kiefer, 1988) is used to explain time to adoption as a function of the independent variables. The hazard rate is here defined as the probability that firm i will adopt the innovation at time t conditional on not having adopted the innovation before t. Appendix B shows how a likelihood function can be derived from the adoption conditions.

Estimation in the absence of a specific functional form for the hazard rate is done by using a version of the general class of proportional hazard models suggested by Cox (1972). The procedure is discussed by Kiefer (1988) and Karshenas and Stoneman (1993). Estimation of such a model including exogenous covariates (independent variables) is founded on the definition of an underlying distribution for the hazard rate (baseline hazard function). This distribution is pre-determined through specification tests.

The examination of the diffusion paths (hazard functions) for the two technologies, presented in Fig. 1a and b, suggests that, in both cases, the rate of diffusion is not uniform over time: the probability that a firm will adopt, given that it has not adopted previously, increases with time. Therefore, the assumption of a constant hazard rate, corresponding to an exponential distribution for the baseline

[8] Karshenas and Stoneman (1993) actually show that, for this specific data set, in the case of CNC machine tools, the hypothesis of state dependence of exit probabilities can be rejected, that is, the probability of exit is independent from the adoption decision.

hazard function (see Heckman and Singer, 1984a,b; Kiefer, 1988), seems unreasonable. The diffusion paths depicted suggest that the Weibull and the log-logistic distributions are more likely to be appropriate.

A useful approach to specification testing of failure time models is based on the concept of *pseudo-residuals*, or generalised residuals[9]. The test compares the

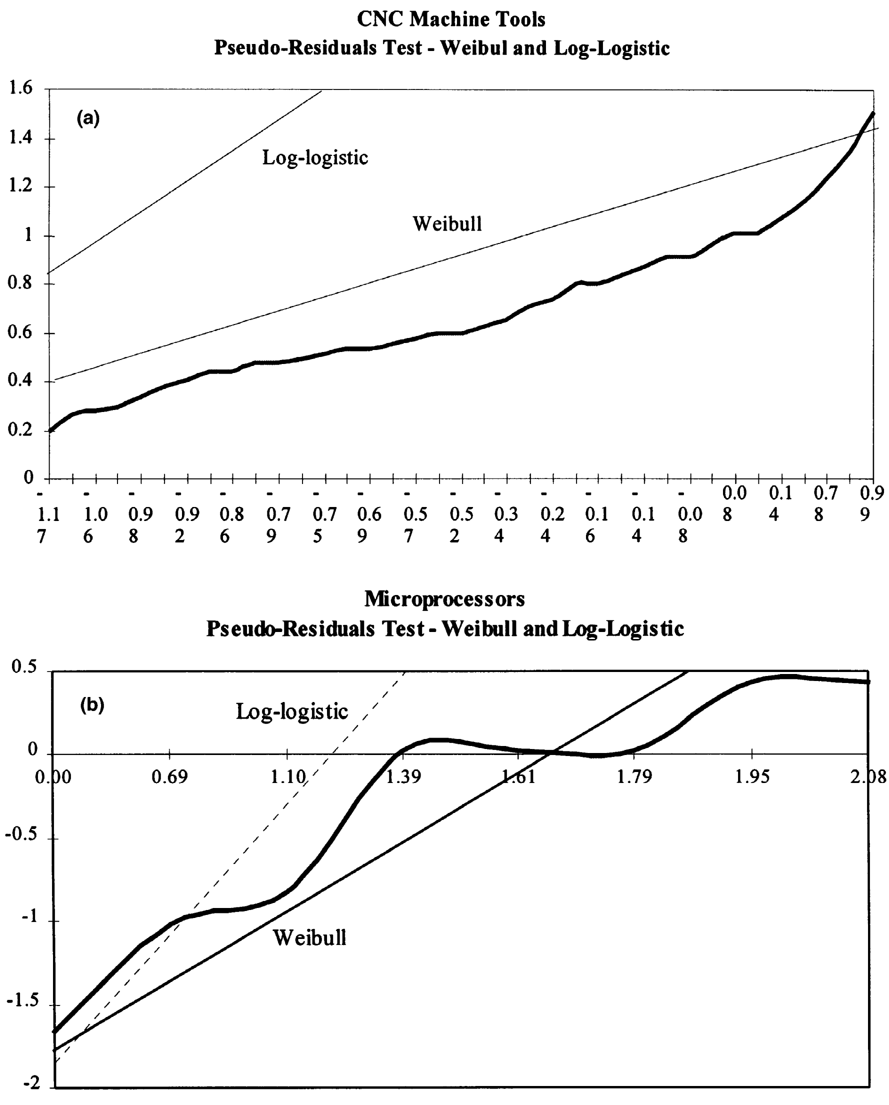


Fig. 2. Pseudo-residuals tests for CNC machine tools and microprocessors

[9] For a detailed presentation of the method see Blossfeld and Rohwer (1995, pp. 198–211).

residuals generated by non-parametric estimation of the hazard function (see, for instance, Kiefer, 1988) with the residuals that would be produced by adjusting a specific distribution (in this case, the Weibull or the log-logistic) to the baseline hazard. It is then possible to examine graphically which one produces the best fit.

Fig. 2a and b show that, for both technologies, the Weibull distribution produces standardised residuals that are closer to the residuals generated by non-parametric estimation. In practice, as suggested Karshenas and Stoneman (1993), the actual choice of a baseline hazard structure seems to make little difference as far as estimates and inferences are concerned[10].

One other issue worth discussion is the question of individual heterogeneity. Although the empirical model does not include every firm or industry-specific variable that might have an impact on the adoption decision, it does encompass the main effects implied by diffusion theory. Therefore, incomplete specification should not be a problem[11]. However, it is possible that the firm and industry level variables included might not pick up systematic individual differences. Hence, a model incorporating a term for unobserved heterogeneity into the Weibull specification was estimated (see Heckman and Singer, 1984b). Estimation of this model, however, showed individual heterogeneity to be insignificant[12].

6. Results

Table 2 summarises the variables used in estimation. Results for both technologies (Weibull baseline hazard) are presented in Tables 3 and 4. When modelling time to adoption, a negative coefficient means a negative effect on duration and, therefore, a positive effect on adoption speed.

The Weibull parameter tests significantly larger than one for both technologies, confirming the existence of positive duration dependence. The problem of collinearity between regional and nation-wide previous adopters is dealt with by the use of the national percentage of previous adopters[13].

Industry-specific fixed effects were estimated through the use of dummy

[10] In addition to the Weibull, estimations for exponential and log-logistic models were also obtained, showing similar patterns of results.

[11] One can, of course, enumerate many individual firm differences which are not explicitly covered by the model, such as quality of management and access to capital. However, it is expected that the firm-specific variables used will pick up most of these effects.

[12] A gamma distribution with mean equal to one and variance equal to a parameter σ was assumed for the heterogeneity term. The value estimated for σ was not significant at the 1% confidence level.

[13] Estimation of alternative models with and without the absolute values for regional and nation-wide previous adopters showed that collinearity was not too important; although coefficients were insignificant when both variables were used simultaneously, signs remained unchanged when each one of them was dropped, while only the regional variable became significant.

Table 2
Variable definitions and descriptive statistics

Variable	Definition	Descrip. stats.[a]	Data source
Time (in logarithms)	year of adoption (1969–80 for CNC machines; 1972–80 for microprocessors)	2.4037 (0.2286) 2.1731 (0.1066)	CURDS database
Age	age of establishment in 1981	31.516 (23.973)	CURDS database
Status	dummy variable set to 0 if establishment is independent	0.58261 (0.49337)	CURDS database
Size	establishment employment in 1981	227.03 (121.1)	CURDS database
R&D employment	full time R&D staff employed in 1981	5.4502 (18.37)	CURDS database
Industry fixed effects (SIC=320, 321, 322, 325, 328, 342)	dummy variables set for the three-digit SIC sectors	–	–
Percent of Previous Adopters	proportion of adopters of the technology in the total number of establishments, prior to current year	0.172 (0.06) 0.023 (0.029)	CURDS database
Previous adopters in region	number of adopters of the technology in establishment's region, prior to current year	19.871 (10.434) 9.6091 (4.6923)	CURDS database
Total expected adopters	expected number of adopters of the technology in current period (perfect foresight)	57.355 (18.369) 14.44 (13.924)	CURDS database
Technology price	price of technology in current period	2.7099 (0.85933) 0.49189 (0.034)	Karshenas and Stoneman (1993), and Swann (1985)
Expected technology price	expected price of technology in the next period (perfect foresight)	2.3707 (0.84918) 0.3951 (0.0318)	Karshenas and Stoneman (1993), and Swann (1985)
Expected variation in output (SIC 32)	logarithm of the expected change in industry output	5.133 (0.31047)	Census of Production
Regional employment (SIC-32)	industry employment in establishment's region in current year (in thousands)	101.44 (59.858)	CSO Census of Production

[a] The numbers presented are the mean and standard deviation (in brackets) for CNC machine tools (above) and microprocessors (below).

Table 3
Time to adoption: Model with Weibull baseline hazard[a]

	CNC machine tools	Microprocessors
Number of observations	11671	9161
Number of establishments	1035	1035
Log-likelihood	−969.3631	−210.9422
Variables[b]		
Age	**−0.001181**	**−0.0011**
	(0.000445)	(0.000018)
Status	−0.10244	−0.002005
	(0.2607)	(0.01021)
Size	**−0.000154**	**−0.000045**
	(0.0000236)	(0.0000102)
R&D employment	0.000682	0.0005244
	(0.000403)	(0.002325)
Percent of nation-wide previous	1.4115	−1.8504
adopters	(1.0365)	(1.45265)
Previous adopters	**−0.004037**	**−0.005918**
in region	(0.001043)	(0.001495)
Total expected	−0.001199	−0.165
adopters	(0.00187)	(0.079)
Price of technology	**0.00994**	**0.2957**
	(0.00505)	(0.02164)
Expected price	**−0.0611**	**−0.5216**
of technology	(0.02141)	(0.1015)
Expected variation	**−0.16967**	**−0.08057**
in output	(0.0259)	(0.007863)
Regional	−0.000099	0.0000821
employment	(0.000206)	(0.0000797)
Constant	2.0409	**1.4342**
	(1.345)	(0.26663)
Weibull	**1.15267**	**1.5698**
parameter	(0.00765)	(0.01864)
Likelihood ratio test[c]	**26724.6** ($\chi^2_{..99}[16]=31.99$)	**7594.6** ($\chi^2_{..99}[16]=31.99$)
Pseudo R^2	0.9323	0.9474

[a] Numbers in brackets are standard errors. Values in bold are significant with 5% confidence.

[b] Industry fixed effects were controlled for as discussed in the text. The coefficients for industry dummies are not reported, since the variables are not significant when taken individually.

[c] The likelihood ratio test and the pseudo R^2 compare the values of likelihood functions for the full model (including the five dummy variables for industry sector) with a model comprising only the constant term.

variables. Although none of the dummy variables was significant per se, the set of variables was significant as a whole[14].

[14] A likelihood ratio test for the inclusion of industry fixed effects showed that the effects were significant at the 1% confidence level (LR=56.4; $\chi^2_{.99}[5]=15.09$).

Table 4
Time to adoption (1969–77): Model with Weibull baseline hazard[a]

	CNC machine tools
Number of observations	8145
Number of individuals	1035
Log-likelihood	−638.21
Variables[b]	
Age	**−0.00481**
	(0.00202)
Status	−0.0397
	(0.101)
Size	**−0.000348**
	(0.000095)
R&D employment	0.00309
	(0.00177)
Percent of nation-wide previous	0.06189
adopters	(0.03919)
Previous adopters	**−1.4631**
in region	(0.3896)
Total expected adopters	−0.01711
	(0.01863)
Price of technology	**0.281**
	(0.0324)
Expected price of	**−0.0881**
technology	(0.0299)
Expected variation	**−0.475**
in output	(0.0511)
Regional	−0.000051
employment	(0.00091)
constant	12.17
	(12.191)
Weibull	**6.2742**
parameter	(1.533)
Likelihood ratio test[c]	**11488.5** ($\chi^2_{.99}[16]=31.99$)
Pseudo R^2	0.9000

[a] Numbers in brackets are standard errors. Values in bold are significant with 5% confidence.

[b] Industry fixed effects were controlled for as discussed in the text. The coefficients for industry dummies are not reported, since the variables are not significant when taken individually.

[c] The likelihood ratio test and the pseudo R^2 compare the values of likelihood functions for the full model (including the five dummy variables for industry sector) with a model comprising only the constant term.

The pattern of results is similar for the two technologies. Regional learning effects do exist and are significant on the adoption of both CNC machine tools and microprocessors. Coefficients in duration models can be interpreted in a way that is similar to that of ordinary least squares models[15]. For both technologies, a change from one standard deviation below the mean to one standard deviation above the mean of previous regional adopters moves adoption forward by about one year[16], which seems to be a large effect when compared to the average time until adoption, which is of about nine years for CNC machine tools and seven and half years for microprocessors. Such an effect demonstrates that firms located in regions with a large number of adopters move adoption forward by a considerable amount of time. One can, therefore, claim that there are significant learning effects arising from the geographical proximity of previous adopters.

The stock of total previous adopters does not have a statistically significant effect on the adoption of both CNC machine tools and microprocessors. Such a result confirms the expected ambiguousness resulting from the conflict between stock/order effects and nation-wide learning effects.

The regional industry dimension, as measured by employment, does not appear to be significant on adoption, suggesting that exogenous learning effects are not sensitive to spillovers coming from firms in the same or related activities. However, the variable *Regional employment*includes employment at both adopters and non-adopters, and it seems likely that spillovers such as the ones described will come mainly from adopters' employees. However, the data only include the number of employees per establishment (the *Size*variable) at the time of the survey (1981), making such distinction impossible for each year.

The results for CNC machine tools present a pattern that is quite similar to the one obtained by Karshenas and Stoneman (1993) for the same technology[17]. The main difference is the coefficient for age of establishment. While they find entry date to have an insignificant effect on adoption, the present study finds a significant positive effect. The effect is similar for both CNC machine tools and microprocessors: a change from one standard deviation below the mean to one standard deviation above the mean for age moves adoption forward by a little less than one year.

Size of firm presents a consistently positive effect on adoption for both technologies, and so do expected increases in industry output. In both cases, the size of the effect is larger for microprocessors than for CNC machine tools; changes from one standard deviation below the mean to one standard deviation

[15] The dependent variable (time to adoption) is entered into the model in logarithms.

[16] The estimate is illustrated for the case of microprocessors: Table 2 shows the standard deviation of the variable *Previous adopters in region* to be 4.6923; the coefficient obtained for this variable (see Table 3) is -0.005918. By multiplying the coefficient by twice the standard deviation, one finds that the explained variable (*Log of time*) changes by -0.05554. Taking the exponential, this corresponds to about 0.95 of a year. The same exercise yields 0.92 of a year for CNC machine tools.

[17] Although also originating from the CURDS survey, the data on CNC machine tools used by Karshenas and Stoneman (1993) is slightly different from those used here, in that subcontractors are included and firms are allocated according to the 1968 Standard Industrial Classification.

above the mean move adoption forward by almost one year for microprocessors, and by about nine to ten months for CNC machine tools.

Ownership status of the establishment and employment in R&D are never significant. Moreover, R&D employment has the opposite sign to the one expected.

The coefficients for technology price and expected technology price are also significant for both technologies, and have the expected signs. The significance and high magnitude of the coefficients for the expected price of technology[18] and expected industry output growth seem to confirm the finding that myopic-type models of diffusion are incorrectly specified (Karshenas and Stoneman, 1993).

The expected number of adopters has a positive significant effect on the adoption of microprocessors, but not on CNC machine tools. The result for microprocessors seems to be the only active kind of stock/order effect, and its magnitude is smaller than that of other explanatory variables[19].

Since it is expected that learning effects, particularly those acting at the regional level, would be stronger in the early stages of diffusion, alternative estimation periods were tested for both technologies. While the data covers 11 years for CNC machine tools and 8 years for microprocessors, models were estimated for smaller time spans[20].

For both technologies, regional learning effects, as measured by the regional stock of adopters, remained significant when smaller estimation time spans were considered. Moreover, in the case of CNC machine tools, the size of the regional learning effect became larger as the estimation period was reduced down to the first eight years. Results for CNC machine tools' diffusion for 1969–77 are presented in Table 4. A change from one standard deviation below the mean to one standard deviation above the mean of previous regional adopters now moves adoption of CNC machine tools forward by about one and a half years.

7. Concluding remarks

The results seem to substantiate the existence of a significant positive regional learning effect influencing diffusion. Moreover, estimation of the model for a

[18] A change from one standard deviation below the mean to one standard deviation above the mean of expected technology price moves adoption forward by almost ten months for CNC machine tools and by about eleven months for microprocessors.

[19] Still, a change from one standard deviation below the mean to one standard deviation above the mean of expected adopters moves microprocessor adoption forward by about seven months.

[20] Estimation periods smaller than five years were not considered, since the number of adopters was not enough to yield any significant results.

smaller time span after first adoption suggests that the effect is likely to be stronger in the early stages of the diffusion process.

Regional learning effects seem to be mediated through the presence of previous regional adopters. The positive regional learning effect on adoption speed overcomes any negative stock/order effects occurring at the same regional level. At the national level, the learning benefits are probably too weak to overcome the stock/order effects. However, such a result may also be caused by a stronger nation-wide stock effect brought about by increased competition because of the accumulation of adopters.

The present study finds what seems to be a significant order effect on diffusion acting through the expected number of adopters. This effect is possibly caused by pre-emption. According to Fudenberg and Tirole (1985), if the decisions of higher-order adopters can affect the adoption dates for lower-order ones, there will be a race to be high in the adoption order, in order to gain first-mover advantages. These advantages could be related to primary access to pools of specialised labour or prime geographical sites (Ireland and Stoneman, 1985).

However, such access does not explain why this effect is picked up for microprocessors and not for CNC machine tools. One possible explanation is that computer numerical control (CNC) devices embody an expensive technology which is often not adopted as a cost-saving measure but because of its ability to process more complex surfaces with less variation than a human machinist can. Therefore, pre-emption might not be an important determinant of the adoption decision. Also, the variables used to account for stock and pre-emption effects might not be the most appropriate ones. Empirical testing of game-theoretic models of diffusion still needs considerable improvement, and studies like Hannan and McDowell (1987) and Karshenas and Stoneman (1993) have not found evidence of any stock or order effects.

Unlike stock and order variables, firm-specific factors such as age and size are shown to have an important bearing on the adoption decision. Adoption of CNC machine tools and microprocessors is expected to reduce average costs, and bigger firms have a larger output in which to profit from lowering average costs. Moreover, firm age is positively correlated with firm size in the data. The positive impact of the growth in the output of the user industries supports the results of Karshenas and Stoneman (1993). The significance of expectations variables confirms that myopic models of diffusion are incorrectly specified.

Exogenous learning and epidemic effects are stronger at the regional level than at the global level, which should have important implications in terms of industrial and regional policies. Externalities related to knowledge tend to grow stronger as the geographical unit of reference becomes smaller; see Jaffe et al. (1993) for the case of knowledge spillovers, and Glaeser et al. (1992) for the case of agglomeration externalities associated with economic growth. The present study implies that the inverse link between knowledge externalities and the size of the geographic market also holds for the diffusion of process innovations.

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Appendix A. Modelling diffusion

A function $g_i(.)$ defines the benefits extracted in period τ by firm i from the adoption of a given new technology at time t ($\tau \geqslant t$), The arguments of $g_i(.)$ are a vector of variables representing firm and/or industry characteristics (rank effects), the number of firms already using the technology, representing the stock effect, and the number of firms expected to adopt in the periods after t, representing the order effects. The number of previous adopters located in the firm's own region is added to the model, in order to account for external effects resulting from localised networking. Defining P_t as the cost of adoption at time t, the net present value of the profits from acquisition at time t (Γ_{it}) will be:

$$\Gamma_{it} = -P_t + \int_t^{\infty} g(.) \cdot \exp[-r(\tau - t)]\,\mathrm{d}t \tag{A.1}$$

where r is the discount rate and no depreciation of the technological capital is assumed.

The choice of the optimum adoption time t^* is determined by two conditions:

1. the profitability condition imposes that acquisition at t^* must yield a positive profit, i.e., $\Gamma_{it} \geqslant 0$
2. the arbitrage condition requires that it must not be more profitable to wait beyond t^* to adopt, i.e., the net benefit from adoption must not be increasing over time:

$$\frac{\mathrm{d}\,[\Gamma_{it} \cdot \exp(-rt)]}{\mathrm{d}t} \leqslant 0 \tag{A.2}$$

It can easily be shown[21] that the arbitrage condition dominates the profitability condition and, thus, that t^* will be determined solely by the arbitrage condition.

[21] See Karshenas and Stoneman (1993).

Appendix B. Derivation of the log-likelihood function

Writing the adoption (arbitrage) condition in Eq. (A.2) as $y_i(t) \leqslant 0$, its stochastic form will be $y_i(t)+e \leqslant 0$, where e is an error term whose distribution is assumed to remain invariant across firms over time and is independent of y. Thus, the hazard rate will be:

$$h_i(t) = Pr\,[y_i(t) + e \leqslant 0] = \Psi\,[-\,y_i(t)] \tag{B.1}$$

where $\Psi(e)$ is the distribution function of the stochastic error term.

The unconditional probability of adoption can be represented as a function $f(.)$ of time and of the variables influencing adoption, plus a set of parameters. If $f(.)$ is defined as the density function for adoption times, then:

$$f = f(t;\, X_{it,}\,\beta) \tag{B.2}$$

The joint density function for adoption times can then be used to set up a likelihood function. Since the observations for some firms may be right-censored (some firms may not have yet adopted the technology by the last observation period, so their adoption time is greater than the censoring time), the likelihood function $L(\beta)$ is:

$$L(\beta) = \prod_1^n \{ f(t;Xit\beta)^\theta \cdot\, [1 - F(t;Xit\beta)]^{(1-\theta)} \} \tag{B.3}$$

where $F(.)$ is the distribution function corresponding to $f(.)$ and θ is an indicator variable which takes the value 1 for firms who had adopted by censoring time and 0 for right-censored firms.

An alternative way of specifying the duration distribution is to define a survival function $S(t)$, which yields the probability of a firm not having adopted the technology by time t. The survival function $S(t)$ is defined as: $S(t) = 1 - F(t) = f(t)/h(t)$. Kiefer (1988) has shown that Eq. (B.3) can be rewritten in terms of the hazard function as follows:

$$h(t) = -\,\mathrm{d}\ln[S(t)]/\mathrm{d}t \tag{B.4}$$

which means that:

$$S(t) = \exp\,[-\int_0^t h(t)\,\mathrm{d}t\,] \tag{B.5}$$

This yields:

$$f(t, X_{it}\beta) = h(t)\cdot S(t) = h(t, X_{it}\beta)\cdot \exp\,[-\int_0^t h(t, X_{it}\beta)\,\mathrm{d}t] \tag{B.6}$$

and, since $1 - F(t) = S(t)$, the likelihood function (B.3) can be rewritten as:

$$(\beta) = \prod_1^n \left\{ h(t;Xit\beta)\cdot \exp\left[-\int_0^t h(t;Xit\beta)\,\mathrm{d}t\right]\right\}^\theta \cdot \left\{\exp\left[-\int_0^t h(t)\,\mathrm{d}t\right]\right\}^{(1-\theta)} \tag{B.7}$$

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