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The Intra-firm diffusion of new technologies

by

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DECLARATION OF ORIGINALITY

I declare that this thesis is my own work and has not been submitted for a degree at any other University.

During the preparation of this thesis a number of conference papers and articles were written as detailed below. The remaining parts of the Thesis are unpublished.

The two following papers contain part of the empirical exploration of the existing literature presented in Chapter 2. This was the result of empirical work carried out during my first year of PhD (while I was also part time research assistant at the Warwick Business School Research Bureau). The theoretical approach of these papers is of Paul Stoneman.

- Stoneman P. and G. Battisti (1997)' Intra-firm Diffusion of New Technologies: the Neglected Part of Technology Transfer' *International Journal of Industrial Engineering*, Ohio-US, (4), 270-82.
- Stoneman P. and G. Battisti (1997), '*The Intra-firm Diffusion of New Technologies: a Preliminary Exploration of Some Recent Data*', Warwick Business School, paper prepared for the Conference on 'The Practice and Policy of Innovation', Cremona (I), May 1997.

A preliminary version of the new intra-firm equilibrium model outsourced from Chapter 5 and part of the theoretical weaknesses of the existing literature in Chapter 2 can be found in:

- Battisti G. (1998) 'The Replacement of the Old With the New: The Investment Decision, Intra Firm Evidence and Policy Guidelines' (forcoming for publication in A.Bartzokas (Ed.) '*The Economics of Industrial Structure and Innovation Dynamics*'
- Battisti G. (1999) '*The Replacement of the Old with the New and the Decision to Invest in a New Technology*', Working Paper n.3, Coventry University, paper presented at the 1999 European Meeting of the Econometric Society - Economic Theory Section.

A further paper extracted from the statistical implications of the methodology used in Chapter 6 is:

- Battisti G. (2000) 'Modeling Censored Continuous Outcomes of an Irreversible Choice with Semi Spatial Data. An Application to the Replacement Decision Under Uncertainty' paper accepted for presentation at the 2000 Royal Statistical Society Conference, Reading , 13-15 September.

ABSTRACT

The intra firm diffusion, that is the process leading a firm to *extensively* use new (or superior) technologies, is a key step to promote the growth and the competitiveness of a nation. However, even when advanced technologies are readily available within the market, the process leading a firm to replace the old with those new technologies can take several years, quite often decades. In existing economic literature this aspect of technological change has been almost completely neglected. In fact, despite its relevance, there exist only two relevant pieces of work in the area (Stoneman, 1981 and Mansfield, 1968). This thesis has pointed out the weaknesses of this literature on both theoretical and empirical grounds and has explored alternative theoretical approaches to modelling the intra-firm diffusion process. This has lead to the derivation of a new theoretical model, solidly grounded within economic theory. This model determines how changes in costs, price expectations (economic constraint), production organisation at plant level, existing and previous technologies (technological constraints), consumer demand and market structure (market constraint) and uncertainty can influence the degree of technology adoption by a firm. The impact of uncertainty, price expectations and market structure play upon the firm's investment decision in a new technology, have never been studied before. Moreover, using sophisticated statistical and econometric tools, this study also tests the validity of this theoretical approach, across a cross section of firms in the UK engineering and metalworking sector.

The theoretical model presented in this thesis is based upon neo-classical investment literature and provides a rationale explaining the potential unprofitability of a rapid transfer of all firm's production to a new technology. This can be seen as a unique contribution to the understanding of the determinants of the adoption of a new technology, while the empirical analysis provides considerable insight into a area where to date, little research has previously been completed.

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Chapter 1.

INTRODUCTION

In an era of increasing globalisation of markets, firms are increasingly exposed to world competition. This means that firms need to be producing at competitive costs in order to sell their products. There are many ways to contain costs and increase productivity. Among the several strategies, the firm might change the structure of its organisation, the qualitative aspect of its product or the production process of its output. Such changes, being new for the firm, are more commonly known as organisational, product or process innovations.

This Thesis focuses on the latter type of innovations and in particular on the process leading the firm to purchase innovative capital goods incorporating a new technology. 'New' technology here means any advanced, cost reducing, technology that is newer than the existing, or 'old', technologies owned by the firm. Consequently the new technology is not necessarily the 'latest technology on the market' but it is a technology that is new to the firm.

The adoption and in particular the extent of use of a new technology by a single firm is a very important step in the process of technology transfer. However, for many years most of the literature on the economics of technological change has been primarily concerned with the generation of innovation, i.e. invention and R&D, which is only the first step in the technological process change. Consequently the application of innovations (adoption/ extent of use) especially at the firm level has been relatively overlooked even though it is a key step in the realisation of benefits from technological change (Karshenas and Stoneman, 1995).

The generation of innovations (i.e. R&D) is important but it is only a sufficient and not a necessary determinant of adoption. It does not guarantee that all the firms within an industry immediately adopt them or adopt them at all. In fact on markets many advanced and old technologies do co-exist and even if they are accessible to the firm, a relevant proportion of old technologies are still available after several years from first appearance of more advanced technologies. This suggests that many firms do not immediately adopt the advanced technologies or if they do, they do not use them extensively in their production processes.

If one looks at existing studies on technology spreading, what is surprising to many is that the spreading of a new technology within an industry often takes several decades from first appearance on the market. Moreover, even after first adoption, firms often decide to only slowly replace their existing capital stock with a more advanced capital stock incorporating new technology. Whether it be a new consumer technology or a new producer (process) technology spreading across or within firms, the time period between first use of the technology and say 100 percent usage of that technology, is often many years and sometimes does not even reach complete diffusion (See for example the spread of steam engines in Mansfield -1968 and 1975-, the work of Battisti and Stoneman -1997, 1999, 2000- on the spread of adoption of Unleaded petrol, Karshenas and Stoneman –1992- on the spread of colour TV; etc).

If one believes that technological progress is the key to success, (or even in some cases survival), in order to reduce costs and remain competitive then, even when a technology is ready available on the market then:

1) Why do some firms not adopt the advanced technology ; what are the constraints to first adoption of a technology by each firm?

2) When firms do adopt a new technology why do firms not transfer immediately all their production to the new technology, but wait; what are the constraints to technology use; and what are the determinants of the rate of replacement of the old by the new?

A simple answer to these questions might be that many firms do not behave rationally or at least not as economic theory would predict. However, this does not sound very realistic. In fact, if one does believe in rational behaviour by economic agents (i.e. agents aim to maximise their profits) there should be an explanation as to why it is rational for a firm not to completely adopt immediately an advanced cost reducing technology, but rather wait. Once the reasons for this are understood, one should also be able to understand the timing and the determinants of the intra firm process of technology transfer within a firm as well as within an industry.

There exists an area of study in the economics of technological change, traditionally referred to as *technology diffusion*, that has looked at the process by which the use and/or ownership of a new technology spreads over time. Most of this literature is almost totally concerned with answering the first set of questions (1) above, concerning the process that leads firms to first adopt innovative technologies and the characteristics of first adopters i.e. inter firm diffusion (see Karshenas and Stoneman, 1995 for a survey of these studies). However, the extent of use of a technology within a firm (2), has been almost completely ignored. This thesis aims at answering the second set of questions deepening the understanding of intra firm diffusion, that is the process determining the time path of use of a technology within a firm from a point immediately after first use until diffusion is complete for that firm. In fact, if one is interested in the *extent of use* of a new technology in an industry, then it is just

as important to understand the development of technology use within the firm after first use (intra -firm diffusion) as it is to understand the pattern of first use across firms (inter firm diffusion).

From the existing intra firm literature on technology diffusion, and even more so the rest of the economic literature, our knowledge of the factors that determine the rate of replacement of old with new technology within a firm is very limited. At present there exists only two relevant pieces of work on intra firm diffusion and they go back to Mansfield (Mansfield, 1968) and Stoneman (Stoneman, 1981), since 1981, no relevant theoretical advancements have been made in the area.

Common to many inter-firm diffusion studies, the Mansfield Model assumes that the spread over time of use of a new process embodied in a new capital good follows an S-shaped curve and what leads to the spread of a technology over time is just information acquisition about the true performance of the technology. This is basically a disequilibrium process driven by passive information acquisition. However, as shown in a later chapter of this thesis, this does not seem to have empirical support or, at least, it is not robust across different technological specifications and presents a series of theoretical weaknesses which are difficult to accept.

Stoneman (1981) presents an alternative sophisticated equilibrium model based upon Bayesian learning showing that diffusion is faster the greater is the true profitability of the new technology. However, despite the sophisticated theory, the Stoneman Model is intractable empirically. This indicates that there is still an enormous gap in the literature concerning the understanding of why, if it is so advantageous to use a new cost reducing technology, some firms do not use it extensively.

This thesis aims at fully covering this gap in the literature, explaining why it might be rational for a firm to not immediately transfer all its output to the new technology but rather to wait. It also aims at harmonising the micro and macro viewpoints bringing attention to the need to more closely look at the complexity of the process of technology transfer within a firm from a point immediately after first adoption until the diffusion is completed for that firm. This involves a new approach to the determinants of the diffusion process based on economic theory and robust to empirical evidence.

The route followed in this study leads to the specification of a new theoretical equilibrium intra-firm model solidly grounded in the economic theory of investment. This model determines, for a single firm, the optimal replacement path of the old with the new technology, taking into account how firm characteristics, changes in costs, uncertainty, expectations and market structure can influence the degree of technology adoption by a firm. Excluding the Stoneman model (1981), equilibrium models for intra-firm diffusion have never been studied. For this reason, the theoretical model presented in this thesis can be seen as a relevant contribution to the theory of the determinants of the adoption of new technology.

The paucity of data on intra-firm diffusion has been for years one of the main limitations to empirical analysis. Data on the level of adoption are not collected systematically and ad hoc periodical surveys are the only, rare, source. The data set used in this study come from a survey of technology adoption carried out over a sample of UK firms in the engineering and metalworking industry sector undertaken by the Centre for Urban and Regional Studies (CURDS) at the University of Newcastle upon Tyne. The survey has been conducted three times: in 1981, 1986 and

1993. It contains longitudinal data on firm characteristics, inter firm measures of diffusion, such as first adoption dates for five technologies, and some other relevant information about the determinants of the diffusion processes. The 1993 survey also contains intra firm measures of diffusion such as the percentage of machines tools of the firm that in 1993 incorporated each of the four (out of five) process technologies in the sample. The four technologies being: Numerical control of metal cutting, forming or joining machinery (NC), Computerised numerically control of metal cutting forming or joining machinery (CNC), Coated Carbide or Ceramic Tools or inserts for metal cutting (CoT) and Microprocessors incorporated into processes (Micro). The fifth technology present in CURDS sample is Robots. However, the lack of information about the firm level of ownership has lead us to exclude it from this study.

The list of the variables and the characteristics of the full data set are detailed in Appendix A.

The thesis is organised along the following lines. Chapter 2 explains why intra firm diffusion is important. Chapter 3 discusses, theoretically and empirically, the existing literature in the area. Chapter 4 presents two different economic approaches to modelling the profitability of adoption (i.e. stock effects). Chapter 5 presents a new equilibrium intra firm model based upon neoclassical assumptions, adjusted for uncertainty and price expectations. Chapter 6 presents the necessary statistical caveats and the econometric techniques used to estimate the intra firm diffusion model. In Chapter 7 the results of the testing procedure is presented in detail for the technologies in the CURDS sample. Finally, Chapter 8 concludes the study with a summary of the main findings.

Chapter 2.

THE INTENSITY OF TECHNOLOGICAL REPLACEMENT IN UK MANUFACTURING. WHY INTRA FIRM MATTERS.

2.1 Introduction

The process of adoption of superior technologies is a very important step in the process of technology transfer. It reflects the dynamism and the flexibility of an industry to be innovative. Consequently, the speed of technology replacement of the old with the new technology is a key variable in generating industry productivity growth and competitiveness (Doms et al, 1995, Barro Sala I-Martin 1995, Aghion 1998, Grossman and Helpman 1991, Verspagen 1991, 1992, Rosemberg 1994, Mansfield 1963a/b, 1968, etc). However, even within a given industry, the timing of first adoption and the extent of use of advanced technologies are very heterogeneous. Despite advanced technologies being available on the market, technology replacement both within a firm and within an industry takes many years and sometimes, for certain technologies, does not even reach 100% replacement of the existing 'inferior' technology.

The inter firm diffusion literature has partly explored technology transfer by looking at the determinants of first adoption, i.e. when the firm adopts for the first time at least one unit of the new advanced cost reducing technology (see Karshenas and Stoneman 1995 for a survey). It also models the speed of technology spread across firms. However, to be an adopter does not necessarily mean to be an extensive user. In fact, within an industry some adopters produce 100% of their output on the innovative cost reducing technology but several other own only small proportions of it and produce, say, only 10% of their output on the new technology. Consequently, the total amount

of technology ownership, or alternatively the industry output produced on the new technology, does not equal the proportion of first adopters. To look only at the inter firm spread of ownership of a technology, i.e. number of users,would overestimate the impact of technology use at the industry level and at the same time it would underestimate the potential benefits from adoption.

In order to evaluate the within industry extent of use of a technology, one needs to understand the dynamics and characteristics of technology spreading. The latter is determined not only by the timing of first adoption by a firm (*inter firm diffusion*) but also by the firm's specific timing and speed of the replacement process of the old with the new technology after first adoption (*intra-firm diffusion*).

The literature on intra firm diffusion is extremely limited even though it is one of the main determinants of the firm's innovative capability.

This chapter, using the information in the CURDS data set, shows why intra firm diffusion is important. It also, preliminarily explores the spread of use of a set of advanced technologies both across and within the sample of UK firms. In particular, section 2 shows the different pattern of intra versus inter firm adoption of a set of technologies in the CURDS sample. Section 3 presents different indicators of technology diffusion and how sensitive they are to the measurement used. A final section measures the relative importance of the within firm level of adoption (intra-firm diffusion) and the total number of adopters (inter-firm diffusion) upon the overall industry level of use of new technology.

2.2. Patterns of technology adoption: *Inter-firm* and *intra-firm* diffusion

In any economy, there are many examples of new technology spreading, where, by new technology is meant a process innovation or an advanced cost reducing technology incorporated in capital goods. However, data upon the spread of use is not systematically collected by any official statistical agencies. The paucity of suitable data for analysing the diffusion of this phenomenon is one of the main reasons why intra firm diffusion has been relatively ignored in the literature.

The CURDS data set is one of the rare data sets that provides information on intra firm diffusion, in this case for a sample of 343 establishments in the UK Engineering and metalworking sector on the pattern of ownership and use over time of four technologies: Numerical control of metal cutting, forming or joining tools (NC); Computerised numerical control of metal cutting forming or joining tools (CNC); Coated Carbide or Ceramic Tools or Inserts for metal cutting (CoT); and Microprocessors incorporated in processes (MICRO). For each technology it provides information on the date at which each firm first adopted the four technologies (if adopted by 1993). This gives direct evidence on the within industry spread of use of the new technology i.e. the pattern of inter-firm adoption since the appearance of the new technology. The survey also provides information on the level of ownership of the new technology by each firm in the 1993 sample[1] and consequently the pattern of intra-firm diffusion of the new technologies.

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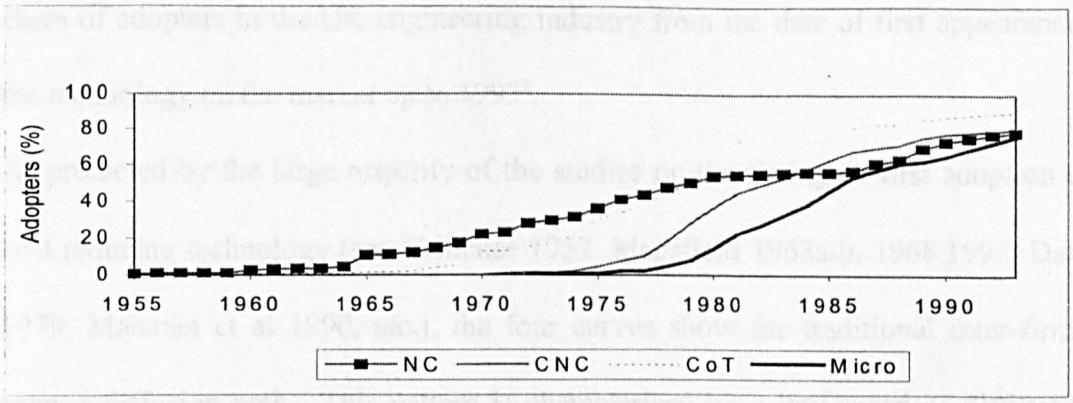
[1] The data set provides longitudinal data on technology first adoption based upon retrospective questions asked in the three surveys carried out in 1981, 1986 and 1993. Data on the extent of use of the technology have been introduced only in the last survey, consequently they are available only for the 343 firms in the 1993 sample.

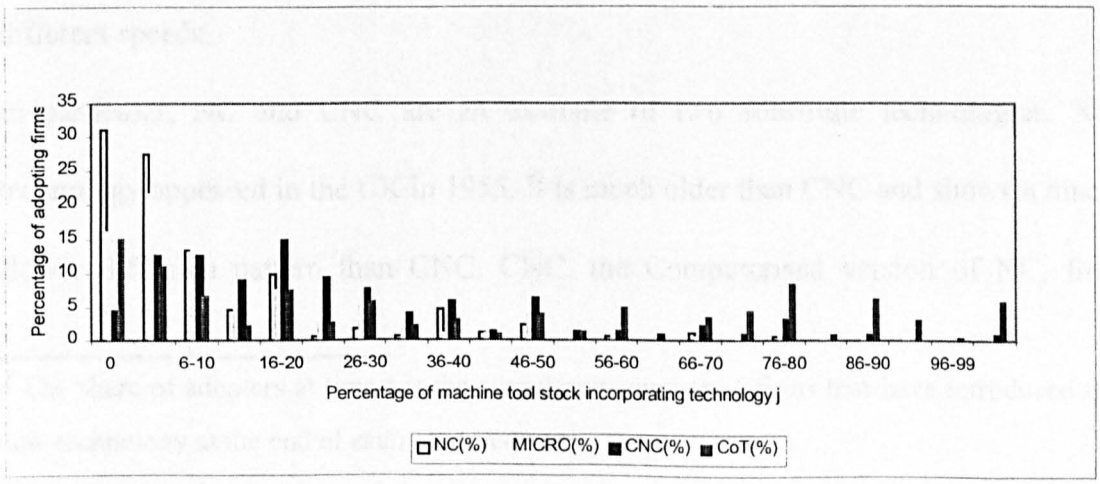
Figure 2.1. Inter firm diffusion of NC, CNC, CoT and Micro



Source: CURDS data set - personal elaboration

In order to give an idea of the difference between inter and intra firm diffusion, the two measures of technology diffusion are illustrated graphically. Figure 2.1 shows the pattern of inter-firm diffusion since the appearance of each new technology up to 1993, while Figure 2.2 plots the level of intra-firm diffusion among the cross-section of firms in 1993.

Figure 2.2 Intra firm diffusion of NC, CNC, CoT and Micro



Source: CURDS data set - personal elaboration

In Figure 2.1 the inter-firm path of the four technologies is measured over time as the share of adopters in the UK engineering industry from the date of first appearance of the technology on the market up to 1993[2].

As predicted by the large majority of the studies on the timing of first adoption of a cost reducing technology (see Griliches 1957, Mansfield 1963a/b, 1968,1993, Davies 1979, Mahajan et al 1990, etc.), the four curves show the traditional inter-firm S-shaped diffusion path. This pattern is characterised by a low speed of diffusion in early years, which increases in the central diffusion period up to the inflection point, after which use tends asymptotically to the ceiling or saturation level (≤100 % of adopters).

Figure 2.1 also shows that, despite the number of years from their appearance, i.e. NC (1955), CNC (1968), CoT (1949), Micro (1971), by 1993 none of the technologies have completed the process of technology spreading, adoption levels being between 78% and 90%[3] of eligible firms. This means that despite the number of years from first appearance of the technologies, between 22% and 10% of the firms still have to adopt them for the first time. Moreover, each technology spreads over time at different speeds.

In particular, NC and CNC are an example of two substitute technologies. NC technology appeared in the UK in 1955. It is much older than CNC and shows a much slower diffusion pattern than CNC. CNC, the Computerised version of NC, first

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2 The share of adopters at time t is the cumulative number of firms that have introduced the new technology at the end of each observed year.

3 A particular characteristic of the data is that for each of the technologies there exists a proportion of establishments that have adopted the technology prior 1993 but that in 1993 register zero ownership. This means that the technology has been dismissed. Those establishments have been included in the measurement of inter-firm diffusion in Figure 2.1.

appeared in the UK in 1971 and spread very quickly. In 1983-84 the number of CNC users becomes greater than the number of NC users. The faster speed of diffusion may be due to the spillovers from the accumulated experience gained by the use of NC, which can be regarded as an old generation of CNC. In 1993 the proportion of firms in the sample that have adopted NC and CNC are, respectively, 76% and 81% of the total eligible firms within the sample.

CoT, first appearing in 1955, is a technology enhancing the performance of both CNC and NC. CoT spreads much more slowly than the other two technologies but, in 1993, the proportion of adopters is much higher than NC and CNC, CoT having being adopted by almost 90% of the eligible firms. This is due to CoT being a (multi) complementary technology and to the increasing number of users of CNC and NC (or both) adopting the technology[4].

Microprocessors incorporated into processes (Micro), similar to CNC, appeared on the UK market at the beginning of the seventies. Its spread of use has occurred at a much slower (and constant) rate than CNC. In 1993 it had been adopted by about 76% of the British engineering and manufacturing firms in the sample reaching almost the same diffusion level as NC and CNC.

Based upon the evidence of the inter-firm diffusion in Figure 2.1 one might conclude that: a) the adoption pattern is technology specific, each technology being

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[4] The joint adoption of NC and CoT is an example of technological complementarity in the production process. Figure 2.1 shows the simultaneously of their adoption path, that is proved to lead to cross technology effects , i.e. the presence of one technology does affect the presence of the other. From Figure 2.1 it is also possible to see the impact on NC of the appearance of its substitute CNC and the complementary of the last one with the CoT. See Colombo and Mosconi (1994), Stoneman and Kwon (1994) on simultaneous diffusion of multiple technology and interconnections between technologies such that the diffusion of any one technology is not independent of the diffusion of another technology.

characterised by its own speed of diffusion; b) in 1993, the within industry processes of technology diffusion of the four technologies is slowly moving towards completion, with level of use ranging between 79% and 90% of users[5]. Furthermore, the high number of years from first appearance of the new technology might legitimate the assumption that, in 1993, the proportion of output produced on the new technology, by those firms that have adopted the technology especially at early years, is quite high, i.e. approaching 100 %. If this were true, a large proportion of the firms would have already completely replaced their old machinery with the new, and the percentage of users would fairly reflect the industry output produced on the new technology.

Figure 2.2 shows the intra firm level of adoption of the four technologies as the percentage of machine tool stock that incorporates the new technology for the sample of adopters in the UK engineering industry in 1993. Contrary to what one might have expected, the level of adoption is quite heterogeneous. In 1993, only a small proportion of firms have completed the replacement process of the old with the new technology and despite extensive first adoption, only a small proportion of total industry output is being produced on the cost reducing advanced technologies.

NC technology is the oldest technology in the sample and thus one might expect that the process of intra-firm diffusion would have proceeded further. In 1993 only 118 firms still had NC machines in their capital stock, implying that 31 % of the sample had previously adopted but were no longer users in 1993.

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5 Only those firms that are potential or actual users of the technology have been included in the sample. Those firms for which adoption is not applicable (i.e. not compatible with their production) are not included. This means that between 21% and 10% of the firms in the sample are still potential adopters.

The rationale for this is obviously going to be related to the supercedence of NC by CNC in that one might expect that as CNC is adopted it replaces NC (see Figure 2.1). Among the users of NC machines, in 1993 only 3.3 % of the sample claim that the tool represented more than 50 % of the machine tool stock of the establishment.

CNC is a relatively young technology complementary to NC machines tools. However, of the sample of 343 firms, 222 had adopted it by 1993, of whom 212 where still users in 1993. The extent of intra-firm use is however limited. The proportion of the machine tool stock of the establishments that incorporates CNC is less than 20 % for 52 % of the firms and only 7 % have a proportion in excess of 70 %.

CoT is a cheap technology complementary to NC and CNC technologies enabling the latter to be more productive. 226 firms in the sample had adopted the technology by 1993 but at that date only 192 still used the technology. However, the extent of intra firm diffusion of CoT is generally higher than for the other two technologies. Thus nearly 6 % of the sample register 100 % use, whereas 36 % report that the proportion of the machines tool stock incorporating CoT is greater than 50 %.

Microprocessors incorporated into processes (Micro) appeared on the UK market at the beginning of the seventies. By 1993, out of the 244 potential adopters, 185 firms have adopted this technology but only 155 of them were still currently using it. The distribution of the within firm extent of use of Micro is very skewed to the right due to the high concentration of firms, which own only a small proportion the new technology. About 66% of the current users report that the proportion of the machine tool stock incorporating Micro technology is less than 30%. Only 7 % have a proportion in excess of 70 %, among them only 2% are using the technology at 100%.

The empirical evidence upon the intra and inter firm adoption pattern of the four technologies in these manufacturing industries seems to suggest that despite the high

level of inter-firm adoption, in 1993, the average industry output produced on the new technologies is very low and highly heterogeneous. Consequently despite the number of adopters, the whole industry is still not fully exploiting the potential benefits from the cost reducing technologies. This proves that, if one is interested in measuring the benefits from adoption of a new technology within an industry then it is as important to look at the the level of ownership within a firm (intra firm diffusion) as it is to look at determinants of first adoption of a new technology among firms (inter firm diffusion).

The next section further explores the relative impact of inter versus intra firm diffusion on total industry output produced on new technologies.

2.3. Measures of technology diffusion

The empirical evidence on the diffusion pattern of the set of technologies in the CURDS data set (i.e. NC, CNC CoT and Micro), has shown that the spread of use of a technology can be measured by either the number of adopters within an industry (inter–firm diffusion) or by the within firm extent of use of the new technology (intra-firm diffusion). It has also been pointed out that the number of adopters, as an indicator of the extent of use of a technology in the industry, can be very biased. It does not take into account that the "within" level of technology use is highly heterogeneous and to be an adopter does not necessarily mean to be an extensive user. Within an industry there are firms that (a) have adopted the technology at some point in the past (adopters),(b) firms that could but have not yet adopted the new technology (potential adopters) and (3) firms for which the technology is not suitable to their production process (non-eligible). For obvious reasons the latter are not considered in

this study and as such have been dropped out of the sample. Among the adopters there are firms that are currently using variable levels of the new technology (users) and those that have in the past but by 1993 are no longer using the technology (ex-users). This shows that further to the definition used, the measure of technology spreading is very sensitive also to the base population used.

The indicator of the overall spread of adoption of a new technology that takes into account this heterogeneity across firms and over time, is the level of industry output produced on the new technology. This reflects both increasing numbers of technology adopters within an industry and their variable level of use of the new technology.

Table 2.1 summarises the main indicators of technology diffusion within the industry for the four technologies over a cross section of firms in the CURDS 1993 sample. In particular column one and two show the average total industry output produced by the new technology and the percentage of firms in the industry that have adopted the technology by 1993. The last two columns show the average extent of use as the average percentage output produced on the new technology by first adopters (column 3) and current users (column 4)[6].

6 The information contained in the CURDS data set concerns the proportion of capital stock of the firm incorporating the new technology. This is the intra-firm definition based upon the stock of new technology owned by the firm. The corresponding flow definition is the proportion of output produced on the existing technology. One might argue that they are not equivalent. However, given the heterogeneity of the firms level of use, the firms productivity differentials, due to the different combination of inputs used their production system, can be reasonably eliminated by calculating the industry average and assuming that the differentials are normally distributed around it.

Table 2.1. Major indicators of within industry technology diffusion in 1993 (percentages)

	1	2	3	4
	Average Industry Output[a]	Industry number of adopters[b] (inter-firm adoption)	Average Output per adopter[c] (intra industry use)	Average Output per current user[d] (intra industry use)
Sample	Total eligible firms	Total eligible firms	Adopters	Current Users
NC	7.0 (268)	78.6 (211)	8.27 (211)	16.32 (115)
CNC	20.6 (270)	82.0 (222)	25.1 (222)	27.8 (212)
CoT	40.0 (250)	90.3 (226)	41.5 (226)	49.0 (192)
Micro	13.8 (244)	76.1 (185)	18.2 (185)	21.7 (155)

NOTES: a) Average industry output produced on the new technology by the total number of eligible firms in the sample (current users, ex users, potential adopters); b) Proportion of adopters over the total number of eligible firms; c) Average industry output produced by those firms that have adopted the technology (users and no longer users); d) Average output produced by current users. Number of firms in brackets.

SOURCE: CURDS data set- Personal elaboration

Table 2.1 shows that despite between 76% and 90 % of the eligible firms in the sample having adopted each of the technologies (column 2), the proportion of output they produce with each technology is only between 8% and 42% (column 3).

If one excludes from the sample those adopters that are no longer using the technology (ex users), this proportion is slightly higher, ranging between 16% and 49% (column 4). At the industry level only 8% to 40% of total output is produced with the new technologies (column 1). This would suggest that, despite the number of adopters (or current users), the potential benefits from the use of the new technology are still far from being fully exploited. Table 2.1 also shows that the different measures of technology diffusion are very sensitive to the definition used and they reflect the fact that, within an industry, current users do coexist with potential adopters and ex-users. This heterogeneity can be better seen looking at each single technology.

NC is the oldest technology in the sample. In 1993, on average, around 16% of the capital stock owned by the current users incorporated NC . However, the current users (115) are around a half of those firms that have in the past adopted NC (211). The other half are no longer using it, presumably because it is now regarded as obsolete technology slowly being replaced by CNC, the advanced computerised version. This proportion is even less if one considers the total sample of eligible firms, i.e. potential adopters, current users and ex users (268). Consequently, despite the number of adopters being about 78.6%, only 7% of total industry output is produced on NC.

Similar to NC, in 1993, about 82% of firms have in the past adopted CNC but in 1993 only 43% are currently using the technology, on which they produce, on average, 28% of their total output. As a result, only about 20.6% of industry output is produced on CNC.

As expected, CoT is the most popular technology being complementary to both NC and CNC. By 1993, 90.3 % of the firms in the sample have adopted it and most of them (95%) are still using the technology in their production processes, producing each an average of 50% of their output on this technology. The resulting total industry average output produced on CNC is around 40%.Consequently the difference between the firm average (50%) and the industry average level of output (40%) produced on the new technology is mostly due to around 10% of the eligible firms within the industry not having yet adopted CoT.

Microprocessors are used in only 13.8% of the total industry production processes. Among the current users (64%) the average current level of ownership is 21.7%. The difference between the average industry use and the firm's average use is due to the fact within the industry there are adopters that, in 1993, have ceased its use (12%) and firms that still have to adopt Microprocessors for the first time (about 24%).

In the light of these results, it is possible to conclude that the measure of use of a new technology is very sensitive to the indicator used as it is a function of both the increasing number of adopters (and ex users) and the output produced by the current users of the technology. As they change over time so does the total industry use of the technology.This also suggest that, if one is interested in measuring the industry benefits from the spread of a cost reducing technology then it is important to look at the average output produced on the cost reducing technology (intra firm diffusion) and not simply at the number of users (inter firm diffusion).

The next step in this preliminary study is to disentangle the relative contribution of the number of adopters (inter-firm effect) and the average firm level of use of a new technology (intra-firm effect) upon the *spread of use of a new technology within an industry* as measured by industry output produced on the advanced technology.

2.4. Relative impact of inter vs intra firm diffusion

In light of the differences in the inter and intra firm approaches to the measurement of the industry extent of use of a technology, it should now be evident that to refer only to the level of industry adopters (inter firm diffusion) does overestimate the industry level of use of a new technology. Moreover, while the decision to become an adopter is irreversible, to extensively use the technology can take several years and can be subject to permanent or temporary interruptions, depending upon the firm's internal and external conditions. The complexity of this investment decision gives rise to different timings of inter firm first adoption and different levels of intra-firm extent of use of the new technology over time.

The level of total industry output produced on the new technology reflects both effects. Leaving aside, for the moment, the ex-ante determinants of the investment decision, this indicator of technology adoption can be used to measure the ex-post-relative importance of intra- versus inter-firm diffusion upon the spread of a new technology within an industry. This can be done by using simple algebra.

Assume that the industry level of use of a new technology (D_t) [7] can be written as the industry output produced on the new technology j, (Y_{tj}) over the total output of the industry (Y_t):

$$D_t = Y_{tj} / Y_t \qquad (2.1)$$

where Y_{tj} equals the sum of the output produced using technology j by each firm i that has adopted technology j ($Y_{tj}=\Sigma_i\ y_{tij}$) and Y_t equals the sum of the total output produced by all firms in the sample ($Y_t=\Sigma_i\ y_{ti}$). Moreover, using averages instead of absolute measures one can rewrite Y_{tj} as the average output produced on technology j ($\bar{Y}_{tj}=\Sigma_i\ y_{tij}/N_{tj}$) times the total number of adopters (N_{tj}) within the industry, i.e. $Y_{tj}=N_{tj}.\bar{Y}_{tj}$. The same can be done for the total industry output Y_t, with respect to the average total output ($\bar{Y}_t= \Sigma_i\ y_{ti}/N_t$) produced by each of the N firms, within the industry , i.e. $Y_t= N_t\ \bar{Y}_t$. This allows one to rewrite (2.1) as :

$$D_t = \frac{(N_{tj}\ \bar{Y}_{tj})}{(N_t\ \bar{Y}_t)}$$

[7] The above preposition is expressed in term of flows rather than stocks, i.e. Yn_t/Y_t. However one could just as easy define D as to represent the stock of the new capital good owned by the firm without materially changing the problem.

or equivalently as (2.2):

$$D_t = \left(\frac{N_{tj}}{N_t}\right) * \left(\frac{\bar{Y}_{tj}}{\bar{Y}_t}\right) \qquad (2.2)$$

(LEVEL ANALYSIS)

where N_{jt}/N_t is the proportion of adopters over the total number of firms (inter firm effect), and $\bar{Y}_{tj}/\bar{Y}_t$ is the industry average output produced with the technology j, by those firms who have adopted, over the average total output produced across all firms (intra firm effect).

Using the log transformation, equation (2.2) can be rewritten in additive form as (2.3):

$$\log D_t = \log \frac{N_{tj}}{N_t} + \log \frac{\bar{Y}_{tj}}{\bar{Y}_t} \qquad (2.3)$$

Further, dividing both side of equation (2.3) by $\log D_t$ and using percentages instead of proportions allows one to derive the relative importance of inter-firm and intra-firm effects upon the spread of use a technology j within an industry at each point in time as:

100% = Relative inter firm effects (%) + Relative intra firm effects (%)

log(inter firm adoption)/log(total industry use) +log(intra firm adoption)/log(total industry use)

(RELATIVE ANALYSIS)

Moreover, by first differencing equation (2.3) one can derive (2.4):

$$\frac{d\log D_t}{dt} = \left(\frac{dN_{jt}}{t}\frac{1}{N_{jt}} - \frac{dN_t}{dt}\frac{1}{N_t}\right) + \left(\frac{d\bar{Y}_{jt}}{dt}\frac{1}{\bar{Y}_{jt}} - \frac{d\bar{Y}_t}{dt}\frac{1}{\bar{Y}_t}\right) \qquad (2.4)$$

(GROWTH RATE ANALYSIS)

Equation (2.4) illustrates that the rate of growth of the industry level of use can be split into two components: (i) the intra firm growth rate and (ii) the inter firm growth rate. This is a useful indicator as it shows the direction and the intensity of the growth of the inter and intra firm effects over time.

The implications of this derivation can be better explained using a practical example. For ease of presentation only the diffusion of CNC machine tools is reported. Similar results have been obtained for the other technologies in the CURDS sample.

In Table 2.2, column 2 shows the average industry usage of CNC, while columns 3 and 4 show, respectively, the inter and intra-firm[8] effect in absolute level as in equation 2 (*LEVEL ANALYSIS*). Column 4 and 5 show the relative impact of inter and intra firm effects upon the total industry current level of technology adoption (*RELATIVE ANALYSIS*). Finally columns 6, 7 and 8 show, respectively, the speed of the spread of industry adoption, inter and intra firm effects, with their relative impact in brackets (*GROWTH RATE ANALYSIS*)[9].

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8 The measure of intra-firm diffusion is available only for 1993. Retrospective information has been interpolated over time from the point of first adoption to 1993 and the resulting pool industry average calculated for each year.

9 One might object that equations 1-3 assume that establishments are homogeneous. In order to take into account that establishments are different in some important characteristics, the same exercise has been carried out weighting each component by the size of the establishment i.e. number of employees and turnover. The results do not change significantly especially when the relative effects are compared. The interested reader can find all the details of this exercise for CNC, in Appendix B. For this reason and for brevity of presentation only the unweighted form is discussed here.

Table 2.2 CNC INTER AND INTRA FIRM EFFECTS

	LEVEL ANALYSIS[a]			RELATIVE ANALYSIS[b]		GROWTH RATES ANALYSIS[c]		
1	2	3	4	5	6	7	8	9
Year	Prop. of Industry Output *(D)*	Prop. of Industry Adopters *(Nn/N)*	Prop. of Output per adopter *(Yn*/Y*)*	**INTER-firm Impact (%)** *Log(Nn/N)*	**INTRA-firm Impact (%)** *Log(Yn*/Y*)*	Industry Usage *D(Yn/Y)*	Industry Adopters (%) *(dNn/Nn-dN/N)*	Output per adopter (%) *(dYn*/Yn*-dY*/Y*)*
1993	0.228	0.82	0.278	**13.41%**	**86.59%**	0.577	0.152 **(23.64%)**	0.489 **(76.36%)**
1986	0.099	0.70	0.142	**15.58%**	**84.42%**	0.675	0.372 **(38.81%)**	0.516 **(61.19%)**
1981	0.032	0.47	0.068	**22.02%**	**77.98%**	0.940	0.912 **(73.56%)**	0.328 **(26.44%)**
1975	0.002	0.04	0.046	**50.96%**	**49.04%**	-	-	-

NOTE: a) Level analysis: $D_{tj}= Y_{tj}/Y_t= (N_{tj}/N_t)(\bar{Y}_{tj}/\bar{Y}_t)$; b) In Log analysis: $\log (Y_{tj}/Y_t)= \log(N_{tj}/N_t)+\log(\bar{Y}_{tj}/\bar{Y}_t)$; c) Growth rate analysis: $d\log D_{tj} = [dN_j/N_j-dN/N] + [d\bar{Y}_{tj}/\bar{Y}_{tj} - d\bar{Y}_t/\bar{Y}_t]$ where: $\bar{Y}_{tj}=\Sigma_i Y_{tij}/N_{tj}$ and $\bar{Y}_t=\Sigma_i Y_{ti}/N_t$ i=1..N

SOURCE: CURDS data set - personal elaboration

Based upon the figures in Table 2.2 (column 3), in 1993 the inter firm diffusion of CNC is still an ongoing phenomena. The number of adopters has increased over time from 4% in 1975 to 82% in 1993. However, in 1993, after about 23 years from first appearance of the technology, about 18% of the eligible firms still have to adopt CNC for the first time.

The speed of inter firm diffusion (column 8) indicates that there is a large increase in the number of first adopters from when CNC first appeared on the market up to the point of inflexion in 1982 (i.e. GR_{1981}=0.972). After that date the growth rate is still positive but decreasing, tending asymptotically to its ceiling or saturation level (i.e. GR_{1986}=0.372 and GR_{1986}=0.152 in 1993). In other words, as already seen in Figure 2.1, the time path of CNC first adoption follows the traditional S-shape growth curve slowly moving ,in 1993, towards its maximum or saturation level.

Table 2.2 also shows the pattern of the intra firm effect over time. Column 4 indicates that the firms over time gradually increase their proportion of output produced on the new technology from about 5% in 1975 to about 14% in 1986. In 1993 the average rate of replacement is still far from 100 %, being, on average, only 28%.

In column 9 the growth rate analysis indicates that the intra firm diffusion does not follow the inter firm S-shape path but rather increases exponentially over time, with a modest start (0.328 in 1981) which increases over time (0.52 in 1986 and 0.50 in 1993). The total industry output produced on the cost reducing advanced technologies (column 2) is slowly increasing over time reaching 23% in 1993. This corresponds to about 82% of adopters each producing on average about 28% of their total output with the new technology. These figures are even lower in previous years.

The comparison of the relative importance of the inter and intra firm effects upon the total average industry output produced on the new technology is illustrated in the central part of the table (column 5 and 6). In the first years after appearance of the new technology the inter firm diffusion process has a relatively higher impact than the intra firm effect and it accounts for almost 51 % of the technology spread. However, its relative importance is annually decreasing over time compared to the intra firm effect. The latter shows an initial relative impact of 49 % while for the rest of the period its magnitude is almost 4 times that of the inter firm effects.

Form this one can conclude that the inter-firm effect has played a significant role in the first years from the appearance of CNC (1970). However, for the remainder of the period up to 1993 the intra firm effect has exerted a much greater impact than the inter firm effect upon the proportion of industry output produced on the new technology.

Counterfactual analysis can show this in a much more straightforward way. Controlling for each single component one can isolate the impact it exerts on the

spread of the new technology. For example, assuming 1986 as the base date and imposing the counter factual assumption of an unchanged inter firm effect up to 1993, the proportion of output produced on the new technology would have been 0.12. Keeping, instead, the inter firm effect stationary as the base case, that is no inter firm diffusion since 1986, the increase in the proportion of output produced on the new technology would have been about 0.20 in 1993. This implies that in 1986 the intra firm level of adoption of a new technology, in absence of inter firm effects, would have increased the average industry output produced on the new technology almost twice as much as inter firm effects alone. If, instead the base case is kept equal to 1975, the total output produced on the new technology in absence of changes in intra and inter firm effects would have been respectively 0.022 and 0.003 in 1981 and 0.03 and 0.01 in 1993. This would indicate that inter firm effects exert a greater impact upon diffusion in early years of adoption than in later years, while the reverse is true as time goes by. It also indicates that in order to increase the proportion of output produced with the new technology, both intra and inter effects should grow over time.

2.5. Conclusion

This chapter, using the information contained in the CURDS data set, has looked at different indicators of inter and intra firm technology diffusion showing that the diffusion path over time is technology specific, occurs at different speeds and the level of ownership of the new technology across firms is quite heterogeneous.

In 1993, the within industry spread of adoption (inter firm diffusion) of the four technologies here examined (NC, CNC, CoT, Micro), is slowly moving towards saturation the technologies having been first adopted by between 76% and 90% of the firms in the industry.

In the same year, the firms' extent of use of each technology (intra-firm diffusion) is quite low, ranging between 8 and 42%. Despite the relatively high number of users and the years since the launch of the technologies, only a small proportion of firms are close to completion (or have completed) the replacement process of the old with the new technology. The resulting proportion of total industry output produced on the cost reducing technologies is even lower, i.e.7% to 40%, the difference between the two measures being due to the coexistence of ex-users with potential, intermediate, and total users. If one further compares these values with the measure of inter firm diffusion, the discrepancy is even bigger. This indicates that to use only the proportion of adopters as a measure of technology diffusion would be quite wrong. What determines the total industry output produced with the new technology and the industry benefits from adoption is a combination of the number of adopters (inter firm diffusion) and the proportion of output produced by the adopters (intra firm diffusion). This chapter has also shown that in early years, the inter firm effects exert a slightly higher impact on diffusion than intra firm effects, while the for the rest of the period the opposite is true. The impact of intra-firm diffusion on the total industry output produced on the new technology is persistently higher than the inter firm level of adoption and its importance greatly increases over time. For these reasons, and because the intra firm effect has been widely overlooked, this thesis concentrates on the spread of the new technology within firms rather than their spreading across firms. The next chapter reviews the existing literature in the area.

Chapter 3.

THE EXISTING THEORY OF INTRA-FIRM DIFFUSION

3.1. Introduction

Within the literature concerning the economics of technological changes a more specific area of research, labelled technology diffusion, focuses on technology adoption. A large majority of such studies looks at inter firm diffusion which is the process leading to first adoption of a new technology (Davies 1979, Stoneman 1986, or more specifically David 1991, Mansfield, 1963a/b, 1993, Reinganum 1981a/b/c, Stoneman and Kwon 1998, Stoneman and Toivanen 1997, Colombo and Mosconi 1995, etc.). However, contrary to inter firm diffusion studies, and despite its relevance, there exist only two significant pieces of work on intra firm diffusion: the seminal contribution of Mansfield (1968), based on a disequilibrium process driven by passive information acquisition, and Stoneman (1981a), which is an example of an equilibrium model based on Bayesian learning. Both models consider information and uncertainty to be the keys to explaining why it is rational for firms to not completely switch immediately to new technology (Stoneman, 1983).

This chapter aims at looking in more detail at the two models present in the existing literature on intra firm diffusion and testing their validity for the technologies in the CURDS data set. Following an equilibrium approach it also preliminary explores the possibility that, similarly to inter firm effects, there exist intra-firm effects and they significantly affect the extent of use of a new technology. Such hypotheses has never been explored in the current literature and as such it is considered a useful route to follow to deepen the understanding of the within firm process of technology transfer.

The chapter is structured as follow. Section 2 presents the Stoneman model. Section 3 presents the theoretical assumption of the Mansfield model and tests econometrically the validity of its predictions using the CURDS data. This section also highlights some of the theoretical weaknesses of this type of approach. In section 4 a distinction is made between equilibrium and disequilibrium approaches to modelling the firm adoption pattern of a new technology. Section 5 presents a preliminary intra firm equilibrium approach to explore, on an empirical basis, the existence of factors traditionally present in the inter firm literature. Section 6 concludes this chapter summarising the main findings.

3.2. The Stoneman model

The Stoneman model (Stoneman, 1981) is the first and only model of intra-firm technology diffusion solidly grounded in economic theory. The basic idea behind this model is that the firm's choice of technique is endogenous and based upon learning from experience about the characteristics of the technology. Learning occurs in a Bayesian manner and together with the adjustment costs associated with the decision to invest, generates the time path of usage of the new technology.

In mathematical terms Stoneman defines α_t as the proportion of the firm's fixed output produced with the new technology at time t and assumes that the firm determines the desired level of α_t, defined as α_t^*, according to a mean-variance approach to technique choice. It is also assumed that the firm has to choose the optimal combination of new (n) and old (o) technology, each having expected anticipated returns Normally distributed ($N(\mu_{nt};\sigma^2_{nt})$ and $N(\mu_{ot};\sigma^2_{ot})$. The resulting combination of old $(1-\alpha_t)$ and

new (α_t) technology generates the expected returns from their joint adoption as in (3.1):

$$\mu_t = \alpha_t \mu_{nt} + (1-\alpha_t) \mu_{ot}$$
$$\sigma_t^2 = \alpha_t^2 \sigma_{nt}^2 + (1-\alpha_t)^2 \sigma_{ot}^2 + 2\alpha_t (1-\alpha_t) \sigma_{not} \qquad (3.1)$$

The entrepreneur then chooses α_t by maximising the utility function U (3.2) in which C is defined as the disutility of the adjustment costs that arise when α_t is changed:

$$U = H(\mu;\sigma^2) - C \qquad (3.2)$$

Following Chipman (1973), Stoneman specifies $H(\mu;\sigma^2)$ as:

$$H(\mu;\sigma^2) = a\mu - 1/2\, b\, \sigma^2 \qquad b>0 \quad a>0$$

Setting $\alpha=1$ and maximising U with respect to μ and σ^2 he determines the level of new technology use (α_t^*) that would be desired if there were no adjustment costs:

$$\alpha_t^* = \{\mu_{nt} - \mu_{ot} + b(\sigma^2_{ot} - \sigma_{not})\} / \{b(\sigma^2_{nt} + \sigma^2_{ot} - 2\sigma_{not})\} \qquad (3.3)$$

After some manipulation and other caveats, assuming that the firm acts in myopic manner, such that given α_{t-1} it chooses α_t to maximise (3.2), Stoneman derives the optimal level of investment in the new technology in presence of non-zero adjustment cost (3.4):

$$d\alpha_t/dt \,.1/\alpha_t = 1/\theta \;\; \{\mu_{nt} - \mu_{ot} + b\,(\sigma^2_{ot} - \sigma_{not})\,[(\alpha_t^* - \alpha_t)/\alpha_t^*]\} \qquad (3.4)$$

where b is a risk coefficient, and σ_{not} is the correlation between the returns to the new and old technologies so that:

$\sigma_{not} = \rho\ \sigma_{nt}\ \sigma_{ot}$

Stoneman further assumes that the returns from the old technology are known, fixed and held with certainty with time invariant distribution, i.e. $N(\mu_o;\sigma^2_o)$, (because the entrepreneur is supposed to already know by experience its properties) so that:

$d\sigma_{not}/dt = \rho.\ \sigma_o.\ d\sigma_{nt}/dt.$

The entrepreneur initially uses the new and old technologies in the proportion ($\alpha_t^{\wedge}$; $1-\alpha_t^{\wedge}$). However, as time proceeds he monitors the performance of the new technology and adjusts his anticipations of the returns to the new technology in a Bayesian manner leading to changes in both α_t and α_t^* (Stoneman, 1986).

The corresponding original a priori distribution of the mean returns to the new technology at time t, $N(\mu_{nt};\ s_{nt})$, is then adjusted every time returns are experienced by the entrepreneur. The adjustment in the anticipated variance, being proportional to the uncertainty of the returns experienced over time (σ^2_{nt}), is expected to fall over time approaching the real variance of the returns ($\bar{\sigma}_n^2$). At the same time, the anticipated mean return (μ_{nt}) may rise or fall depending on whether the expected mean return is greater or less than the true mean return approximating the real average return ($\bar{\mu}_n$).

As the anticipated estimate of σ_{nt}^2 and μ_{nt} change over time also the desired level of new technology (α_t*) will change, until the true mean and variance of the returns to the new technology is established and this will establish the post diffusion level of use ($\bar{\alpha}$). The latter results from the combination of: (i) the true mean and variance of returns to the new technology; (ii) the true mean and variance of the old technology; (iii) the firm's initial estimate of μ_{nt} and σ_{nt}; and (iv) the firm's risk, yielding:

$$\bar{\alpha} = (\bar{\mu}_n - \mu_o + b\,(\sigma_o^2 - \rho.\,\bar{\sigma}_n^2.\sigma_o) \,/\, b(\bar{\sigma}^2_{nt} + \sigma_o^2 - 2.\rho.\,\bar{\sigma}_n\,\sigma_o)$$

where $\bar{\mu}$ and $\bar{\sigma}_n^2$ are respectively the true mean profitability of the new technology and the variance of its returns.

Stoneman (1981) shows that under certain conditions the path of α_t, as it tends towards $\bar{\alpha}$, will be sigmoid. His model also justifies why some technologies do not diffuse as, based upon consideration about the 'true' profitability of the new technology, the preferred level of use α_t* may decline over time, and once α_t^* falls below α_t the diffusion is halted and perhaps reversed. If, however, α_t^* remains above α_t for all $t < \infty$, then the diffusion does proceed (Stoneman, 1983).

In summary the Stoneman model is a sophisticated theoretical model based upon economic theory, where the decision to further adopt a technology is based upon an instantaneous decision (Tonks, 1986). The latter is rational, in that at all times the level of use maximises the utility of the decision maker, given his anticipations of returns, risk and costs of adjustment. However, despite its sophisticated theory based upon profitability considerations, it is intractable empirically.

The alternative existing model of intra firm diffusion was first developed by Mansfield (1968). This model, traditionally referred to as epidemic model, has played a dominating role within the diffusion literature. Contrary to the Stoneman model, in this model learning is by infection and not from experience.

Its theoretical assumptions and the testing of its validity on empirical grounds over the technologies in the CURDS data set, are explored in the following section.

3.3. THE MANSFIELD MODEL

3.3.1. Epidemic modelling: the Mansfield information based approach

According to Mansfield (1968) the spread of technology can be likened to an epidemic where diseases are assumed to spread by contact between individuals. By implication the use of a new technology will be spread as individuals make contact with one another[1].

The Mansfield model assumes that a firm acquires a new technology by purchase of a capital good that embodies the technology (i.e. the disease) and defines S_{ijt} as the amount of new technology j the firm i owns at time t and S^*_{ij} as the amount of new technology j that the firm i will own when the diffusion process is complete. Then he rewrites the proportion of capital stock become 'infected' by the new technology in the interval t to t+1 as the additions to the stock of the new technology in time t over the gross additions still to be made:

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[1] For example, if, in a constant population P, one allows N_t to be the number of individuals affected by the disease, and N* the number not immune to the disease, then at time t there are $P-N_t$ individuals not affected, of whom N^*-N_t are susceptible to the disease. In mathematical terms this is can be written as:

$$dN_t = \beta.(N_t/N^*)(N^*-N_t)dt$$

where, under the assumption of homogeneously mixing population, the average number of persons infected, dN_t, in a small time interval dt, would be equal to the probability for a susceptible individual to meet an infected person and being infected in the small time interval, $\beta.(N_t/N^*)$, times the susceptible number in the time t, (N^*-N_t). Solving this differential equation yields the well known Logistic curve:

$$N_t/N^* = 1/(1+\exp-(\alpha+\beta t))$$

where α is the constant of integration and β is the constant rate of infection from the infected to the non infected. This is just one example of models based on epidemic spread of a disease (Banks,1991).

$$W_{ijt} = \frac{S_{ijt+1} - S_{ijt}}{S^{*}_{ij} - S_{ijt}} \qquad (3.5)$$

He then hypothesises that, for firm i adopting technology j, the rate of technology transfer $\beta_{ij,}$ is a positive function (G) of: π_{ij}, the expected profitability of adoption (modelled as time invariant); U_{ijt} ,a time varying measure of the risk attached to adoption; M_{ij} ,a measure of the size of the firm and C_i ,a measure of the liquidity of the firm (both these latter terms being considered time invariant). In mathematical terms he writes:

$$\beta_{ij} = G(\pi_{ij}, U_{ijt}, M_{ij}, C_i,...) \quad G_{\pi}'>0 , G_U'<0, G_M'<0 \; G_C'>0 \qquad (3.6)$$

Mansfield then argues that the risk of adoption, U_{ijt}, depends upon the number of years from the first adoption by any firms to the date when the technology is first used by the firm i, L_{ij}. The longer the firm waits, the more information about the true profitability of the technology it gains from the experience of other adopters. As time proceeds the amount of information available lowers the firm's uncertainty and as it does so diffusion proceeds. On this ground he then assumes that the reduction in uncertainty is inversely related to the level of usage of the technology by the firm, i.e. S_{ijt}/S^{*}_{ij}.

Specifically he assumes that:

$$U_{ijt} = J(L_{ij}, S_{ijt}/S^{*}_{ij}) \qquad J_1<0 \text{ and } J_2<0 \qquad (3.7)$$

yielding, after substitution of (3.7) into (3.6.), that:

$$\beta_{ij} = G(\pi_{ij}, L_{ij} , S_{ijt}/S^{*}_{ij}, M_{ij}, C_i,...) \qquad (3.8)$$

On the basis that there would (seem to) exist an important analogue to the classic psychological laws relating reaction time to the intensity of the stimulus, Mansfield assumes that W_{ijt} in (3.5) can be approximated within a relevant range by a quadratic function of π_{ij}, L_{ij} , S_{ijt}/S^*_{ij}, M_{ij}, C_i . By taking Taylor's series expansion and the dropping of higher order terms, it is further assumed that (3.5) may be written as:

$$W_{ijt} = \beta_{ij}.S_{ijt}/S^*_{ij} \tag{3.9}$$

where $\beta_{ij} = c_1 + c_2\pi_{ij} + c_3L_{ij} + c_4M_{ij} + c_5C_i$, which by specification is time invariant. Substituting from (3.5) into (3.9) and writing the result as a differential rather than a difference equation yields:

$$dS_{ij\,t} = \beta_{ij}.(S_{ijt}/S^*_{ij})(S_{ij}^*-S_{ij\,t})dt \tag{3.10}$$

Equation (3.10) indicates that, for a firm, the increase in use of a new technology (dS_t) is a function of the probability of obtaining 'information by contact' about the technology in a small time interval dt, $\beta_{ij}(S_t/S^*)$, times the additions to the new stock still to be made (S^*-S_t). This is the expression typical of several sigmoid epidemic models[2]. It is the standard logistic curve with the speed of intra-firm diffusion given by the linear combination β_{ij} and has the solution:

$$S_{ijt}/S^*_{ij} = 1/(1-\exp(-\beta_{ij}t_{ij}-\alpha)) \tag{3.11}$$

$$\beta_{ij} = c_1 + c_2\pi_{ij} + c_3L_{ij} + c_4M_{ij} + c_5C_i \tag{3.12}$$

where α is a constant of integration and it represents the date of first adoption by the firm.

2 See footnote 1.

The element of novelty of this model with respect to the traditional epidemic models, is that β_{ij} (the rate of diffusion) is firm specific and is a linear combination of exogenous time invariant factors.

The Mansfield model in essence states that there is a final level of use of the technology S^*_{ij} and over time the firm will approach this level as it accumulates experience from use and the uncertainty attached to use declines. So, basically it is uncertainty from the poor information on the performance characteristics of the technology that deters risk averse firms from further acquiring such technology. He thus constructs the model where the uncertainty is reduced over time as a result of learning from experience. The resulting diffusion path is logistic (see 3.11). The factors determining the decision to further use the technology enter into β, the speed of diffusion, which is assumed to be constant and a linear function of the date of first use, firm characteristics (size and liquidity) and the expected profitability of adoption (see 3.12). It is further assumed that the end point of the diffusion process, i.e. the saturation stock, is 1, that is at the end of the diffusion process all the existing technology is replaced by the advanced technology.

Although the Mansfield model has been widely used in the empirical literature it has a number of problems, many of which are common to the standard epidemic models.

Some of the empirical weaknesses and theoretical inconsistencies are quite difficult to ignore. The next section 3.3.3.considers empirical and section 3.3.4. theoretical problems.

3.3.2 Testing of the Mansfield model

The Mansfield model suggests that the intra-firm adoption pattern tends to follow a sigmoid path. This means that the firm will gradually transfer its production to the new technology and the pattern can be modelled over time by a Logistic curve, with use ranging from some positive number at the date of first use, to a saturation point at the date of complete diffusion. Moreover, it suggests that its rate of growth is a function of economic factors, such as profitability, size of the firm, liquidity and risk, yielding the model specification:

$$S_{ijt}/S^{*}_{ij} = 1/(1-\exp(-\beta_{ij}t_{ij}-\alpha)) \qquad (3.11)$$

$$\beta_{ij}=c_1 + c_2\pi_{ij} + c_3L_{ij} + c_4M_{ij} + c_5C_i \qquad (3.12)$$

This section aims to test empirically some of the main hypotheses underlying the Mansfield model[3] and in particular whether for each technology j:

H1) the intra firm diffusion path is Logistic;

H2) the end point of the diffusion process is 1, i.e. at the end of the diffusion process all the old technology is replaced by the new technology;

H3) the speed of diffusion is a linear function of the other users at the date of first use (L_{ij}), firm characteristics, such as size (M_{ij}) and liquidity of the firm (C_{ij}) and the expected profitability of adoption (π_{ij}).

H4) the speed of diffusion (β_{ij}) is a time invariant constant;

The testing of each of the above hypothesis has been carried out comparing the performance of:

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3 Part of this study has already been published in Stoneman and Battisti,1997.

T1) alternative statistical distributions of technology ownership such as the Gompertz statistical distribution[4].

T2) alternative models with fixed (ϕ_j=1) and variable saturation points (ϕ_j<1)

T3) the same model but with and without the inclusion of exogenous variables, i.e. univariate and multivariate specification

T4) both fixed and stochastic parameter model specifications, i.e. Harvey's structural vs classical parameter specification

All of these hypotheses are tested over the sample of UK engineering and metalworking establishments and for three technologies in the CURDS data set: Numerically Controlled machine tools (NC), Computerised Numerically Controlled machine tools (CNC) and Coated and Carbide Tools (CoT)[5].

The statistical packages used for this analysis have been chosen ad hoc for each type of model specification: SPSS for non linear modelling, STAMP5 for Structural (stochastic parameters) modelling, LIMDEP7 for Two Stage Least Squares, Weighted and Unweighted NLS, OLS and other distributional functions.

Below the variable specifications and the testing of the model are presented by steps.

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4 Example of Gompertz distribution of technology spread (T1) was proposed by Dixon (1980) in alternative to the Logistic distribution proposed by Mansfield (1968) then used by Griliches (1957) with variable saturation point (T2).

5 Only three out of the four technologies available in the CURDS survey were chosen. The main reason being that they are a good example of complementary (Cot) and substitute technologies (NC and CNC); their testing was enough to give a clear indication of the robustness of the Mansfield model.

a) Variable specifications

The dependent variable in the first equation (3.7) of the Mansfield model concerns the firm's level of ownership of the new technology (S_{ijt}/S_{ij}*). This key variable on intra firm diffusion can be found in the CURDS 1993 survey and is measured as the percentage of the machine tool stock of the firm that in 1993 incorporates each of the four advanced technologies (D_{ijt}).

In order to take into account that the model is a disequilibrium one, S_{ijt}/S_{ij}^* is here measured for each technology j by the multiple, $1/\phi_j$,of the proportion of machine tools stock ($\mathbf{D}_{ijt}$) of establishment i that incorporates the new technology j at the date of survey in 1993, i.e.

$$S_{ijt}/S_{ij}^* = \mathbf{D}_{ijt}/\phi_j$$

where ϕ_j is the limiting value of D_{ij} as t_{ij} tends to infinity. In Mansfield's theory $\phi_j=1$, meaning that at the saturation point –at the end of the diffusion process- the firm will have replaced 100% of the old with the new technology.

For each technology j, $\mathbf{t}_{ij}$ in equation (3.11) is measured by $\mathbf{T}_{ij}$ the number of years in 1993 since first adoption of the technology j by the establishment i, so that the estimating equation becomes:

$$D_{ijt} = \phi_j /(1-\exp(-\beta_{ij}*T_{ij} - \alpha)) \qquad \text{with} \quad \phi_j=1 \qquad (3.13)$$

Some of the elements of the β_{ij} vector as specified in the second equation (3.12) of the Mansfield model were not directly observable in the CURDS data set, however it contains information on:

i) For each j the proportion of firms in the sample using the technology j at the date of adoption by establishment i, $\mathbf{L_{ij}}$

ii) An indicator of firm size, the employment level of the firm in 1993, 1986,1980,1975 and 1970, $\mathbf{M_i(t)}$.

Data concerning the expected profitability, π_{it}, and the liquidity of the firm, C_{ij} are not available. There is no obvious measure for C_{ij} but π_{ijt} may be approximated by a linear function of firm characteristics and industry dummies with coefficients to be estimated but differing across j. Thus data on the following variables have been used as (imprecise) proxies for these but which may also be of interest in their own right:.

iii) whether the establishment undertakes in house R&D, a dummy variable, $\mathbf{R\&Ddum_i}$, taking the value 1 if it does and 0 if it does not (data available for 1993, 1986, 1980, 1975)

iv) whether the firm is export intensive or not, a dummy variable, $\mathbf{Expdum_i}$, equal to 1 if the percentage of total output going for export is greater than 20% and 0 otherwise (data available for 1993, 1986 and 1980).

This allows one to specify the final estimating equations of the Mansfield model (3.11 and 3.12) as (3.14):

$$D_{ijt} = \phi_j /(1-\exp(-\beta_{ij}*T_{ij} - \alpha)) + e_{ij} \qquad \text{where } \phi_j=1$$
$$\beta_{ij} = c_1 + c_2 .R\&Ddum_i + c_3 .Expdum_i + c_4 .M_i + c_5.L_{ij} \qquad (3.14)$$

A particular characteristic of the data is that for each technology, and especially for NC machine tools, there is a considerable proportion of establishments which have adopted the technology at some date prior to 1993 but in 1993 register zero ownership. Thus it is necessary to distinguish between adopters (i.e. firms that have adopted a

technology at or before 1993) and users (adopters with a positive value for D_{ij} in 1993). This implies that, for each technology there are two samples that one can use: (i) *sample A*, which covers all adopters of the technology for some of whom D_{ij} will be zero in 1993 and (ii) a restricted sample, *sample B*, covering only those firms for whom $D_{ij} \geq 0$ in 1993. Theoretically the Mansfield model is unable to deal with firms that have adopted the technology but no longer use that technology and as such one would expect that the results from using sample B will be the better results[6].

b)Testing procedure

By its non linear nature the above model is very difficult to estimate, often yielding quite unsatisfactory residuals, i.e. they are highly autocorrelated and heteroscedastic and give spurious results (see Dixon 1980, Heeler and Hustad 1980, Granger and Newbold 1977, Mahajan and Wind 1986, Karshenas and Stoneman 1992, Zettelmeyer and Stoneman 1993, etc). One way to overcome this problem is to estimate several specifications (both nonlinear and linearised versions) and choose ad hoc estimators of the logistic curve which would allow one to model most of the variability of the diffusion process. This is the standard general to specific econometric procedure (Harvey, 1987). Consequently, various logistic specifications are separately estimated for each technology j. Below, for notational consistency, greek letters are used for population parameters, while roman letters for their sample estimates[7].

6 Further details on definitions and descriptive statistics for all variables are detailed in Appendix C.

7 This section only comment on some of the estimates, selected upon their relevance to the argument. For space limit and for ease of presentation the other estimates are omitted.

There are several approaches to the estimation of the Logistic curve. Harvey (1989, 1993, 1984a/b) summarises the possible approaches to estimating Growth curves as: (a) level analysis (i.e. non linear specification); (b) proportions (i.e. linearised model); and (c) differences. Moreover, he further distinguishes between the structural and the classical parameter specification of each type of model. For the univariate case these are summarised in Table 3.1. and their extension to the multivariate case is straightforward.

Table 3.1. The model specification

GENERAL MODIFIED EXPONENTIAL FUNCTION		
	$y_t = \mu_t + \varepsilon_t$ $\mu(t) = \phi(1 + \beta e^{\gamma f(t)})^k$	
where K=1 → Simple Modified Expo; K=1 → Log(Gompertz) ; K= -1 → Logistic		
LOGISTIC MODEL (K=-1) SPECIFICATIONS (classical approach)		
Levels	$D_t = \dfrac{\phi}{(1 + \beta e^{\gamma f(t)})}$	Weighted/Unweighted Non Linear Least Squares
Proportions	$\text{Log}\,[D_t/\alpha - D_t)] = \log\beta + \gamma t + \varepsilon_t$	Ordinary Least Squares (see Harvey, 1989)
Differences -	$\text{Log}\,\Delta D_t = \rho \log D_{t-1} + [\delta + \gamma\, t] + \varepsilon_t$	Ordinary Least Squares: (see Mar-Molinero ,1980)
-	$\Delta \log D_t = -\gamma + \gamma^{\dagger} D_t + (\gamma^{*} D^{-1}_t) + \eta_t$	(see Levencach and Reuters, 1976)
LOGISTIC MODEL (K=-1) SPECIFICATIONS (classical approach)		
Levels	$\text{Log}\, D_t = \mu^{\dagger}_t + \varepsilon_t$ $\mu^{\dagger}_t = \mu^{\dagger}_{t-1} - \gamma_{t-1} + \gamma^{\dagger}\exp(\mu^{\dagger}_{t-1}) + \eta_t$ $\gamma_t = \gamma_{t-1} + \xi_t$	Maximum likelihood (see Harvey, 1989)
Proportions	$\text{Log}\,[D_t/\phi - D_t)] = \log\beta + \mu^{*}_t + \varepsilon_t$ $\mu^{*}_t = \mu^{*}_{t-1} + \beta_{t-1} + \eta_t$ $\beta_t = \beta_{t-1} + \xi_t$	Maximum likelihood (see Harvey, 1989)
Differences	$\log \Delta D_t = \rho \log D_{t-1} + \mu^{*}_t + \varepsilon_t$ $\mu^{*}_t = \mu^{*}_{t-1} + \beta_{t-1} + \eta_t$ $\beta_t = \beta_{t-1} + \xi_t$	Maximum likelihood (see Harvey, 1984b)

Notes: The classification of the Logistic specifications is outsourced from Harvey (1993 pg149-150) to which one should refer for the proofs

In this study only the level (a) and proportion (b) analysis have been used. The third one (c) would have required the dependent variable, i.e. the level of use of the new technology (D_t), to be specified in terms of first differences. However, the lack of lagged terms for the dependent variable has excluded this possibility.

The initial model estimates are restricted to a simplified version of the Mansfield model that specifies the extent of diffusion simply as a function of the number of years from first adoption (Table 3.1. Univariate levels specification) and tests the hypothesis that the time path of diffusion is logistic (H1), with a fixed saturation point, i.e. $\phi_j=1$ and with a constant speed of diffusion β_{ij}. The estimating equation specified as (3.15) with an additive error term e_{ij} is estimated using non linear least squares:

$$D_{ij} = 1 / (1+\exp(-\hat{\alpha} - \hat{\beta} T_{ij}) + e_{ij} \qquad (3.15)$$

The best diagnostics are given by weighted NLS (where the weights are T_{ij}) with the weighting being used to correct for heteroscedasticity in the estimates. However in these estimates, using either sample A or sample B, none of the coefficients are significantly different from zero and the explanatory power of the regression (adjusted R^2) peaks at 0.1. The result suggests that the Logistic curve is in fact a very poor summary of the data.

Given that very few firms have actually replaced all the existing technology with the new technology the next step is to allow the ceiling, ϕ_j, to be estimated directly by the model (see Griliches 1957, Dixon, 1980). By comparing estimates when ϕ_j is predetermined ($\phi_j=1$) with those when ϕ_j is estimated within the model ($\phi_j = \hat{\phi}_j$), one is also able to test whether $\phi_j \leq 1$ (H2). The model reduces to (3.16):

$$D_{ij} = \hat{\phi}_j / (1+\exp(-\hat{\alpha} - \hat{\beta} T_{ij}) + e_{ij} \quad (3.16)$$

The estimates of this variant using unweighted least squares (Table 3.2) are a slight improvement on the previous estimates.

Table 3.2. Logistic model –NLS

	Sample A			Sample B		
Technology	CNC	CoT	NC	CNC	CoT	NC
Sample size	133	198	92	210	154	151
Ceiling ($\hat{\phi}_j$)	**0.3474** **(7.584)**	**0.6288** **(6.320)**	0.5115 (0.082)	**0.3391** **(7.048)**	1.0006 (1.347)	0.3038 (0.038)
Constant ($\hat{\alpha}$)	**-0.7289** **(-1.875)**	-0.9551 (-1.574)	-0.3420 (-0.017)	**-1.8162** **(-2.075)**	**-1.3639** **(-1.866)**	-0.407 (0.992)
Adj speed ($\hat{\beta}$)	**0.2835** **(1.869)**	0.15453 (1.744)	-0.0027 (-0.170)	**0.2770** **(1.960)**	0.0660 (1.467)	-0.0189 (-0.076)
Adjusted R^2	0.098	0.116	0.039	0.095	0.111	0.013
F	10.02 [p=0.274]	7.98 [p=0.0005]	1.31 [p=0.274]	11.51 [p=0.00]	8.56 [p=0.00]	0.48 [p=0.62]

Note: t-value in brackets significant at 5% in bold
Source: CURDS-personal elaboration

However for NC machine tools none of the estimated coefficients are significantly different from zero. For CoT using sample B the estimate of ϕ_j ($\hat{\phi}_j$) is greater than unity although using sample A it is less than unity at 0.63. For CNC, using sample B yields significant estimates of ϕ_j, α and β of the right sign. Again, however the adjusted R^2 is less than 0.1. Restricting the value of ϕ_j to equal unity for all j does tend to lead to some improvements in the results. For NC technology the results are still poor (although the estimate of β is significant it is of the wrong sign), but for CNC and CoT technologies using either sample A or B, the estimates of α and β are both significant and of the correct sign (although again R^2 is only 0.1).

Despite the several attempts none of the empirical results are very supportive of the logistic hypothesis (H1). As an alternative hypothesis the Gompertz growth curve has

been used to test how well it would approximate the data. The Gompertz curve may be written as (3.17)

$$D_{ij} = \exp(-\exp(\hat{\alpha} + \hat{\beta}.T_{ij}) + e_{ij} \qquad (3.17)$$

Using NLS on either sample A or sample B, the Gompertz curve works as well (or as badly) as the Logistic curve. When applied to NC it yields an insignificant estimate for β, but for CNC and CoT our estimates for α and β are of the right sign and significant (see Table 3.3.).

Table 3.3. Gompertz model –NLS

$D_{ij} = \exp(-\exp(\hat{\alpha} + \hat{\beta}.T_{ij}) + e_{ij}$

	Sample A			**Sample B**		
Technology	CNC	CoT	NC	CNC	CoT	NC
Sample size	169	133	92	210	154	151
$\hat{\alpha}$	**-0.7508 (-5.721)**	**-0.3564 (-1.948)**	**-0.4333 (-3.864)**	**-0.8180 (-6.235)**	**-0.5512 (-3.012)**	**-0.7506 (-4.375)**
$\hat{\beta}$	**0.0410 (4.166)**	**0.0439 (3.861)**	-0.01E-1 (-1.581)	**0.0426 (4.383)**	**0.0449 (3.995)**	-0.0054 (-0.996)
Adjusted R^2	0.09	0.12	0.04	0.10	0.11	0.012
F	18.65 [p=0.10]	6.00 [p=0.00]	2.70 [p=0.10]	21.27 [p=0.00]	17.43 [p=0.00]	0.95 [p=0.33]

Note: t-value in brackets; significant at 5% in bold
Source: CURDS-personal elaboration

This result indicates that there is almost no evidence that the pattern of intra firm technology adoption strictly follows a Logistic distribution, leading one to conclude that hypothesis (H1), that the intra firm diffusion follows a Logistic curve, is difficult to accept. However, these initial estimates constrain β_{ij} to be the same for all i whereas the Mansfield model allows the speed of diffusion, β_{ij}, to vary across firms (H3), i.e.

$$D_{ij} = \frac{\phi_j}{(1+\exp(-\hat{\alpha} - \hat{\beta}_{ij}*T_{ij})} + e_{ij} \qquad (3.18a)$$

where

$$\hat{\beta}_{ij} = \hat{\beta}_0 + \hat{\beta}_1 * RDdum_i + \hat{\beta}_2 * Expdum_i + \hat{\beta}_3 * M_i + \hat{\beta}_4 * L_{ij} \qquad (3.18b)$$

This model can be estimated by two stage weighted least squares which is similar to the procedure applied by Mansfield in his original article (1968). However, as suggested by Dixon (1980) one should take into account that the explanatory regressors are themselves estimates with different standard errors. More advanced econometric techniques such as a non linear least squares method are here used in testing the reduced form of the logistic model specification for each j (see Griliches 1957,1980, Srivasan and Mason, 1986, etc.)[8]. This implies specifying the model as:

$$D_{ij} = \frac{\hat{\phi}_j}{(1+\exp(-\hat{\alpha}-(\hat{\beta}_0 + \hat{\beta}_1 * RDdum_i + \hat{\beta}_2 * Expdum_i + \hat{\beta}_3 * M_i + \hat{\beta}_4 * L_{ij}) * T_{ij}))} + e_{ij} \qquad (3.19)$$

Alternatively this specification may be linearised (Table 3.1. Proportions approach) and estimated by OLS using fixed ($\hat{\phi}=1$) or variable ($\hat{\phi}\leq 1$) saturation levels as in Romeo (1975):

$$\log[D_{ij}/(\hat{\phi}_j - D_{ij})] = \hat{\alpha} + \hat{\beta}_1 * RDdum_i + \hat{\beta}_2 * Expdum_i + \hat{\beta}_3 * M_i + \hat{\beta}_4 * L_{ij} + e_{ij} \qquad (3.20)$$

In both cases the best results are achieved if the estimate of ϕ_j is restricted to unity and one considers only those firms that use the technologies at some positive level in 1993 (i.e. Sample B).

8 Also non-weighted non-linear least squares have been estimates but these are no improvement over those reported in this section.

Table 3.4: Logistic curve, weighted non-linear least squares (sample B)

$$D_{ij} = \hat{\phi}_j / 1+\exp(\hat{\alpha} + (\hat{\beta}_0 + \hat{\beta}_1 . R\&Ddum_i + \hat{\beta}_2 . Expdum_i + \hat{\beta}_3 M_i + \hat{\beta}_4 L_{ij}) T_{ij}) + e_{ij}$$

Technology	CNC	CoT	NC
Sample size	194	129	91
ϕ	1	1	1
$\hat{\alpha}$	**-3.2803** **(-3.996)**	**-3.3109** **(-2.762)**	**-2.6484** **(-6.749)**
$\hat{\beta}_0$	**0.1073** **(2.570)**	**0.0899** **(2.188)**	**-0.22333** **(-2.114)**
$\hat{\beta}_1$	01877 (1.234)	**0.04402** **(2.761)**	0.0469 (1.189)
$\hat{\beta}_2$	-0.0180 (-1.714)*	-0.0130 (-1.022)	0.0682 (1.889)**
$\hat{\beta}_3$	0.21E-4 (1.862) **	-0.11E-4 (0.820)	**-0.51E-3** **(-2.053)**
$\hat{\beta}_4$	**0.0018** **(2.561)**	**0.0023** **(2.356)**	**0.0093** **(2.775)**
R^2-adjusted	0.11	0.18	0.15
F [p(F)]	4.27 [p=0.001]	5.22 [p=0.000]	2.72 [p=0.02]

Notes: weights T_{ij} ; asymptotic t-test in parenthesis; significant at 5% in bold; *p=0.09 and **p=0.06
Source: CURDS-personal elaboration

Table 3.5. : Logistic curve: linearised version, OLS estimates (sample B)

$$\log(D_{ij} / \hat{\phi}_j - D_{ij}) = \hat{\alpha} + (\hat{\beta}_1 + \hat{\beta}_2 . R\&Ddum_i + \hat{\beta}_3 . Expdum_i + \hat{\beta}_4 . M_i + \hat{\beta}_5 . L_{ij}) T_{ij} + e_{ij}$$

	CNC	CoT	NC
Sample size	193	123	91
ϕ	1	1	1
Intercept	**-3.4375** **(-7.949)**	**-2.1674** **(-3.166)**	**-2.3792** **(-6.163)**
T_{ij}	**0.1044** **(3.741)**	0.0453 (1.431)	**-0.0706** **(-2.254)**
$R\&Ddum_i T_{ij}$	0.0285 (1.501)	**0.0488** **(1.979)**	0.0412 (1.685)*
$Export_i * T_{ij}$	-0.0128 (-0.878)	-0.0042 (-0.204)	0.0113 (0.692)
$M_i * T_{ij}$	0.118E-4 (0.652)	0.18E-4 (0.874)	-0.255E-4 (-1.322)
$L_{ij} * T_{ij}$	**0.00149** **(2.597)**	0.00104 (1.321)	**0.00257** **(2.515)**
Adj.R^2	0.15	0.12	0.13
F [p(F)]	8.01 [p=0.000]	4.45 [p=0.001]	3.57 [p=0.006]

Notes: t-test in parenthesis; significant at 5% in bold; *p=0.096
Source: CURDS-personal elaboration

Table 3.4 and Table 3.5. present the estimates across the three technologies only for those models giving the best diagnostic and goodness of fit (see also Stoneman & Battisti, 1997). One may note that in each case the explanatory power of the regressions judged by the R^2 value or the F statistic is still low. Whatever the specification, it never explains more than 18% of the variance of the (restricted) sample. It is also clear that the patterns of significance found are sensitive to the estimation method employed. The NLS estimates are very sensitive to the starting values assumed. Moreover, although there is some evidence based on the significance of the estimate of β_2 that time since first adoption does affect the diffusion process, for NC machine tools the sign is wrong in both sets of estimates. This in itself leads one to believe that even under the most favourable circumstances ($\beta_0 = 1$ and using Sample B) the hypothesis that the Mansfield model adequately represents the diffusion process for NC machine tools cannot be accepted.

For CNC and CoT the results are an improvement although still very sensitive to the estimation method. Using the linearised estimates the estimate of β_2 for CoT is not significant (in fact only the coefficients β_1 and β_3 are significant). For CNC only β_2 and β_6 are significant).

To allow for a more dynamic and flexible structure, and to test whether the parameters do change over time (H4), the Mansfield model has also been estimated with parameters varying over firms (see Harvey 1989, 1984a). This is the correspondent of the structural modelling over a sample of cross sectional observations (see Table 3.1./Structural approach). By the means of the Kalman Filter and Maximum Likelihood estimator the model can test for the presence of structural stylised facts not

picked up directly by the traditional fixed parameters regression models (see Harvey, 1984b, 1989, 1990). The econometric specification of the Mansfield model, based on the structural model with explanatory variables and local trend being:

$$\log[D_{ijt}/(\hat{\phi}_j - D_{ijt})] = \alpha_{it}^* + (\beta_1 + \beta_2 * RDdum_i + \beta_3 * Expdum_i + \beta_4 * M_i + \beta_5 * L_{ij}) * T_{ijt} + \varepsilon_{ijt}$$

$$\alpha_{it}^* = \alpha_{i,t-1}^* + \beta_{i,t-1} + \eta_{it}$$

$$\beta_{it} = \beta_{i,t-1} + \xi_{it}$$

where α_{it}^* is the stochastic drift, β_{it} is the stochastic slope and the residuals (ε_{ijt}, η_{it} and ξ_{it}) are Normally independent distributed variables with zero mean and variance σ_ε^2, σ_η^2 and σ_ξ^2 respectively. In economic terms this specification allows the speed of diffusion to be stochastic (i.e. to change over time) and to be updated each time a new observation is made available in the system (i.e. changes in the exogenous variables). Given the cross sectional nature of the data set, the dynamic structure has been modified as to change across firms rather than over time. The resulting dynamic drift accounts for firm specific affects. However, the results from estimating this type of model over the technologies in the CURDS sample are not reported as they do not show any significant improvement with respect to the previous models.

Considering these results in their totality one can conclude that the Mansfield predictions (i) are not consistent with the NC diffusion patterns observed and (ii) have limited explanatory power when applied to the diffusion of CNC and CoT technologies. The most common problems are: a) wrong parameter estimates, the parameter estimates often show the wrong signs or magnitudes compared to what the theory would suggest; b) poor forecasting performance, which varies across different technologies; c) unsatisfactory diagnostics and d) very low explanatory power (max R^2

≈ 0.18). In addition, going back to the four basic original hypotheses of the Mansfield Model, it seems that the actual diffusion patterns (H1) can be just as well summarised by a Gompertz growth curve as a logistic curve. This implies the non-uniqueness of the model specification, i.e. different curves with different properties fit the data equally well. There is also no clear cut indication as to whether a fixed saturation point (H2) and a variable speed of diffusion (H4) improve the modelling of the three technologies in the CURDS data set. Moreover, neither the estimating procedure originally used by Mansfield nor any other estimating technique has given satisfactory evidence that the speed of diffusion (β_i) is a linear function of exogenous variables (H3).

On the basis of these results it is very difficult to accept that the Mansfield approach is a valid method for modelling the intra firm diffusion process. Thus the Mansfield model explains only a small part of the diffusion pattern of NC, CNC and CoT. This leads one to conclude that the model seems to rely overly on 'inappropriate' a priori restrictions on the nature of the process of information spreading. In other words, Mansfield's learning seems to explain very little of the diffusion process.

In the next session the theoretical weaknesses of the Mansfield Model are further discussed.

3.3.3 Theoretical weaknesses of the Mansfield model

The previous study has shown that for the three technologies in the CURDS data, there is little support for the predictions of the seminal disequilibrium model. On empirical grounds the Mansfield model fails to give satisfactory results.

Further to the empirical weaknesses there are also theoretical weaknesses which are difficult to accept. They can be found in the existing literature and some of them are summarised below.

First of all there is no good reason to believe that the within firms ownership of new technology follows a logistic distribution. 'The Logistic function results purely from the arbitrary restrictions placed on the Taylor's series expansion used in the model' (Stoneman, 1983). Moreover, on empirical grounds, for the CURDS sample of UK firms and for three technologies, the Gompertz function fits the data as well (as badly) as the Logistic curve (see section 3.2. and also Stoneman and Battisti, 1997).

As pointed out by Griliches (1957), Dixon (1980) and also Chow, (1967) the satiation stock of the diffusion process is not always unity. The intra firm process does not necessarily lead to full replacement of the new technology, in which case the maximum level of adoption is less than the maximum and should be modelled empirically. The information spreading model explains only a small part of the observed diffusion pattern and the model relies overly on unjustified a priori restrictions on the nature of the process of information spreading (Stoneman, 1983). This criticism is in line also with the finding when testing the model over the CURDS sample. The latter indicates that the distributional shape of technology ownership does not follow a Logistic curve (see section 3.2. and also Stoneman and Battisti, 1997).

Mansfield assumes a constant diffusion speed, β, but there is no justification why profitability, liquidity and the size of the investments of a further increase in the level of usage of a new technology (Π_i, C_i, M_i) are constant over time (Karshenas and

Stoneman, 1995 and Stoneman, 1984)[9]. This is also in line with the empirical findings (over the firms in the CURDS sample) providing no evidence that the speed of technology diffusion is either a time invariant constant or a linear function of the variables specified in the Mansfield model (see section 3.2. and also Stoneman and Battisti, 1997)

Another objection concerns the assumption of homogeneous population. In fact Mansfield assumes that the population of potential adopters is homogeneous and constant over time. This sounds quite unrealistic given that the spread of a new technology can take several decades and the population size of the industry changes over time (see Davies, 1979 for a discussion on heterogeneous population) and as it does so also the base population changes.

It is also assumed that adopters do not incur any costs of search. The epidemic model considers potential adopters to be passive recipients of information rather than active seekers of information. (see Midgley et al, 1992).

Mansfield neglects any cost of acquiring new technology and advertising in time t (Glaister 1972; Gould, 1970; Tonks, 1986; Metcalfe, 1981). To think that all that is necessary is that firms purchase a new capital good that embodies the technology may be itself too limiting. In fact it is important to consider the cost of acquiring new technology in time t, or at least the price q_t (or the quality adjusted price) which may

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9 In the Mansfield model the decision on use depends on risk, uncertainty and profitability, but how and why is not specified. In Mansfield, risk is risk as to the uncertainty attached to the profitability of the new technology. It reduces over time, but the firm estimate of the expected profitability (Π_i) is constant, the uncertainty with regard to which reduces over time. It must therefore be only learning that its estimate of Π_{ij} is the right one. The only driving force is that risk will reduce with usage and is related to S_{it}/S^*_i. But this seems to be a very strange story (Stoneman, 1983).

be changing (falling) over time (Karshenas and Stoneman, 1993, Stoneman and Kwon, 1994)[10].

Mansfield completely ignores any technology generations. He assumes that the nature of the technology is unchanged over time or at least ignores any changes in the nature of the technology (See for an example the discussion by Griliches (1980) in reply to Dixon (1980), on changing technology over time and also Mahajan and Wind (1986) [11]. This is unreasonable if one thinks, for example, of computer based technologies or other technological improvements which might arise over time.

Mansfield's information spreading mechanism ignores any external information sources. In fact, one would tend to think that if a firm had information, the whole firm would have access to that information so the information spreading of the epidemic model is irrelevant (see Davies, 1979 and Karshenas and Stoneman 1995).

The Mansfield Model does not take into account any technology complementarity and substitutability, (see pioneering work of David, 1975 or Wozniak, 1984) or more generally the process of replacement of the old with the new when complementary or substitute technologies are introduced into the system. In fact the presence of a

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10 The incorporation of a supply side in such models can internalise the reduction in quality adjusted price over time. Moreover, the firm may in fact face a number of adoption costs when introducing the new technology. Thus, for example, it may be that off-the- shelf embodiments are not available and the technology must be adapted to meet requirements (for an example see Stoneman, 1990). In addition there may be training costs or further management and organisational costs attached to introducing new technology. In the limit, technology may be purpose built for a firm in which case the study of diffusion becomes a study of customer supplier relationship

11 The cost of technology acquisition are also addressed in the work of Cohen and Levinthall (1989) who illustrate that firms that spends upon R&D are more easily able to assimilate new technology. There may thus be complementarities between technology generation and technology adoption.

substitute technology within the firm might speed up the diffusion process due to the increasing 'endogenous learning' from the experience of the old technology. The same should apply to the extent of use of a complementary technology, aimed at enforcing the performance of the existing technology. There may thus be complementarities between technology generation and technology extent of use (examples of this kind of epidemic or endogenous learning effects can be found in applications to inter firm studies by Karshenas and Stoneman (1993), Stoneman and Kwon, 1996, Colombo and Mosconi, 1995 and also Hannah and McDowell (1984)).

Further to the weaknesses outlined by the existing literature, there are other limitations of the model.

Mansfield assumes that learning is at the heart of technology spreading. However, it is not clear whether the learning Mansfield refers to is learning about how to use the new technology (learning by doing) or learning about the existence of the technology by other firms (learning by the experience of the others). In both cases this interpretation doesn't seem to be very realistic considering that the diffusion process within a firm might take many decades[12]. If one interprets learning as the capability of the firm to catch up with most advanced and competitive systems of production Mansfield's explanation doesn't sound very acceptable (Battisti 1998).

The Mansfield model is not capable of dealing with those firms that have used the new technology in the past but that are no longer users of the technology despite inter firm diffusion not being completed. In fact ex users and first adopters do coexist in the same industry. In the Mansfield model only the sample of users is modelled. The

12 See Chapter 2 for examples of timing and pattern of adoption of technologies outsourced from the CURDS data set.

reasons for dismissal of a technology before reaching complete replacement by some of the firms is completely neglected.

The Mansfield model does not take into account that firms, for several reasons, might decide to temporarily suspend the adoption of the new technology. This would imply that there is no reason to believe that the firm monotonically increases its level of output up to complete replacement of the old with the new technology. There are many circumstances in which the firm might decide to suspend the replacement process. Moreover, this decision might be a) temporary, due for example, to an unfavourable temporary financial position; b) permanent, due, for example, to a superior technology appearing on the market or to the disappointing performance of the new technology, the latter leading the firm to simply dismiss the new technology and shift back to the old technology. This suggests that the process of technology transfer might be better modelled by a step function rather than a monotonic continuous logistic curve (Battisti, 1998).

The epidemic model also implicitly assumes that there exists some investment schedule followed by the innovative firm, according to which the replacement of new over old technology changes over time until (full) replacement is completed. Considering once again that intra-firm diffusion might take several decades, uncertainty as to changes in factor prices, market characteristics (in the long run) and unexpected appearance of superseding technology might easily lead to unsuccessful investment plans. Consequently, the firm might change its schedule and not necessarily increase the level of adoption of the new technology. In fact what seems to be a more reasonable explanation of the firm's investment decision is that the firm decides upon the basis of short (or medium) run considerations on profitability of the investment. This will depend on the firm's specific production system, its economic

and financial conditions and the market characteristics in which the firm operates at the time the decision is made. Moreover, given the increasing competitiveness of markets, a firm, in order to remain competitive, should be able to introduce new cost minimising technologies and to remain flexible to changes. This means that the firm should operate at its optimum at each moment in time, upgrading its position as new information about changes in the environment in which she operates occur and consequently changing its medium and long run plans (Battisti, 1998).

The Mansfield model does not adequately deal with the uncertainty surrounding investment in a new technology. In fact, the new technology can be compared to any other assets where the buyer (i.e the entrepreneur) can exercise the option to wait. There are many reasons further to learning that might cause the firm to delay buying the new technology. They are, for example, the financial position, changes in the market conditions via changes in the demand and inputs prices etc. Moreover the new technology being new to the firm is expected to be characterised by uncertainty about: i) its productivity, ii) the capability of the firm to fully exploit its potential; and iii) the real profitability of the technology.

Another aspect ignored by the Mansfield model is that the profitability of adoption might change under different market scenarios and this might influence the decision to further invest in the new technology. Market scenarios may be expected to exert different pressure upon the firm depending on the position of the firm in the market. Whether a firm is a monopolist or a competitive firm should have some relevance upon the intensity of technology adoption.

All these theoretical and technical limitations lead one to abandon the epidemic disequilibrium approach (i.e. Mansfield type approach) in favour of the equilibrium,

Stoneman type approach which seems to be better capable of dealing with the dynamism of the firm and its surrounding environment. This should also release one from the constraints of the epidemic approach and thus allow one to deal with most of its weaknesses. Equilibrium models have been widely explored in the inter firm literature, which provides a good starting point for intra-firm diffusion analysis.

In the next session the salient features of the equilibrium versus disequilibrium approaches are explored.

3.4 Equilibrium versus Disequilibrium models

The existing literature on intra firm diffusion is quite scarce and it mainly relies upon the two existing information based models: the Stoneman model and the Mansfield model. However, for different reasons, neither of them seems to provide a comprehensive and exhaustive explanation of the process of intra-firm technology transfer. Consequently, this study explores alternative approaches to modelling the intra firm diffusion process that move away from reliance on information spreading. As suggested by Karshenas and Stoneman (1995) particularly useful routes are indicated by the *inter firm literature* where *equilibrium approaches* have been widely explored, as opposed to the *disequilibrium approach*es typical of the epidemic models. The difference between the two approaches relies on the relationship, as time proceeds, between the current level of use (S_{ijt}) and the post diffusion level of use of the new technology (S_{ijt}*), i.e. the stock of the new technology that the firm i will own when it is saturated with the good, or equivalently the post diffusion proportion of output produced on the new technology.

According to epidemic modelling, in each period the firm adjusts its current level of use of the new technology until the satiation point, is reached. What drives this adjustment process over time is mainly information acquisition. This is a disequilibrium approach which, in essence, states that diffusion is a disequilibrium process (see also Gold's Critique to these type of models, Gold 1981). There is a final level of use, S_{di}*, and a current level of use, S_{dit}, of the technology and over time the firm i will approach this level of use

$$S_{di}^{*} = \lim_{t \to \infty} S_{dit} \tag{3.21}$$

Moreover, at industry level the final level of usage (S_d*) is equal to the sum of the firms' final level of use of the new technology (S_{di}^{*}):

$$S_d^{*} = \Sigma_i S_{di}^{*} \qquad i=1,.....N \tag{3.22}$$

What this is telling us is that, basically, the equilibrium industry level of use, S_d^{*}, is not time dependent.

The Mansfield model is an example of a disequilibrium model where as the firm accumulates experience from the use, the extent of the further use induced by a given reduction in risk is dependent upon the date of first use, firm characteristics (size and liquidity) and the expected probability of adoption. In other words economic factors influence the diffusion process through the speed of adjustment.

The alternative *equilibrium approach* tends to assume that there is perfect information in the economy on the existence and nature of new technologies and thus, for a given population size and in each point in time, the stock of new technology owned (S_{eit})

equals the optimal level of adoption (S_{eit}*), as if the technology were not new at all but were like any other good.

$$S_{eit}^{*} = S_{eit} \tag{3.23}$$

At industry level the final level of usage (S_{et}*) equals the current level of usage (S_{eit}^{*}) across firms:

$$S_{et}^{*} = \Sigma_i S_{eit}^{*} \tag{3.24}$$

Contrary to disequilibrium models, the equilibrium industry level of use does change over time. It is also believed that S_{eit}^{*} is a function of at least relative prices and income. For this reason it does change with prices and incomes and as such it is time dependent. S_{eit}* may therefore be compared to the demand for the good that would be derived from the standard utility maximising perfect-information models of consumer/producer behaviour found in a standard micro-text book (Stoneman 1984, pag.65). As a result, the factors concentrated upon in the epidemic/information spread approach play no role in the diffusion process.

The Stoneman (1981) model is the first attempt to modelling *intra firm* diffusion using an equilibrium model. However, apart from the Stoneman Model, equilibrium models have never been applied to intra-firm studies.This seems, however, to be a particularly useful route to follow. There exist many examples of equilibrium models applied to inter firm studies summarised as Order, Stock and Rank effect models. They are discussed in the following section where a preliminary intra-firm empirical model derived from this literature is presented.

3.5. PRELIMINARY ANALYSIS OF A NEW APPROACH

3.5.1.Exploring an alternative equilibrium intra-firm approach

The existing literature upon inter firm technology diffusion argues that the determinants of first adoption of a new technology by a firm can be summarised in Rank, Stock and Order effects.

The *rank effect model* ranks firms in terms of the benefit to be obtained from the use of the new technology assuming that potential users are different in some important dimensions (see. David 1991, Davies 1979, etc.). The benefit from adoption is independent of the number of users of the new technology and adoption is mostly determined by the characteristics of the firm (i.e. firm size, liquidity,etc.).

In the *stock effect models* (Reaganum, 1981a, 1981b, 1983, Quirmbach, 1986, etc.) it is assumed that the larger is the number of users of the new technology the lower is the gross benefit from adoption (due to the decline in price of the final product as supply increases).

In the *order effect model*, the firm's position in the adoption order determines its gross return from adoption. So firms high in the adoption order get greater return than those lower down in the adoption order on the ground of pre-emption (see Funderberger and Tirole, 1985) or factors such as prime geographic sites or limited pools of skilled labour (Ireland and Stoneman, 1985). In other words, as opposed to the epidemic effect, as use grows the stock and order effects exert a negative impact on adoption behaviour. The higher the number of rivals who have adopted the technology within or across industry, the lower is the profit gain and the less is the firm motivated to increase the level of adoption.

A first attempt to use an 'equilibrium' approach to modelling the intra firm diffusion processes would suggest that it is necessary to incorporate the above inter firm type effects as well as epidemic effects into models of intra firm diffusion (see Karshenas and Stoneman, 1993). The resulting equilibrium model would then predict that factors that drive the intra firm diffusion process for a new technology are firm heterogeneity and firm interaction. These kind of effects have been widely explored in inter firm studies (see Colombo and Mosconi, 1995, Karshenas and Stoneman 1993, Stoneman and Kwon 1996, etc. or Karshenas and Stoneman 1995 for an extended survey) but have never been applied to intra firm studies.

Following the intuition of Karshenas and Stoneman (1993) rank, stock and epidemic effects have been incorporated into a model of intra firm diffusion (although for obvious reasons the order effects had to be excluded from the model not being applicable to intra-firm studies[13]).

On a pure empirical basis[14], to get some preliminary insight into the role of such factors, the model has then been tested for the technologies available in the CURDS data set. In addition, in order to take into account some of the problems met with the Mansfield model, the new model is formulated so as to be distribution free and to allow the inclusion of those firms that, despite have used the technology in the past, are no longer user in 1993. In essence this model extends the economic factors

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13 Order effects assume the existence of higher profit gains due to first movers advantage and factors such as pools of skilled labour or geographic sites (see Ireland and Stoneman, 1985 and Fudenberg and Titole, 1985). This effect would suggest that returns depend upon the order of adoption. This means that once first adopted, the firm would always find profitable to immediately shift to the new technology. For this reason the order effect is abandoned.

14 Part of this preliminary analysis has already been published in Stoneman and Battisti (1997).

included in the vector of independent regressors beyond those suggested by Mansfield (see section 3.1.2), using the insights provided by inter firm diffusion theory. Therefore, following the 'alternative' equilibrium inter-firm approach to modelling the intra firm diffusion process, the new model of intra firm diffusion is specified as:

$$D_{ijt} = f(\text{Rank}, \text{Stock}, \text{Epidemic Effects})$$

The variables used to measure the impact of the equilibrium and the epidemic effects are sourced from the CURDS data set for the three technologies: NC, CNC and CoT. The epidemic effects are represened by T_{ij} and L_{ij} as in the Mansfield model. The rank and stock effects are represented by: (i) the profitability of adoption and (ii) some measure of the cost of adopting the technology, by assuming that the extent of use of a technology j by firm i is to be related to the profitability and the cost of extending use over time. The latter is, for example, the case when late adopters benefit from lower purchase prices in the years following first adoption. However, in this analysis, given the cross sectional characteristics of the data set, the time dimension of this variable is lost as the cost of extending use (i.e. buying new technology) in 1993 is the same for all firms. For this reason it does not show any variability across the sample of firms and thus cannot be included as an independent regressor [15].

The profitability of extending use can be proxied by a number of variables. These fall into three classes:

(i) Firm characteristics in that one might expect different types of firms to have different expected profit gains. M_i, R&Ddum and Expdum are included as independent regressors to which is also added, R_i the turnover of the firm, as an alternative size indicator.

15 An alternative would be to pool the technologies and thus introduce variance in costs but

(ii) Other technologies owned by the firm in that it is quite possible that different technologies are complements or substitutes in the production process. Thus for example it has been argued that a firm with CNC or NC machines will get greater return from the use of CoT than a firm without. Alternatively it may be that if a firm acquires CNC then this will replace NC machines. Further, a firm with NC machines may get a greater or lesser return by installing CNC machines than a firm without NC machines. To take account of these arguments a series of dummy variables, Dj (j=CNC, NC and CoT), are created taking value 1 if the firm has adopted CNC, NC or CoT technologies prior to 1994, (i.e. allowing simultaneous adoption in 1993) and 0 otherwise.

(iii) Use of the technology by other firms. The inter firm diffusion literature argues (on the basis of economic theory) that the profit gain from adoption of a technology by a firm will be negatively related to the number of previous adopters in the industry to which it belongs (on the grounds that adoption forces down industry prices). One might thus expect that profit gains from further intra firm diffusion will also be related to the number of other firms in the industry using the technology. In addiction, other industry characteristics e.g. the rate of growth of sales may also affect profitability. A series of Dummy variables, D1 –D15, reflecting the industry in which the firm is located, and ISHARE for each j as the share of firms in the industry to which the firm belongs that have adopted technology j by 1994 are also included.

In summary the determinants of adoption of the 'alternative' intra-firm model can be summarised as:

$$D_j = f(M, R\&Ddum, Expdum, R, D_{z1}, D_{z2}, Ishare, D1\text{-}D15, T)$$

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this goes behind this preliminary investigation.

Where D_j defines the current level of ownership of the technology j , while D_{z1} and D_{z2} indicate whether the firm has also introduced in its production process the other two technologies ($z_1 \neq j$ and $z_2 \neq j$).

Before proceeding further it is worth remembering that a particular characteristic of the CURDS data is that for each of the technologies, and especially for NC machine tools, there is a considerable proportion of establishments which have adopted the technology at some date prior to 1993 but in 1993 register zero ownership. It is thus necessary to distinguish between adopters (i.e. firms that have adopted a technology at or before 1993) and users (adopters with a positive value for D_{ij} in 1993) . The two groups from now on are simply referred to as samples A and B, respectively.

In the estimates of the Mansfield model the best results were achieved using sample B, where previous adopters with zero use in 1993 were excluded from the sample. Such a restriction on the sample, means that it not only does not explain zero use, but also wastes information by not including those firms that have zero use and yields inconsistent parameter estimates. In statistical terms the specification that allows one to test for the shape of different distributions over both the restricted and the complete sample, without losing any information in the sample, is the Tobit model or Censored regression model. The statistical details of the Tobit model and the final model specification are provided in the following section.

3.5.2. Testing the alternative intra-firm model: the Tobit specification

The alternative specification of the intra firm model presented in the previous section, aims at modelling the extent of use of the new technology. However, for a significant proportion of firms that could use the technology, the proportion of output produced with the new technology is zero. Traditional regression analysis fails to account for the qualitative difference between limit (zero) observations and nonlimit (continuous) observations (Greene, 1981, 1993 and Amemiya, 1984). In fact one cannot use any continuous density to explain the conditional distribution of the proportion of machinery incorporating the new technology, because the continuous density is inconsistent with the fact that there are several observations at zero.

To exclude the zero observations causes censoring in the sample while their inclusion destroys the linearity assumption of the linear regression model and makes OLS inappropriate (Maddala, 1994). The standard approach that enables one to use the extra information and to overcome the censoring, is the Tobit or Censored regression model (Tobin, 1958).

The Standard Tobit model (or Type I Tobit) for a dependent variable y over a set of independent regressors X is defined as in (3.25) :

$$
\begin{aligned}
&y^* = \beta' X + \varepsilon_i \qquad \varepsilon_i \sim N(0,\sigma^2) \\
&y_i = 0 \qquad \text{if } y_i^* \leq 0 \\
&y_i = y_i^* \qquad \text{if } y_i^* > 0
\end{aligned}
\tag{3.25}
$$

where X is the vector of independent regressors and ε_i are residuals, normally distributed with mean zero and common variance σ^2. The censored variable (y) is a random variable transformed from the original (y*). This model can be easily applied to estimate the parameters of the 'alternative' model, such as:

$$D_{ijt}^{*} = \beta' X_{ijt} + \varepsilon_{ijt} \qquad \varepsilon_{ijt} \sim N(0,\sigma^2)$$
$$D_{ijt} = 0 \qquad \text{if } D^{*}_{ijt} \leq 0$$
$$D_{ijt} = D^{*}_{ijt} \qquad \text{if } D^{*}_{ijt} > 0 \tag{3.26}$$

where D_{ijt} is the current firm level of ownership of the new technology, X is the set of regressors representing stock, rank and epidemic effects and β represents the marginal effect of the index or latent variable ($ME[D^{*}]$) . β also measures the impact of the economic factors on the intra-firm diffusion level over the total sample of firms, whether they are users or not:

$$\frac{\partial E[D_i^{*} | x_i]}{\partial x_i} = \beta \tag{3.27}$$

The impact of the independent regressors on the diffusion level of only those firms that use the new technology at a positive level ($D_{ijt}>0$), is measured by the marginal effect on D_{ijt}, given the censoring at point zero. Such a value can simply be obtained by scaling the vector of the parameters by the probability of positive use in the uncensored regression calculated over the sample mean of X, i.e.$ME[D_{ijt}|D_{ijt}>0]$:

$$\frac{\partial E[D_{ijt} \backslash x_{ijt}, D>0]}{\partial x_{jti}} = \beta \frac{\phi(\beta' \overline{X})}{\sigma} \tag{3.28}$$

where $\overline{X}$ is the sample mean of X_{ijt}. The resulting vector of coefficients shows the direct impact of changes in the independent regressors on the level of use of the technology by firms that use at a positive level.

Given that there is no clear expectation as to the statistical distribution of the intra-firm diffusion process it is here assumed that D^*_{ijt} is Normally distributed[4] as in the original Tobin (1958) exposition. This is reasonable given that data on the current level of ownership of a new technology are only available in the 1993 survey, yielding a single cross-section specification of the model. This assumption also simplifies the estimating procedure. All coefficients can simply be estimated by Maximum Likelihood (ML). In fact when D^*_{ijt} is assumed to be Normally distributed, ML estimates are very similar to those provided by the OLS. In fact the slope of the highly non-linear conditional mean function in this model appears to be approximated rather well by the OLS estimates. However, OLS estimates are not consistent and usually give smaller estimates than ML estimators. OLS can approximate ML values if divided by the proportion of the non limit observations in the sample, i.e. (OLS/number of firms which have already adopted) $\cong$ ML.

The testing procedure used in this section consists of estimating the Tobit model separately for each of the three technologies including all the above variables as regressors and to then refine the estimates into a more parsimonious model by removing non significant variables (in order of least significance) until further removals affect the explanatory power of the regression. However some of the independent regressors may violate the assumption of exogeneity so Instrumental

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5 The Tobin model (Tobin, 1958) presented in this session is not robust to variations from the normality assumptions (see Amemiya, 1984). However, research is ongoing on alternative distribution, where non-normality is present, such as: Weibull, exponential or log-normal (see Maddala, 1994). For the moment Normality is the best assumption for the intra firm model discussed in this session (i.e. normal distribution in time t of the level of ownership over the cross section of firms). For future research, if a panel data set became available, alternative distributions will be considered.

Variable methods have been used with regressors being instrumented by their lagged values (Maddala, 1992).

Table 7.6 presents the results of the parsimonious regressions for each of the three technologies. For each technology there are two columns of coefficients. The first refers to the impact of the independent regressors on the diffusion level of all firms, whether they are users or not, the second measures the impact of the independent regressors on the diffusion level of only those firms that use the new technology at a positive level in 1993, i.e. marginal effects[16].

For CNC technology the diagnostic statistics of the regression are reasonable. The j-test[17] for non nested models (J=0.791 , t-statistics 4.705) indicates that the Tobit is a better model than the Mansfield logistic model and thus the model is explaining a greater proportion of the variance of diffusion. T_{ij}, i.e. time since first use, impacts positively and significantly but L_{ij}, the proportion of firms using the technology at date of first use is never significant. Several measures of firm size have been tried. The revenue measure is never significant. However the employment measure is significant with a positive coefficient.

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16 The sample statistics for the data set (using Sample A) can be found in Appendix C.

17 The J-test (Davidson and McKinnon, 1981) is used to compare the forecasts of the Logistic Mansfield model (d_M^*) against those of the Tobit model (say d_T^*) on the basis that their combination should produce a level of technology ownership (D) with smaller forecast error. The compound model being $D = (1-\psi)\, d_M^* + \psi\, d_T^*$

This model can be estimated by OLS and if ψ is not significantly different from zero, then the Tobit model does not add anything to explain D. If it is significant then the Tobit model explains D over and above the Mansfield model.

Table 3.6. Tobit Estimations

Technology	CNC		CoT		NC	
Variable	Censored	Adjusted	Censored	Adjusted	Censored	Adjusted
Sample size	194	194	154	154	91	91
T_{ij}	**0.01287**	**0.012**	**0.009**	**0.007**	0.00087	0.00081
	(3.595)	**(3.592)**	**(2.602)**	**(2.548)**	(0.384)	(0.104)
M(1970)					0.00011	**0.0001098**
					(1.825)*	**(1.853)**
M(1975)			0.00005	0.00004	**-0.1625**	-0.00015
			(1.827)*	(1.859)*	**(-1.763)**	(-1.629)*
M(1993)					-0.00017	-0.00015
					(-1.394)	(-1.331)
D 0-25	**0.180**	**0.167**				
	(2.981)	**(3.015)**				
D 25-75	**0.239**	**0.223**				
	(3.861)	**(4.006)**				
D 75-125	**0.279**	**0.2597**				
	(3.909)	**(2.959)**				
D> 125	**0.235**	**0.218**				
	(3.381)	**(3.589)**				
RDdum	0.0352	0.033	0.049	0.037	0.0121	0.01129
	(0.969)	(0.985)	(0.820)	(0.121)	(0.766)	(0.298)
Expdum	-0.047	-0.044			0.06189	0.05744
	(-1.449)	(-1.417)			(1.611)**	(0.104)
DCoT	**-0.155**	**-0.144**			**-0.14054**	-0.1304
	(-3.412)	**(-3.057)**			**(-2.271)**	(-1.111)
DCNC			**0.243**	**0.183**		
			(3.569)	**(4.599)**		
ISHARE					**0.27825**	0.25823
					(3.906)	(0.571)
			**p=0.068*	**p=0.058*	**p=0.068*	**p=0.103*
					***p=0.10*	
Conditional Mean	*0.282*		*0.277*		*0.229*	
Scale factor	*0.929*		*0.754*		*0.928*	
LogL	49.135		-62.40		41.3997	

Note: Sample A. Industry dummies suppressed to save space. Figures in parenthesis are the ratio of the coefficient estimate to the estimated asymptotic standard error. Significant at 5% in bold

Various forms have been specified for the employment measure including instruments reflecting employment in 1970, 1975, and 1986. However, the empirical results indicate that a series of dummy variables, reflecting the class size to which the firm belongs in 1993, are most effective. Up to 125 employees the level of intra firm diffusion increases with firm size after which it declines. The R&D and Export

dummies are not significant in the parsimonious form but are occasionally significant in other formulations. They always however carry positive and negative signs respectively.

Of the technology use dummies, nearly all firms that have CNC have previously installed NC and thus there is insufficient variation to estimate a coefficient on the NC dummy. The CoT dummy is significant but negative. One would have expected that as CoT and CNC are complementary that the dummy would carry a positive coefficient but this is not so. A possible explanation for this is that DCOT is in fact an endogenous variable and explained by the other variables already incorporated in the model. Few of the industry dummies are significant (only that for industry 3, Pumps, Valves and Compressors, is significant in the parsimonious version. This is the industry with the highest proportion of adopters). If the industry dummies are replaced by ISHARE, the share of firms in the industry to which the firm belongs that have adopted technology j by 1993, this variable carries a positive coefficient, the opposite to that expected, but the coefficient is not significant at the 5% level. These results thus suggest that significant factors affecting the diffusion of CNC technology are basically time since adoption, firm size, and the use of CoT technology.

The results for CoT technology are reasonably similar. T_{ij} again acts positively and significantly but L_{ij} does not. Firm size, here instrumented by employment in 1975 also acts positively and significantly. The export and R&D dummies again are not significant. The coefficient of DNC is not significant that of DCNC is significant and positive (although recall that most firms with CNC have also previously installed NC). This is as expected. If CoT is complementary to CNC (and NC) then one would expect those firms that have CNC to be more likely to use CoT and to use CoT to a greater extent. Only the dummy for industry 13 (Ball, Roller Plain and Other Bearings) is

significant. The ISHARE variable generally was not significant. For CoT therefore, as with CNC, the significant factors affecting intra firm diffusion are basically time since adoption, firm size, and the other technologies in use. Again the diagnostic statistics are good and the J-test (J=0.646 with t=2.703) suggests that this is a better model than the Mansfield model.

It is with NC technologies that the Tobit estimation should come into its own for this is the technology with the largest proportion of firms with zero use. The superiority of this model is also shown by the good diagnostic statistics and the significance of the J-test (J=0.718 with t=5.625) indicating that this model can account for a higher variability of the diffusion process than the Mansfield Logistic specification. In none of the estimates did T_{ij} ever carry a positive coefficient. This would be consistent with a technology that was at one time being diffused but has for some years been in the process of replacement. The replacement technology is probably CNC but there is not sufficient variability in the sample to test for this. The L_{ij} variable is never significant. Firm size instrumented by employment in 1970 and 1975 is significant, but the coefficients imply a negative relationship. The larger the firm the smaller the proportion of NC machine tools in the machine tool stock in 1993. This would be consistent with larger firms installing more CNC and thus replacing NC machines. The export dummy is significant but the R&D dummy is not. The DCOT dummy carries a significant negative coefficient and two industry dummies (Industrial Plant and Steelwork and Electrical Machinery) are significant. The ISHARE dummy is also significant if included alongside these two industry dummies. These results are obviously different from those for CNC and CoT, but perhaps what one might expect for a technology now being replaced.

In summary, in the Tobit model the factors that drive the intra firm diffusion process for a new technology are basically time since first adoption, firm size, and the other technologies in use. Moreover, this model suggests that as newer technologies are introduced, older technologies (e.g. NC) will be used less extensively. These results hint that what is significant in the determination of the use of a new technology within the firm are: rank effects, represented by the size of the firm; technological complementarities, (i.e. technological characteristics of the firm production system); and epidemic effects via the significance of time since first adoption. So epidemic effects are significant but are not the only determinant of adoption.

Few of the dummies representing the intra industry number of adopters (ISHARE) were not significant for CNC and CoT, but they were from NC, which is a very old technology which is no longer sold on the market. This finding can be interpreted as indicating the non significance of stock effects (implicitly represented by the increasing number of competitors which have adopted the technology), given that the epidemic effects are picked up by the time from the firm's first adoption (T).

This preliminary result also indicates that rank effects are important although largely neglected by the existing intra-firm literature. Among such effects are the impact of the price and cost of adoption (i.e. profitability) of a new technology, technology constraints (i.e. input substitutability) and technology expectations.

3.6. Conclusion

Intra firm diffusion is one aspect of the process of technology transfer that has largely been ignored by economists. In the existing literature there exist mainly two models: the Mansfield (1968) and the Stoneman (1981) model.

The Stoneman model proposes a theory of intra-firm diffusion grounded solidly within economic theory. Its strength relies on the mean-variance approach to the choice of techniques based on rational maximising behaviour. In this framework learning occurs in a Bayesian manner and the expected level of use of the new technology is related to relative profitability, uncertainty, attitudes to risk and adjustment costs. The Stoneman approach is an example of an *equilibrium model* where at each point in time the current level of use of the new technology equals the optimal level of use so that the firm is in equilibrium at each point in time. However, despite its sophisticated theory the Stoneman model is intractable empirically.

The Mansfield epidemic model predicts that the infectiousness of the innovation is determined by its financial characteristics, such as liquidity, size of the firm, expected profitability and risk.It also predicts that the diffusion path is logistic. The Mansfield model is basically a *disequilibrium model* according to which the firm increasingly uses the new technology until it reaches over time the optimal level of adoption, i.e. when it has adopted the new technology 100%. The Mansfield model has been tested empirically however, it does never explain more than 18% of the total variability of the intra firm diffusion process for the technologies in the CURDS data set. Moreover, there is only limited support for the hypothesis that the diffusion process follows a logistic curve. Alternative distributions, like the Gompertz (see Dixon, 1980), seem to fit the adoption pattern just as well as the Logistic one, throwing severe doubts about the Logistic assumptions. A further problem is with firms that have adopted a technology at some past date but now have zero use of that technology, i.e. ex users or firms that have temporarily suspended the adoption. The Mansfield model does not provide any explanation for this. The Mansfield model is inherently a disequilibrium model and also on theoretical grounds the Mansfield model fails to consider important

aspects of the diffusion process. In alternative to this, the equilibrium approach has been discussed leading to some insights on how it can be extended to the analysis of intra firm diffusion. Examples of equilibrium models can be found in the inter firm diffusion literature but, if one excludes the Stoneman model, have never been applied to intra–firm studies. For these reasons an alternative preliminary approach has been defined, based around the use of a Tobit model. This model takes into account the role of rank, stock and the epidemic effects, outsourced from the inter-firm literature, as well as technology complementarities in the process of intra-firm diffusion. It also enables one to better exploit the information in the CURDS sample and the observations on zero use.

Although the Tobit model should be considered only as a preliminary exploration of the possible equilibrium approach to intra-firm technology diffusion, it provides a number of new insights into the understanding of the process of technology adoption within a firm.

The empirical estimates hint that what is significant in the determination of the use of a new technology within the firm are rank effects and epidemic effects, via the significance of time since first adoption. So, epidemic effects are significant but are not the only determinant of adoption, moreover there is ambiguity as whether epidemic effects also pick up stock effects. The latter are in fact significant only for NC, the oldest of the technologies. In order to draw a more conclusive answer as to the importance of profitability considerations upon further extent of use of a new technology, it is necessary to further explore their role upon intra-firm diffusion. In fact, although stock effects do play a major role in inter-firm studies, this aspect has been largely neglected by the existing intra-firm literature. There is also still

uncertainty about the role played by different market structures upon the speed of technology replacement.

The inter firm literature would also suggest that price expectations, the cost of adoption of a new technology as well as technology constraints (due to inputs substitutability in the production process of the firm) play an important role upon diffusion (see for example the empirical inter-firm analysis of Stoneman and Kwon 1996, Karshenas and Stneman 1993). However, their impact upon intra firm diffusion has never been investigated.

All this indicates that there is a clear need for an economic theory of intra firm diffusion based on an equilibrium approach, which is able to deal with the role of: (i) technological constraints to adoption and complementarities between technologies; (ii) the cost of acquiring the technology (and price expectations); (iii) uncertainty; (iv) market structure, i.e. monopoly or competition between firms.

The next two chapters aim at developing such a theoretical model capable of dealing with the weaknesses of the existing literature on intra-firm diffusion.

Chapter 4.

DIFFERENT WAYS OF REPRESENTING A NEW TECHNOLOGY AND THE INTRA FIRM STOCK EFFECT

4.1. Introduction

The previous chapters have highlighted the importance of intra firm technology transfer and the weaknesses of the existing literature in the area. On a purly empirical level they also explored the possible impact of those factors that have already been proved to affect inter firm diffusion, i.e. rank, stock and epidemic effects (order effects do not apply). Among these only rank effects significantly affect the intra-firm diffusion of the three technologies in the CURDS sample, i.e. NC, CNC and Micro. It was not possible to reach a definite conclusion about the significance of the epidemic and the stock effects.

In the inter firm literature the stock effect would predict that the benefits from acquisition for the marginal adopter decrease as the number of adopters increases. In each point in time, for a given cost of aquisition there will be a number of adopters beyond which adoption is not profitable. However, as time proceeds, those costs tend to fall making adoption more attractive. In such models the return from adoption results from endogenising the output decision of the firm. As firms acquire the new technology, their production costs fall. This leads firms to expand output and to reduce price and this reduces the profitability of further adoption (see Reinganum, 1981a, 1981b, 1983, Qurmbach, 1986 and also Karshenas and Stoneman, 1995 for a survey of the empirical applications of these effects). This type of model basically predicts that the adoption of a technology is mainly driven by changes in the returns from adoption over time.

Similar to the inter firm literature, it is plausible to assume that what determines the intra firm extent of use of a new technology is related to the expected profit gains from its further use. In fact, in equilibrium, the optimal level of adoption of the new technology is such as to equal the marginal increase of operating profits with the marginal cost of adding one unit of the new technology. Consequently, it might be that for a given cost of adoption in time t, the extent of use will be limited. As the firm adopts the advanced technology its marginal cost of production reduces, generating higher marginal profits. However, as it does so the firm might want to expand its output. At the aggregate level (or alternatively for a monopolist firm), in order to meet the demand for that good, the increased amount of output has to be sold at a lower price, leading to a shift in the marginal profit from the extensive use of the technology. Consequently, if marginal profit gains decrease with the extent of use of the new technology (or if marginal costs of adding new capital equipment increases, for whatever reason) there is no incentive to immediately replace the entire stock of the old production technology (i.e. there is intra-firm diffusion).

Figure 4.1. Impact of a cost reducing technology

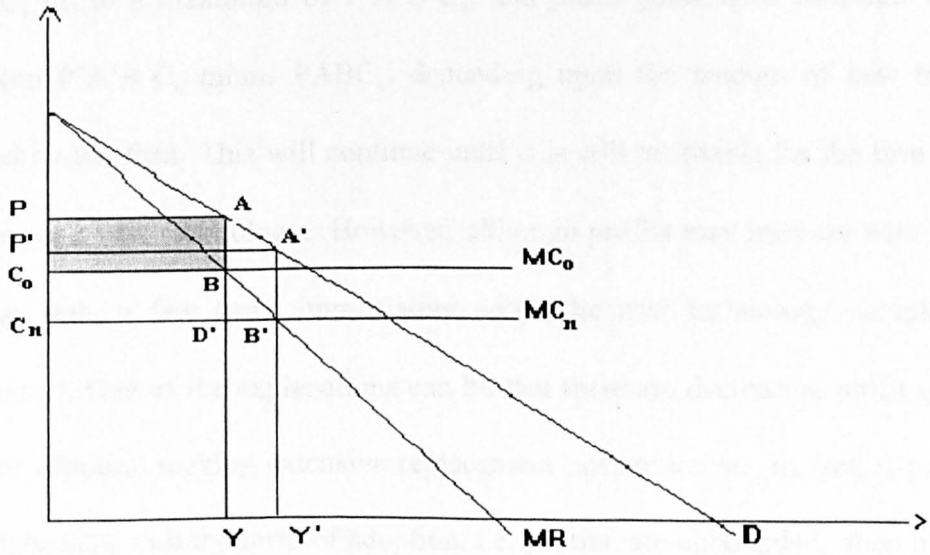

Figure 4.1 shows the implications of different levels of adoption of a new cost reducing technology for a monopolistic firm (or equivalently an industry).

In the pre-adoption period the firm produces output Y which is determined where marginal costs equal marginal revenue (B). The firm sells that amount at the price P that consumers are willing to pay for that quantity, which is represented by the (inverse) demand function, D. In the pre diffusion period, when the firm owns only Ko, the production costs are MC_o and profits are $PABC_o$.

As soon as the firm adopts the first unit of the technology its marginal cost of production shifts down from MC_o to MC_t, where MC_t lies somewhere between MC_o and MC_n. The shift (MC_0-MC_t) is a function of the proportion of the capital stock in time t incorporating the new technology, or equivalently the reduction in costs associated with the use of the new technology. If a firm decides to replace all its existing capital stock with the new technology, without output expansion, its profit gains will be C_oBC_nD'. However, as costs decrease the firm might wish to increase its supply of output up to Y'. If the firm is a monopolist it will have to reduce its price from P to P', in order to sell this amount of output. In Figure 4.1, as output expands from Y to Y', profits from the extent of use of the new technology increase from $PABC_o$ up to a maximum of $P'A'B'C_n$, and profit gains from adoption will range between $P'A'B'C_n$ minus $PABC_o$, depending upon the amount of new technology owned by the firm. This will continue until it is still profitable for the firm to extend the use of a new technology. However, although profits may increase with the extent of use, only a few firms immediately adopt the new technology completely (see chapter 2). One of the explanations can be that there are decreasing profit gains from further adoption making extensive replacement not attractive. In fact, if profit gains are increasing with the level of adoption, i.e. profits are unbounded, then it would be

rational for the firm to immediately adopt all the technology. If instead profit gains decrease with the extent of use of the technology, as hypothesised by the inter firm literature, then these profits are bounded and decreasing with the extent of adoption. This would provide the rationale as to why the firm might not find it profitable to soon adopt all the new technology. One might then conclude that, similarly to the inter firm stock effect, to any given acquisition cost corresponds an optimal level of intra firm adoption of the new technology.

In the intra-firm literature this hypothesis is still unexplored. Consequently, in order to understand whether the speed and the extent of further use of a new technology is subject to 'intra-firm stock effects', one has to look at the pattern of profit gains from adoption. In particular one has to answer the following questions:

- Do profit gains shift to the right or to the left as more output is produced on the new technology ? That is, are profit gains bounded or unbounded as new technology ownership increases?

- What is the optimal level of adoption for a competitive firm compared to a monopolist firm?

This chapter aims at answering the above questions and explores the presence of such intra-firm stock effects upon the spread of use of a new technology. The final aim is to define a new intra firm stock model capable of explaining the determinants of the replacement process of the old with the new technology.

There are several ways of representing a technology and the benefits associated with its use. This study looks at two of them. On the basis of the assumption that the

optimal level of adoption is given by the combination of inputs and the level of output that minimise the firm costs and maximise the firm revenue, the first approach defines the new technology via the reduction in costs brought about by the further adoption. The resulting profit gains from adoption are expressed as a function of the reduction in total production costs (ΔC_t) associated with the extent of use of the new technology (i.e. Cost function approach). The second approach defines a technology via the flow of output that is produced on the set of technologies owned by the firm, where the new technology is just one out of the wider set used by the firm. In essence this approach assumes that there exist technology specific operating costs depending upon the characteristic of the machines in use. The corresponding total costs are the sum of the cost of production using each technology ($C_t=\Sigma_j C(\gamma_j y_{jt})$), which in turn are a function of the technology specific proportion of output (γ_j) produced on each machinery (i.e. multiple technology approach).

The main difference between the two approaches is that in the first case a small increase in the new technology ownership leads to a shift in total cost and an output expansion so that at the margin, the relative benefits from adoption are determined by supply-output effects (see figure 4.1.a). In the second case the cost reduction is proportional to the extent of use of a new technology and is independent of output expansion so that the resulting benefits from adoption are independent of demand.

This chapter looks at the contribution of each approach to the specification of the intra firm diffusion model of technology adoption and at the possible implications under different demand curves and different market scenarios. The impact of market structure upon the extent of use of a new process (intra firm diffusion) has never been explored before. For this reason the behaviour of the firm in deciding how much to

adopt will be examined within both a monopolistic and a competitive environment. The oligopolistic market is represented by the intermediate situation between the two.

This chapter is structured as follows. Section 2 investigates whether profit gains from a shift in total operating costs are bounded or unbounded by looking at the supply–output effect brought about by a reduction in costs and the firm's decision to expand its production. The implicit assumption is that the reduction in costs is due to the further acquisition of a new technology ('Cost function approach'). To more explicitly measure the extent of use of a new technology, total cost are also expressed as a linear combination of the cost of producing on each type of capital stock owned by the firm (i.e. new and old). Moreover, to allow for more flexibility in the model this hypothesis is also tested under different demand constraints, namely a constant elasticity demand and a linear demand function.

Section 3 aims at defining the optimal level of intra firm adoption of the new technology, based upon the impact of technology substitution on the total capacity of the firm. The replacement of the old with the new technology is here driven by the fact that new, advanced machines are designed to produce at lower costs and with higher productivity ('Multiple technology approach'). Moreover, the decision to adopt a new technology can be affected by the position of the firm in the market. The impact of the market structure upon the extent of use of a new process incorporated into a capital good, i.e. intra firm diffusion, has never been explored before. For this reason the behaviour of the firm in deciding how much to adopt will be examined under different market scenarios. A final section summarises the finding of this chapter.

4.2. COST FUNCTION APPROACH

4.2.1. The profitability of increasing use of a new technology:

Consider the case of a single firm (a monopolist) that sells a single output good (y_t) The total revenue of the firm will depend on the amount of supply it chooses to produce, $R(y_t)=p(y_t).y_t$, at the current costs c_t. The profit maximisation problem of this firm can be written as:

$$\max R(y_t) - C(y_t) = \max\ p_t(y_t).y_t - c_t.y_t \qquad (4.1)$$

where, for the moment, costs are simply costs per unit of output.

The amount of output that the firm wants to sell depends upon the price at which it sells its output and the current production cost. The relationship between price and output can be represented by: i) the *Inverse Demand Function,* p(y), which is the price that consumers are willing to pay for any given amount of output, or ii) the elasticity of substitution $\varepsilon = y/p.\ dp/dy$, which is negative for ordinary down sloping demand curves, i.e. $dp(y)/dy<0$ (Stafford, 1971).

From (4.1) the change in profits due to an output expansion is defined as (4.2a):

$$d\pi_t/dy_t = p(y_t) + p'(y_t)\, y_t - c_t \qquad (4.2a)$$

The first order condition for profit maximisation indicates that the level of output that maximises profits is such that Marginal revenue ($p(y_t) + p'(y_t)\, y_t$) equals Marginal Costs (c_t)[1]:

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[1] In terms of differentials (4.2b) can be rewritten as : $p(y_t)\, d(y) + p'(y_t)\, d(y).y_t = c_t\, .d(y)$
This means that a monopolist considers producing an extra unit of output (dy), he will increase his revenue of $p(y^*)\, d(y)$, but in order to sell dy he has to reduce his price by $p'(y^*)dy$ and will loose his revenue on each of the y^* units he is selling. The sum of these two effects gives his marginal revenue. If MR exceeds the (Marginal) costs of production, the monopolist will expand output. The excess stops when MR and MC balance out (Varian, 1984).

$$d\pi_t/dy_t = p(y_t) + p'(y_t)\, y_t - c_t = 0 \qquad (4.2b)$$

and

$$p(y_t) + p'(y_t)\, y_t = c_t$$

Assuming that c_t falls as the use of the technology increases, one may derive from (4.2b) that:

$$d\pi_t/dc_t = p''\, y_t \,.\, dy_t/dc_t + p'\, dy_t/dc_t - c\, dy_t/dc_t - y_t \qquad (4.2c)$$

Imposing the first order condition (4.2b), the first three terms cancel out and (4.2c) reduces to (4.3):

$$d\pi_t/dc_t = -y_t \qquad (4.3)$$

This indicates that decreasing unit costs will yield profits increases proportionately to the level of output. (4.3) can also be rewritten as (4.4), which shows that profit gains per unit of output are proportional to the reduction in costs (c_t-c_{t-1})

$$d\pi_t / y_t = -\, dc_t > 0 \qquad (4.4)$$

From (4.3), the impact on the profit gain of a change in costs can be defined as (4.5):

$$\boxed{d^2\pi_t/d^2c_t = -\, dy_t / dc_t} \qquad (4.5)$$

The sign of (4.5) determines the curvature of the profit function with respect to changes in costs. Consequently, in order to determine whether profit gains from costs reduction are bounded or unbounded ($d^2\pi_t/d^2c_t$ >/<0) it is important to determine the sign of the rhs of (4.5) , i.e. dy_t / dc_t

From (4.2a) the optimal level of output y_t* is given by (4.6):

$$y^*_t = (c_t - p_t)/\, p'(y_t) \tag{4.6}$$

which after substitution in (4.1) allows one to express profit just as function of the optimal level of output and the slope of the (inverse) demand curve:

$$\pi_t = -y^{*2}_t \,.p'(y_t) \tag{4.7}$$

Using (4.7) one can derive the first order condition of profit maximisation per unit cost as:

$$d\pi_t/dc_t = -\,2.\, y_t .\, p'(y_t).\, dy_t/dc_t \;-\, y_t^2 .\, p''(y_t)\, dy_t/dc_t$$

or equivalently:

$$d\pi_t/dc_t = -\, dy_t/dc_t .\, y_t\; (\,2 .\, p'(y_t) + y_t .\, p''(y_t)\,) \tag{4.8}$$

From (4.8) and (4.3) one gets (4.9):

$$dy_t/dc_t = \{\, p'(y_t) + [\, p'(y_t) + y_t .\, p''(y_t)]\}^{-1} \tag{4.9}$$

and substituting (4.9) into (4.5) one can rewrite (4.5) as (4.5'):

$$d^2\pi_t/d^2c_t = -\,\{\, p'(y_t) + [\, p'(y_t) + y_t .\, p''(y_t)]\}^{-1} \tag{4.5'}$$

The term into brackets is the inverse of the second order condition for output maximisation, i.e.:

$$d\pi_t^2/dy_t^2 = p_t'(y_t) + [p_t'(y_t) + p_t''(y_t)\, y_t] \tag{4.10}$$

where $p_t'(y_t)$ is the slope of the demand curve and $[p_t''(y_t)\, y_t + p_t'(y_t)]$ is the slope of MR. However, the sign of (4.5') is not as straightforward as it might seem, and the results in the literature are in fact contrasting. Hahn (1962) has proved that (4.10) is negative, i.e. $d\pi_t^2/dy_t^2 < 0$. This concavity condition indicates that the MR curve is steeper than demand, i.e. $[p_t''(y_t)\, y_t + p_t'(y_t)] < p_t'(y_t)$ and would imply that unit profits

from unit cost reduction (see 4.5) are convex ($d^2\pi_t/d^2c_t > 0$), and bounded , i.e. with decreasing profit gains from adoption.

However, Seade (1980) proves that the negativity assumption of (4.10) holds only for local linearizable stability solutions. In fact he adds a further interpretation of this inequality. He rewrites:

$$d\pi_t^2/dy_t^2 = p_t' (p_t'' y_t / p_t' + 1) + p_t' \qquad (4.11)$$

where p' is the slope of the demand curve and the term $p_t'' y_t / p_t'$ is the <u>elasticity of the slope of demand</u> (ε_{SD}). He then proves that certain kinds of demand curves might violate Hahn's assumptions especially when some dynamic adjustment is introduced. Seade concludes that the slope of the demand curve matters and it is the sign of the elasticity of the slope of demand that determines the concavity or the convexity of the relationship.

Seade demonstrates his theory within an oligopolistic framework. This section deals with a monopolistic market but the argument still holds. In fact, if we assume that the monopolistic firm faces an isoelastic (inverse) demand such as:

$$p_t = Ay_t^{\eta} \qquad (4.12)$$

then $p'(y_t)$ and $p''(y_t)$ are respectively:

$$dp_t/dy_t = A\,\eta\, y_t^{\eta-1} < 0 \qquad (4.13)$$

$$dp_t^2/dy_t^2 = A\,\eta\,(\eta-1)\, y_t^{\eta-2} > 0 \qquad (4.14)$$

Given that the monopolist will always produce where the elasticity of demand $1/\eta < -1$ (see Varian, 1990), than the rhs of (4.13) is negative, while the rhs of (4.14) is positive.

From (4.13) and (4.14) one can derive the *elasticity of demand* ($\varepsilon_D = p'p/y$) as $\varepsilon_D = \eta$, and the *elasticity of the slope of the demand* ($\varepsilon_{SD} = p''y/p'$) as (4.15):

$$\varepsilon_{SD} = \eta - 1 < 0 \tag{4.15}$$

which is negative.

Substituting (4.13) and (4.14) into (4.10) allows to specify the second order condition for profit maximisation with respect to output as (4.16):

$$\boxed{d\pi_t^2/dy_t^2 = A \,.\, y^{\eta-1} \,.\, \eta \,.\, (\eta + 1) < 0} \tag{4.16}$$

(+). (+) .(-). (+)

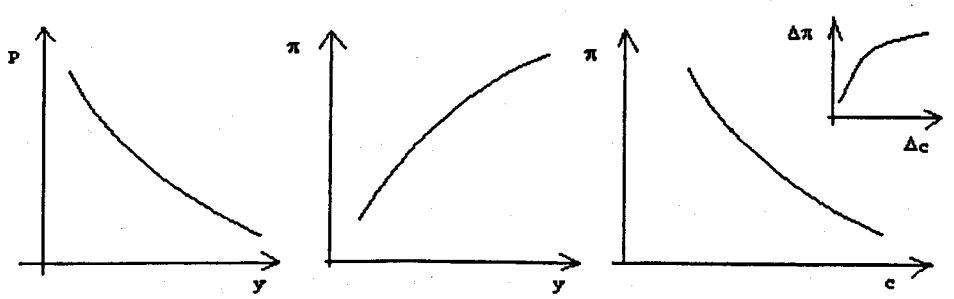
and correspondingly (4.17):

$$\boxed{d^2\pi_t/d^2c_t = - \{ A \,.\, y^{\eta-1} \,.\, \eta \,.\, (\eta + 1)\}^{-1} > 0} \tag{4.17}$$

(-) (+). (+). (-). (+)

The sign analysis (signs are in brackets) tells us that the relationship between profits and output (4.16) is concave while the relationship between profit and costs (4.17) is convex. This means that there are decreasing profit gains from output expansion and increasing profit from cost reduction but the corresponding profit gains are concave, i.e. decreasing with the cost reduction[2]. These results are represented in Figure 4.2.

Figure 4.2.Monopolist facing an isoelastic (inverse) demand curve:$P_t = aY^{\eta}_t$ ($\varepsilon_{SD}<0$)



2 The shape of profit gains is determined looking at the second and third order condition of cost minimization: $d^2\pi_t/d^2c_t = -\{A.y^{\eta-1}.\eta.(\eta+1)\}^{-1} > 0$;

$d^3\pi_t/d^3c_t = -\{A.y^{\eta-2}.\eta(\eta+1).(\eta-1)\}^{-1} < 0$

While the first indicates that profit gains increase with the cost reduction, the second indicates that they are concave, i.e. bounded.

The first plot simply shows the negative relationship between output and prices via the constant elasticity demand curve. The second plot shows the results of (4.16) indicating that profits from output expansion are increasing but bounded. The last plot shows the cost constraint (4.17) indicating that there are increasing profits from cost reduction. However, the shape of the profit gains is concave, i.e. they are bounded, therefore they increase but less than proportionally with cost reduction (see footnote 2). Moreover, from the comparison of (4.16) and (4.17) the growth rate in profit gains per unit of output is greater than the profit gains from the reduction in costs.

If, instead of an isoelastic curve, the firm faces a negatively sloped linear (inverse) demand curve such as:

$$p_t = a + by_t \qquad b<0$$

then $p'(y_t)$ and $p''(y_t)$ are:

$$dp_t/dy_t = b \tag{4.18}$$

$$dp_t^2/dy_t^2 = 0 \tag{4.19}$$

The rhs (4.18) is negative while (4.19) is equal to zero, meaning that the demand function has got a constant and negative slope, i.e. with *elasticity of the slope of the demand* equal to zero:

$$\varepsilon_{SD} = 0 \tag{4.20}$$

Substituting (4.18) and (4.20) into (4.5') yields:

$$\boxed{d\pi_t^2/dy_t^2 = 2b < 0} \tag{4.19}$$

which is negative.

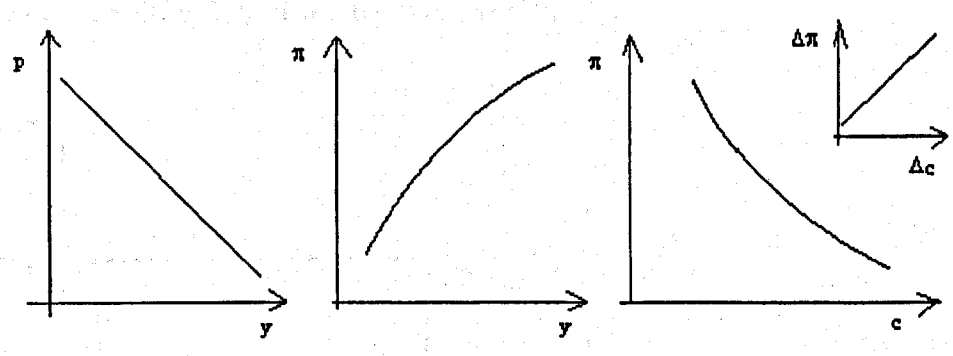
Moreover, from (4.19) condition (4.5) becomes:

$$\boxed{d\pi_t^2/dc_t^2 = -1/2b > 0} \qquad (4.20)$$

which is positive.

(4.19) and (4.20) show that, similar to the constant elasticity of demand case, when the firm faces a linear demand function, the relationship between profits and output is concave while the relationship between profits and costs is convex.

Figure 4.3. Monopolist firm facing a linear (Inverse) Demand curve: p_t=a+by_t (ε_{SD}=0)



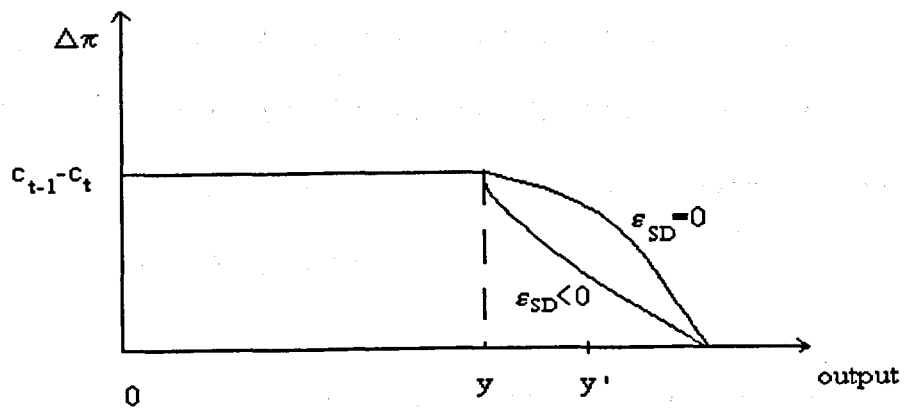
These results are summarised in Figure 4.3. The linear demand function is represented in the first plot. The second plot shows that there are decreasing profit from output expansion (equation 4.19), while in the third plot profit gains are constant and they do increase with the reduction in costs (equation 4.20)[3]. In other words, profits from a cost reduction linearly increase with the cost reduction so that the monopolistic firm will always find it profitable to switch immediately to lower costs of production, i.e. the new technology.

3 The shape of the profit gains under linear demand function is determined looking at the second and third order condition of cost minimization: $d^2\pi_t/d^2c_t = -1/2b > 0$; $d^3\pi_t/d^3c_t = 0$. While the first indicates that profit gains decrease the second indicates that they are constant, i.e. unbounded.

Moreover, profit gains due to output expansion (4.19) increase faster than the increase due to the reduction in cost (4.20).

The previous results, (4.17) and (4.20), indicate that the elasticity of the slope of demand (ε_{SD}) is inversely related to the curvature of the (inverse) demand function, and it takes its sign from whether the latter is concave or convex. The higher in absolute value the elasticity of the slope of demand (i.e. the more is the demand curve convex) the lower are profit gains from further adoption.

Figure 4.4. Profit gains with output expansion



Note: see equation (4.4): $d\pi_t/y_t = - dc_t > 0$

Figure 4.4. represents this result graphically. For a firm producing output y, the profit gains from a cost reduction ($c_{t-1}-c_t$) are constant and depend on the current level of output produced (y) (see equation 4.4). However, in the case of output expansion (i.e. from y to y') , the corresponding benefits from cost reduction are inversely related to the slope of the elasticity of the demand (ε_{SD}).

If the firm faces a negative ε_{SD} (inverse) demand curve, when expanding output the profit gains from a cost reduction are bounded and decreasing relatively to the

reduction in costs. This indicates that the firm might not necessarily decide to immediately shift all its production to the new cost reducing technology but instead wait; a simple output expansion might generate high enough profits without requiring further investments in production. On the other end, if the firm faces a zero ε_{SD} (inverse) demand curve , i.e. a linear demand curve, then profit gains from further adoption are constant and unbounded.

In summary one can conclude that the benefits from cost reduction and/or output expansion are a function of the level of output produced. More importantly, profit gains depend upon the curvature of the (inverse) demand function, and their sign depends on whether the latter is concave or convex.

Based upon these results, for a monopolist, the speed of the introduction of a new cost reducing technology depends upon the elasticity of the slope of the (inverse) demand curve it faces in the market for its product.

Table 4.1. Profitability of adoption in presence of output expansion

	ε_{SD}	$\pi_t=f(c_t)$	$\pi_t=f(y_t)$	$d\pi_t=f(dc_t)$
Monopoly				
-isoelastic demand function	Negative	Convex	Concave	Positive/Bounded
-linear demand function	Zero	Convex	Concave	Constant/Unbounded

In particular, if the firm faces a demand with zero elasticity of the slope ($\varepsilon_{DS}=0$), (for example a linear elasticity curve) then profits per unit of output are bounded and profit gains decrease with the cost reduction. If instead the elasticity of the slope is negative ($\varepsilon_{DS}<0$) (for example a isoelastic demand curve) profits per unit of output are bounded and profit gains decrease (more than proportionally) with the cost reduction per extra unit of output.

If one assumes that the shift in MC is brought about by the purchase of a cost reducing capital embodied technology, this result would suggest that in absence of output expansion the profit gains from adoption (c_{t-1}-c_t) are proportional to the level of ownership of the new technology. The higher the extent of use, the greater the cost reduction and the higher the profits gains will be. However, as the firm decides to expand its output, the benefits from the use of the new technology will depend upon the shape of the demand curve. This is an important result, showing that the marginal benefits from adoption do not necessarily increase with the extent of use of a new technology; this might explain why firms do not immediately adopt all the new technology but instead wait. However, the result does not hold across different demand functions. This leads one to conclude that, consistently with the inter firm diffusion studies, for a profit maximising firm profitability considerations may play a relevant role in the decision to invest. However, as specified in this model, the intra-firm stock effect does not necessarily slow down the extent of use of a new technology. Even if very informative, this approach does not provide a measure of the optimal level of intra firm ownership of a new technology. So far the extent of use of the advanced technology has been implicitly measured via the reduction in production costs.

The next section aims at deriving the optimal level of intra-firm adoption, by imposing that the shift in costs (or equivalently profit gains) can be expressed as related to the proportion of new technology incorporated into the capital stock of the firm.

4.2.2. The optimal level of technology adoption

The model presented in this section is an extension of the one presented in the previous section. The only difference is that now total costs are specified as a combination of the cost of production associated to each type of technology. Assume, for simplicity, that the firm owns two sets of technologies: the 'new' technology (K_n) and the set of existing, or 'old', technologies (K_o).

One way of representing a superior technology is via the reduction in production costs brought about by its relative level of use. This is done by expressing the total costs of production of the firm (C_t) as the combination of the unit costs of production of the new ($C_{nt}= c_n.K_{nt}$) and the existing technologies ($C_{ot}= c_o.K_{ot}$) so that:

$$C_t(C_{ot}, C_{nt})$$

where C_{nt} and C_{ot} are the technology specific cost of production and are a function of the level and type of technology in use by the firm. For simplicity, assume also that:

I) marginal costs equal average costs both for the advanced (MC_n) and the existing (MC_o) technology:

$$MC_o=AC_o=c_o$$
$$MC_n=AC_n=c_n$$

where c_n, the unit cost of production with the new technology, is less than c_o, i.e. $c_n<c_o$.

II) Total marginal costs can be represented by a convex function of c_o and c_n which lies between MC_o and MC_n (see figure 4.1):

$$c_t= \alpha_t c_n + (1-\alpha_t)c_o \qquad (4.21)$$

where $\alpha \in [0;1]$.

α, the proportion of production undertaken with the new technology, is here taken as a measure of intra-firm diffusion.

(4.21) also implies that a change in cost (dc_t) due to a change in the optimal combination of new and old technology ($d\alpha_t$) is equal to the shift in the costs of production with the old and the new technology :

$$dc_t/d\alpha_t = c_n - c_o < 0 \qquad (4.22)$$

which is negative, being $c_n < c_o$, and constant, being $d^2c_t/d^2\alpha_t = 0$.

After substitution of the cost function (4.22), the generic profit function of the firm can be specified as (4.23):

$$\pi_t = p_t\, y_t - [\, \alpha_t c_n + (1-\alpha_t)c_o]\, y_t \qquad (4.23)$$

The optimal combination of input, proxied by α_t is defined by imposing the first order condition for profits maximisation:

$$d\pi_t/d\alpha_t = d\pi_t/dc_t \,.\, dc_t/d\alpha_t \qquad (4.24)$$

In the previous session (4.2.1) it has been proved (see equation (4.3) that whatever shape of the demand function , the first term on the rhs of (4.24) leads to :

$$d\pi_t/dc_t = -y_t \quad < 0 \qquad (4.25)$$

This means that there are increasing benefits from technology adoption. In order to see whether profits are bounded or unbounded one has to determine whether the relationship between profits and α is concave or convex.

Substituting condition (4.25) and (4.22) into (4.24) yields:

$$\boxed{d\pi_t / d\alpha_t = (-y_t).(c_n - c_o) > 0} \tag{4.26}$$

$$(-) . (-)$$

Which is positive, $(c_n - c_o)$ being less than zero. That means that there are positive profit gains and they are a function of the cost reduction brought about by the use of the advanced technology.

From (4.24) the second order condition of profit maximisation with respect to α_t is:

$$d^2\pi_t / d^2\alpha_t = d^2\pi_t /^2 dc_t . dc_t / d\alpha_t + d\pi_t / dc_t . d^2c_t / d^2\alpha_t \tag{4.27}$$

The second term of (4.27) equals zero as $d^2c_t/d^2\alpha_t=0$ Moreover from (4.24) one can rewrite (4.28):

$$d^2\pi_t / d^2\alpha_t = d^2\pi_t /^2 dc_t . (c_n - c_o) \tag{4.28}$$

(4.28) indicates that the convexity or concavity of profits depends upon the sign of $d^2\pi_t / d^2c_t$. The latter, as already shown in section 4.2.1, depends upon the elasticity of the slope of demand (ε_{SD}). Consequently, in the <u>monopolist case</u> one might want to distinguish two cases according to the shape of the (inverse) demand curve, yielding the following results:

a) If the firm faces an isoelastic demand function ($p_t = Ay_t^{\eta}$) with $\varepsilon_{SD} = \eta - 1 < 0$ then from (4.17) (see section 4.2.1):

$$d^2\pi_t / d^2c_t = - \{ A . y^{\eta-1} . \eta . (\eta + 1) \}^{-1} > 0$$

This indicates that:

$$\boxed{d^2\pi_t / d^2\alpha_t = d^2\pi_t / d^2c_t . (c_n - c_o) < 0} \tag{4.29}$$

$$(+) . (-)$$

while

$$\boxed{d^3\pi_t / d^3\alpha_t = d^3\pi_t /^3 dc_t .(c_n - c_o) \quad >0}$$
$$(-) \quad . \quad (-)$$

It is straightforward to see that the sign of (4.29) is negative, meaning that the benefits from the extensive use of a new technology are concave and therefore decrease with its level of use, i.e. profit gains are bounded.

b) If the firm faces a linear demand function ($p_t = a + by_t$) with $\varepsilon_{SD}=0$ then from (4.20) (see section 4.2.1):

$$d\pi_t^2/dc_t^2 = -1/2b > 0$$

and

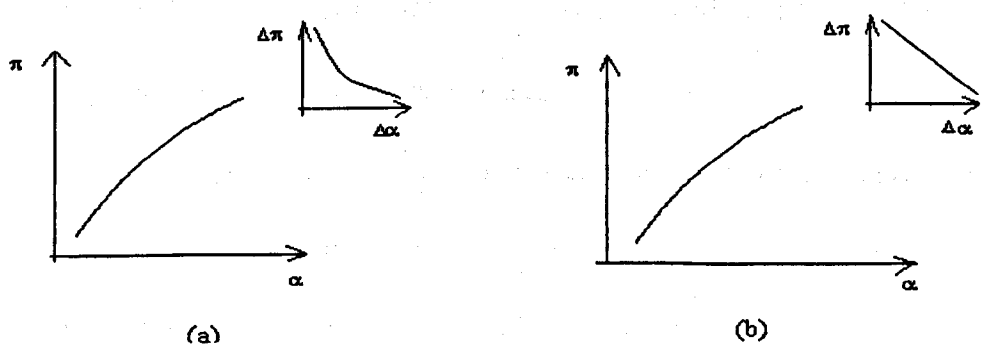
$$\boxed{d^2\pi_t / d^2\alpha_t = d^2\pi_t /^2 dc_t .(c_n - c_o) \quad <0} \qquad (4.30)$$
$$(+) \, . \, (-)$$

while:

$$\boxed{d^3\pi_t / d^3\alpha_t = d^3\pi_t /^3 dc_t .(c_n - c_o) \quad =0}$$
$$(0) \, . \, (-)$$

In this case there are positive and concave profit from adoption (α), while profit gains associated with the extent of use of a new technology are decreasing and constant.

Figure 4.5. Extent of use (α) and profitability (π)



Note: (a) non-linear demand function; (b) linear demand function.

These results are consistent with the previous finding (see section 4.2.1.) and are summarised in Figure 4.5. The first two graphs on the left (Figure 4.5/a) show that for a firm facing a isoelastic demand curve, there are increasing concave profits from adoption. This indicates that profit gains do decrease with the extent of use of the new technology (α) or equivalently they decrease with the reduction in cost brought about by a decrease in α. In the case of linear elasticity case (see figure 4.5/b): profit gains from the adoption of a new technology increase with the level of adoption (α). Similar to total costs (see table 4.1), the benefits from the extensive increase in the adoption of a cost reducing technology are constant /unbounded and the greater the level of new technology ownership, i.e. the lower the cost reduction, the higher profit gains are In particular, in the case of linear demand the firm will get decreasing but constant return proportional to further adoption, while in the case of isoelastic demand, the firm will face returns less than proportional to the increased extent of use. Consequently, decreasing profit gains, expecially for isoelastic demand goods, could lead the firm to delay adoption until costs of acquisition fall.

These results show that the hypothesis of decreasing returns from adoption (i.e. Stock effects) as the inter firm stock effect would suggest, do exist but both intensity and direction depend upon the shape of the demand curve and their sign is determined by the elasticity of the slope of the demand curve (ε_{SD}).

For these reasons and because we have not been able to derive an expression for the optimal level of capital accumulation, the Cost function approach is abandoned.

An alternative route defined the "Multiple technology (or Vintage) approach" is explored in the following session.

4.3. The multiple technology approach

Another approach to explaining the dynamic of technological replacement is to look at the flow of output that is produced with the current technologies and the benefits associated with the extensive use of the latest ones. In fact at each moment in time the firm's capital stock can be represented as made up of machines with different productive potentials, where older machines embody more outmoded techniques which were best practice at the time they were introduced. On the contrary newer machinery embodies improvements in knowledge and can produce more efficiently at best practice standards of efficiency in the use of all the input of production (Salter and Reddaway, 1966). This means that each machine is characterised by different productivity and different marginal costs so that within a firm the same amount of output can be produced at different costs according to the characteristics of the machines in use. Because the extent of use of each technology is related to the type of machinery, this approach is defined Multiple technology[4].

Under the assumption that the firm produces at maximum capacity all the time, the capacity (x_{ji}) of each unit of capital good can be assumed to be equal to the amount of output it can produce, which, in turn, is determined by the productivity of the specific type of technology it embodies. In this way each unit of machinery in use by the firm

4 This approach similar to the Vintage literature in the sense that they both look at the impact of the introduction of a new technology on the total capacity of the firm and assume that is the aging of the existing machinery what determines its replacement rate (see Malcomson, 1975, 1982, etc.). However, contrary to the Vintage literature, the proportion γ is not a function of the age but rather the type of technology incorporated in the machinery j in use: $x_j = \gamma_i y$. A similar approach can also be found in Salter and Reddaway (1966) in explaining the replacement process of the existing capital stock and the scrapping of old with newer more advanced machinery. In their model, they relate the age of each machinery to the output per man hour.

is technology specific and can be represented by the proportion (γ) of total output (y_t) it can produce. Moreover, this proportion (γ) is technology specific and reflects the productivity of each technology in use, that is:

$$x_j = \gamma_j y_t \tag{4.31}$$

Being $\gamma \in [0;1]$ and $\Sigma \gamma_j = 1$, it is immediate to see that the total capacity of the total capital equipment owned by the firm equals total output[5]:

$$\Sigma_j x_{jt} = \Sigma_j \gamma_j y_t = y_t$$

In this light total operating costs C_t can no longer be expressed simply as the cost per unit of output, i.e. $TC = C_t . y_t$. as the cost approach would suggest (see section 4.2). Costs are rather a function of the flow of output that each machine is capable of producing, i.e. $C_t(\gamma_j y_t)$, and total costs , i.e. $TC = C_t(y_t)$ are the sum of the costs of producing on each machinery:

$$TC = \Sigma_j C_t(x_{jt}) \tag{4.32}$$

or equivalently, assuming that costs are homogeneous of degree one and using 4.31, they can be rewritten as:

$$C_t(y_t) = \Sigma_j \gamma_j C_t(y_t)$$

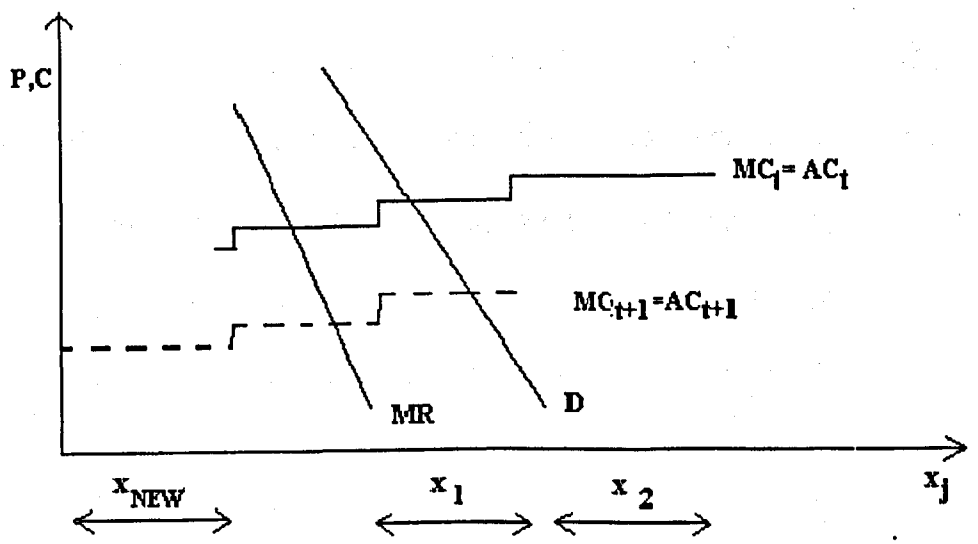
where by definition $\Sigma \gamma_j = 1$.

5 On the same line it is possible to show that the output produced on each machinery is determined by the technology specific productivity and equals $y_{tj} = (\gamma_j)^{-1} x_{jt}$ where total output is a function of the sum of each technology specific capacity, $y_t = \Sigma_j (\gamma_j)^{-1} x_{jt}$.

In Figure 4.6. the total capital stock of the firm ($x = \Sigma_j x_j$) is represented on the horizontal axes, as the sum of each type of capital embodied technology j. Moreover, each type of technology j owned by the firm is represented as x_j (where j=1,..n.) and it is sorted from the newer (j=1) to the older (j=n). The vertical axes define the operation cost associated with each type of machinery.

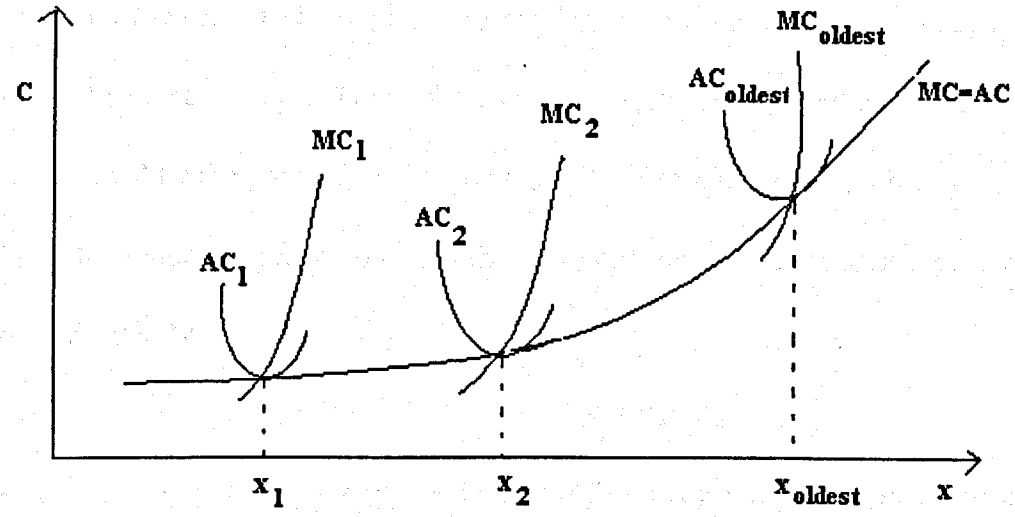
For ease of presentation, for each technology it is assumed that marginal cost equals average cost. Under this assumption each step of the cost function represents the cost associated to the characteristics of each technology the firm owns at time t, where x_1 is superior to, i.e. more cost reducing than, x_2. Given that the cost to produce on old machinery is higher than to produce on newest machinery the total costs at time t are represented by the straight split line.

Figure 4.6. Costs and the capacity of each machinery owned by the firm



Alternatively, plotting the average and marginal cost of production for each technology, the total cost step function of the firm can be represented in terms of continuous functions as in Figure 4.7.

Figure 4.7. Total costs and multiple technology choice



By assuming that any new investment is made up of machines of the latest type, more productive than the older ones , and assuming that the firm uses these machines at full capacity, technology replacement can be measured as the impact of the introduction of a new technology on the total production costs of the firm. In fact, going back to Figure 4.6. as the firm acquires a new technology x_{NEW}, the cost function (MC) shifts to the right due to the further reduction in production cost, i.e. $MC_t \rightarrow MC_{t+1}$, and some of the oldest technologies (i.e. those on the right) are eventually disregarded. The impact of the adoption of the new technology is represented by the dotted line in Figure 4.6. Consequently the higher the extent of use of the new technology the lower is the cost of production. The minimum cost corresponds to the complete replacement of the existing capital stock with the more advanced technology.

In mathematical terms assume, for simplicity, that the firm owns only two sets of technologies: the advanced technology (x_{nt}) and the existing technologies (x_{ot})[6].

6 This assumption greatly simplify the mathematical complexity of the models in presence of multiple technologies, without changing the nature of the problem.

Assume also that the productivity of each type of capital is technology-specific, i.e. lower for the older technologies ($\gamma_o<\gamma_n$ and $\gamma_o+\gamma_n=1$) and that each machinery is fully utilised so that $x_{jt} = \gamma_j\, y_t$. Under these conditions, the capacity of each machine can be represented by the proportion of total output it can produce $x_{jt} = y_{jt}$ where j=o,n, so that in each moment in time total output the firm produces equals the total capacity $y_t=\Sigma_j\, x_{jt}$ or equivalently:

$$y_t = y_{ot} + y_{nt}$$

where $y_{ot} = \gamma_o \cdot y_t$ and $y_{nt} = \gamma_n \cdot y_t$ are the units of output produced in time t, respectively on the old (x_{ot}) and the advanced technology (x_{nt}).

In this framework the profit maximising problem for a monopolist firm can be re-written as:

$$\max \pi_t : TR_t - TC_t = p_t\,(\Sigma_j\, x_{jt}) - \Sigma_j\, C(x_{jt}) \qquad j = \text{old, new} \qquad (4.33)$$

where total revenue (TR) depends on the total quantity produced on each machinery (i.e. the current capacity of the firm $\Sigma_j\, x_{jt} = y_t$), while total cost (TC) is the cost of producing on each type of technology j available within the firm (see equation 4.32). The first order condition for profit maximisation with respect to the capacity of each technology j is given by the partial derivative with respect to each technology j:

$$d\pi/dx_o = p'(\Sigma_j\, x_j) - C(x_o)'$$

$$d\pi/dx_n = p'(\Sigma_j\, x_j) - C\,(x_n)' \qquad (4.34)$$

Using the Lagrangean multiplier it can be easily proved that, in equilibrium, the marginal cost of producing on each technology should be equal (see figure 4.8) [7]:

$$C(x_o)' = C(x_n)' \tag{4.35}$$

Figure 4.8. Total costs of multiple technology plant and extent of use of a technology

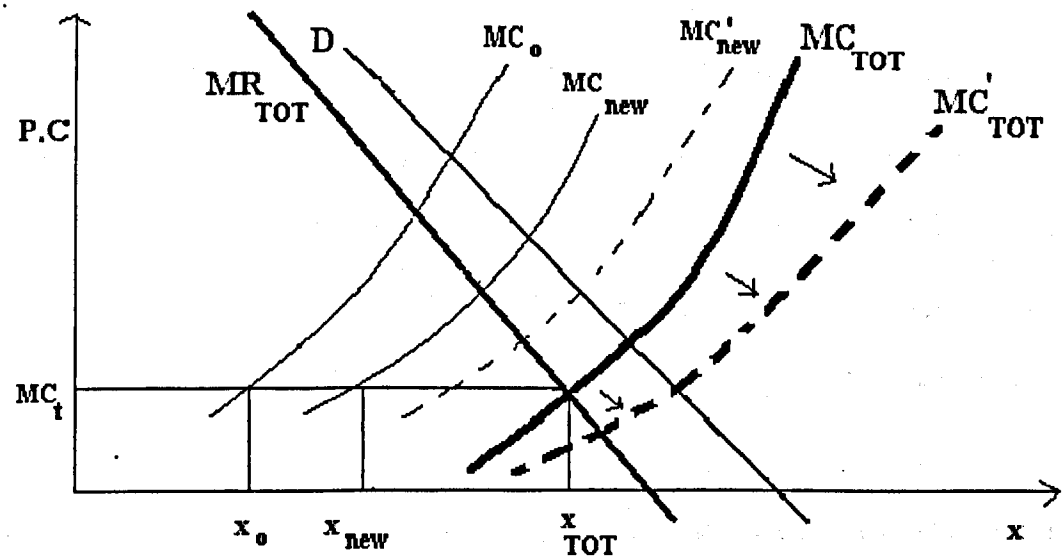


Figure 4.9 shows this property for a firm using two technologies. For this firm the total marginal cost curve is simply the horizontal summation of the individual MC_j curves of producing on each type of technology ($MC_{TOT} = \Sigma_j MC(x_{jt})$). The quantity x_{TOT} is sum of the production capacity on each type of technology ($x_{TOT} = x_o + x_{NEW}$) and

7 This case is similar to the multiplant monopolist, for which total revenue depends on the quantity produced in each plant and the total costs in each plant. Marginal analysis indicates that the marginal revenue for the output as a whole must equal MC in each plant. In fact if the MC were lower in one plant, additional production would take place in the plant until

$$MC_i = MC_j = MR_{TOT}$$

where MR_{TOT} is the overall marginal revenue $MR_t = p_t (\Sigma_j x_{jt})$. In addition, for the first order condition of output maximisation to hold MR must increase less rapidly than the MC in each plant, i.e. MR-MC ≥ 0 (Kamerschen, Valentine, 1977).

correspond to where MC_{TOT} intersects MR_{TOT}. Graphically, this is represented by the distance of each type of x_j from the origin of the axes, i.e. $0x_{TOT}=\Sigma_j\ 0x_j$ (and it can be seen that $d(0;xo) = d(x_{TOT}-x_{NEW})$). Given that the firm uses the existing machinery at full capacity, the optimal amount of each technology is determined where marginal cost of producing on each technology are equal, i.e. $MC_{jt} = MC_t$. Any amount of technology produced above that level would move total production cost away from MC_t.

In a dynamic framework as the firm acquires more technology with superior capacity, the latter replaces an existing one, and eventually the oldest and more expensive technology, i.e. the one on the extreme left like MC_1, is no longer used. In this case the total cost curve (MC_{TOT}) shifts to the right (MC_{TOT}') and the shift is proportional to the amount of output (i.e. total capacity) produced on each unit of new technology.

Returning to the mathematical modeling, assume that the cost of producing on each technology are Co and Cn and that they are a function of the capacity corresponding to the new (x_n) and the old technology (x_o):

$$C_{jt}(x_{jt})=C_t(\gamma_j\ y_t)$$

Further, apply a translation of the axis where the origin is at the intercept of the cost functions (i.e. d=(0;0)), then allow that total costs and marginal costs to be specified as a function of the total capacity of the firm:

$$TC_j = 1/2\ b_j\ y_j^2 \tag{4.36}$$

$$MC_j = b_j\ y_j \tag{4.37}$$

where j = new, old and b_n is less than b_o because the new technology is cost reducing. If one interprets b_j as the slope of the MC_j curve, then $b_n<b_o$ implies that the cost function MCo is steeper than MCn (see Figure 4.9).

Equation (4.35) has shown that under profit maximising behaviour the marginal costs of production of each technology must be equal (MCn =MCo) and they are determined where MR_{ToT} intersects MC_{ToT}. In mathematical terms this means that:

$$b_n y_n = b_o y_o \tag{4.38}$$

From (4.38) one can derive the optimal level of output produced on the old technology (y_o*) as a proportion (b_n/b_o) of the output produced on the latest technology (y_n):

$$y_o^* = y_n b_n / b_o \tag{4.39}$$

(4.39) allows us to endogenise y_o such that the total output y_t in (4.32), can be written solely as a function of y_n:

$$y_t = y_n (b_o+b_n)/b_o \tag{4.40}$$

from which the optimal level of output (y_n*) is:

$$y_n^* = y_t [b_o/(b_o+b_n)] \tag{4.41}$$

(4.41) indicates that the optimal level of output produced on the new technology is a proportion ($b_o/(b_o+b_n)$) of the total firm' output (y_t). Symmetrically, substituting (4.41) into (4.39) one can express the total output produced on the old technology as a function of y_t:

$$y^*_o = y_t [b_n/(b_o+b_n)] \tag{4.42}$$

The total costs corresponding to the optimal level of output produced on the old and the new technology ,i.e. TC= $f(y_o^* ; y_n^*)$, can now be written solely as a function of y_t and b_n. In fact substituting (4.41) and (4.42) into (4.36) and adding them together yields:

$$TC_t = 1/2\, b_o\, [y_t\, b_n/(b_o+b_n)]^2 + 1/2\, b_n[y_t\, b_o/(b_o+b_n)]^2$$

or equivalently:

$$TC_t = (1/2)\, y_t^2\, (b_o + b_n) \qquad (4.43)$$

For a monopolist that produces its output using only two technologies (y_n and y_o) and facing the generic (inverse) demand function, i.e. $p_t = f(y)$, and the cost function (4.43) the profit maximising function is:

$$\pi_t = p(y_t) \cdot y_t - z_t \cdot y_t^2 \qquad (4.44)$$

The first order condition of (4.44) with respect to output is:

$$d\pi_t/dy_t = p'(y_t) \cdot y_t + p(y_t) - 2.\, y_t.\ z = 0 \qquad (4.45)$$

where $z_t = 1/2.\, (b_n .b_o)/(b_o + b_n)$.

Then the change in profits due to a change in the proportion of new technology in use is measured by differentiating (4.44) with respect to b_n:

$$d\pi_t/db_n = (p'(y_t) \cdot y_t + p(y_t) - 2 \cdot z \cdot y_t) \cdot dy_t/db_n - y_t^2 \cdot dz/d\, b_n \qquad (4.46)$$

From (4.45), the first term in the rhs of (4.46) must be zero. Calculating the derivative of z with respect to b_n in the second term of (4.46) and substituting in (4.45) yields:

$$d\pi_t/db_n = - y_t^2 \,.\, 1/2.\, [\, b_o/(b_n+b_o)]^2 \qquad (4.47)$$

which can be further simplified using (4.41) so that:

$$\boxed{d\pi_t/db_n = - 1/2 \,.\, y_{nt}^2 \quad <0} \qquad (4.48)$$

which is negative. This suggests that the lower is b_n , i.e. the slope of the cost function, the flatter is the cost curve and the higher are the profits from the cost reduction (see Figure 4.9).

In order to see whether the profit gains from adoption are bounded or unbounded one has to look at the sign of the second order condition for profit maximisation . From (4.47) it is possible to write:

$$d^2\pi_t/d^2 b_n = - 2\, y_t .\, dy_t/db_n .\, [b_o/(b_n+b_o)]^2 - y_t^2 .\, [b_o/(b_n+b_o)] .\, \{d[b_o/(b_n+b_o)]/\, db_n\}$$

where from (4.40) it is easy to derive (4.49) :

$$dy_t/db_n = y_n \,.\, b_n/b_o \qquad >0 \qquad (4.49)$$

Moreover, with some simple manipulation one can also derive:

$$d[b_o/(b_n+b_o)]/\, db_n = - b_o/\, (b_o-b_n)^2$$

where, given (4.40) , the above expression can be rewritten as:

$$d[b_o/(b_n+b_o)]/\, db_n = - y_{nt}^2/y_t^2 \qquad (4.50)$$

Finally replacing (4.40), (4.49) and (4.50) into (4.58) yields:

$$d^2\pi_t/d^2 b_n = - y_n^2 \,.\, 1/(b_n+b_o) + y_n^2 \,.\, 1/(b_n+b_o)$$

which is equal to zero:

$$\boxed{d^2\pi_t/d^2 b_n = 0} \tag{4.51}$$

This indicates that profit gains from the further use of a new technology are constant. Together, conditions (4.48) and (4.51) imply that total profits are a positive function of the cost reduction brought about by the adoption of a new technology, indicating that profit gains from adoption would not be binding in the decision to extensively use a new technology.

So far the Multiple technology approach has assumed that the firm is a monopolist. To take into account that firms might operate in different market scenarios, the Multiple technology approach model has been extended to the competitive case. Given that the extent of use of a new technology is independent of demand, the same results are obtained for the monopolistic and the competitive case. Profit gains from extensive use do linearly increase with the extent of use. Contrary to the 'cost function' approach they are not constrained by the (inverse) demand of the firm' final product and are unbounded whatever the specification of the demand curve is.

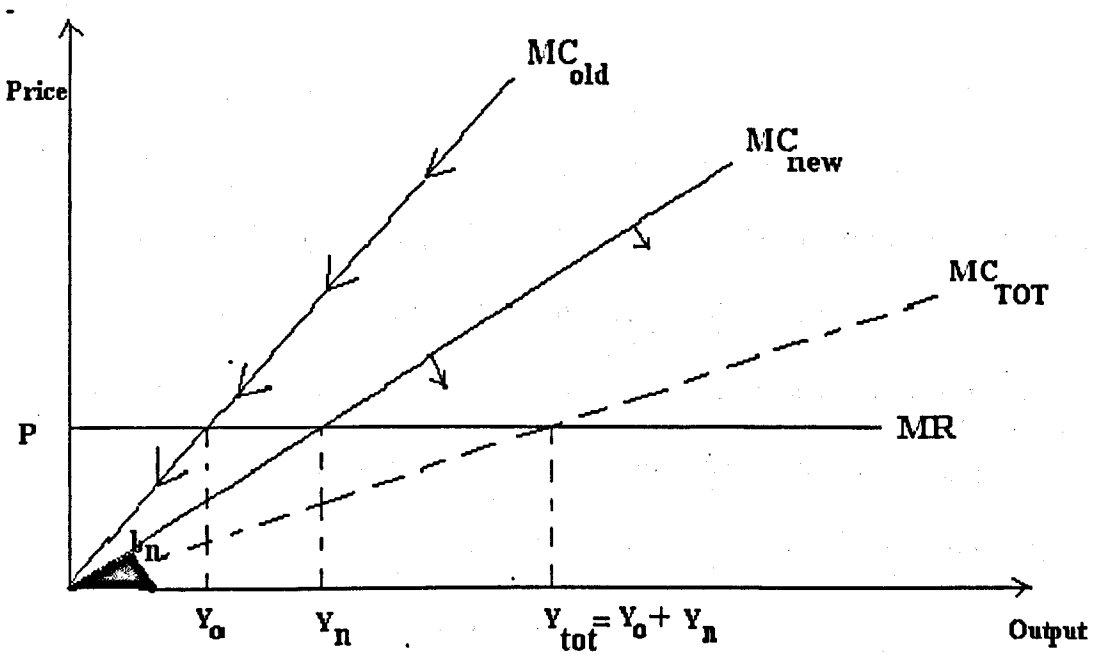
In summary the Multiple technology approach assumes that the impact on π_t of a unit change in b_n is proportional to the output produced on the new technology (equation 4.48) or similarly to the total output of the firm (equation 4.47). In equilibrium (4.47) and (4.48) are equal, and both equal to zero ($d\pi_t/db_n=0$) and the optimal proportion of output produced on the new technology can be expressed as:

$$y^*_{nt}/y_t^* = b_o/b_o+b_n$$

This indicates that the proportion of output produced on the new technology is a function of the slope of the marginal cost curve. The higher is b_n in absolute value, the

lower the proportion of output produced on the new technology. This situation is represented in Figure 4.9 where b_n, the inclination of the MCn curve, indicates the intensity of use of the new technology. The more the new technology is used (i.e. the lower is b_n) the lower will be the total MC of production (MC_{TOT}) due to the reduction in MC_n. On the contrary, the greater is b_n the higher is the slope of the marginal cost curve and the higher TC will be.

Figure 4.9. The intensity of technology replacement (b_j j=n,o)



Moreover, the first and second order conditions for profit maximisation (4.48 and 4.51) have shown that profits increase with the level of intra-firm diffusion ($d\pi_t / d b_n<0$) but profit gains from further use of a new technology are constant ($d^2\pi_t / d^2 b_n=0$). This means that the benefits from adoption do increase over time with the extent of use of a new technology but profit gains are constant.

This result indicates that the level of use of a new technology is related to the profitability from extended use, but it does not provide evidence to support the inter

firm stock effect hypothesis of decreasing marginal profits from the further use of a new technology.

It also shows that the optimal combination of new and existing technologies is independent of the demand for the final output and yields the same results in both the competitive and monopolistic case. This would indicate that the optimal level of ownership of a new technology is independent of market structure.

Finally, like the Cost function approach, it does not tell us why it is profitable for a firm not to switch immediately to the new technology but wait.

4.4.Conclusion

This chapter aimed at explaining whether the stock effects, proposed by the inter firm literature, do significantly affect the level of intra firm diffusion.

Stock effects would predict that what determines the current level of ownership of a new technology are mainly profitability considerations about decreasing profit gains for further adoption. In fact, if the profit gains are bounded then they may be a disincentive to immediately replace all the existing capital with the most advanced one. This would explain why firms do not immediately switch to the new technology but wait. Moreover, if it is assumed that profit gains are firm specific and that some firms might find it profitable to switch only when costs reach a certain level, this would also explain the heterogeneity of the technology ownership across firms.

This chapter has used two different approaches to modelling the relationship between profits gains and total production costs in order to determine whether profit gains are bounded or unbounded. The first approach (cost function approach) implicitly assumes that the cost reduction is proportional to the extent of use of the new technology: as the

firm adopts more technology its total costs reduce and as they do so the firm increases its output. In order to meet the demand for the increased output the firm has to sell it at lower prices reducing the profit gains from the cost reduction. The resulting benefits from the extent of use, generated by the difference between the gains from cost reduction and the marginal revenue from the reduced price, have been measured by the profit gains from further adoption. However, it was not possible to determine a priori whether profits gains are increasing constantly or exponentially with the level of adoption of a new technology (Δc_i). In particular the shape of the profit gains - differential of the cost-profit curve- has been proved to depend upon the type of the demand function for the firm's final output. In the case of an isoelastic demand profit gains are concave and decrease more than proportionally with the change in the extent of use, i.e. follow a concave/bounded curve; whereas using a linear demand function profits gains are constant and increase, constantly, with the change in the extent of use. This is an important finding that, contrary to Hahn (1962)'s assumption, indicates that optimality conditions and convergence in economic modeling can be highly affected by the type of demand specified (via the elasticity of the slope of the demand).

To determine the optimal level of adoption of the new technology the cost approach has also been extended to make explicit assumptions about the cost of production with the new (K_n) and the old (K_o) technology. By expressing total costs as a function of the proportion of capital stock, profits gains remain undetermined, as they depend upon the curvature of the demand function. Moreover, this does not lead to a final specification of the optimal level of ownership.

The last approach used in this chapter defines the extent of use via the impact of the introduction of a new technology on the total capacity of the firm. However, with the

Multiple technology approach the benefits from adoption are again unbounded, while the optimal combination of the new and the existing technologies is independent of the shape of the demand curve and yields the same results in both the monopolistic and the competitive case.

In summary the approaches followed in this chapter aimed at explaining why it might not be rational for a firm not to immediately switch to a new technology but wait. The results seem to indicate that there exist stock effects but the direction and the intensity of its impact is not consistent across different specifications, instead depending upon the shape of the demand curve. What the results consistently seem to suggest is that the decision of the firm to increase the proportion of more advanced machinery is mostly driven by: a) the relative reduction in the price of the technology over time; b) the higher productivity of the new technology with respect to the existing one. However, these factors are not explicitly modelled by either of the two approaches explored in this Chapter. Moreover, neither of the specifications takes into account that the reduction in costs might have a cost itself: the investment cost to buy the new technology.

Together with these weaknesses there are still several unanswered questions which have emerged from the review and the testing of the existing literature (see Chapter 3).

For these reasons the next chapter presents an alternative approach, here defined as the Production Function Approach, to explaining why it might not be rational to immediately switch to a new technology.

This approach based on neo-classical economic theory and can be considered an extension of the milestone Jorgenson model of investments (1970 and 1965).

The innovative contribution with respect to the neo-classical theory is that the total capital stock of the firm needs to be explicitly modelled as a stock incorporating the

new (K_n) and the old technology (K_o) each characterised by different productivity, α_o and α_n respectively. This implies a new definition of the inputs in the production function and consequently a new specification of the production function of the firm so that: $Y= f(L, K_o, K_n; \beta, \alpha_o, \alpha_n)$, where $\alpha_n > \alpha_o$ due to the advanced property of K_n with respect to K_o. Moreover, by the means of mathematical optimisation procedures, it can be modified to account for the role that price expectations, technological constraints, existing and previous technologies and uncertainty play in the adoption decision of the firm. By its nature it can be considered an equilibrium intra firm model aiming at determining, for a single firm, the optimal replacement path of an old with a new technology in each point in time. This model should also specifically take into account the impact of different market scenarios upon technology diffusion.

This approach will be presented in detail in the next chapter.

Chapter 5.

A NEW EQUILIBRIUM INTRA FIRM MODEL

5.1 Introduction.

This chapter aims at developing a dynamic equilibrium model that addresses the major issues arising from the analysis carried out in previous chapters. The latter has pointed out that, to better understand the spread of ownership of a new technology within a firm, it is important to understand the role exerted by:

(i) profitability considerations (stock effects);

(ii) technical constraints to the adoption of, and complementarities between technologies;

(iii) the cost of acquiring the technology and price expectations;

(iv) market structure, i.e. monopoly *vs* competition between firms;

(v) uncertainty.

In order to do so, one needs to redefine the concept of technology adoption at firm level. This can be done considering that the current level of ownership is the result of economic, technical and market evaluations about further use of a new technology.

In Chapter 4, even if it was not possible to exactly measure their impact, it has been shown that stock effects may play a relevant role in the decision to further use a technology. Stock effects suggest that the decision to further acquire a new technology is based upon profitability considerations driven by the reduction in operating costs (economic evaluations) and the resulting decline in output prices from output expansion (market evaluations). Given that what triggers the possibility of further adoption of a new technology are its cost-reducing properties, this must have a cost

itself, which is the investment cost to buy the new technology. Because of this characteristic, the decision to further adopt a new technology can be likened to an investment decision, which has been widely studied in the economics literature. However, a new technology has the characteristic of being productively superior to the existing old technology owned by the firm, and therefore cannot be treated as any other good. Further to economic and market evaluations, the investment decision must take into account the necessary adjustments that the investment would impose on the existing production process at plant level (technical evaluations). In fact, both chapter 2 and 4 have shown that higher productivity of the new technology plays a key role in the decision to further expand its use.

Moreover, the decision to invest in a new technology is influenced by the relative reduction of acquisition costs over time; this indicates that acquisition prices are important and that expectations about future (quality adjusted) prices might have a role in the decision to further invest in a new technology (see for example Stoneman and Karshenas and Kwon, 1996). A theoretical model of intra firm technology diffusion must explicitly account for this possibility

There are also reasons to believe that the speed of adoption could also be affected by the level of market concentration via, for example, the impact on factor and output prices, therefore affecting the profitability of further adoption. So far, the question as whether the position of the firm on the market might influence its decision to invest in a new technology has been left unanswered.

Other factors that still need to be dealt with have emerged since Chapter 2, indicating that within a firm the spread of use of a new technology takes several years. This implies that the decision to use a new technology is better modelled within an

intertemporal scenario where variables and objectives are not timeless, but change over time according to the evolution of the firm and the market in which it operates.

In this framework, the firm's decision to increase the proportion of more advanced machinery could be subject to uncertainty about its future performance due to possible changes in: the demand for its final good; the price of the technology (possibly a decline); the price of the other inputs; its financial position, etc. Despite its relevance, this hypothesis has not been explored in intra firm studies and needs to be taken into account

This chapter aims at developing a new intra-firm model built around stock effects that can deal with all these aspects affecting the decision of the firm to invest in a new technology.

Chapter 3 has pointed out that the best route to modelling the firm's decision to use a new technology is to use the equilibrium approach, as an alternative to the disequilibrium approach. This would assume that the outcome of the firm's choice is optimal at the time the decision is made and it is in equilibrium in each moment in time from soon after first adoption until the firm is saturated with that capital good. The resulting adoption pattern can be discontinuous and not necessarily increasing over time; this suggests that one should use a dynamic maximisation problem to select the time paths of the variables. For this reason the theoretical model presented in this chapter is built using the *optimal control theory*. This dynamic optimisation procedure, unlike the disequilibrium approach, is distribution free and not necessarily monotonic.

The route followed to modelling all the aspects of intra firm technology adoption has lead to the definition of a model that is built upon standard neo-classical investment

theory. This approach is built upon profitability considerations (i.e. stock effects) and can be considered an extension of the milestone Jorgenson model (1963). However, in contrast with Jorgenson's model, capital is no longer treated as a homogeneous and unique good (K_t). It is instead considered here as a combination of new or superior (K_{nt}) and old or existing (K_{ot}) technologies, where the new technology is superior, and has a higher productivity than the existing technology ($\alpha_n > \alpha_o$). Moreover, the intra firm technological process is defined from when the firm adopts the first unit of a new technology. This implies that the firm's production possibility set shifts from a standard two factors to a three factor production function, i.e. from $y_t = f(L_t, K_t; \beta, \alpha)$ to $y_t = f(L_t, K_{nt}, K_{ot}; \beta, \alpha_n . \alpha_o)$. The model is distribution free and it is specified so that after the diffusion process is completed for the firm, one returns again to a two factors production function, i.e. $y = f(L, K_n; \beta, \alpha_n)$ or $y = f(L, K_o; \beta, \alpha_o)$, depending on whether the firm decides to fully replace its capital stock or to switch back to the old technology.

With respect to Jorgenson's approach this model has also been modified to take into account: the influence of the relative cost of the two technologies and the expectations about their future prices; the technological characteristics of the current production system (such as complementarities between technologies and technological constraints to the adoption; uncertainty and market structure.

This chapter is structured as follows. Section 1 defines the main assumptions of the model. Section 2 describes the main steps of its mathematical specification. In section 3 the optimal replacement rate is discussed under different market scenarios. Section 4 summarises the results derived under different market scenarios, i.e. monopoly and

perfect competition. Section 5 comments on the measures of intra firm diffusion and the optimal path of technology replacement. Section 6 shows how uncertainty is included in the model and section 7 presents the role of expectations. A final section derives the final equation that will be used in the next chapters to empirically test this new framework.

5.1 Theoretical assumptions

Assume that two kind of technologies are available on the market: the standard or old (o) and the advanced, or new (n) technology. The standard technology includes the combination of the existing, or old, technology/ies while the advanced technology includes only the new one [1]. Moreover, the firm can acquire any, both or only one of the technologies and the firm's level of ownership can be identified as the proportion of capital stock incorporating the new (K_n) and the set of existing technologies (K_o). Suppose also that the firm uses only the standard technology until it decides to adopt the advanced technology after which the firm can decide to invest in both, neither or only one of the available technologies.

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[1] In reality, the firm produces its final output using a wide range of capital goods whose age and technological content is often highly heterogeneous. This implies that the firm faces multiple, rather than dual, investment decision. The best model for this type of investment would ideally underpin from the vintage literature (see for example the original 'clay-clay' model, e.g. Smallwood (1972), Isard (1973), etc. and the 'putty-clay' model, e.g. Bishoff (1971), King (1972), Mizon (1974), Malcomson (1975, 1982,) Salter (1966), etc.). This hypothesis has been explored. However, the mathematical complexity becomes intractable when the technological content and uncertainty are added to the vintage of each technology. For this reason it has been preferred to simplify the model to two sets of technologies hereafter defined as 'old technology', which includes all the existing technologies, and new or advanced technology whose extent of use is here investigated.

In this model capital is always utilised and, following the equilibrium approach, at each instant t the firm decides how much to invest in each technology according to profitability considerations. The firm's *objective* is to maximise the discounted stream of profits net of Investment expenditure on each technology at each point in time, which can be written as (5.1):

$$\int e^{-rt}(p_t Y_t - w_t L_t - q_{nt} GI_{nt} - q_{ot} GI_{ot})\, dt \qquad (5.1)$$

where e^{-rt} is the discount factor and Y_t ,L_t ,GI_{nt} and GI_{ot} are output, labour and investments in existing or old (o) and advanced or new (n) technology and prices are respectively: p_t, w_t, q_{nt} ,q_{ot}.

Assuming that the capital stock of the firm evolves over time by investments in physical capacity, which are firm specific and sunk, leads to the definition of the <u>*transition equations or equations of motion*</u> for the *state* (K_{ot} and K_{nt}) and the *control variables* (GIo_t and GIn_t):

$$dK_{nt} = GI_{nt} - \delta K_{nt}$$

$$dK_{ot} = GI_{ot} - \delta K_{ot} \qquad (5.2)$$

This is the *capital accumulation constraint*, where dK_{jt} (j=n,o) is the rate of change of the flow of capital services, K_{jt} (j=n,o) is the level of the stock of capital j and $\delta \in [0;1]$ is the depreciation rate. This indicates that, at each moment in time, the net investment in each capital good (K_n and/or K_o) equals gross investments (GI_n and/or GI_o), less depreciation (δ), which is itself proportional to the capital stock.

Equation (5.2) has the following properties:

i) Investments are irreversible by assumption (Arrow, 1968) and non-negative:

$$GIn_t \geq 0 \quad \text{and} \quad GIo_t \geq 0 \qquad (5.3)$$

ii) Capital reduces by depreciation

This means that the capital stock owned by the firm reduces over time by an amount equal to the depreciation rate. This can be seen by replacing condition (5.3) into (5.2.) in the absence of gross investments, i.e. when $GI_{jt}=0$:

$$dK_{jt} = -\delta K_{jt} \qquad j= \text{new, old}$$

This also implies that capital has zero second-hand value, i.e. investment is a sunk cost (Takayama, 1995).

One would expect that, from the moment soon after the adoption of the first unit of the advanced technology, the firm would start replacing its existing capital stock so that $GI_{nt}>=0$ and $GI_{ot}=0$[2]. However, for several reasons, an advanced technology might not necessarily end up dominating the existing one[3]. Unlike disequilibrium models, there is no optimal (or saturation) point to technology adoption. Consequently, no constraints are imposed in the maximisation procedure as to which technology to invest into at each moment in time. The firm's decision is determined

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[2] This the case when the firm decides to invest only in the advanced technology ($GI_{nt}>0$) so that the existing level of K_{ot} reduces over time by an amount proportional to the depreciation rate, e.g. $dK_{ot}=-\delta K_{ot}$.The letter occurring every time gross investment equal zero ($GI_{ot}= 0$).

[3] This can be the case of a new technology with a performance lower than expected, leading the firm to switch back to the old technology. It might also happen that, for several reasons the advanced technology does not completely dominate the standard technology (see for example the case of NC and CNC in chapter 2 figure 1).The diffusion process of an advanced technology might also be interrupted by the appearance on the market of a newest even more profitable technology (K_S). This is the case of nested and multiple technologies (see for example Stoneman and Kwon, 1994; Colombo and Mosconi, 1995,etc) which are not explicitly considered here. However, their inclusion in the model would be straightforwardas K_S would simply become "the' new technology (K_n) replacing the set of technologies already owned by the firm.

by what is optimal at that very moment in time, i.e. is firm specific. This also means that the adoption path of the new technology must be distribution free.

On this reasoning the *initial conditions* of the model are defined such that at the beginning of the period soon after first adoption (t_{o+}) the firm owns an unspecified initial stock of each technology ($K_{nto+} \geq 1$ and $K_{oto+} \geq 1$) so that:

$K_n(0^+) = K_{n,\, to+}$ $\qquad$ $K_o(0+) = K_{o,\, to+}$

$\lim K_{n,to+} \geq 1$ $\qquad$ and $\qquad$ $\lim K_{o,to+} \geq 1$ $\qquad$ (5.4a)

However, over time the firm moves away from this initial level choosing its optimal inputs combinations according to profitability conditions.

One would expect that the proportion of advanced technology (K_n) over the total capital stock (K_n+K_o) progressively increases over time from initial adoption, say 1 per cent, up to 100 per cent. However, as time proceeds, the firm might not find it profitable to continue investing in the new technology, and the maximum level of adoption at the end of the diffusion process might be less than 100 per cent. This implies that at the end of the period, the optimal accumulation path might lead to different terminal conditions: i) the complete replacement of the old with the new technology ($K_o(T)=1$; $K_n(T)$ Free); ii) the complete replacement of the new with the old technology after an initial period of adoption ($K_o(T)$ free; $K_n(T)=1$); iii) the replacement of the existing technology with a third even newer technology K_s, so that both K_n and K_o reduce over time ($K_o(T)$ Free; $K_n(T)$ Free).

Given that the diffusion path of a new technology is not known, no a priori restriction is imposed on the capital accumulation path of the firm and both *terminal conditions* are left to be free such that:

$K_o(T^-) = K_{oT^-}$ $\qquad$ $K_n(T^-) = K_{nT^-}$

$\lim K_{oT^-} \geq 1$ $\qquad$ $\lim K_{nT^-} \geq 1$

The corresponding *transversality conditions for $K_{it}(T)$ = FREE imply that*

$\lim \lambda(T^-) = 0$

$\lim \lambda(T^-)\ K_i(T^-) = 0 \qquad i=\text{new, old}$ (5.4b)

This is equivalent to saying that the shadow price ($\lambda(T)$) of the stock of capital (K_n or K_o) left at the end of the diffusion period (T) must be zero. For this relation to hold, if the quantity of capital at the end of the period is positive, then its shadow price must be zero. If, on the contrary, at the terminal date the shadow price has a positive value, then the optimising agent must leave no capital at the end of the period, i.e. K(T)=0 (in our case K(T) =1). Hence the product is zero either way (see Barro Sala I Martin, 1995)[4].

Assume also that the firm is *constrained* by its own production possibilities defined by the modified Cobb-Douglas production function, $F(L_t, K_{ot}, K_{nt})$ where labour (L_t),

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[4] Another interpretation of the terminal condition can be given looking at the following specification for a general maximisation problem in the presence of only one kind of capital good (K) where both initial and terminal constraints have been added to the end of the function:

$L=\int [H(\lambda; t;K;u)+ \lambda' K]dt -\lambda(T)K(T)+\lambda(0)K(t_0)$

where the multiplier $\lambda(T)$ (i.e. the costate variable) can be interpreted as the marginal effect on the maximum value of a small reduction in the level of K_T, $\partial V/\partial K_T = -\lambda(T)$ (see Lambert, 1985) .In our case, given that K(T) = Free, in order not to be binding the end-point K^(T) that is achieved cannot be bettered in maximum value terms and the marginal value $\lambda(T)$ is zero, or vice versa, K^(T) should tend to zero and $\lambda(T)>0$. On the light of this interpretation a reduction in K_T ($[K\hat{}_T - K_T]<0$) is a relaxation of the constraint and cannot reduce the max value, i.e. $\lambda(T) \geq 0$. Further if the constraint does not bind $[K\hat{}(T) > K_T]>0$ then a small change in K_T makes no difference to the solution and $\partial V/\partial K_T = -\lambda(T)$ should be 0. Conversely if $\partial V/\partial K_T = -\lambda(T)<0$ then the constraint must bind

existing (K_{ot}) and advanced technologies (K_{nt}) are the inputs with parameters (β, α_o, α_n):

$$Y_t = A_t L_t^{\beta} K_{ot}^{\alpha 0} K_{nt}^{\alpha n} \qquad \text{where } \alpha_o < \alpha_1 \qquad (5.5)$$

Moreover, (5.5) has the following properties:

(i) constant economies of scale, i.e. $\alpha_o + \alpha_n + \beta = 1$ [5]

(ii) positive marginal rate of substitution among inputs:

$dK_{ot} / dK_{nt} = \alpha_n / \alpha_o . K_{ot} / K_{nt}$

$dL_t / dK_{nt} = \alpha_n / \beta . L_t / K_{nt}$

$dL_t / dK_{ot} = \alpha_0 / \beta . L_t / K_{ot}$

(iii) different marginal capital productivities, i.e. $\alpha_o < \alpha_n$

(iv) the function is twice differentiable with positive and diminishing (strictly convex) marginal productivity with respect to each input (i.e. the production function marginal productivity rule) so that:

$F_{Kn} = \partial F_t / \partial K_{nt} = \alpha_n (Y_t / K_{nt})$

$F_{Ko} = \partial F_t / \partial K_{ot} = \alpha_0 (Y_t / K_{ot})$

$F_{Lt} = \partial F_t / \partial L_t = \beta (Y_t / L_t)$ (5.6)

(v) each input is essential for production, that is the marginal product of capital or labour, approaches infinity as K_j or L goes to zero and approaches zero as K_j or L goes to infinity:

$\lim_{-Kjt>0} F_{Kjt} = \infty$ $\qquad$ $\lim_{-Kjt>\infty} F_{Kjt} = 0$ $\qquad$ j=n,o

$\lim_{-Kjt>0} F_{Lt} = \infty$ $\qquad$ $\lim_{-Kjt>\infty} F_{Lt} = 0$

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5 Although the latter assumption is not strictly necessary.

The latter is called the Inada condition (Inada, 1963) and in order to avoid this limiting situation one also has to impose that the minimum amount of each technology owned by the firm is at least one unit over the whole period of observation i.e. $K_{it} \geq 1 \ \forall \ t \in]t_o;T[$ where t_o is the adoption date and T is the end of the diffusion process. This means that we focus exclusively on the process of technological replacement within the intra-firm diffusion period, when the firm owns at least one unit of the new technology, until almost the end of the diffusion process, when the firm owns at least one unit of the old technology. In this way the pre and post-diffusion period, when the firm operates within a different technological possibilities set (represented by the standard two factors $(L,K_j,0)$ production function) is excluded from the model[6].

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[6] Even if the Inada condition (Inada 1963) was originally defined for a two factors production function, its extension to a three factors production function is straightforward and does apply at the extreme points of the intra firm diffusion curve. In fact at the initial and terminal point of the diffusion path one would expect:

$t=to^-$ $F(L_{to}, K_{oto},0)= 0$ and $t=T^+$ $F(L_T, 0, K_{nT})=0$

representing the pre-diffusion period, when the advanced technology has not been adopted yet ($K_n(t_o^- =0)$, and the post diffusion period, when, in theory, the old technology is completely replaced by the advanced technology ($K_o(T^+)=0$).

This type of problem has been overcome by the specification of the initial and the end point conditions which assume that immediately after first adoption (when $t=t_{o+}$) $\lim Kn(t_{o+})\geq 1$ and $K_o(t_{o+})>1$ and at the end of the diffusion process (when $t= T^-$) $\lim K_o(T^-\geq 1$ and $K_n(T^-)\geq 1$, which is equivalent to saying that at the extreme points of the observation period the firm always owns at least one unit of each technology. This can be better understood thinking that in the pre and the post-diffusion process the set of technological possibilities of the firm is a function of only two factors $Y_t=f(L_t,K_{it})$ where i=n/o, and during the process of technological replacement the firm shifts to a three factors production function $Y_t=f(L_t,K_{ot}, K_{nt})$.

$Y_t=f(L_t,K_{ot})$ $Y_t= a\, L_t^{\beta}\, K_{ot}^{\alpha o}\, K_{nt}^{\alpha n}$ $Y_t=f(L_t,K_{nt})$

----------o----------o----------> time

$t= t_o$ $t \in]t_o;T[$ $t=T$

Equation (8) (property (iii)) also shows that the two sets of technologies incorporated in capital goods are not perfect substitutes. K_n is superior to K_o, and therefore has a higher elasticity of substitution with respect to output, $\alpha_0<\alpha_1$. This means that in order to produce a given level of output, under constant economies of scale and constant labour input, the amount of K_n needed to replace K_o is less than the amount replaced of the existing capital good (K_o), due to the higher productivity and the cost reducing property of the more advanced technology.

A second constraint concerns the market characteristics of the firm.

In the original traditional neoclassical model (1963 and 1965), it is assumed that the firm is a price taker for all p_t, w_t, q_t. This means that output can be sold in any quantity at time t at price p_t, and the firm's choice of Labour (L_t) and investments (GI_{it}) does not affect their respective prices (w_t and q_t) for each time t. Moreover, in his empirical testing Jorgenson uses both level of output and prices as independent variables ignoring the demand function constraint, leaving completely unexplored how the capital accumulation path differs under different market scenarios.

The exclusion of the extreme points is justifiable on the ground that, firstly the process of *intra-firm* technology adoption, by definition, focuses only on what happens within the interval from a point immediately after first adoption (t_0^+) until the diffusion is (almost) complete for the firm (T^-), that is when the firm owns at least one unit of each capital goods, i.e. $K_{it}\geq 1$ $\forall$ i=new, old and $t \in]t_0+;T^-[$ and uses three factors of production.

Secondly the determinants of first adoption, i.e. when the firms first introduces the new technology and first changes its production system to a three factors production function, have been widely explored by the inter-firm literature.

Thirdly the post-diffusion process, i.e. when the firm uses only the advanced technology, despite interesting on its own, is of no particular interest here as the process of technology replacement is terminated and the advanced technology is no longer a new technology to the firm.

The inter-firm diffusion literature has looked extensively at the influence of different market scenarios upon the investment decision of the firm. However, its impact upon intra firm diffusion has never been studied. Chapter 4 has attempted to explore this possibility but the results about the impact of market concentration upon the within firm extent of use of a new technology were inconclusive. For this reason, the replacement decision is here explicitly modelled under the two extreme cases of monopolistic and competitive markets. The different scenarios are modelled via the demand function the firm faces on the market;[7]

In the monopoly case, the firm is allowed to be a price setter where prices are determined by the inverse demand function[8] (5.7) explicitly introduced as a constraint in the maximisation procedure:

$$P_t = A\, Y_t^{\eta} \tag{5.7}$$

In the competition case the final price is a function of the industry price determined by the total industry output (Y^I_i) of that final product ($P^I_t = f(Y^I_t)$ with the elasticity of the inverse of demand equal to η^I. This means that the final price is exogenous to the firm and independent of the firm's final output (Y_t). In this framework the firm is a price taker and can produce any amount of its final good, as long as it sells it at the market-determined price, i.e. $P_t = P^I_t$:

$$Y_t = f(P^I_t) \tag{5.8}$$

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7 Extension of the decision theoretic approach to the oligopoly case should result in an intermediate solution between competition and monopoly. However, if the hypothesis of no strategic interaction among firms is relaxed the current model might need extra attention in the derivation of the optimal solution.

8 The constant elasticity function has arbitrarily chosen. However there is no a priori expectation on the shape of the demand curve and the model can be easily extended to other specifications

(5.8.) is the demand function for the firm with constant infinite elasticity of output with respect to price.

The mathematical derivation of the optimal conditions for capital accumulation, for both the monopolistic and the competitive firm, are presented in the following section where the different market scenarios are compared.

5.2 DERIVATION OF THE MODEL

5.2.1. The Monopolistic firm

The present value of the firm is here represented by the integral of discounted profits and the market value of the assets of the firm, or equivalently as the net present value of net cash flows for all future times. For a monopolist, the Hamiltonian for the optimal control problem can be written as:

$$H_t = e^{-rt}[\,P_t(Y_t)\,Y_t - w_tL_t - q_{nt}GI_{nt} - q_{ot}GI_{ot}] - \lambda_{nt}[GI_{nt} - \delta K_{nt}] - \lambda_{ot}[GIo_t - \delta K_{ot}] \qquad (5.9.m)$$

The first term on the RHS of (5.9.m) is the discounted stream of profits , i.e. total revenue ($P_t\,Y_t$) minus the current costs of production ($w_tL_t - q_{nt}GI_{nt} - q_{ot}GI_{ot}$), where the discount factor is (e^{-rt}) and r is the interest rate. The remaining two terms of (5.9m) account for the investment expenditure on the new and old technology at each point in time, where δ is the depreciation rate and the λ's are the costate variables (mathematical multipliers) for the two capital accumulation constraints. Moreover, as the firm is a monopolist, it faces an inverse demand function such that $P_t = A\,Y_t^{\eta}$, so that (5.8.) can be rewritten as:

$$H_t = e^{-rt}[A\,Y_t^{\eta} - w_t L_t - q_{nt} GI_{nt} - q_{ot} GI_{ot}] + \lambda_{nt}[GI_{nt} - \delta K_{nt}] + \lambda_{ot}[GI_{ot} - \delta K_{ot}] \qquad (5.10m)$$

Since the market value of the assets of the firm is fixed, the maximisation of the integral of discounted profit results in the path of accumulation of capital resulting from the maximisation of the present value of the firm.

The Hamiltonian first order conditions for a maximum are:

I) $\partial H_t/\partial GI_{it} = 0$ i=n,o II) $\partial H_t/\partial L_t = 0$; III) $\partial H_t/\partial K_{nt} = -\lambda_{nt}$ IV) $\partial H_t/\partial K_{ot} = -\lambda_{ot}$

Conditions I-IV, applied to (5.10m) yield the following equilibrium conditions:

I) the market price of capital equals the shadow demand price of capital:

$$\lambda_n = q_{nt}\, e^{-rt} \qquad \text{and} \qquad \lambda_o = q_{ot}\, e^{-rt}$$

II) marginal product equals factor price:

$$A(\eta)\, Y_t^{\eta-1}\, (dY_t/dL_t) = w_t$$

III) and IV) are the so called costate equation of motion yielding:

$$e^{-rt}(A\,\eta\; Y_t^{\eta-1}\, (dY_t/dK_{nt})) = +\delta\lambda_{nt} - d\lambda_{nt}$$

$$e^{-rt}(A\,\eta\; Y_t^{\eta-1}\, (dY_t/dK_{ot})) = +\delta\,\lambda_{ot} - d\lambda_{ot}$$

$d\lambda$ indicates how the policy decisions of the firm will affect the rate of change of capital via the depreciation of the shadow price (Chiang, 1984 p.208).

Moreover, after substitution from I) the latter can be rewritten as[9]:

$$(A\,\eta\,Y_t^{\eta-1}\,(dY_t/dK_{ot})) = (r+\delta)\,q_{ot} - dq_{ot}$$

$$(A\,\eta\,Y_t^{\eta-1}\,(dY_t/dK_{nt})) = (r+\delta)\,q_{nt} - dq_{nt} \qquad (5.10m)$$

Equation (5.10m) shows that in equilibrium the marginal revenue per extra unit of output produced with the recently acquired technology, equals its marginal costs.

The LHS of (5.10m) is the impact on total marginal revenue ($A\,\eta\,Y_t^{\eta-1}$) of the shift in capital marginal productivity per extra unit of capital stock (dY_t/dK_{jt})while the rhs of (5.10m) is the Jorgensonian (Jorgenson, 1963,1965, 1967, 1970, etc) 'user cost of capital' per extra unit of capital:

$$c_{jt} = q_{jt}(\delta+r) - dq_{jt} \qquad j = \text{new, old} \qquad (5.11m)$$

c_{nt} and c_{ot} are the implicit rental values of capital services supplied by the firm to itself where q_{it} is the unit price of capital, δ is the depreciation rate of the existing capital stock and r is the discount rate.

The interpretation of (5.11m) is straightforward if one looks at each separate element of the shadow price of c_{jt}. In fact, following Junankar (Junankar, 1972) '$q_{it}r$ is the opportunity cost of putting q dollars in capital goods, i.e. q dollars would earn, if put on the financial market, qr dollars; $q_t\,\delta$ is the depreciation cost, if δ of capital goods 'vanishes' then its value in dollar is $q_t\,\delta$; dq_t is the time derivative of q, i.e. the rate

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[9] In the first step of the maximisation procedure (condition I) yields that $q_{jt}=\lambda_{jt}e^{rt}$ (j=new, old), the differential of which is $dq_{jt} = r\lambda_{jt}\,e^{rt} + d\lambda_{jt}e^{rt} = rq_{jt} + d\lambda_{jt}e^{rt}$ (j=new, old). From the above it easy to derive that $\lambda_{jt} = q_{jt}\,e^{-rt}$ and $d\lambda_{jt} = (dq_{jt} - rq_{jt})e^{-rt}$

of appreciation of the price of capital goods' So if capital goods are appreciating rapidly then the implicit cost of capital, c_{jt}, is lower. In other words, c_{jt} decreases the lower the purchase price q_{jt} of the j technology but increases the larger the rate of depreciation ($-dq_{it}$) of the capital good.

In summary, this condition indicates that the current cost of the new technology corresponds to an increase in capital stock (dK_{jt}) which is optimal to the firm. The resulting profit gains from cost reduction lead the firm to further produce on the cost reducing technology and expand its output. Moreover, in order to meet the demand for that output the firm has to lower its selling price, reducing the marginal revenue from the original output expansion. This will continue until it is still profitable for the firm to extend the use of the new technology. In summary, there exist intra firm stock effects and the optimal level of technology ownership can be explained by profitability considerations.

From the Hamiltonian first order conditions II) III) and IV), one can derive the Hamiltonian productivity conditions of each input:

$$\partial Y_t/\partial L_t = w_t / A\,\eta\, Y_t^{\eta-1}$$
$$\partial Y_t/\partial K_{nt} = c_{nt} / A\,\eta\, Y_t^{\eta-1}$$
$$\partial Y_t/\partial K_{ot} = c_{ot} / A\,\eta\, Y_t^{\eta-1} \qquad (5.12m)$$

Substituting the production function marginal productivity rules (5.6.), and after some manipulation, (5.12.m) can be rewritten as the *marginal product constraint* (5.13m), according to which, what determines the optimal level of each input (L^*, K_n^*, K_o^*),

are: input price, technological constraint (via the elasticity of substitution of the inputs) and output supply constraints (the elasticity of demand)[10]:

$$L_t^* = (\beta/w_t)\, A\, \eta\, Y_t^{\eta}$$

$$K_{ot}^* = (\alpha_o/c_{ot})A\, \eta\, Y_t^{\eta}$$

$$K_{nt}^* = (\alpha_n/c_{nt})\, A\, \eta\, Y_t^{\eta} \qquad (5.13m)$$

In this case , all the variables that the firm can control can be specified as a function of the demand constraint (Y_t, η), the technological production possibilities (β; α_o; α_n) and the input prices (w_t; c_{ot}; c_{nt}).

In summary (5.13m) confirms the presence of stock effects, as the optimal level of technology ownership is inversely related to its current marginal cost and is proportional to the firm marginal revenue. Consequently, in a dynamic framework, what determines the further use of that input over time is its relative speed of growth, i.e. the profit gains.

The optimal input levels of the firm (5.13m) can also be used to determine the optimal output path (Y*) given its technological possibilities (5.5) -i.e. the output

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10 Junankar (1972) commenting on Jorgenson's model says 'these marginal productivity conditions are the so called 'myopic decision' criteria': they say that although the firm is involved in dynamic optimisation process it equates the marginal product of each input at time t with the ratio of input and output prices also at time t'. However, it is here the view that the presence of the implicit cost of capital incorporates a sort of expectation about future prices and it is preferable to refer to those conditions as 'quasi-myopic' decision criteria. The details of which are discussed in a later section on price expectations and uncertainty.

corresponding to the optimal level of the control variables $Y_t^* = f(L_t^*, K_{nt}^*, K_{ot}^*)$- and the corresponding optimal price ($P^* = f(Y_t^*)$) as:

$$Y^*_t = f(L_t^*, K_{nt}^*; K_{ot}^*) = [A(\eta)(\beta/w_t)^{\beta}(\alpha_n/c_{nt})^{\alpha n}(\alpha_o/c_{ot})^{\alpha o})]^{1/(1-\eta)} \quad (5.14m)$$

and

$$P^*_t = f(Y_t^*) = A^{1/(1-\eta)}[\eta[(\beta/w_t)^{\beta}(c_{nt}/\alpha_n)^{\alpha n}(c_{ot}/\alpha_o)^{\alpha o}]^{\eta/(1-\eta)}$$

Equation (5.14m) shows that the current level of output is a function of the technological constraint of the firm, the input prices and the elasticity of the demand for its final good, ($Y_t^* = f(\beta, \alpha_n, \alpha_o, w_t, c_{nt}, c_{ot}, \eta)$.

(5.14m) also shows that the optimal price is endogenous and is proportional to the level of output that can be produced with the current production function. The proportionality factor is related to the inverse elasticity of the demand for the good ($\eta > -1$). This means that the optimal level of output implicitly incorporates the price adjustment to meet the demand for that good.

After substitution of the optimal output path (5.14m) in the marginal product constraint (5.13m) it is possible to derive (5.15m) the optimal level of ownership of the new technology K_{nt}^{**} corresponding to the firm's optimal inputs output ($K_{nt}^{**} = f(L_t^*, K_{ot}^*, Y_t^*)$, that is:

$$K_{nt}^* = (A\eta)^{1/(1-\eta)}(\beta/w_t)^{\beta\,\eta/(1-\eta)}(\alpha_n/c_{nt})^{1+\alpha n\,\eta/(1-\eta)}(\alpha_o/c_{ot})^{\alpha o\,\eta/(1-\eta)} \quad (5.15m)$$

According to (5.15m) the optimal demand for the advanced capital good (K_{nt}^{**}) is a function of the demand for the final product (market constraint), the input costs (economic constraints) and the optimal combination of inputs used in production

which in turn are a function of their relative prices and their productivity (technological constraint): i.e. $K_{nt}^{**} = f(w_t, c_{nt}, c_{ot}, p_t ; \beta, \alpha_n, \alpha_o, \eta)$.

In a dynamic framework (5.15m) shows that what leads to a decrease over time of c_{nt} (and thus to an increase of K^{**}_{nt}) is a decrease over time of q_{nt}. It also shows that a rapid reduction in the price of the new technology over time ($dq_{nt} = q_n(t)-q_n(t-1) < 0$) can lead to an opposite effect: it might slow down the diffusion of the new technology. In other words, while price (q_{nt}) speeds up intra firm diffusion, expectations of rapidly decreasing prices have an opposite effect they might lead the firm to wait (see fur further discussion on price expectations pp. 163).

However, equation (5.15m) also shows that the optimal level of ownership of the new technology does not only depend upon its current acquisition cost, but also on the optimal amount of output the firm decides to produce. The firm, in deciding the current level of production, is constrained to meet the demand for its final output via the elasticity of demand η (market constraint). In fact, an output expansion would lead the firm to reduce the selling price of its products reducing the profit gains from cost reduction.

Similarly to (5.13m), equation (5.15m) shows the existence of stock effects and that the optimal level of K_{nt}^{**} depends upon the reduction in production costs and the shift in the marginal revenue from output expansion. In a dynamic framework, the decision to extend the technology ownership will be determined by their speed of reduction (profit gains), or similarly by the slope of the marginal revenue and marginal cost curves. The optimal level of output depends upon the speed with which they decrease over time.

Takayama (1985, 1994, etc.) has pointed out that one of the weaknesses of the neo-classical model of investments arises from looking at the marginal product constraint used by Jorgenson, where $K_t^* = (\alpha P_t Y_t)/c_t$. He bases his criticism upon the fact that, assuming unlimited output expansion, investment are unbounded, i.e. they go to infinity[11].

Jeorgenson, in his two-input model does not specify any demand constraint and consequently considers only the generic competitive case where prices are exogenous to the firm. In this framework, the result in (15m) is extremely important because, using three, rather than two factors of production and allowing for different market scenarios, it provides a rationale as to why investments cannot simply go to infinity in the presence of price changes (dq_{nt}).

(15m) also shows the existence of stock effects, and that these determine the intensity of technology diffusion. Moreover, further to the market (p_t) and economic effects (c_{nt}), the optimal level of capital ownership is also determined by the technological constraints of the firm, via the current cost of the other inputs and the existing production system of the firm. The latter can be better seen by endogenizing the final demand for Y^*_t, i.e. using (5.14m) into (5.15m), and defining, in time t, the

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[11] Also Haavelmo (1961) and Lerner (1944) and later also Tobin (1967), commenting on the final specification used by Jorgenson (i.e $dY_t/dK_t=c_t/p_t$) have argued that 'according to the Neoclassical theory, i.e. Jorgenson model, if the firm is competitive and small enough and all prices are assumed or expected constant, then also the amount of investment is also constant over time. Moreover, as price changes then the firm can and would adjust instantaneously to the desired stock of capital. The instantaneous adjustment of capital implying that investments I_t are unbounded' (see Takayama 1985, pp.685 and also Takayama 1994, pp.517).

firm's optimal 'Capital-output' ratio path as the proportion of current optimal output (Y^*_t), produced on the new technology (K^{**}_{nt}):

$$Y^*_t/K^{**}_{nt} = (\beta/w_t)^{\beta} (\alpha_n/c_{nt})^{\alpha n-1} (\alpha_o/c_{ot})^{\alpha o} \qquad (5.16m)$$

Equation (5.16m) indicates that, given the optimal amount of current output Y^*, the extent of use of a new technology is determined by input costs and the relative partial elasticities ($Y^*_t/K^{**}_{nt}=f(w_t, c_{nt}, c_{ot}; \beta,\alpha_n,\alpha_o)$). While the latter are constant and firm specific, the former do change over time and the direction of their change determines the firm's extent of use of the new technology . This shows that not only 'costs' and 'marginal revenue' considerations determine the level of new technology ownership, but also the firm specific productivity arising from the current input mix.

With simple algebraic manipulation, assuming constant economies of scale, i.e. $\beta+ \alpha_o+ \alpha_n=1$, (5.16m) can be rewritten as:

$$Y^*_t/K^{**}_{nt} = (c_{nt})^{\beta+\alpha o} (c_{ot})^{-\alpha o} (w_t)^{-\beta} (\alpha_n)^{-(\beta+\alpha o)} (\alpha_o)^{\alpha o} (\beta)^{\beta}$$

This shows that the extent of use of the new technology, for a given current (optimal) level of output, is directly proportional to the level of its price q_{nt} (i.e. increase in c_{nt}), while it is inversely proportional to changes in the other factors' prices. The proportionality factor, is given by the elasticity of substitution of the relative inputs, i.e. β, α_o and α_n. Moreover, it shows that, under constant economies of scale, the impact of the cost of the advanced technology, i.e. $|\beta+\alpha_o|$, is higher than for each of the other two production inputs, i.e. $|\beta+\alpha_o|>|\beta|$ and $|\beta+\alpha_o|>|\alpha_o|$.

As an alternative to the flow specification (5.16m) of the optimal pattern of technology ownership, one can define a stock specification as the proportion of the firm's total capital stock incorporating the new technology (5.17m).

$$K^*_{nt}/(K^*_{nt}+K^*_{ot}) = 1/(1+(\alpha_o/\alpha_n)(c_{nt}/c_{ot}) \qquad (5.17m)$$

Equation (5.17m) shows that what determines the optimal replacement path of the new technology are the relative change in the costs of the two technologies (c_{nt}/c_{ot}) and the firm specific technological constraint (α_o/α_n) corresponding to the current firm specific productivity of the two capital stocks

The next section discusses the perfectly competitive market model

5.2.2. The Competitive firm

In the case of perfect competition most of the model remains the same, except that now the output price is exogenous and independent of the final output produced by the firm. This means that the firm is a price taker, and produces its output (Y_t) so that its marginal cost equals the current market determined price P^I_t. In an optimal control framework the competitive firm will maximise the Hamiltonian function subject to the (constant elasticity) demand function constraint $Y_t = f(P^I_t)$. All the other assumptions remain the same as in the monopoly case yielding:

$$H_t = e^{-rt}[P^I_t Y_t(P^I_t) - w_t L_t - q_{nt} GI_{ntj} - q_{ot} GI_{otj}] + \lambda_1 [GI_{nt} - \delta K_{nt}] + \lambda_o [GI_{ot} - \delta K_{ot}] \qquad (5.9c)$$

The Hamiltonian first order conditions for a maximum are:

I) $\partial H_t/\partial GI_{it} = 0$ i=n,o II) $\partial H_t/\partial L_t = 0$; III) $\partial H_t/\partial K_{nt} = -\lambda_{nt}$; IV) $\partial H_t/\partial K_{ot} = -\lambda_{ot}$

In the competitive case condition (I) yields:

$q_{nt} = \lambda_1 e^{-rt}$ and $q_{ot} = \lambda_o e^{-rt}$

The second condition (II) indicates that marginal product equals factor price yielding:

$$P^I_t (dY_t/dL_t) = w_t$$

Condition (III) and (IV) are the costate equation of motion and it easy to prove that they equal (5.10c):

$$P^I_t(dY_t/dK_{jt}) = q_{jt}(\delta + r) - dq_{jt} \qquad j = \text{new, old} \qquad (5.10c)$$

and

$$c_{jt} = q_{jt}(\delta + r) - dq_{jt} \qquad j = \text{new, old} \qquad (5.11c)$$

The rhs of (5.10c) shows that the marginal revenue per unit expansion of capital stock equals the marginal physical productivity of new technology, i.e. current output price, P^I_t per unit of output times the capital output ratio for that specific technology j, dY_t/dK_{jt}. Moreover, given that output price is exogenous, the optimal level of technology use will be determined by the size of the unit cost reduction (5.11c).

Similarly to the monopolistic case, (5.10c) indicates that, in equilibrium, the marginal revenue from producing on one extra unit of new technology equals the marginal user cost of capital of that technology, i.e. the implicit rental value of capital services supplied by the firm to itself (5.11c).

After substituting in (5.10c) the production function marginal productivity rule (5.6), one can derive the Hamiltonian marginal productivity rule as in II), III) and IV):

$$dY_t/dL_t = w_t / P^I_t$$
$$dY_t/dK_{ot} = c_{ot} / P^I_t$$
$$dY_t/dK_{nt} = c_{nt} / P^I_t \qquad (5.12c)$$

From condition (5.12c) it is possible to derive the *marginal product constraint* for each input of production as in (5.13c):

$$L_t^* = (\beta/w_t)P^I_t Y_t.$$
$$K_{ot}^* = \alpha_o/c_{ot} P^I_t Y_t$$
$$K_{nt}^* = \alpha_n/c_{nt} P^I_t Y_t \qquad (5.13c)$$

Equations (5.13c) show that the control variables are a function of the technological production possibilities (β; α_o; α_n), the input prices (w_t; c_{ot}; c_{nt}) and the current output price (P_t). Contrary to the monopolistic case the optimal inputs combination is independent of the demand constraint, because the firm is a price taker.

Similar to the monopoly case, the optimal inputs level (L^*, K_n^*, K_o^*) are determined by economic constraints (costs), the technological constraint (elasticity of substitution of the inputs) and a market constraint (output price).

Substituting (5.13c) in (5.5), that is constraining the optimal level of inputs (5.13c) to lie within the technological possibilities of the firm (5.5), and assuming constant

economies of scale, allows one to specify the optimal output path as a function of the optimal level of the control variables $Y_t^* = f(L_t^*, K_{nt}^*, K_{ot}^*))$:

$$Y^*_t = f(L_t^*, K_{nt}^*; K_{ot}^*) = P^I_t Y_t . (\beta/w_t)^{\beta} (\alpha_n/c_{nt})^{\alpha_n} (\alpha_o/c_{ot})^{\alpha_o} \qquad (5.14c)$$

where the firm's optimal output price, being independent of the firms current output, is simply :

$$P^*_t = P^I_t$$

Equation (5.14c) shows that the optimal level of output is proportional to total revenue ($P^I_t Y_t$) where the proportionality factor is a function of the technological constraint of the firm ($\beta, \alpha_n, \alpha_o$) and the input prices ($w_t, c_{nt}, c_{ot}$).

Substituting (5.14c) in the marginal product constraint (5.13c) one can derive the optimal accumulation path for K_{nt}, as :

$$K^{**}_{nt} = Y^*_t \, a(\beta/w_t)^{-\beta} (\alpha_n/c_{nt})^{1-\alpha_n} (\alpha_o/c_{ot})^{-\alpha_o} \qquad j = \text{new, old} \qquad (5.15c)$$

which states that in equilibrium the optimal level of capital accumulation for a given level of output (Y^*_t) is independent of market demand and is a function of: (a) the level of output; (b) the relative substitutability of the inputs (technical constraints) and (c) the current price of the inputs of production (economic constraints). In contrast with the monopolistic case, the optimal level of technology ownership is independent of output demand (market constraint) .

One might argue that, in line with the Takayama's critique (see footnote 10), under competition the accumulation path could grow unbounded due to changes in the factor prices or to the decision to produce an infinite amount of output. However, it can be

shown that, also in this case, the investments in a new technology are bounded and only under very strict conditions, they equal to immediate replacement. The bounding factors are determined by the characteristics of (and the compatibility with) the current production system of the firm, so that for a given level of output the optimal capital ownership is determined by the relative cost and the technological performance of the existing (old and new) capital stock. This can be better seen by using the Marginal product conditions (5.13c), that show that the optimal proportion of capital stock incorporating the new technology equals the productivity ratios and the costs of both existing and old technologies. This yields (5.16c):

$$K^*_{nt}/(K^*_{nt+} K^*_{ot}) = 1/ (1+ (\alpha_o/ \alpha_n) (c_{nt}/c_{ot}) \qquad (5.16c)$$

Furthermore, using equation (5.14c) and the advanced capital marginal product property (5.13c) (or alternatively 5.15c), it is possible to derive, for a competitive firm, the optimal 'Capital-output' ratio as in (5.17c):

$$Y^*_t/K^*_{nt} = (\beta/w_t)^{\beta} (\alpha_n/c_{nt})^{\alpha n -1} (\alpha_o/c_{ot})^{\alpha o} \qquad (5.17c)$$

Equations (5.16c) and (5.17c) suggest that the determinants of the speed of replacement of the old with the new technology is the productivity ratio (α_n / α_o) and the price differential of the two technologies (c_{ot}/c_{nt}).

Moreover, equation (5.16) and (5.17) are the same in both the monopolistic (m) and competitive (c) cases.

5.3. MONOPOLISTIC VERSUS COMPETITIVE BEHAVIOUR

5.3.1. Two measures of intra firm diffusion

The previous section highlights the differences between the optimal behaviour of the firm under two extreme market scenarios, the monopolistic and competitive cases, whose main results are summarised in Table 5.1.

The first step of the optimal dynamic control modelling has used the Hamiltonian first order conditions and the production function (technological) marginal productivity rules to derive the Hamiltonian productivity conditions of the variables of interest (see Table 5.1/1.a). The Hamiltonian marginal productivity rules show that the optimal output-input ratios are a function of the respective marginal cost and marginal revenue. In essence this condition indicates that there exist stock effects in the spread of use of a new technology as the marginal revenue from increasing its use $MR(dY_t/dK_{nt})$, is a function of the reduction in marginal cost that it brings about ($c_{nt} = (r+\delta)\, q_{nt} - dq_{nt}$):

$$A\, \eta\, Y_t^{\eta-1}\, (dY_t/dK_{nt})) = (r+\delta)\, q_{nt} - dq_{nt} \qquad (5.10m)$$

and

$$P^I_t(dY_t/dK_{nt}) = q_{nt}(\delta+r) - dq_{nt} \qquad (5.10c)$$

Under perfect competition, (5.10c) is exactly the same as in Jorgenson model, showing that the marginal product is a function of the relative prices of output (P_t) and input costs (c_{jt}). However, if the competition assumption is relaxed the output/capital expansion, due to a cost reduction, starts to influence its market price (see 5.10m). The latter is represented by the implicit consumer demand.

In essence (5.10m) and (5.10c) show that the firm will choose its optimal level of inputs on the basis of profitability considerations: the contribution to profits of the cost reduction and the shift in marginal revenue from output expansion.

The rhs of (5.10m/c) is the same in both competitive and monopolistic case which indicates that the expected profit gains from further adoption depend upon the shape of the marginal revenue function. While in the competitive case, in each time t, this linearly increases with the output expansion ($MR_c = (P^I_t).Y_t$), in the monopolistic case it depends upon the shape of the demand function ($MR_c = A\ \eta\ Y_t^{\eta}$).

In essence, this result is in line with the finding in chapter 4, stating that the extent of use of the new technology depends upon the shape of the demand function for the final good (market constraint).

However, this section has also proved that this is not the only constraint the firm has to face in determining the level of use of the new technology. This can be seen looking at the optimal value of the control variables, i.e. the variables the firm can control for, in Table.5.1 row b. There, what determines the optimal level of each input are: (i) input price (economic constraint); (ii) input elasticity of substitution (technical constraint); and (iii) output supply constraints, such as the elasticity of demand in the monopolistic and simply output prices in the competitive case (market constraint).

(i) and (ii) indicate that the decision to further invest in a new technology reflect the relative cost of the input and is not independent of the current status of the plant and the means of production already in use by the firm. This would also justify why it is important to look at the role of complementary and substitute technologies in the spread of use of a new technology.

This is an important result stating that the level of use of a new technology depends upon the size of profit gains from adoption (stock effects), but also on: a) the market position of the firm, i.e. whether monopolistic or competitive market; and b) the technical and the economic characteristics of the new relative to the existing technologies.

While the former is bounding only for a monopolistic firm, the latter affect any firm despite its market position.

Table 5.1. Summary of the intra-firm model: monopoly Vs competition

	Monopoly	Competition
a. Marginal Productivity (Hemiltonian)	$dY_t/dL_t = w_t / A(\eta)Y_t^{\eta-1}$ $dY_t/dK_{nt} = c_{nt} / A(\eta)\, Y_t^{\eta-1}$ $dY_t/dK_{ot} = c_{ot} / A(\eta)\, Y_t^{\eta-1}$	$dY_t/dL_t = w_t / P^I_t$ $dY_t/dK_{nt} = c_{nt} / P^I_t$ $dY_t/dK_{ot} = c_{ot} / P^I_t$
b. Marginal products	$L_t^* = (\beta/w_t) A(\eta)\, Y_t^{\eta}$ $Ko_t^* = (\alpha_o/c_{ot}) A(\eta)\, Y_t^{\eta}$ $Kn_t^* = (\alpha_n/c_{nt})\, A(\eta)\, Y_t^{\eta}$	$L_t^* = (\beta/w_t)\, P^I_t\, Y_t$ $Ko_t^* = (\alpha_o/c_{ot})\, P^I_t\, Y_t$ $Kn_t^* = (\alpha_n/c_{nt})\, P^I_t\, Y_t$
c. Optimal output path $Y_t^* = f(L_t^*, K_{nt}^*, K_{ot}^*)$	$Y^*_t = [A(\eta)\, (\beta/w_t)^{\beta}\, (\alpha_n/c_{nt})^{\alpha n}\, (\alpha_o/c_{ot})^{\alpha o})]^{1/(1-\eta)}$	$Y^*_t = P^I_t Y_t \cdot (\beta/w_t)^{\beta} (\alpha_n/c_{nt})^{\alpha n}\, (\alpha_o/c_{ot})^{\alpha o}$
d. Optimal price (P^*_t)	$P^*_t = A^{1/(1-\eta)}\, [\eta\, [(\beta/w_t)^{\beta}\, (c_{nt}/\alpha_n)^{\alpha n}\, (c_{ot}/\alpha_o)^{\alpha o}]^{\eta/(1-\eta)}$	$P^*_t = P^I_t$
e. Optimal capital path given optimal output $K^{**}_{nt} = f(Y^*_f)$ j=n,o	$K^{**}_{nt} = [a(\eta+1)]^{1/(1-\eta)}\, (\beta/w_t)^{\beta(\eta/(1-\eta)}$ $(\alpha_n/c_{nt})^{1+\alpha n \cdot \eta/(1-\eta)}\, (\alpha_o/c_{ot})^{\alpha o\, \eta/(1-\eta)}$	$K^{**}_{nt} = Y_t^*\ a(\beta/w_t)^{-\beta} (\alpha_n/c_{nt})^{1\, \alpha n}\, (\alpha_o/c_{ot})^{-\alpha o}$
Measures of intra-firm diffusion		
f. Optimal capital-output ratio	$Y^*_t/K^*_{nt} = (\beta/w_t)^{\beta}\, (\alpha_n/c_{nt})^{\alpha n - 1}\, (\alpha_o/c_{ot})^{\alpha o}$	
g. Optimal stock of New technology	$K^*_{nt}/(K^*_{nt} + K^*_{ot}) = 1/(1 + (\alpha_o/\alpha_n)\, (c_{nt}/c_{ot})$	

Replacing the optimal values of the production inputs , i.e. L_t^*, K_{nt}^*, K_{ot}^* (as in 5.1./b) into the Cobb-Douglas production function it is possible to derive the optimal output path (Y^*_t) for each optimal combination of inputs (Table 5.1./c), the optimal price for

that output (Table 5.1./d) and the optimal accumulation path of the stock of advanced technology corresponding to that output via the marginal product condition (Table 5.1./e). For a monopolist both Y* and K** show that the optimal accumulation path of output and capital are a function of technological constraints, supply constraints and inputs prices, while the output price effect changes considerably according to the position of the firm in the market, i.e. competition and monopoly.

In the monopolistic case, in presence of labour (L_t) and shadow price of K_{ot} constancy, a reduction in c_{nt} leads to an increase in the optimal level of advanced capital, which is proportional to the size of the inverse elasticity of demand (η) and the current level of the other inputs. The market demand and the technological constraint are binding for the firm, and therefore investments cannot just go to infinity as price decrease[12].

In the competitive case if the shadow price of K_{nt} (c_{nt}), labour costs (w_t) and output are all kept constant, an increase in c_{ot} leads to a decrease of the optimal level of K_{nt}, However, given that the firm can produce any amount of output at the given price, the only binding factors to investments are the technical constraint (Table 5.1./e).

This is a very important result because it demonstrates that, contrary to the Jorgensonian model[13], investments can be bounded. This also provides a rationale for why firms do not immediately switch to the new technology. Furthermore, from the

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12 See previous discussion on the Takayama (1991) critique to the Jorgensonian approach to unbounded investments

13 Jorgenson in many of his paper on the econometric testing of his theory, uses the following specification (i.e. marginal product of capital): $K^*_t = \alpha (Y_t P_t)/c_t$

In our view, this is a serious mistake as he completely ignores the different degree of industrial concentration leading to different output demand conditions. The higher is the degree of market concentration the more collinear both prices and input will be. Secondly, he

marginal conditions (5.13), it has been proved that the optimal level of use of the stock of new technology is proportional to the factors relative prices and substitutability. (see table 5.1/g):

$$K_{nt} / (K_{nt}+K_{ot}) = 1/ (1+ (\alpha_o/\alpha_n) (c_{nt}/c_{ot}) \qquad (5.16m/c)$$

In (5.16) the optimal capital input combination for a given level of output, is a function of both economic (c_{nt}/c_{ot}) and technology specific factors (α_o/α_n). It also indicates that the proportion of capital stock incorporating the new technology is a proportion of user cost of capital of the two capital inputs (c_{nt}/c_{ot}). The proportionality factor (α_o/α_n) is the elasticity of substitution of K_o and K_n, with respect to Y_t.

The second measure of intra firm diffusion derived in the model shows that the capital output ratio Y_t/K_{nt} depends on the optimal technological combination of all the inputs (L_t, K_{nt}, K_{ot}) whose optimal level is determined by their relative prices (see table 5.1/f):

$$Y_t/K_{nt} = (\beta/w_t)^b (\alpha_n/c_{nt})^{\alpha n-1} (\alpha_o/c_{ot})^{\alpha o} \qquad (5.17m/c)$$

The main difference between (5.16) and (5.17) is that one refers to the flow while the other to the stock of new technology. Moreover, the capital accumulation constraint is the same for both the monopolistic and the competitive case.

(5.17) is in essence the output to capital ratio and models the proportion of output produced on the existing capital stock. However, the current proportion of output may be the result of not only the current investment in K_n but also past investment in K_n as

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does not consider that there are technological constraints due to the existing inputs of production and completely ignores the factors substitutability.

well as other changes occurred within the firm. As such it cannot be used for comparisons across firms and over time (see Demetriades, Devereux and Luintel, 1998 discussion on productivity of capital over time).

The next section further discusses the implications of the two expressions for the capital accumulation path of the new technology.

5.4. The capital accumulation path equation

The intra firm model has led to the definition of two expressions for the optimal accumulation path of the capital embodying the new technology. These are the proportion of output produced per unit of new technology (5.16) and the proportion of total capital stock incorporating the new technology (5.17):

$$Y_t/K_{nt} = (\beta/w_t)^b (\alpha_n/c_{nt})^{\alpha_{n-1}} (\alpha_o/c_{ot})^{\alpha_o} \qquad (5.16m/c)$$

and

$$K_{nt}/(K_{nt}+K_{ot}) = 1/(1+(\alpha_o/\alpha_n)(c_{nt}/c_{ot}) \qquad (5.17m/c)$$

Equation (5.17m/c) shows that the optimal level of use of the new technology depends upon both the economic and technological substitutability between the two capital inputs used in the production process, and not on the level of output produced.

Equation (5.16m/c) shows that the capital output ratio Y_t/K_{nt} depends upon the optimal technological combination of all the inputs (L_t, K_{nt}, K_{ot}) whose optimal level is determined by their relative prices. While the first one refers to the stock, the second refers to the flow of optimal technology ownership.

Together (5.16) and (5.17) yield an important result showing that:

i) both the optimal capital output ratio (5.16 m/c) and the proportion of output produced on the new technology (5.17 m/c) are independent of the output demand constraints and show exactly the same value for the monopolistic and competitive cases;

ii) whether one uses a flow or a stock definition, the spread of new technology, for a given level of output, is mostly driven by the relative cost (c_{nt}/c_{ot}) and technological performance (α_o/α_n) of the existing types of capital.

The latter is immediate if one looks at equation 5.17 where for the firm it would be optimal to immediately switch completely to the new technology only if (α_o/α_n) (c_{nt}/c_{ot})=0. This can occur only if the user cost of capital of the old technology increases (in absolute value) much faster than for the new one so that it would no longer be profitable for the firm to use it. This might be the case for an old technology whose (quality adjusted) price is very high due to obsolescence and restricted availability on the factor market. This reasoning also proves that lower prices (or at least quality adjusted prices) can speed up the diffusion of a technology via a change in its user cost of capital. Another way to see this is to rewrite (5.17) as (5.18)[14]:

$$K_{nt}/K_{ot} = (\alpha_n/\alpha_o)\,(c_{ot}/c_{nt}) \qquad (5.18)$$

(5.18) shows that the ratio of the new to the existing technology is a function of the relative shadow prices and the firm specific rate of substitution between the two

[14] Using simple algebra the rhs of (5.17) can be written as: $K_{nt} / (K_{nt}+K_{ot}) = 1/ (1+ (K_{ot}/K_{nt})$, so that: $1/ (1+ (K_{ot}/K_{nt})) = 1/ (1+ (\alpha_o/\alpha_n)\,(c_{nt}/c_{ot})$. At this point, the derivation of (5.18) is immediate.

capital inputs. Given that the productivity ratio is constant over time (α_{nt}/α_{ot}), the proportion of advanced technology will increase as $c_{ot}>c_{nt}$. The higher the price difference the faster the diffusion will be. Moreover, given that by definition $\alpha_n>\alpha_o$, if the cost of the two technologies were equal, $c_{ot}=c_{nt}$, the proportion of new technology that would be optimal to the firm would be:

$K_{nt}/K_{ot} = \alpha_n/\alpha_o>1$ (or equivalently $K_{nt}> (\alpha_n/\alpha_o) K_{ot}$)

This indicates that the proportion of capital stock incorporating the new technology should be higher than the existing/old capital stock, due for example, to the higher productivity of the new technology, but not necessarily equal to one.

Relaxing the assumption of α's constancy across firms it is possible to incorporate firm heterogeneity and firm specific competencies (rank effects). In fact, different firms do have different core competencies and technological capabilities and this lead to different firm-specific production systems and firm-specific optimal levels of ownership of the new technology. As such, it is reasonable to expect that the productivity of each technology is firm specific, i.e. α_{ji}, and is different across firms. This would explain why, at the same point in time, firms coexisting on the same market do have different equilibrium levels of adoption of a new technology. This leads to a redefinition of firm skills and learning about the production possibilities of the firm. In fact, the firm is not a passive recipient of information, like in the Mansfield (1968) approach, but it is rather a processor of information with its own speed of learning from its own experience. The higher are the core competencies of the firm in processing information and in making it operative, the faster diffusion will be. This would also justify why the adoption of certain technologies might be faster if

the firm currently uses, or has in the past used, a previous generation of the technology, or why firms doing R&D are more likely to adopt advanced technology. This definition of learning is also different from the Stoneman (1981) approach where it is assumed that the firm does not have perfect information about the performance of new technology but learns about it over time from its own experience about the true profitability of the technology. In fact it is not only learning based upon the true profitability what influence the decision to further use a new technology.

In essence the intra firm model suggests that, whether information reaches the firm exogenously, like in the Mansfield Model, or endogenously, like in the Stoneman Model, what is really important is the firm's capability to process that information and to be dynamic and flexible to changes. In fact, what differentiates firms is the speed of processing this information, and the capability to innovate its production process.

While information can be bought, the capability to use it depends upon the expertise of the firms (i.e. accumulated experience from the adoption of similar technologies, current status of the production system, entrepreneur attitude to risk, etc.) and some firms might not have the skills for doing so. In other words, the core competencies of the firm are what generate different speeds of technological adoption. Learning is in fact firm specific and different firms do learn in different ways from their own experience and the experience of the others, even when this is readily accessible. In this light, the spread of information cannot be the main determinant of adoption, particularly after decades since the appearance on the market of a new technology, like in the case of NC, CNC, and Micro. It is not the accessibility of information but rather the capability to decode , assimilate and process information and of making it operative that is different from firm to firm. This would explain why, even if firms can access the same amount of information, they use it differently. This would also be

in line with Battisti and Pietrobelli (2000) who found that, within an industry, clusters of firms with different technological competencies do coexist on the same market. The clusters are determined by the characteristics and the technological (and human) competencies of the firms.

This section has presented an equilibrium inter-firm model based on the neo-classical theory of investment, aimed at explaining the optimal replacement of an old with a new technology by a firm over time. This model provides evidence that there exist stock effects and that their influence upon the level of usage of a new technology depends upon the shape of the market demand faced by the firm (market condition). This model also shows that the spread of new technology is also driven by changes in costs (economic condition) and technological performance of the advanced technology (technical condition). While the former are exogenous, the latter reflect the core competencies of the firm in processing information about the new technology and its own technological capabilities in combining and efficiently using the inputs in its production system. The higher are both the performance characteristics of the advanced technology and the reduction in its shadow cost, the faster will be the replacement process of the old with the new technology. This model also indicates that the extent of use of a new technology is not independent of the existing technology in use by the firm. This indicates that the decision to further use a new technology is influenced by the existing complementary and substitute technologies in use within a firm.

The proportion of output produced on the new technology is equally affected by the same conditions. Finally, whether a firm is a monopolist or operates on a perfectly competitive market , the investment decision over the new technology and its optimal

level are driven by the same factors and are bounded by the technological conditions of the firm.

In fact, whatever definition of intra firm diffusion (i.e. optimal capital output ratio or proportion of output produced on the new technology) the optimal level of adoption is independent of the output demand constraints and shows exactly the same value for both the monopolistic and the perfectly competitive case.

The next session presents how uncertainty associated with the investment decision of the firm, can be inserted into this intra-firm model.

5.4. THE REPLACEMENT DECISION UNDER UNCERTAINTY

5.4.1. Uncertainty: a real option approach to investments in a new technology

The intra-firm diffusion model presented in the previous section is strongly based upon the neo-classical theory of investment (see Jorgerson 1963) which provides a list of possible explanatory variables for investment expenditures. The variables are: interest rate, changes in the price of investment goods, labour cost, output, and changes in output prices in the competitive case. By means of optimal control techniques the model has been modified to determine the specification of the optimal accumulation path for the control variables (K_o, K_n and GI_o, GI_n). The resulting optimal firms technology ownership is shown to be a function of relative productivity (α_o,α_n) and the relative costs of each type of capital (c_{ot}, c_{nt}). While the former is firm specific, the letter changes over time. This model basically indicates that the firm decides upon the combination of inputs according to the level of prices at the time the decision is made, assuming that the firm has rational expectations and perfect

information about the characteristics of the market and the technology itself. However, given that investments are irreversible, the uncertainty of future demand or cost conditions should be taken into account because once the firm decides to invest it cannot just disinvest should the market conditions change adversely[15]. In fact, the firm might find it more profitable to wait for new information about prices, costs and other market condition before it commits its resources. The value of waiting can profoundly affect the decision to invest and its opportunity cost must be included as part of the total cost of investing. As a result the Net Present Value rule 'Invest when the value of a unit of capital is at least as large as the purchase cost and the installation cost of the unit ' is not appropriate in an uncertain world (Pindyck, 1988).

Irreversible investments under uncertainty have been studied by financial economists and their Option pricing technique have resulted in an elegant solution to the problem. The milestone work of McDonald and Siegel (1986), proves that in the case of a single irreversible investment project with uncertain pay-offs, a firm should invest in the project only when the expected pay-off exceeds the cost by an amount that depends on the level of uncertainty. As a result the investment decision should be taken when the marginal value equals the total cost of the unit, the total cost, including the purchase and installation cost plus the opportunity cost of exercising the option to buy the unit. In this light, the problem of investing is similar to exercising an option. The higher is the uncertainty about the future the higher is the value of the firm's investment option and hence the opportunity cost of irreversible investing (Pindyck, 1988). This is because the higher the variability of its environment the more

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15 Is not profitable to disinvest due to the sunk cost of the investments. In absence of second hand market the optimal scrapping would be by obsolescence- see Arrow's condition, Arrow (1968).

reluctant the firm is to invest, as higher variability worsens the 'worst case scenario in which the firm regrets the irreversible investment decision' (Bertola, 1998).

Within a firm several technologies are used at the same time, each being characterised by different levels of uncertainty depending on their performance, productivity, average profitability, price, age (date of their first appearance on the market and date of first adoption by the firm), etc. This would require a multiple uncertainty approach to the firm decision to invest. However, its mathematical complexity would make the model almost intractable.

An alternative approach is to look at the uncertainty associated with investments in two different sets of technologies: the old technologies, including all the existing technologies (o); and the new technology (n), including only the advanced one.

One approach would be to assume that the set of old technologies, being already known to the firm, is characterised by a lower degree of uncertainty than the advanced technology. The latter, being new, is more uncertain. Alternatively following the Stoneman (1981) approach to intra-firm technique choice one might assume that only the new technology is surrounded by uncertainty about true profitability while the profitability of the set of old technologies is already known with certainty having already been extensively used by the entrepreneur.

However, given that the replacement process takes several years, there are several other elements of uncertainty that might affect the investment decision. They are not necessarily technology specific and concern uncertainty about: future demand or input (or competitive output) prices, interest rate, performance of the new technology, etc. To select only one factor would yield biased results while to include too many would make the mathematical derivation of the model too complicated.

For these reasons, it is here preferred not to specify the sources of uncertainty affecting the specific investment decision but to proceed by adopting a generic specification of uncertainty about the firm's future revenue[16].

In the intra-firm diffusion model, the investment decision can be compared to the decision to invest in a project (e.g. to 'invest in a technology'). In mathematical terms, the benefit from an investment project can be expressed in terms of the discounted cash flows given the flow of information available at time t[17]. Define this present value as V_t. Because its future values are unknown, it is assumed that V_t evolves as a Brownian motion where the future values are lognormally distributed and with a variance that grows linearly with the time horizon:

$$dV_t = \varpi V_t \, dt + \sigma V_t \, dz \qquad (5.19)$$

where z is a standard Wiener process and equals $\varepsilon_t (dt)^{1/2}$ and ε_t is a normally distributed random variable with mean 0 and a standard deviation of 1. The remaining parameters are growth (ϖ) and uncertainty (σ).

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16 This approach is similar to the summary indicator of business conditions used by Bertola (1998) that defines a summary variable as a loglinear function of geometric Brownian motion processes like wages, productivity and demand which are expected to growth at a some constant mean rate but the realised growth rate are random, normally distributed and independent over time. The corresponding drift and standard deviation parameters of the process of the variable payoff being the linear combination of the primitive processes. In other words, uncertain profitability is a result of different level of uncertainty affecting any of the determinants of the investment decision.

17 Alternatively following McDonald and Siegel (1986) the present value is the market value of a claim on the stream of net cash flows that arise from installing the investment at time t.

Following Dixit and Pindyck (1994) one can suppose that the investment project is like an infinitely lived factory that produces a profit flow, π_t, that follows a geometric Brownian motion with drift:

$$d\pi_t = \varpi \pi_t dt + \sigma \pi_t dz \tag{5.20}$$

The above equation tells us that the current value π_t is known to the firm , but future values of π_t are unknown and are lognormally distributed with a variance that grows with the time horizon. In other words it is assumed that the value of the project (i.e. to invest in a technology) grows at some constant mean rate, but the realised growth rates are random, normally distributed and independent over time.

If V_t is the value of the investment opportunity (i.e. the value of the option to invest), then the payoff from investing at time t is V_t-I, where I is the cost of the investment assumed known and fixed. The decision to invest is here compared to the decision as to when to exercise an option, i.e. the right but not the obligation to buy a share of stock at a specified price.

Furthermore, it is reasonable to assume that an intra firm investment in a new technology does not last forever, contrary to the opportunity to invest which is4 available in 'perpetuity'. This means that the firm has got the chance to start investing in further projects, as the old expires due to capital obsolescence. Following Dixit and Pindyck (1994 pag.202) if one assume that the lifetime of the project is random and follows a Poisson process then if the project has survived up to time T , there is a probability δdT that the project will die within the following short time interval dT at the rate of depreciation δ. The corresponding probability distribution function of the

random lifetime, e.g. the probability that the project dies by obsolescence before T, is $1-e^{-\delta t}$ and the corresponding probability density function of T is $\delta\, e^{-\delta T}$.

In this light the firm would want to maximise the expected present value of the option, subject to (5.20) so that:

$$F(V) = \max E[(V_T - I)\, e^{-(r+\delta)T}] \quad \text{with } r>0 \text{ and } |\delta|<1$$

where r is a discount rate and δ is the depreciation rate. The resulting condition for the existence of a maximum imposes that the variable growth rate (ω) is greater than the discount and the depreciation rate i.e. $\varpi < r+\delta$.

Hence, following Dixit and Pindyck (1994) V_t is given by [18]:

$$V_t = E \int_t^{\infty} \pi_s\, e^{-(r+\delta)(s-t)}\, ds = \pi_t / (r+\delta-\varpi) \qquad (5.21)$$

The usual Marshallian rule is to invest as long the value of a unit of capital is at least as large as the cost of the unit ($V_t \geq I$) would yield (5.22):

$$\pi_t \geq (r+\delta-\varpi)I \qquad (5.22)$$

where $(r+\delta-\varpi)$ is the overall option value multiple. The flow cost equivalent part of (5.22) would suggest that $|\delta|$ increases by the Poisson death parameter because the sunk cost of investment (I) must be recouped over a shorter expected lifetime.

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18 It is possible to prove that if π_t is given by equation (5.20) then $V(\pi_t)=\log(\pi_t)$ is the following simple Brownian motion with drift: $F=(\omega-1/2\sigma^2)\,dt+\sigma\,dz$. So that over a finite interval t, the change in the logarithm of π is normally distributed with mean $(\omega-1/2\sigma^2)t$ and variance σ_t^2 (see Dixit, 1991).

However given that V_t is stochastic the dynamic modelling approach suggests that the firm should invest when V_t reaches the critical value V* (rather then $Vt \geq I$) so that it is optimal to invest once $V_t \geq V^*$. By using the Bellman equation and expanding the function using Ito's Lemma it is possible to find the optimal solution under the boundary constraint : $F(0) = 0$, $F(V^*)=V^*-I$ and $F'(V^*)=I$ (see Dixit and Pindyck, 1994). The resulting critical value V* at which it is optimal to invest ($V_t \geq V^*$) is:

$$V^* = \beta_1/(\beta_1 - 1)\, I \tag{5.23}$$

where β_1 is the larger root of the Bellman quadratic (differential) equation, i.e. $\beta_1 = 1/2 - \varpi/\sigma^2 + \sqrt{[\varpi/\sigma^2 - 1/2]^2 + 2\ (r+\delta)/\sigma^2}$, σ^2 is a measure of the random variability of the future value of the investment, while ϖ , r and δ are respectively the drift of the payoff from the project, the interest rate and the depreciation rate.

Substituting (5.23) into (5.21), the optimal critical value for the payoffs yields

$$\pi_t^* = (r+\delta-\varpi)\,[\beta_1/(\beta_1 - 1)]\, I \tag{5.24}$$

This is clearly greater than (5.22), indicating that uncertainty increases the option value to wait. However, this can be seen more explicitly by substituting the root (β_1) into (5.24), yielding

$$(r+\delta-\varpi)\,[\beta_1/(\beta_1 - 1)] = (r+\delta) + 1/2\sigma^2\beta_1$$

The latter allows rewriting the critical level of profit (5.24) as (5.25):

$$\pi_t^* = [(r+\delta) + (1/2\sigma^2\beta_1)]\, I \tag{5.25}$$

Equation (5.25) is almost identical to the formula of the infinite lived project (5.22), except that now the option value multiple is increased by the uncertainty factor. The flow cost equivalent indicates that uncertainty can increase the investment cost. When this happens, the firm might find it more profitable to exercise the option to wait.

In the absence of uncertainty (σ =0), the right hand side of (5.25) equals the neo-classical investment Jorgensonian rule, invest if the profit per unit of capital equals its cost [19], i.e. $\pi_t^*/I=(r+\delta)$ or :

$$\pi_t = (r+\delta)\, I \tag{5.26}$$

In summary, equation (5.25) says that when future profits are uncertain the threshold π^* must exceed the user cost of capital. So when profits are uncertain the firm must wait before investing. Moreover, Dixit and Pindyck prove that (5.26) is the optimal timing rule ($\pi_{t^*} = (r+\delta)I$). This would suggest that in the case of the Marshallian investment rule it is better to wait before investing even if there is no uncertainty, because waiting allows the postponement (and thus) discounting of the payment I.

The next step of the analysis concerns how the intra-firm diffusion model presented above in this chapter can take into account uncertainty in future profits in the presence of a dual investment decision.

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19 In terms of total cost, the neo-classical optimal initial investment into an infinitely lived factory would equal the initial investment ($I_{to}=K_{to}p_{to}$) based only on current prices, i.e. dq_t =0, where the user cost of capital would simply equals $c_{to}=(r+\delta)q_{to}$. The rule invest when the profit gain ($d\pi=\pi_{to}$) per unit of capital (I) equals its user cost $d\pi/dK=c_{to}$, reduces to $\pi_{to}/K_{to}=(r+\delta)p_{to}$. Or in term of total investment $(\pi_{to}/I_{to})=(r+\delta)$ as in (5.8). See next section for more details.

5.4.2. Uncertainty and intra-firm investment decision rules

Contrary to the traditional neo-classical approach, i.e. the Jorgenson model (1963), the model of intra-firm investment behaviour does not treat capital as a unique and homogeneous good. It rather focuses on the replacement process of the old or existing technology by a new more advanced technology. In this framework, the infinitely lived factory project can be extended so as to allow two types of investments. Let I_n and I_o be the values of two investment projects on a certain number of units of old (o) and advanced technology (n) so that for an existing firm $I_{j,to}=dK_{j,to}p_{j,to}$ j=n,o. Then assume that they are affected by the same market uncertainty but they are independent of each other, i.e. the firm can choose to invest in any of the two projects or in a combination of both projects. The Hamiltonian first order conditions and the costate equations of motion of the intra-firm model would yield two different expressions for the two types of projects (i.e. investments in the two capital goods) which are:

$$d\pi_t/dK_n = c_{nt}$$
$$\pi_t/dK_o = c_{ot} \qquad (5.27)$$

(5.27) indicates that, for each project, the payoff per unit of capital introduced should be equal to the user cost of capital (or the rental value) of the technology specific machinery.

Assuming that: (i) the firm decides upon the initial investment in the initial stock of capital ($dK_j=K_j$) such that the incremental variation of the payoff equals the total initial payoff ($d\pi_{to} = \pi_{to}$); (ii) changes in prices are zero at initial point (dq_{to} =0) and consequently $c_{j,to}=(r+\delta)p_{j,to}$; and (iii) both types of capital are subject to the same

depreciation rate, conditions (5.27) can be rewritten, in the absence of uncertainty, as (5.28):

$$\pi_{nt} = (r + \delta)\, p_{ot} * K_o = (r + \delta)\, I_o$$

$$\pi_{ot} = (r + \delta)\, p_{nt} * K_n = (r + \delta)\, I_n \qquad (5.28)$$

This expression is similar to (5.25) and indicates that profit gains from the introduction of a certain amount of capital input is proportional to the investment on each capital stock.

In absence of profit uncertainty, the firm will invest when total benefits from each project (I_j) are a proportion ($r+\delta$) of the value of the total Investment on each capital stock (I_n+I_o):

$$\pi_t = (r + \delta)\, (I_n + I_o) \qquad (5.29)$$

However, when there is uncertainty about future profits, the real option model (5.25) suggests that the two factors should be corrected so that (5.29) becomes:

$$\pi_t = [\, (r + \delta) + (1/2\, \sigma^2 \beta_1)\,]\ (I_1 + I_2) \qquad (5.30)$$

and the two marginal investment decisions in K_o and K_n are respectively:

$$\pi_t/K_o = (r + \delta + 1/2\, \sigma^2 \beta_1)\, p_{it} \qquad (5.31a)$$

$$\pi_t/K_2 = (r + \delta + 1/2\, \sigma^2 \beta_1)\, p_{2t} \qquad (5.31b)$$

The model thus assumes that the profit from an investment in a technology is proportional to its price and the proportionality factor is subject to uncertainty about future profits[20].

As it is specified, condition (5.31a/b) treats investments as a single initial investment ($dK_{to}=K_{to}$) and this can be a problem. In fact, by definition, the intra firm model excludes the initial (as well as the end point) investment decision and looks only at the firm decision to investing in further units of capital after first adoption.

This problem can be easily overcome by assuming that incremental units of investments are independent of the amount of technology already owned by the firm (Pindyck, 1988)[21]. So, if model (5.30) holds at the initial point t=0 then it should be

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[20] The basic model of irreversible investments has introduced the parallelism between the firm's option to invest and a financial call option where the state variable was the value of the project, V, for which is stipulated an exogenous stochastic process. Alternatively, one could have used a more specific definition of the source of uncertainty. In fact fluctuations in V can be due to fluctuations in the input prices, final output demand, technology conditions in various markets, etc. On purpose this has been avoided and we do not go too deep into the details of all the sources of uncertainty. To work with such a level of generalisation has allowed to greatly simplify the mathematical complexity of the problem.

[21] Following Pindyck (1988) the optimality condition that must hold if the firm is investing is $\Delta V(K^*,Z)=k+\Delta F(K^*;Z)$ Where K^* is the optimal capital stock while ΔV is the value of the unit of capital or the present value of the expected flow of incremental profit generated by the existing installed unit and ΔF is the value of the option to buy one more unit of capital, at any time in the future. Though the firm should invest until the value of a marginal unit of capital $\Delta V(K;Z)$ is equal to its cost: the purchase cost, k, plus the opportunity cost $\Delta F(K^*;Z)$ of irreversibility exercising the option to invest in the unit rather than waiting and keeping the option alive. So the amount of capital already in place and the value of the firm W, is the sum of two parts: $W=V(K)+F(K)$ This can justify the adaptation of the model to the intra-firm diffusion decision rule, where incremental units of new/old capital stock the firm are continuously added over time.

valid at each subsequent moment. This allows rewriting (5.30) in terms of differentials as:

$$d\pi_t/dK_n = (r + \delta + 1/2\,\sigma^2\,\beta_1)\,p_{nt} - dp_{nt} \qquad (5.32a)$$

$$d\pi_t/dK_o = (r + \delta + 1/2\,\sigma^2\,\beta_1)\,p_{ot} - dp_{ot} \qquad (5.32b)$$

(5.32) is equivalent to the Hemiltonian first order maximisation condition constrained by the costate equations of motion and after substitution of the marginal product as derived in section 5.2. Moreover, the rhs of 5.32a and 5.32.b are the user cost of capital corrected for uncertainty, i.e.

$$c^*_{nt} = (r + \delta + 1/2\,\sigma^2\,\beta_1)\,p_{nt} - dp_{nt} \qquad (5.33a)$$

$$c^*_{ot} = (r + \delta + 1/2\,\sigma^2\,\beta_1)\,p_{ot} - dp_{ot} \qquad (5.33b)$$

They are a positive function of a reduction in the price of the technology ($-dq_{jt}$ j=n,o) and are proportional to the level of the price of the technology (q_{jt} j=n,o), the proportionality factor being the sum of discounting (δ), depreciation (r) and uncertainty ($1/2\,\sigma^2\,\beta_1$).

It is immediate to notice that in absence of uncertainty , i.e. $\sigma^2 = 0$, (5.33a/b) reduces to the Jorgensonian user cost of capital , i.e. $c_{jt} = (r + \delta)q_{jt} - dq_{jt}$. Uncertainty, if present, would lower the impact of a price decrease ($dq_{jt}<0$) upon the further extent of use of the new technology. This also means that in order to increase the proportion of new technology via a price change, i.e. a reduction in c^*_{jt}, the relative increase of the price of the technology j should be at least as large as the depreciation plus interest rate and uncertainty:

$$dq_{jt}/\,q_{jt} > (r + \delta + 1/2\,\sigma^2\,\beta_1) \qquad j = \text{new, old}$$

The adjustment for uncertainty to the intra firm model of technology adoption presented in Chapter 5 is straightforward. Substituting (5.33a/b) in the optimal capital accumulation path of the firm, it is possible to derive the optimal level of intra firm diffusion corrected for uncertainty as:

$$K_{nt}/ K_{ot} = \alpha_n/\alpha_o . . c^*_{ot}/c^*_{nt} \qquad (5.34)$$

or equivalently

$$K_{nt}/ (K_{ot}+K_{nt}) = 1/[1+ \alpha_o/\alpha_n . c^*_{nt}/c^*_{ot})] \qquad (5.35)$$

where the α's are the parameters of the production function, while the c's are now the Jorgensonian user cost of capital adjusted for uncertainty (5.35).

Equation (5.34) basically indicates that the optimal level of intra-firm technology adoption of a new technology is: (i) directly proportional to the relative capital productivity i.e. relative elasticity of substitution of the inputs and (ii) inversely proportional to the relative cost (i.e. the user cost of capital) of the new to the old technology subject to a certain degree of uncertainty ($1/2\ \sigma^2 \beta_1$). Uncertainty as here specified, refers mainly to future profitability the firm cannot directly control for. As such it will affect the level of ownership of the two sets of technologies with the same intensity. Consequently, what influences the relative costs in (5.34) are merely the level (q_{jt} j =n,o) and the change in the prices of the two inputs, ($q_{j,t+1}$ -q_{jt}j=n,o).

The changes in the price implicitly assume that the firm operates under perfect foresight and knows exactly what prices will be from one period to another. This is equivalent to saying that the firm has got perfect information about the market and future price changes. This assumption is quite strong and should be tested empirically as it might as well be that the firm knows only part of the information about the

variables of interest. Not knowing what the level of prices will be, its investment decision could be a function of the expected ($q^E_{j,t}$) rather than the current price ($dq_{j,t}$). To use only the latter might lead to serious misspecification. The neo-classical investment model does not explicitly take into account the possibility of price expectations even though they can play a determinant role in the decision to invest. The following section presents different ways price expectations can affect the decision to invest in a new technology.

5.5. Price expectations

In the neo-classical literature, (Jorgenson, 1963 1965, 1967a/b, 1970) the firm decides upon how much to invest according to the level of prices at the time the decision is made, except for the price of capital services, or the user cost of capital, specified in this study as:

$$c_t = q_t(\delta + r) - dq_t$$

Moreover it is assumed that the firm chooses the optimal level of capital (K^*_t) for the period such that the profit gain from an extra unit of capital input equals its cost[22]:

$$E(d\pi_t/dK_t) = q_t(r+\delta) - dq_t \qquad j=\text{old, new} \qquad (5.36)$$

The first part of the rhs of (5.36) accounting for discounting and depreciation, i.e. $(r + \delta)$, the second accounting for price changes, i.e. dq_t.

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[22] See Blanchard and Fisher (1989) pp. 296 for a proof.

These assumptions remain almost unchanged when applied to the dual model of replacement of the old with the new technology under uncertainty. Introducing uncertainty into the surrounding environment of the firm, the expected profitability of an extra unit of one of the two types of capital, yields:

$$E(d\pi_t/dK_{jt}) = (r + \delta + 1/2\, \sigma^2 \beta_t)\, q_{jt} - dq_{jt} \qquad \text{where } j = o, n \qquad (5.37)$$

The difference with respect to (5.36) is that in (5.37) the firm faces two different types of capital inputs, with technology specific user costs of capital and productivity. The user costs of capital being equal to the actual price of an extra unit of technology specific capital stock, adjusted for interest rate, depreciation and uncertainty, i.e. $(r+\delta + 1/2\, \sigma^2 \beta_t)\, q_{jt}$, plus the change in price, i.e. dq_{jt}[23]. One might also reinterpret the user cost of capital (in the rhs of 5.36) as a measure of the long term price path once short run oscillations (dq_{jt}), around its observed values (q_{jt}) are subtracted.

This seems to suggest that the firm adjusts its investments in each moment in time (instantaneously) according to the underlying movements in the secular trend rather than to short run price oscillations and that the firm knows with certainty what the price change will be from one period to the other. This assumption is quite strong as it assumes that the firm operates under perfect information about changes in the variables of interest. Moreover, as assumed by the theoretical intra-firm model,

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[23] In future study it might be interesting to extend this model as to include capital price expectations (weighted or unweighted with certain probability distributions) also for the other prices in order to take further account of uncertainty.

investments are irreversible and capital disposal occurs by depreciation, i.e. with zero second-hand value. Under this assumption the profit maximising firm is more likely not to respond instantaneously to changes in price but rather adjusts its current level of use of each capital stock to the desired optimal level based upon expected future price changes. This is an important aspect of the model as it directly affects the intra-firm level of use of the existing technologies via the changes in the user cost of each type of capital (see equation (5.35)). This implies that the type of price extrapolation the firm bases its decision upon may be a crucial element in the derivation of the optimal intra firm level of use of a new technology.

For ease of presentation let the current proportion of each technology j (S_{jt}) be simply expressed only as a function of the past and current level of prices ($dq_{jt}= q_{jt}-q_{jt-1}$) so that:

$$S_{jt} = f(dq_{jt}) \qquad j=\text{new, old}$$

The implicit assumption behind this specification is that the time lag between the decision to invest and the delivery of the goods is only one period . Moreover, the adjustment to the desired capital stock j to price changes occurs immediately and is a function of the level of prices which are known by the firm with certainty. This is equivalent to say that the firm operates under rational expectations and formulates its investment decision under prefect foresight about future changes in the input prices. However, it is also possible that the firm does not know exactly the price of the technology from one period to another and it bases its investment decision upon partial information. Consequently the current level of ownership, S_{jt}, corresponds to

its price expectations (q_{jt}^e) rather than the price (q_{jt}) when the actual investment takes places, so that:

$$S_{jt} = f(dq^e_{jt})$$

The rational expectation approach was firstly introduced by Muth (1961) and subsequently implemented by Lovell (1986), Pesando (1975), Friedman (1980), etc. The basic idea behind these models being that the specification of expectations should be consistent with the rest of the model rather than being ad hoc. Basically, it assumes that the difference between the realised and the expected value should be uncorrelated with all the variables in the information set at the time the expectation is formed. This is because the economic agents are supposed to have perfect information (i.e they know all the variables in the information set) and they know the exact values of the parameters of the model. There exist different tests for rationality (see Wallis (1980), Revankar (1980), Hoffman and Shmidt (1981), etc), among them, one could use the *weak rationality test* based upon the significance of the relationship between forecast error ($q^e_{jt+1} - q_{j(t)}$) and the variables in the information set (I_{t1}) so that:

$$q^e_{jt+1} - q_{j(t)} = a_0 + a_1 I_{t-1} + \varepsilon_t$$

or

$$q^e_{jt+1} - q_{j(t)} = a_0 + a_1 (q^e_{j(t-1)} - q_{j(t-1)}) + \varepsilon_t$$

Rationality would imply that $a_1=0$ and the observed values (dq_{jt}) can simply replace the expected values in the final model estimate (i.e. the firm knows exactly what prices will be). If the forecast errors exhibit a significant non zero mean and serial correlation (significant a_1), then the information contained in past forecast errors is

not fully utilised in forming future predictions and the hypothesis of price expectations must be accepted (Maddala, 1992). This test, even if quite straightforward, would require that q^e_{jt+1} is known and should be collected using ad hoc surveys. Alternatively, there are two approaches to estimating and testing rational expectation models. One involves obtaining an explicit expression for the expected value from the model, substituting this in the model and then estimating the model using any parameter constraints that are implied (e.g. Wickens, 1982). The second involves substitution of the realised value and using some appropriate instrumental variables (see for examples Maddala, 1992).

Price expectations are not available to us and the alternative approaches would be of limited applicability in the intra firm model presented in this and later chapters. The stochastic nature of the price approximation and the resulting forecasting error, would make it difficult to handle the non linear nature of the technology replacement equation (5.34). This, together with the significant loss of degrees of freedom and multicollinearity arising from the exogenous information set would make the model intractable empirically. An alternative would be to just test for the presence of price expectations, rather their absence.

There exist a wide literature on expectations, which basically assume that expectations are based upon the observation of past realisations of the relevant variables for which expectations were formed. This type of models can be categorised as *Static* or simple lag models of instantaneous adjustment and *Dynamic Models*. The static models would assume that the current optimal level of ownership of the capital stock is a function only of the price level in the previous period, i.e. $S_{jt}=a+\beta_1 q_{j(t-1)}$. Dynamic models are more sophisticated and make use of time lags to account for

incomplete or lagged responses by the economic agents to changes in economic conditions. Examples of this type of approach are the finite polynomial lags model (see the milestone work of Fisher (1937) or more specifically Almon (1965) for an application to capital appropriation and expectations) or infinite lags or geometric lags model (Koyck 1954, Cagan 1956 and Nerlowe 1958). They basically assume that the effect of one variable upon the other is not contemporaneous but can be gradual over a sequence of time periods, yielding a distributed lag relationship, i.e. $S_{jt}=a+\beta_1 q_{j(t-1)} +...+\beta_z q_{j_{t-z}}$ with z= finite/infinite. The resulting expected price q^e is a weighted average of past values of q_{it} with geometrically declining weights. These types of models have in common that they are difficult to estimate. Among the several problems, the number of lags can cause a relevant loss of degrees of freedom, multicollinearity among the lagged variables and unreliable parameter estimates. An alternative specification, derived from the geometric lag approach, is the Adaptive Expectation model which basically assumes that expectations are upgraded in each moment in time with an adjustment proportional to the error in the previous realisation:

$$q^e_{jt} - q^e_{j(t-1)} = \gamma_j \left(q_{j(t-1)} - q^e_{j(t-1)}\right)$$

or equivalently

$$q^e_{jt} = \gamma_j \, q_{j(t-1)} + (1-\gamma_j) \, q^e_{j(t-1)}$$

where the weight of the error lies between zero and 1 ($0<\gamma_j<1$) and the nearer is γ_j to 1 the greater the influence of the latest observations in determining the current price expectation.

Further to the Adaptive Expectation model there are other approaches to price expectations and there are also several models that explicitly take into account dynamic adjustment of the dependent variable (S_{jt}) to price expectations (if they exist). They basically assume that when variables are disturbed from their equilibrium, they do not adjust instantly but there are some lags in adjustments to the new equilibrium position. Examples of such models are the Partial Adjustment model, the Nerlowe (1958) model, the Error Correction model (Granger, 1986; Engle and Granger, 1987; Johansen and Juselious, 1990, etc.) and the rational lags distribution model (Maddala 1977, Lucas and Rapping 1969, etc.)[24]. The latter has also been used by Jorgenson (1963, 1965, 1966, 1970 etc.) in testing his neo-classical investment model. However, even if of interest of their own, the nature of their dynamic adjustment is not compatible with the dynamic of the intra-firm model for mainly two reasons. Firstly the model is basically an equilibrium model assuming that, in each moment in time, the observed level of capital equals the desired level of capital (see Chapter 3 for a full discussion). Secondly, the non linear nature of the intra firm model would make very uneasy the introduction of lagged values of the dependent variable. Moreover, the structure of the residuals would yield to a model almost intractable empirically. Thirdly, even in absence of price expectations, past levels of use of a new technology (i.e. dependent variable) are not available, except for 1993.

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[24] See also Fisher and Tanner (1978) for a comparison of the empirical study on adaptive expectation and polynomial distributed lag models and also Bischoff (1978) for applications to modeling the demand for capital goods including Jorgenson's approach.

A third approach to investigating the nature and the role of prices is based upon the belief that there might exist an asymmetric response to price rises or falls. If so, the best model specification should be based upon the irreversible function approach. The reason for different reactions to price rises or falls is that the fixed or durable assets of the firm have an opportunity cost, which is usually referred to as the scrap value, which is well under their acquisition costs. Consequently, while a rise in input price might lead to the acquisition of a new technology, a fall in prices does not lead to the scrapping of such durables whose acquisition was justified when prices were high. The irreversible or asymmetric response functions do take into account the asymmetric elasticity of substitution of investments with respect to price rise or fall. This type of approach was first explored by Twenteen and Quance (1968) in their applications to the agricultural supply function and afterwards by Saylor (1974), Houck (1977), etc. In their model they split the price variable (q_t) in two parts, one accounting for positive (q_t^r), the other for negative (q_t^f) changes in prices. In terms of technology adoption this can be rewritten as:

$$S_{jt} = a + \gamma^r q_{jt}^{\ r} + \gamma^f q_{jt}^{\ f} + u_t \qquad j=o,n$$

where a is the intercept, γ^r and γ^f are coefficients and prices can be specified as:

$$q_{jt}^{\ r} = q_{j(t-1)}^{\ r} + \gamma_1 [q_{jt} - q_{j(t-1)}]$$

$$q_{jt}^{\ f} = q_{j(t-1)}^{\ f} + \gamma_2 [q_{jt} - q_{j(t-1)}]$$

so that when $\gamma_1=1$ if $[q_{jt} - q_{j(t-1)}]>0$ and 0 otherwise, and $\gamma_2=1$ if $[q_{jt} - q_{j(t-1)}]<0$ and 0 otherwise.

In a later study Wolffram (1971) proposed a modified version of the above, saying that it is more likely that changes occur when prices are higher/lower than the maximum/minimum level reached in the past i.e. threshold level:

$$q_{jt}^{r} = q_{j(t-1)}^{r} + \gamma_1 \; [q_{jt} - q_{jt}^{MAX}]$$

$$q_{jt}^{f} = q_{j(t-1)}^{f} + \gamma_2 \; [q_{jt} - q_{j(t-1)}]$$

where $\gamma_1 = 1$ if $q_{jt} > q_{jt}^{MAX}$ and 0 otherwise, and $\gamma_2 = 1$ if $q_{jt} < q_{jt}^{MAX}$ and 0 otherwise where the threshold can be calculated, for example, by weighted or simple non-centred moving averages (Traill et al, 1978).

It is reasonable to expect that, when the price of the capital stock increases the firm is more likely to wait. Vice versa, when prices decrease, the firm might be more willing to invest immediately. Which one of the two specifications is the best can be determined only empirically. However, also in this case the nature of the price specification, i.e. via the user cost of capital, would make it very difficult to test these assumptions empirically.

In summary, there are several approaches to the formulation of price expectations and rationality. However, there are several empirical and conceptual constraints to their applicability and testing over the intra firm model of technology replacement. The alternative route followed in this section moves from a slight modification of the naïve extrapolative expectation models (e.g. Ferber 1953, Maddala, 1992). It allows one to test the hypothesis of rationality against the hypothesis of imperfect information without specifying ex ante the nature of the price expectations. This

model would simply assume that the relationship between expected prices and observed prices could be written as:

$$dq^e_{jt} = \gamma_j \, dq_{jt}$$

The intra firm model (equation 5.17 or 5.18 or similarly 5.34 or 5.35) would assume that γ_j=1, so that, in each moment in time, the change in the expected price equals the observed change (dq^e_{jt}=dq_{jt}), i.e. the firm operates under perfect foresight and has got perfect information about future prices (rational expectations) [25].

This hypothesis can be tested empirically via the significance of the coefficient of the change in price (γ_j)[26]. If γ_j turns out to be is significantly different from 1, the hypothesis of rational behaviour must be rejected in favour of price expectations

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[25] Despite the term 'rational' appears in the definition of this type of expectations, it is worth emphasising that the specification used in this model is not the rational 'old' lag distribution tipical of the rational lag model heavily criticised by Lucas. The Lucas' critique (Lucas 1972, 1976) is not in favour of the ex-post estimate of exogenous changes in the variables, on the ground that the structure of economic models is based upon behavioural relationship derived from optimal decision rules of economic agents who can anticipate the movements of relevant variables (Wallis, 1980). Consequently, he believes that any exogenous changes in the nature of these movements cause themselves changes in the optimal decision rules, hence 'any change in policy will systematically alter the structure of econometric models' (Lucas 1976, pp.41). This invalidate any ex post analysis of the effectiveness of an actual policy, or equivalently of any ex-post changes in the exogenous variables in isolation, based upon their impact before and after this change occurred (i.e. lags structure). This is because as soon as the economic variables change also the economic system does making difficult to isolate their impact (see Wallis 1980 for more technical details). However, it is not in the aim of this chapter, to enter this discussion about rationality.

[26] Given the cross sectional nature of the data set and the nature of the (non linear) model (5.17) this study will be limited to the testing of any possible deviations from the assumption of perfect foresight, rather than the testing of possible types of expectations and dynamic adjustment of the investment in the new technology.

($dq^e_{jt} = \gamma_j . dq_{jt}$). This would indicate that there is a discrepancy between the firm's expectation and the observed price. The resulting discrepancy, (γ_j), being proportional to the forecasting error made by the firm in predicting the level of prices[27] can approach 1 from above or below ($\gamma_j \gtrless 1$), depending on whether the firm expectations over-estimate or under-estimate the change in prices. The nearer is γ_j to 1 the closer is the expected value to the observed value..

How the firm reacts to changes in price is very important, especially if one is interested in policies aimed at promoting diffusion via price interventions and fiscal incentives to the acquisition of further technology by innovative firms[28].

This section has presented how prices expectations affect the level of a new technology ownership. It has also shown how the intra-firm diffusion model enables one to test the hypothesis of perfect foresight and rationality versus incomplete information or, more generally, the role of price expectations.

Some might argue about using a completely empirical approach to the definition of the problem. However, as Granger (1995) has emphasised, to follow an empirical approach to the optimal dynamic structure is common practice in economics given

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[27] One possible specification of the formulation of expectations being, for example, that the expected price change in the next period (dq^e_{jt}) is proportional to that in the previous period (dq_{jt}), so that: $q^e_{jt+1} - q_{j(t-1)} = \gamma_j (q_{j(t)} - q_{j(t-1)})$

or equivalently $q^e_{jt+1} = \gamma_j q_{j(t)} + (1-\gamma_j) q_{j(t-1)}$

where, again, γ_j measures the discrepancy between the firm forecast and the observed price that in absence of expectations should be equal to 1. However, this is only one of the possible price expectations that is not necessarily imposed to the testing of the model.

that, quite often, the dynamic structure of theoretical economic models is not specified.

The next session summarises the main determinants of intra-firm adoption and how they have been specified in the final estimating equation.

5.6. The estimating equation

The model of intra firm diffusion presented in this chapter defines the optimal adoption path of a new technology via the rate of substitution of the existing (K_o) by the advanced (K_n) capital stock of the firm:

$$K_{nt}/ K_{ot} = \alpha_n/ \alpha_o \cdot c^*_{ot}/c^*_{nt} \qquad (5.34)$$

where α_n and α_o are the productivity parameters (i.e. $Y_t=A_t K_{ot}^{\alpha o} K_{nt}^{\alpha n} L_t^{\beta}$) and c^*_{nt} and c^*_{ot} are the shadow prices or the user cost of capital corrected for uncertainty.

This section aims at deriving the final specification of the intra-firm model suitable to empirical testing. By means of statistical and econometric tools the validity of its assumptions and the robustness across different technologies will be tested over the sample of firm in the CURDS data set. However, there are a number of problems associated with the nature of the model (5.34) and the information available in the CURDS data set.

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28 See for further discussion on the role of expectations Karshenas and Stoneman, 1993, Nickel, 1978, etc. Other approaches to expectations, i.e. expected technological improvements can be found in Rosemberg 1976a/b, 1971, 1994, etc).

The first problem is, that due its non linear nature, this model is very difficult to estimate econometrically[29]. A solution is to express the dependent variable in terms of proportions of total capital stock of the firm, so that: i) $k_{jt}=K_j/(K_n+K_o)$ j= new, old and ii) $k_{nt}+k_{ot}=1$. Then applying a log-linearisation to (5.34) yields (5.38):

$$\log[k_{nt}/(1-k_{nt})] = \log(\alpha_n/\alpha_o) + \log(c^*_{ot}) - \log(c^*_{nt}) \qquad (5.38)$$

In logarithmic terms, (5.38) indicates that the proportion of capital stock incorporating the new technology is a function of the relative productivity and the difference in the shadow costs of the new and the old technologies. Equation (5.38) can now be easily estimated by OLS.

The other problems one has to fact in testing the intra-firm model are:

1)The first element of the rhs of (5.38) is firm specific and *differs across firms* (α_{ni}/α_{oi}).

The CURDS data set contains several indicators of firm characteristics and technology adoption over time, but does not explicitly contain information about the firm specific capital productivity (α_{ni}, α_{oi}) This implies that the first element in the rhs of (5.38) is not directly observable.

2) The second element of (5.38) *changes over time*, but not across firms, (c_{ot}/c_{nt}).

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[29] Alternative simulation techniques might have been used to test the validity of the model. This possibility has been excluded on the basis that the marginalist analysis allows to determine the relative impact of each determinant of adoption. It is less subjective than simulations and allows to use the rare empirical evidence upon adoption behaviour of the firm over different technologies.

The CURDS data set does not contain information upon the level of ownership of the technology over time. The level of technology ownership being available only in 1993, restricts this analysis to the behaviour of the cross section of firms in 1993[30].

Moreover, as specified in (5.38) the model does not allow one to explicitly test the hypothesis of rationality versus price expectation and to measure the impact of uncertainty in determining the extent of use of the advanced technology.

The following sections explain how those limitations have been overcome in the final model specification. In particular it looks at how the time dimension of (c_{ot}/c_{nt}) and the space dimension of (α_n/α_o) are combined in the final model specification. Below each component is discussed in detail and describes how the information in the CURDS data set has been used in the modelling of the determinants of adoption.

5.6.1. Space dimension of $(\alpha_{ni}/\alpha_{oi})$

As seen in section 5.3. of this chapter, the productivity ratio α_n/α_o in (5.38) reflects the firm's technological constraints at time t, and depends upon the firm's modality of production. This type of information is not available in the CURDS data set and for this reason cannot be directly specified in the model.

However, α_n/α_o, being firm specific, reflects the core competencies of the firm, such as: dimension, management, organisation and other technology in use, etc. For its nature, it can be compared to what is defined as a rank effect in the inter-firm diffusion literature. The latter recognises that (potential) users differ in some

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[30] See appendix A for the variables contained in the CURDS data set

important dimensions proxied by the characteristics of the firm (David, 1969, 1991; Davies, 1979). Similarly, in the intra firm diffusion model the (capital specific) productivity ratio can be interpreted as a measure of the firm specificity determining the technological production frontier and the optimal adoption rate. If the α's differ across firms one has a reason why, despite firms facing the same shadow prices, they decide to adopt different levels of technologies. It is difficult to define and measure the intra firm rank effects , not only from the theoretical point of view , but also empirically. However, the CURDS data set contains several indicators of firm characteristics that can be used as a proxy for this. Their definition and the justification for their inclusion are summarised below:

Establishment Characteristics in 1993

It is generally argued that larger firms can diversify the risk of experimenting with new technologies better than smaller firms, due for example to economies of scale or to participation in research and development (Shumpeter, 1911, 1984). The consequence for this being that adoption will be faster the larger the firm. The majority of the empirical studies, based upon inter-firm rank effects to technology diffusion do confirm this prediction. Early work of Mansfield (1968), Romeo (1975) as well as Hannah and MacDowell (1984), Karshenas and Stoneman (1993), Saloner and Shephard (1995), Noteboom (1993) and more recently also Colombo and Mosconi (1995) find that size of the establishment shows a significant and positive impact upon the spread of technology adoption. However, there are also some other studies that reach the opposite conclusion such as the Oster study (1982) on the diffusion of the basic oxygen furnace and continuous casting. She finds a negative effect of firm size on adoption probabilities. This controversial result will be kept in

mind, but being less a common finding, the expected coefficient sign will be left to be positive.

The variable used in the testing of the size effect is the number of employees (le_{it}) (available for 1993-1986-1981-1975 and 1970), where lagged, weighted and unweighted smoothing averages have been used to avoid simultaneity and endogeneity problems. Moreover, binary size-class variables, will be specified to capture size effects in both absolute and relative measures.

The Shumpeterian hypothesis that formalised R&D exerts a positive impact upon the use of a technology is also 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. On the other hand Karshenas and Stoneman (1993) found no significant impact of R&D upon inter firm adoption. The variable accounting for R&D is here defined by the ratio of employees doing in house R&D to the total employment of the firm(R&D). The alternative, due to the high number of missing values for some of technologies, is a dummy variable also available in the CURDS data set ($Rdum_{it}$). The latter takes value 1 if firms do in house R&D and zero otherwise, without requiring the exact number of full time equivalent employees engaged in R&D. Whether one uses the former or the latter indicator, the impact upon intra firm diffusion, if significant, is expected to be positive.

Another variable used to proxy the rank effect is the age of the establishment (AGE). It is included on the basis that older firms generally have accumulated knowledge that allows them to assess new technologies better than younger firms do. However, also the opposite might be true. Younger plants may be better able to adopt advanced technologies than older plants whose capital stock may be outdates and less compatible with new technologies being adopted (Baldwin et al. 1998). Empirical

studies upon the spread of adoption of a sample of technologies in US manufacturing industry have yielded contrasting results. Dunne (1994) has found no significant relationship between establishment age and inter firm adoption for a range of technologies and for several industrial sectors, while Little and Triest (1996) has found a negative relationship between the number of new technologies adopted by the firm and the firm age. The latter indicating that older firms are slower to take up with new technologies. On the contrary, in a study by Noteboom (1993), the impact of age upon the adoption of computers in small scale retailing, in the Netherlands has turn out to be positive and significant. Therefore, the impact of age is difficult to predict a priori and its significance is left to the empirics.

Other variables included in the model are: whether the firm is export intensive, i.e. exports >20% or >50% of its output (EX20 and Ex50) and the industry sector the firm belongs to (dummy- D_{It} where I=1, ..15, up to two three digits SIC classification). They are included on the basis that each firm faces different markets for their products and different input costs depending also upon the sector to which they belong. Consequently the coefficient may be significant but the expected sign, being sector specific, is difficult to predict a priori.

The last two variables are whether there has been any change in the ownership of the firm since 1986, (dummy-OWNER) and whether the firm, as an establishment, belongs to an industrial group (dummy-GROUP). The former reflects the possible impact of a change in management, while the second reflects the impact of information via internal routes about technology performance and technological competencies. While the sign of the first one, if significant, is undetermined, the

second, if significant, is expected to be positive. In fact, Cainarca et al (1990) have found that 'business groups' compared to 'indipendent firms' do show higher rates of adoption of FA systems. However, Karshenas and Stoneman (1993) using the CURDS data set found that the distinction between establishments and firms is not an important one for inter firm diffusion. The same result can be found in Dunne (1994) in his study on a range of technologies in the US manufacturing industries, where single plant and multiplant producers have turn out to utilise the technology at similar frequencies.

Financial Status/liquidity of the firm

Financial conditions of the firm, at the time the investment decision is taken, are believed to play a relevant role in the adoption decision. This hypothesis has been tested by Mansfield (1963) in the diffusion of diesel locomotives in the US between 1925-1959. He finds that liquidity of the firm has a positive and significant sign. However, since his study the firm credit system has become much more sophisticated and diversified, For this reason the expected sign can (but not necessarily must) be significant and positive. Three different variables have been used to model the financial position of the firm they are: (i)dummy variable profit or loss in 1990/91, 1985/86, 1980/81 (dummy- PL_{it}); (ii) N years average real profit per unit of turnover between 1986 and 1993 ($lturnoverNy_{it}$); and (iii) the average real turnover between 1986 and 1993 weighted by the number of employees ($larwt_{it}$). While the first refers to a point observation the other two take into account that the firm might use the smoothing average of its financial liquidity in recent years. The smoothing average also avoids problems of simultaneity in the model due to causality between the investment decision and the consequent reduction in liquidity. The best variable will

be selected empirically according to the relative contribution to the model explanatory power.

Production System Characteristics in 1993

The characteristics of the production system are expected to affect the adoption of a new technology considerably. For example, Colombo and Mosconi (1995), suggest that CAD and CAM systems, like NC stand alone machine tools, were originally oriented towards the realisation of highly complex (often customised) parts typical of plant of the 'job shop' kind, i.e. with a wide product mix composed of highly differentiated products and production to order in small batches. On the contrary Flexible Automation production were originally aiming at coping with the need of conversion to flexibility of mass production by plants with no job shop, mainly involved in line productions of a limited number of rather standardised designs. On this basis they conclude 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.

The type of production organisations available in the CURDS data set have been specified by a series of dummy variables such as: engineer to order (PS1), make to order (PS2), make to stock (PS3), Job shop (PS4), mixed (PS5). Their expected sign is technology specific and cannot be generalised to all the technologies in the CURDS sample.

Colombo and Mosconi (1995) also report that systems like CAD, CAM or NC stand alone, were originally oriented towards the realisation of highly complex (often customised) parts, which were produced in small batches, and were particularly

suitable for firms which required very rapid introduction of new or improved products (Carlsson, 1984).

Under this aspect also the average batch size (Lbatch) is included on the rhs of the model. Being technology specific, its significance and its sign will be determined empirically.

Introduction of new technology/systems by 1993

Interdependencies and complementarities are believed to play a relevant role upon 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, 1998). Despite the theoretical attempts to model the adoption of complementary or substitute technologies, there exist very few empirical studies of this. Among them Karshenas and Stoneman (1993), Stoneman and Kwon (1994), Colombo and Mosconi, 1995, Stoneman and Toivanen (1997) etc. have found that inter firm adoption of a technology is not only affected by variables related to itself but also by variables relating to other technologies. Moreover, the degree of complementarity can affect the probability of simultaneous adoption. Consequently a series of dummy variable outsourced from then CURDS data set is here used to indicate previous adoption of complementary and substitute technologies such as NC, CNC, CoT, Micro and Robot. Other innovations introduced by 1993 are: CAD, Microprocessors incorporated in products (M-PROD)

Managerial innovations and quality awarding by 1993

As emphasised by the managerial literature, managerial as well as organisational innovation can generate complemetarities 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, and also Colombo and Mosconi 1995, for empirical evidence in support of this hypothesis).

The presence of interactions among best practice technologies and different spheres of the firm's activity is tested via the inclusion of dummy variables indicating whether, by 1993, the firm has adopted: Computer Aided Production Management system (CAPM); Total Quality Management principles (TQM) and Just in Time principles (JIT). Another variable accounting for quality of the production practice of the firm is whether the firm has been awarded the BS5750/ISO9000 accreditation (BS575) by 1993. Given that they are plant and technology specific, their significance and their sign will be determined empirically.

Allowing all these effects to enter the model, one can approximate the productivity ratio as:

$$\log(\alpha_{ni} / \alpha_{oi}) = f(\text{intra-RANK})$$

$$= \log(\text{Charcteristics}_i) + \log(\text{liquidity}_i) + \log(\text{Prod-system}_i)$$

$$+ \log(\text{Technologies}_i + \text{other innovations}_i) + \log(\text{Managerial}_i)$$

$$+ e_i$$

There are no a priori reasons to eliminate any of these variables[31]. Their significance will be tested empirically when the final model is estimated.

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[31] Lagged values of the independent variables, such as employment, turnover in previous years, are not explicitly specified but they are being used to correct for endogeneity.

5.6.2. Time dimension of (c_{ot}/c_{nt})

The second element of the rhs of (5.38) represents the impact over time of changes in costs upon the level of use of a new technology and can be rewritten as (5.39):

$$\log (c^*_{ot}/c^*_{nt}) = \log (c^*_{ot}) - \log (c^*_{nt}) \qquad (5.39)$$

where $\log(c^*_{jt})$ $\forall$ j=old, new, are the log of the Jorgensonian user cost of capital of the new and the old technologies, corrected for uncertainty, that can be written more explicitly as:

$$\log(c^*_{jt}) = \log [(r+\delta + 1/2\, \sigma^2 \beta_1)q_{jt} + (-dq_{jt})] \qquad j = \text{old, new}$$

The user cost of capital is not directly estimable as some of its components, i.e σ^2 and β_1, are not directly observable. However, making use of the approximation, $\log(x+1)= x$, it can be rewritten as:

$$\log c^*_{jt} = \log (-dq_{jt}) + [- (r+\delta + 1/2\, \sigma^2 \beta_1)q_{it}/dq_{jt}] \qquad (5.40)$$

Moreover, substituting (5.40) into (5.39) yields:

$$\log c^*_{ot} - \log c^*_{nt} = \log (-dq_{ot}) - \log (-dq_{nt}) - (r+\delta + 1/2\, \sigma^2 \beta_1)\, (q_{o.t}/dq_{ot} - q_{nt}/dq_{nt})$$

or

$$\log c^*_{ot} - \log c^*_{nt} = \log (-dq_{ot}) - \log (-dq_{nt}) - (r+\delta + 1/2\, \sigma^2 \beta_1)\, [q_{nt}/(-dq_{nt\#}) - q_{o.t}/(-dq_{ot})]$$

The equivalent parameterised version being:

$$\log c^*_{ot} - \log c^*_{nt} = \gamma_1 \log (-dq_{ot}) - \gamma_2 \log (-dq_{nt}) - \gamma_3\, [q_{nt}/(-dq_{nt\#}) - q_{o.t}/(-dq_{ot})] \qquad (5.41)$$

where $\gamma_3 = r + \delta + 1/2\, \sigma^2 \beta_1$, dq_{jt} and q_{jt}/dq_{jt} are the difference and the reciprocal of the relative change in price of the two sets of technologies j=new, old , while $r + \delta$ are respectively the interest and the depreciation rate , σ^2 is the volatility of profitability, β_1 is the root of the Bellman equation.

One of the problems arising with the estimation of (5.41) is that prices do not change across firms but change over time, while the level of technology ownership is available only in 1993. In order to overcome the lack of cross-sectional dimension the change in price has been specified as the difference in the price at time of first adoption ($t=\tau_o$) and the current price (t=1994). However, to avoid the price effect (in absolute value) being larger for early adopters than for latecomers, it has been assumed that the change in the price $dq_t=q_t-q_{t-1}$ can be approximated by the average incremental change from the date of first adoption ($t-\tau$), so that:

$$(q_t-q_{\tau o})/(t-\tau_o)$$

Taking the log of this expression it yields $\log(q_t-q_{\tau o}) - \log(t-\tau_o)$, where the second term can simply be approximated by a time tend. In other words, it is here assumed that the sum of the smoothed incremental variations over time would reasonably approximate the current capital ownership of the firm, i.e. the dependent variable in the final model specification. Although this assumption might be regarded as one of the weaknesses of the model testing, this is the best approximation of the price effect one can get from the data available to this study. In fact, this allows one to add, an otherwise absent, time dimension to the cross sectional dimension of the study.

The first implication of this assumption is that the time trend is also the term used to pick up the epidemic effect, but with opposite expected sign. As such it should be distinguished in the final interpretation of the time coefficient. The second implication

is that it is implicitly assumed that price expectations are firm specific, being based upon the firm specific experience of price changes since its first adoption. Again, if we assume that expectations are influenced by past values of prices, to use this expression might reflect the fact that earlier adopters have greater experience of past pattern of price changes, while later adopters might have based its decision upon a shorter observation period. For these reasons the interpretation of the expectation coefficient should be considered only as a reasonable approximation due to the limitations of the cross-sectional nature of the information available in the CURDS data set.

In this study the variables used for the testing of the price effects have been specified as follows: 1) the growth rate of the price of the advanced technology ($dq_{jt}= q_{j\,(t=1994)}- q_{j\,(t=\tau_0)}$, j=NC, CNC, Micro); 2) the growth rate of the price of the firm's existing capital stock ($dq_{ot}= q_{o(t=1994)}-q_{o(t=\tau_0)}$) measured by the Index of the price of Real Domestic Fixed Capital Formation ; 3) The reciprocal of the relative growth rate in the price of the existing and new technology since first adoption ($q_{ot} /dq_{ot} -q_{nt} /dq_{nt}$) or alternatively, using the absolute value of the price derivatives: $[q_{ot} /(-dq_{ot}) -q_{nt} /(-dq_{nt})]$. The price effect in (5.41) is tested using the prices of the technologies (q_{NC} , q_{CNC}, and q_{MICRO}) at the factory gate adjusted for inflation and the quality content of the product over time (Quality adjusted real price index) [32].

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[32] Quality adjusted prices are used when a technology, or any other producer or consumer good, has been on the market for several decades. A technology is a good for which quality changes can be spectacular (like in the case of computers) and the price that a producer charges at the factory gate for a machine in 2000 is much less than in 1950 (Stoneman et al.1992). For some goods, it is reasonable to expect that the price fall over time while technological improvements do increase the quality of the final products. If one wants to compare prices over time it is therefore important to correct prices for quality changes and to use a factory gate price at 'constant quality' and constant prices. Some of the quality adjusted

The adjustment for the different purchasing power is quite straightforward and can be done using a deflator such as the retail price index calculated by the National Statistical Office. The adjustment for quality improvements of the product over time is not straightforward and needs some further elaboration. The basic approach used to calculate the quality adjusted prices of the technologies included in the CURDS data set refers to the Hedonic price method (see Griliches , 1971, Triplett, 1989, Stoneman et al. 1992) in which the product prices are related to the characteristics that the products embody. Unfortunately, the price index of Coated and Carbide tools machines was not available. Consequently, CoT had to be excluded from the testing of the model (see Appendix D for more details).

The expected sign of the parameters can be derived looking at each single component of the price effect. The first two elements of the rhs of (5.41) measure the impact of a change in the price of the existing ($-dq_{ot}$) and the new ($-dq_{nt}$) technology upon the level of adoption of the advanced technology[33]. In both cases the elasticity to price changes should equal 1, but with opposite sign ($\gamma_1=1$, $\gamma_2=-1$)[34]. An increase in level of ownership of the new with respect to the old technology is directly proportional (i.e.

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price series have been outsourced from existing studies such as the price of Microprocessors (Tyson (1992) Gruber (1992), Dosi (1984), Stoneman et al. (1992), Stoneman (1976), Triplett (1989), Parking and Bade (1988)) and the price of Computers used to derive the price series of quality adjusted of CNC and NC.

[33] For the logarithmic property the term in brackets ($-dq_{it}j=n,o$) must be always positive and this is true for at least quality adjusted prices of the technologies that do normally decline over time.

[34] When both dependent and independent variables are in logs then the coefficient of the variable is simply the elasticity of substitution, e.g. $\log S=\gamma.\log Q$ then $\gamma = d\log S/d\log Q$, where the log ratio can be rewritten as $d\log S/d\log Q = [d(\log S)/dS.dS/dQ.\ dQ/\ d(\log Q)]$ yielding

positive unit elasticity of substitution) to the decrease in the price of the old technology (dq_{ot}), while it is inversely proportional (negative unit elasticity of substitution) to a decrease in the price of the new technology (dq_{nt}). This indicates that while low prices (q_{jt}) speeds up intra-firm diffusion, rapidly decreasing prices (dq_{jt}) increase the shadow cost of capital and create a sort of expectations about future reduction and this slows down the intra-firm diffusion process. Consequently, the expected sign of the coefficient of the change in price is positive for the old ($\gamma_1>0$) and negative ($\gamma_2<0$) for the new technology[35].

The coefficient of third element on the rhs of (5.41), i.e. γ_3 measures the (negative) impact, corrected for uncertainty, of the relative growth rate of the price of the (existing and the advanced) technologies. It also indicates that the relative impact of relative prices is proportional to depreciation and devaluation ($r+\delta$) of the capital stock owned by the firm and uncertainty surrounding future profits ($1/2\ \sigma^2 \beta_1$). In absence of uncertainty, the marginal impact would be simply equal to the interest rate plus the depreciation factor ($r+\delta$).

Unfortunately the impact of uncertainty in γ_3 cannot be isolated from the other factors, i.e. ($r+\delta$) and the empirical estimates will provide only an aggregated measure accounting for both factors. One way to overcome this problem is to subtract from the estimate of γ_3 the current interest rate for 1993 and to outsource the estimate of the

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dlogS/dlogQ=dS/dQ.Q/S which is by definition of the point elasticity of substitution of S with respect to Q. Consequently $\varepsilon=\gamma$.

35 The role of price expectations have been addressed by the theoretical model presented by Ireland and Stoneman (1986) and also by the empirical work of Stoneman and Kwon (1994) and Karshenas and Stoneman (1993). In the latter paper it is found that price expectations

depreciation rate from existing empirical studies. The discount rate could be measured by the yield on Treasury Bills expressed as an annual interest rate (i.e. r_{1993}= 0.0495 source: NSO) while the depreciation factor can be, for example, outsourced from Jeorgenson (1963) which assumes that a unit of capital looses about 85% if its real value in 18 years (i.e. δ=0.025)[36]. This would yield $(r+\delta)$=0.075. Whether the coefficient γ_3 is significantly different from this value can be tested empirically. Alternatively, given that devaluation and depreciation are constant across firms, the size of uncertainty effects can be derived by comparing the size of the price coefficient γ_3 across technologies[37]. According to equation (5.41) the firm knows exactly what prices will be from one year to another (dq_{jt} j= n, o) and it decides the optimal level of adoption according to the observed prices for the current and the past period. However, it is more likely that the firm plans each year the optimal investment for the following year according to its own expectation rather than the certainty about future price movements.[38] It might also be possible that the firm holds expectations

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such as $(p_{t+1}-p_t)$ play a major role in technology diffusion, suggesting that myopic type of studies such as Hannan and McDowell (1987) where $p_{t-1}=p_t$ may be seriously misspecified.

[36] This figure is also very similar to the one used by Shapiro (1986) in his empirical study on investment output and cost of capital. Specifically he uses an average depreciation rate of 0.024 a quarter, implicitly modelled in the Bureau of Economic Analysis's net capital stock figures when one takes the gross flows from the national income and product account (NIPA).

[37] See for further studies on uncertainty and capital investments such as Devereux (1995 and 1989) on the impact of taxation; Scaramozzino (1997) and the relationship between Investments and q models under uncertainty, etc. see also and Carruth et. al (1997) for a survey on empirical studies in the area. However, contrary to the intra firm model, these studies do restrict the attention to the aggregated investments rather than investments in two competing gods.

[38] The firm also ignores that there might be any gap between the decision to invest and the

about future change in prices (i.e. decline) and each year the level of investment is decided upon the difference between the expected and the observed prices. Furthermore, there might exist minimum (maximum) expected price thresholds that might speed up (delay) the firm's investment decision, like for example under the asymmetric response type of expectations (see section 5.5 for a full discussion about price expectations). In summary, there are reasons to believe that the firm plans its investment according to its price expectations rather than the price at the time the investment is made.

Expectations are assumed to affect the investment decision via the price of the technologies and this hypothesis can be tested empirically via (5.41).

The information concerning the level of ownership of the advanced technology in the CURDS sample is available only for 1993. The resulting cross sectional nature of the available data constrains the range of formulation of possible price expectations and their impact upon the adoption of the new technology. This lack of time dimension can be reasonably overcome simply assuming that each firm owns an expectation about what the price will be when planning its investment. Consequently, the firm's expectations (dq^e_{ijt}) of the observed price change (dq_{jt}) may be under or over estimated by a factor (γ_j) so that:

$$\log(-dq^e_{jt}) = \gamma_j \log(-dq_{jt-1})$$

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capital acquisition within the production system of the firm. The time lag being due, for example, to the time required to the delivery and installation of the new capital good. However, dynamic adjustments in the demand for the new technology are not explicitly considered here due to the lack of data upon technology use over time. For this reason the study is limited to price expectations (see Section 5.5 for a discussion on this issue).

This formulation assumes that the current level of technology adoption is a function of the expected prices (which might also be an optimal threshold price under asymmetric response) rather than the observed current price. The discrepancy between the expected and the current price being measured by γ_j where j=new, old. In the standard specification $\gamma_j = 1$ (see equation 5.41) meaning that the expected price equals the current price and the firm operates under 'quasi' myopia as assumed by the neo-classical literature. This also indicates that the firm operates under rational expectations with perfect information. However, if γ_j is significantly different from 1, the hypothesis of price expectations cannot be rejected and it can approach 1 from above or below ($\gamma_j \gtrless 1$) depending on whether the firm expectations do over-estimate or under-estimate the change in prices. The nearer is γ_j to 1 the lower is the discrepancy between the expected and the current price.

In summary, allowing both uncertainty and price expectations to be explicitly modelled within the user cost of capital, the shadow price ratio $\log(c^*_{nt}/ c^*_{ot})$ can be rewritten as:

$$\log c^*_{nt} - \log c^*_{ot} = f(\text{ price, expectations, uncertainty}) =$$

$$+\gamma_{1(\text{EXPECTATION})} \log(-\text{dPRICE}_o) \; -\gamma_{2(\text{EXPECTATION})} \log(-\text{dPRICE}_n)$$

$$-\gamma_{3(\text{UNCERTAINTY, interest rate and depreciation})} (\text{PRICE}_{o/n})$$

This specification allows testing the impact upon the use of a new technology of:

(i) price effect via testing of $\gamma_1=1$ and $\gamma_2=-1$

(ii) price expectations ($|\gamma_j| > 1$) as an alternative to the neo-classical specification of 'quasi myopia'(i)

(iii) uncertainty (σ^2) via the magnitude of γ_3, i.e ($r+\delta$) significantly different from 0.075.

Previous empirical evidence based on inter firm study (see Hannah and McDowell (1984), etc..) has found a strong negative relationship between the relative price of the technology and the adoption probability. The same result was found by Baldwin (1998) in relation to technology extent of use. The role of price expectations has been explored in Stoneman and Kwon (1994) and Karshenas and Stoneman (1993) and in both studies, they have found a significant impact of price expectation upon adoption times. The expected sign and the significance of the price effects is in line with these findings (even if expectations are tested using a different specification).

Price expectations upon intra-firm diffusion have never been studied before. Moreover, contrary to the several empirical studies, this model provides a solid theoretical framework as to why the price effect is important. Its significance will be tested empirically.

5.6.3. Other inter firm effects

The inter-firm literature would predict that stock, rank , order and epidemic effects determine the spread of adoption of a new technology across firms.

The possibility that intra –firm rank effects might affect the level of technology over time has been explored in section 5.6.1. where the productivity ratio ($\alpha_n./\alpha_o$) as been modelled in terms of firms characteristics and core competencies of the firm.

The inter-firm literature also assumes that the stock effect provide the rationale as to why some firms might delay the first adoption of a new technology over time on the basis that incremental profits gained from the adoption of a cost-reducing innovation decline with the number of rival firms which are already using it (Reinganum,

1981a/b/c,). This can be due, for example, to effects of technology adoption on the price in the final market (p_t), that lowers the gross benefits from adoption as the number of users increases or through effects on prices in factor market (in this case q_{jt} or c_{jt}). In terms of intra-firm diffusion the stock effect would predict that there exist decreasing profits from the further use of a new technology (by the firm and the industry) and this might justify why the firm does not immediately replace all its capital stock with the new technology.

In Chapter 4 the possibility of decreasing profit gains from further use of a technology have been explored without reaching a conclusive answer. Profits can be bounded or unbounded depending on the type of model, the market structure and the specification of the demand curve of the final good. The Intra firm equilibrium model presented in this chapter, overcomes this problem as it already incorporates both input and output prices effects via the Hamiltonian marginal product of capital rule:

$$dY_t/dK_{nt} = c_{nt}/P_t$$

In fact, a reduction in the price of final output, due to increasing adoption, leads to an output expansion which in turn increases profits. On this basis the firm might decide to further invest in the new technology however, from the first order Hemiltonian condition (i.e the constate equation of motion), the marginal benefit associated with further adoption of the new technology is equal to:

$$dH/dK_n = -\lambda_t$$

where $\lambda_t = e^{-rd} p_{nt}$, is the constate variable (see Chapter 5 pp.110).

However, after some manipulations, one could also rewrite the more familiar expression in terms of the corrected user cost of capital

$$c^*_{nt} = (r + \delta + 1/2\, \sigma^2 \beta_1)\, q_{nt} - dq_{nt}$$

stating that incremental profits per unit of capital are proportional to the user cost of capital[39] whose magnitude depends upon the relative changes in prices and the volatility of future profitability.

The impact of the stock effect (i.e. output price reduction) upon intra-firm diffusion can be twofold: 1) the impact of the level of industry use ('intra-*inter firm* effect) and 2) the impact of incremental use by the firm itself (intra firm stock effect).

The first reflects the impact upon a firm of the industry (rival firms) extent of use of the cost reducing technology. The second concerns the impact on firm's profitability of increasing use of the technology by the firm itself, given the current level of prices.

The intra-firm model estimating equation is specified in terms of the proportion of stock ($K_{nt}/(K_{nt}+K_{ot})$) rather than flow (y_t/K_{nt}) of technology ownership incorporated into capital good.

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[39] In economic terms the change in the acquisition costs (user cost of capital) is captured via the change in the acquisition price (dq_{nt}) whose impact is smoothed by uncertainty about future profitability ($1/2\ \sigma^2\ \beta_1$). Low uncertainty reduces the rental cost of capital and fastens the diffusion process. The same happens in presence of a price decrease (dq_{it}). Uncertainty affects the expected profit of adoption via the parameters (ϖ,σ^2) in $\beta_1=1/2 -\varpi/\sigma^2 +\sqrt{[\varpi/\sigma^2 - 1/2]^2 + 2(\rho+\delta)/\sigma^2}$, where ϖ and σ^2 are the drift (i.e. growth rate) and the volatility of the value of the investments i.e. $d\pi_t = \varpi\ \pi_t\ dt + \sigma\ \pi_t\ dz$. One might be tempted to use ϖ as an indicator of the performance of the investment in the new technology. However, seen in section 5.4.1, there are several other elements of uncertainty that might affect the investment decision that are not necessarily technology specific. They can be related to uncertainty about future demand or input (or competitive output) prices, interest rate, performance of the new technology, etc. For this reason ϖ cannot be simply used as a measure of stock effects due to further extent of use of the new technology.

Being built around the intra-firm stock effects, it also implicitly accounts for the impact of a price change upon the profitability of further adoption. As a result its specification will be independent of market concentration.

The inter firm order/stock effects can alternatively be captured by the proportion of industry output produced on the new technology over the total industry output produced by rival firms (Iusers/Jdiff). To take into account that firms belonging to different industrial sectors might face different profitability of adoption one could also hypothesize the above variable has also been split by multiplicative dummies into within industry stock differences (sh_d d=1,2,...15).

These variables are allowed to enter the model as a pure empirical exercise. However, if the predictions of the intra firm equilibrium model are correct, their coefficients should be insignificant.

The Order effects traditionally present in the inter firm literature assume that the return to a firm from adopting a new technology increase the higher is the firm position in the order of adoption due to pre-emption or first acquisition of prime geographic sites, or limited pools of skilled labour (Funderberg and Tirole, 1985: Ireland and Stoneman, 1985: etc.). On this reasoning, order effects would suggest that for a firm would also be optimal to immediately replace all its existing capital stock at time of first adoption, i.e. profits are unbounded. As seen in Chapter 2, only few adopters do immediately adopt all the technology.

At the intra firm diffusion level, the extent of adoption (and the benefits from further use) is spread over time and is not limited to the first mover advantages considerations. For this reason, they are not specified in the tested model.

The inter firm epidemic effects are related to learning as a process of self-propagation of information about a new technology that grows with the spread of the technology (Karshenas-Stoneman, 1993). In fact information based models often assume that it is mainly the spread of information about the new technology that drives the diffusion process. Contrary to stock and order effects the higher the number of users the greater is the chance for a firm to first adopt a new technology[40]. An alternative approach has been proposed by Stoneman (1981) which assumes that the firm learns about the technology in a Bayesian manner from its past experience of adoption. Even though it is difficult to explicitly model this approach proves that the role of information should have some importance upon the decision to use a new technology.

The intra firm model presented in this chapter predicts that neither the epidemic nor the Stoneman types of model determine the adoption of a new technology. It is rather the way in which the firm processes the information available on the market what determines the adoption of a new technology. This is reflected by the production system characteristics and the choice of the production means (L, K_n, K_o) used for producing the current output. Firm specific learning capability, such as increasing skills, know how in handling the innovation and general capability to process information are already implicitly included in the model via α_{ot}/α_{nt}.

However, information and learning effects, of the Mansfield and the Stoneman type, have played such a major role in the existing literature that they cannot be ignored. For this reason they are included into the model and their significance has been tested empirically.

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[40] There are several examples of empirical applications of learning effect in the *inter-firm* literature where the firm acquires information about the existence of a technology by contact with earlier adopters (Colombo and Mosconi, 1995, Stoneman and Kwon, 1993, etc.).

The variables specified are:

1) endogenous learning from the firm past experience – the Stoneman (1981) type of model- proxied by the number of years since first adoption of the first unit of the new technology (LYj where j = NC, CNC, CoT);

2) Information spreading within the industry, related to the knowledge about the true performance of the new technology based upon the experience of other firms (epidemic model) proxied by the cumulative number of users at the time the decision to increase one of the technology is made (**USERS**).

The inter firm literature would predict that these have a positive sign. However, if the predictions of the intra-firm model are correct, they should show an insignificant coefficient.

A word of caution should be stated on these last two variables. They might also pick up other indirect effects like: a) positive spillovers from the increasing supply of technical services to the innovation, e.g. an increasing number of technician; b) acquisition of transferable human capital, via the employment of individuals that have received their training somewhere else or c) epidemic effects.

For this reason their presence in the model may be doubtful but it will be left to the empirics to determine their significance.

5.6.4. The final model specification

The equilibrium intra firm model of technology replacement derived in section 5.2. indicates that for a firm i the proportion of total capital stock of the firm incorporating the new technology ($K_n/(K_o+K_n)$) is a function of both technological ($\alpha_n;\alpha_o$) and economic factors ($c^*_{nt;}\ c^*_{ot}$) and this is true from the moment immediately after first

adoption, i.e. when the firm uses at least one unit of each technology, until the diffusion is almost completed for the firm:

$$K_{nt}/(K_{ot}+K_{nt}) = 1/[1+(\alpha_o c^*_{nt}/\alpha_n c^*_{ot})] \qquad K_j \in]0\text{-}100\%[\ \forall\ j=n,o \qquad (5.35)$$

where α_n and α_o are the productivity parameters (i.e. $Y_t=A_t K_{ot}^{\alpha o} K_{nt}^{\alpha n} L_t^{\beta}$) and c^*_{nt} and c^*_{ot} are the shadow prices or the user cost of capital corrected for uncertainty.

Expression (5.35) is inherently non linear and, as such, it is difficult to handle econometrically. However, it has been shown in the previous section that applying a logarithmic transformation and expressing K_j in terms of percentages so that $k_{nt}+k_{ot}=100\%$, the reduced form estimating equation can be expressed in terms of the optimal accumulation path of the new over the existing technologies, leading to the linearised version of (5.35):

$$\text{Log}[k_{nit}/100\text{-}k_{nit}] = \log(\alpha_o/\alpha_n) + \log(c^*_{nt}/c^*_{ot}) \qquad (5.38)$$

The advantage of this specification is that the model can now be easily estimated by OLS. The determinants of adoption $\underline{\alpha_n}$ and $\underline{\alpha_o}$ are firm specific. They are a function of the firm *core competencies or rank effects* proxied by the firm characteristics such as liquidity, size, R&D, production system characteristics, etc. On the contrary, $\underline{c^*_{nt}}$ and $\underline{c^*_{ot}}$ do not change across firms but do change over time. They are the user cost of capital of each technology corrected for uncertainty, i.e. $c^*_{jt}=\{(r+\delta+1/2\sigma^2\beta_1)q_{jt}-dq_{jt}\}$ j= new,old , and are a measure of *intra firm price effects*.

The above model can be further extended as to explicitly measure the impact of uncertainty and expectations. After simple manipulation and applying a parameterisation, (5.35) can be rewritten as (5.39):

$$\log[k_{nt}/(100-k_{nt})] = \kappa_1 \log(\alpha_n/\alpha_o) + \gamma_1 \log(-dq_{nt}) - \gamma_2 \log(-dq_{ot}) - \gamma_3 [(q_{nt}/(-dq_{nt}) - q_{ot}/(-dq_{ot})]$$

where $\gamma_3 = (r + \delta + 1/2\, \sigma^2 \beta_1)$. (5.39)

This is the final estimating equation indicating that the optimal proportion of new technology is a function of: a) technological performance of the two technologies, i.e. α_n/α_o (rank effect -κ_1); b) price changes i.e. dq_{jt} and dq_{jt}, and relative growth rate in the level of prices of the set of technologies, i.e. $[(q_{nt}/(-dq_{nt}) - q_{ot}/(-dq_{ot})]$ (price effect-γ);

The model as in (5.39) assumes that the parameter κ_1, γ_n and γ_2 equal 1 (in absolute value), while γ_3 equals the sum of the interest rate (r), depreciation factor (δ) minus uncertainty via the volatility of profitability (σ^2, β_1) about future profit growth. In (5.39) the uncertainty effect is measured by the size of γ_3, once $(r+\delta)=0.075$ is subtracted or alternatively it can be derived by comparison of its estimate across technologies.

The presence of price expectations can be tested via the hypothesis of γ_1 ,γ_2 being equal to (+/-) unity. If this hypothesis is accepted, it provides evidence that the firm operates under rational expectations with perfect information about future price changes. On the contrary, if this hypothesis is rejected, then the alternative hypotheses that the firm decides the optimal level of ownership according to price expectations must be accepted.

The traditional learning effects (epidemic effects- ζ), widely present in the existing literature do not enter (5.41). However, given the importance they have been given in the literature they cannot be ignored and are allowed to enter the estimating equation in a multiplicative way. The prediction being that they do not play any relevant role in the spread of adoption, consequently their coefficient should not be significant.

The intra firm model is built around profitability considerations and, even if the sign remain undetermined, it already incorporates the intra firm and intra industry stock effect. However, similarly to the epidemic effects, the 'inter firm stock effects' (ξ) are allowed to enter the model multplicatively. According to the inter firm literature, contrary to the epidemic effects, they should exert a negative impact upon inter-firm diffusion. Their inclusion into the model can be considered only as a further crosscheck, even if they should not have a significant impact upon adoption.

Furthermore, inter firm stock effects are traditionally proxied by the within industry share of adopters or alternatively by the within industrial sector share of adopters. This measure has been severely criticised for its lack of representativeness (see Chapter 2). Consequently, the proportion of total output produced on the new technology is used instead.

Replacing the rank (κ) effects in $log\ (\alpha_o/\ \alpha_n)$ and the price and intra firm stock effects (γ), in $log\ (c^*_{nt})$-$log\ (c^*_{ot})$ and further allowing for epidemic (ζ) and inter-firm effects (ξ), equation (17) can be rewritten as:

$$
\begin{aligned}
\log[k_{nt}/(100-kn_t)] &= f\,(Rank_{it}, Price_t, Uncertainty_t, Intra\text{-}stock_t, Epidemic_t, Inter\ stock_t) \\
&= \kappa\ \log(RANK_i) + \\
&+\gamma_{1(EXPECTATION)} \log(-dPRICE_o) \\
&-\gamma_{2(EXPECTATION)} \log(-dPRICE_n) \\
&-\gamma_{3(UNCERTAINTY)} \log(PRICE_{o/n}) \\
&+\zeta\ \log(EPIDEMIC) \\
&-\xi\ \log(INTER\text{-}STOCK_t) \\
&+\varepsilon_t \qquad (5.42)
\end{aligned}
$$

where: $|\kappa|=1$, $|\gamma_j|=1$ $\gamma_3<0$, $\zeta=0$ and $\xi=0$(?).

The intra-firm model (5.39) would predict that rank effects are significant and their coefficient equal to 1 ($|\kappa|=1$). The price effect, in absence of expectations, should be significant and equal, in absolute value, to 1 ($\gamma_1=1$ $\gamma_2= -1$) Expectations, if present, should affect the estimates of $\gamma_{1/2}$, in which case will show a value different from 1 (positive or negative according to the under or overestimate of the observed price change).

Uncertainty is expected to influence the size of γ_3, once $(r+\delta)=0.075$ is subtracted.

The sign of γ_3 is negative and its size undetermined depending upon the significance of uncertainty. Epidemic and inter stock effects should have opposite ($\zeta>0$ and $\xi<0$) but insignificant signs.

The intra firm model in equation 5.39 will be tested over a sample of 434 establishments in the UK Engineering and metalworking sector (CURDS data set) for the following technologies: 1) Computerised Numerically Controlled machine tools; 2) Numerically Controlled machine tools; 3) Microprocessors in Processes.

The list of the variables used in the model specification has been discussed in the previous sections and is summarised in Table 5.2.

The details of the estimating procedure are presented in the following chapter.

5.7. CONCLUSION

This chapter has presented an equilibrium inter firm model based on the neo-classical theory of investment. It aims at explaining the optimal replacement of an old with a new technology by a firm over time. On the basis that the advantages of adoption of a new technology can be determined by its profitability (i.e. stock effect), it suggests that the spread of new technology is mostly driven by changes in costs and

Table 5.2. The determinants of intra-firm technology diffusion: variable definitions and expected sign

			Expected Sign
Dependent Variable			
KnKo	•	(Kn/(1-Kn))	
		PRICE Effect	
$DTOT_t$	•	Price differential of **Ko** : Po(t+1)-Po(t)	
		Real Index of quality adjusted Gross Domestic Fixed Capital Formation	+
DKn	•	Price differential of **Kn** : Pn(t+1)-Pn(t) where Kn=new technology (CNC, NC, MICRO)	-
		Real Quality Adjusted Produced Price Index of Kn	
QNQTOT	•	Relative price change (Pn/(-dPn) - Po/(-dPo))	-
		RANK Effect	
Employment			
E t	•	Nnumber of employees t= 1993, 1986, 1981, 1975, 1970	+/-
Ez	•	Nnumber of employees z =small , medium , large	
Age			
Age	•	Years from start-up (1993-sturtup year)	+/-
Export			
$Ex20_t$	•	Dummy –Exports in 1993 (>20%=yes ; 0=otherwise)	+/-
R&D			
RDE_t	•	In House R&D employees/Total employees in 1991; 1986;1991	+
$R\&D_t$	•	In House R&D dummy (yes=1, no=0) in 1991; 1986;1991	+
Turnover			
$turnoverNy_t$	•	N years Average Real Turnover in 1990/91; 1986/86 ; 1980/81 (deflated by RPI)	+
RT_t	•	Real turnover in 1990/91; 1986/86 ; 1980/81 (deflated by RPI)	+
Liquidity			
PT_t	•	Current Profits/Turnover in 1993; 1986; 1981	+
PL_t	•	Dummy – Profits or loss in 1991/1986/1981 (1= Profits ; 0= Loss)	+
Production System Characteristics			
PSI_t	•	Dummy – Firm Prod. System (Yes=1; 0= otherwise)	+/-
	•	I=engineering to order; Make to order, Make to stock, Job shop, Mixed	
BATCH	•	Average batch size	Tech specific
Ownership			
GROUP t	•	Dummy (1 =Group establishment ; 0 = Independent) t=1993, 1986, 1981	+/-
Industrial Sector			
Di_t	•	Dummy-Industry the firm belongs to (1=sector code, i.e. 1,2,..15))	+/-
Complementary and/or substitute technologies			
DJ_t	•	Dummy – adoption of J (1=Yes ; 0= No) of J=Cot; Micro; Robot; CAD, CNC, NC, etc	Tech specific
Managerial Innovation			
DJM	•	Dummy (1=Yes ; 0= No), – adoption of JM , JM=CAPM, JIT,TQM;BSISO-ISO900	Tech specific
		EPIDEMIC and other INTER-FIRM STOCK EFFECTS	
YSTUR	•	Years from startup to fisrt adoption	
T J	•	Years from firm first adoption up to 1993 ('93-1"adopt) , J = new technology	+
J y	•	Years from first appearance of the technology to first adoption by the firm (1"adop - 1970), J = new technology	+
IFout93	•	Average within industry *Firms* output produced on the new technology in 93 (INTRA-IND. average firm level of use)	
JDIFF	•	Average industry output produced on the new technology in 93 (INTRA INDUSTRY average total level of use)	-
Iusers93	•	Within industry share of adopters in 1993	+/-
shI**	•	Within Industry I (I=1,2,...15) share of adopters at time of the firm first adoption , i.e. Iusers93*DI	+/-
$Iusers\tau$	•	Within industry share of adopters at time of firm first adoption (τ_o)	+/-
Ish**	•	Within Industry I (I=1,2,...15) share of adopters at time of the firm first adoption , i.e. $Iusers\tau$*DI	+/-

NOTE: * Variables are NOT log transformed; ** Within Industry related variables (i.e. where 1,...,15 variables are specified) are in some cases aggregated in sub groups (i.e. Sh678=Sh6+sh7+sh8 or shgroup, etc). The details and the tests of parameters homogeneity and validity of the restrictions are detailed in the discussion of the specific models.

technological performance (see section 5.1 and 5.2). This is equivalent to saying that the internal rate of return depends upon the direct benefits of a new technology, i.e.

time saving, costs reduction, etc., as well as its compatibility with existing equipment. The higher the performance characteristics of the advanced technology and the greater the reduction in its shadow cost, the faster the replacement process of the old with the new technology will be. Moreover, whatever definition of intra firm diffusion is used (i.e. optimal capital output ratio or proportion of output produced on the new technology) the optimal level of adoption is the same for both monopolistic and competitive cases (section 5.3) and the optimal combination of capital inputs, in absence of output expansion, *is independent of the two types of markets the firm may face.* This model has also been extended to incorporate the impact of uncertainty about future profitability (section 5.4) and the role of expectations (section 5.5) among the factors that might delay the decision to further invest in a new technology. Both uncertainty and price expectation, if present, could significantly affect the speed of intra firm diffusion reducing the positive impact of the reduction in prices of a new technology. The model specification indicates that the implementation of the new technology is lead by physical benefits (via the firm specificity- α_n/α_o) and economic costs (acquisition costs under uncertainty and rational expectations- c^*_{ot}/c^*_{nt}). The first determines the heterogeneous level of use across firms (rank effect), the second determines the within firm extent of further use of the new technology over time (price effect). This chapter has also discussed how the above space and time dimension have been combined into the final model specification using the information in the CURDS data set. Further comments upon the possible existence of other effects already tested in the inter firm literature (stock, rank, order and epidemic effects) has lead to the estimating equation of the intra firm model (presented in section 5.6.). The next chapter presents a discussion of the empirical testing (econometrics) of the model.

Chapter 6.

SAMPLE SELECTION PROBLEMS IN THE TESTING OF THE INTRA-FIRM MODEL

6.1 Introduction

The equilibrium intra firm model of technology replacement indicates that the firm's current level of ownership of capital stock incorporating the new technology (K_n) is a function of both technological ($\alpha_n;\alpha_o$) and economic factors ($c^*_{nt;}\ c^*_{ot}$):

$$Kn_t/\ (Ko_t+Kn_t) = 1/[1+\ (\alpha_n\ c^*_{ot}/\ \alpha_o\ c^*_{nt})] \qquad (5.35)$$

The lhs of (5.35) is the proportion of capital stock incorporating the new technology (k_{nt}) while on the rhs α_n and α_o are the productivity parameters (i.e. $Y_t=A_t\ K_{ot}^{\alpha o}\ K_{nt}^{\alpha n}\ L_t^{\beta}$) and c^*_{nt} and c^*_{ot} are the shadow prices of the user cost of capital corrected for uncertainty, so that:

$$c^*_{jt}=(r+\delta+1/2\sigma^2\beta_1)q_{jt}-dq_{jt}.$$

where q_{jt} and dq_{jt} (j= new, old) are the levels and the relative changes in the prices of the two sets of technologies, $(r+\delta)$ are the interest rate and a depreciation factor, and $1/2\sigma^2\beta_1$ is a factor reflecting the uncertainty about future profits, measured via the volatility of profitability (σ^2), and the larger root of the Bellman quadratic (differential) equation ($\beta_1=1/2-\alpha/\sigma^2+\sqrt{[\alpha/\sigma^2-1/2]^2+2(r+\delta)/\sigma^2}$).

Moreover, (5.35) is assumed to hold for the whole diffusion period, from the point immediately after first adoption i.e. when the firm uses at least one unit of each

technology, until the firm has almost replaced all its capital stock with the new technology.

The final estimating equation of the intra firm technology replacement (TR) model was derived in Chapter 5, yielding:

$$\log[k_{nt}/(100-k_{nt})] = \kappa_1 \log(\alpha_n/\alpha_o) + \gamma_1 \log(-dq_{ot}) - \gamma_2 \log(-dq_{nt}) - \gamma_3 (q_{nt}/dq_{nt} - q_{ot}/dq_{ot}) \quad (5.39)$$

where $\gamma_3 = (r + \delta + 1/2\, \sigma^2 \beta_1)$

where k_n is the percentage of capital stock incorporating the advanced (new) technology; k_o or equivalently $(100-k_n)$, is the percentage of capital stock incorporating the existing (old) technology; α_n and α_o reflect the core competencies of the firm i.e. a rank effect $-\kappa$; c^*_{nt}/c^*_{ot} are the price effect-γ, incorporating uncertainty about future profitability of the investments (via the significance and the size of the parameter γ_3) and rational expectations (via the assumption that $\gamma_1=1$ and $\gamma_2=-1$)[1].

One of the problems arising from this specification, is that (5.39), similarly to (5.35), is defined only for those firms that have started the process of technology transfer currently owning at least 1% of k_n , with the exclusion of those firms that are saturated with the new technology, i.e. owning 100% of k_n. This condition imposes some constraints on the estimating procedure as the decision to use a new technology is conditional to the irreversible choice of having adopted it in the past and not using it at 'extreme' levels (0 and 100%).

The CURDS sample, for each of the four technologies, provides the firm's date of first adoption (τ_{ij}), the proportion of capital stock of the firm incorporating the

[1] See Chapter 5 for more details about the derivation of the estimating equation and the assumption of the model.

advanced technology in 1993 ($k_{nit}=Kn_{,i,1993}/(Ko_{i,1993}+Kn_{i,1993})$) and whether the advanced technology is compatible with the production system of the firm. This allows one to classify the sample of firms into three different categories:

1) Non adopters:the firms that may but have not yet adopted the new technology;

2) Adopters: the firms that by 1993 have adopted at least one unit of the new technology;

3) Non eligible: the firms for which the technology is not suitable to their production system.

In this study, the *non-eligible* firms are excluded for obvious reasons. The remaining two categories define the status of the firm and the decision taken at some point in time (before or by 1993) to adopt or not to adopt the technology. As being an *adopter* does not necessarily mean to be a current user in 1993, one can further classify the firms in that category according to their level of use of the advanced technology (see figure 6.1). In particular one can distinguish between:

1) *Non users* that despite having in the past adopted the new technology, in 1993 are no longer using it ($k_{n,\,1993}=0$)[2];

2) Current users that in 1993 are using at least one unit of both new and existing technology, ($0<k_{n,\,1993}<100\%$ and $0<k_{o,1993}<100\%$), and are still undertaking the process of technology replacement;

3) Total users that have replaced all the existing capital stock with the new technology ($k_n=100\%$), reaching the maximum point of technology transfer.

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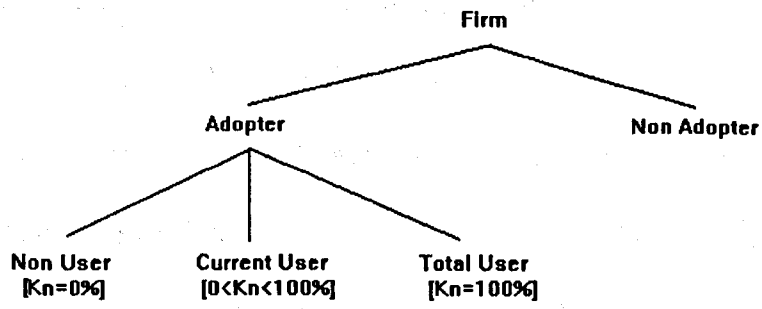
2 This might be due to a temporarily suspension or the dismissal of the use of the new technology ,i.e. post diffusion stage of technology transfer, without non necessarily having reached 100% of technology replacement

Figure 6.1 Mapping the decision path of the firm and the final status in 1993.



The theoretical intra-firm model (5.35) defines the determinants of technology substitution from a point immediately after first adoption, that is when the firm has already changed its production process and uses at least one unit of both old and new technology. This assumption does not hold at the saturation (k_n=100%), pre ($k_n=0^-$) and post diffusion period ($k_n=0^+$) or whenever the firm owns only one of the two technologies. Consequently the testing of the model must be restricted to the sample of *current users* (owning at least one unit of one of the two technologies) currently undertaking the process of technology transfer.[3] However, to use only the sub-sample of *current users* can cause two types of errors. Firstly, one would ignore the firm's choice whether to become or not to become an adopter (see first level in figure 1). This possibility not being observable after 1993 leads to a truncated probability distribution of adoption (and use). This type of error will obviously be reflected in the

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3 In mathematical terms this means that the production possibilities of the firm must lye in the iperplan defined by a three factors production function, i.e. Y=f(L; Kn; Ko). The model does not hold at the pre i.e. Y=f(L; Ko) and post diffusion i.e. Y=f(L; Kn) period when the production possibility set is defined by a two factor production function

Further to this assumptions there is also a mathematical constraint arising from the log linearisation of the original model (5.35) where the LHS variable is specified as: log(Kn/Ko), or equivalently in terms of proportions as $\log(k_n/(k_o)$. As a result the *Non adopters* ($k_{n,1993}= 0^-$), *Non-users* ($k_{n,1993}= 0^*$), and *Total users* ($k_{n,1993}$= 100%) must necessarily be excluded form the testing of the model (5.39).

final model of ownership of the technology. Secondly, among the sample of adopters one would have to ignore those firms that are currently using the 'extreme levels' of technology (see second level in figure 2). Their exclusion from the testing of the model would cause both right (k_n =100% use) and left (k_n =0% use) censoring of the sub-sample of adopters/users.

The potential misspecification error resulting from ignoring the conditional probability to use a technology (conditional on being an *adopter* and a *current user*) can cause systematic heteroscedasticity in the residuals of the final intra-firm model. The parameter estimates and the marginal impact of the determinants of adoption would be biased toward the specific sub-sample (i.e. truncated and censored) and might over or under estimate the overall impact upon the whole sample of firms.

This type of sample selection bias is particularly dangerous if one wishes to control for some of the variables and their marginal effect upon the whole industry.

Only once these problems are dealt with can one proceed with the testing of the decision model on how much to use the new technology and the determinants of technology transfer. The following sections present a series of methodological approaches used to overcome these types of conceptual and empirical problems.

Section 6.2 presents the two stage sample selection approach used to overcome the sample selection bias arising when looking at the adopters up to 1993 (truncation). It also discusses the problems caused by the exclusion of the extreme users from the subsample of adopters (censoring) and introduces the multinomial probability model. Section 6.3. derives an *ad hoc* specification of the selection criterion equation, proposing a time versus a space specification of the determinants to be an adopter in or by 1993.

A final section concludes the chapter summarising the derivation of the final estimating equation of intra-firm technology replacement corrected for both truncation and censoring of the sample.

6.2 Regression models with sample selection: the self-selectivity two stage approach.

This section deals with the sample selection bias that might arise in modelling the determinants of technology substitution in (5.39) using only the sub-sample of current users. In fact, the level of use of the advanced technology is conditional on the firm's choice to have become an adopter in or by 1993 (truncation) and on the decision to currently use the new technology with the exclusion of the pre and post diffusion stages (censoring).

The most straightforward way to eliminate this type of potential error is to use a two stage procedure. In the first stage the firm' decision to be an adopter is modelled and its variability summarised in a new variable. This variable is then modelled within the decision on how much to use the new technology, correcting the technology replacement specification for the sample selection of adopters.

The correction for censoring can occur at different steps of the selection process.

It can be introduced either in the Sample Selection stage (6.1) or in the final Technology Replacement equation (6.2). The details of the final model specification corrected for both truncation and censoring are given in the following sections.

6.2.1. Sample selection and the binary selection model

From (5.39), rewriting the log of the ratio of the new (k_n) over the existing technology ($100-k_n$) as the proportion of new technology j owned by the firm i (y_i), the theoretical intra firm model can be rewritten as:

$$y_i = \beta' x_i + \varepsilon_i \qquad y_i \in]0\text{-}1[$$

(*Technology replacement equation*)

The TR equation predicts that $y_i = \log(k_n/(100-k_n))$ with $k_j \in]0\text{-}100\%[$ is a function of technological and economic factors (x_i) and a residual ε_i with variance σ_ε. It also predicts that this is true from when the firm adopts the first unit of advanced technology up to when it is almost saturated with it and eventually owns only one unit of the old technology, i.e. from the point immediately after first adoption until the diffusion is (almost) completed for that firm. Moreover, x_i is the set of regressors accounting for rank, order, stock and epidemic effects.

One of the problem with the OLS estimation of this equation is that $E(\varepsilon_i \mid x_i) = \mu_\varepsilon$ but $\mu_\varepsilon \neq 0$ due to the selection of the sample of adopters from the total sample of firms. In fact, the level of use of a new technology is a consequence of the decision to belong to the group of current adopters but it is not observable for those firms that decide in the future to first adopt and use the technology. The lack of observations about future behaviour leads to a truncated probability distribution and a biased sample selection of the group of adopters. One way to solve this problem is to correct $E(\varepsilon_i)$ by using the conditional probability to become an adopter by 1993 and then to proceed with the OLS estimation (Maddala, 1994)..

By specifying the choice to adopt a new technology as a function of a set of independent variables, one can define the equation that determines the sample selection as[4]:

$$z^*_i = \psi' w_i + u_i \qquad (6.1)$$

(selection criterion equation)

and

$z_i=1$ if firm i has adopted technology j by 1993

$z_i=0$ if firm i has not adopted technology j by 1993

where z^*_i is a binary variable ,w_i is the vector of the determinants of first adoption and u_i is a normally distributed residual correlated by an amount ρ to the residual of the Technology Replacement equation such that :

$E(\varepsilon_i | x_i, w_i)=0$, $V(\varepsilon_i | x_i, w_i)=\sigma^2_\varepsilon$, $Cov(\varepsilon_i , u_i | x_i, w_i)= \rho\, \sigma_u\, \sigma_\varepsilon$

$E(u_i | x_i, w_i)=\mu_u$, $V(u_i | x_i, w_i)=\sigma^2_u$

The link between the residuals of both selection criterion and the technology replacement equation is provided by Olsen (1980a) who suggests assuming that the conditional expectation of ε_i, given u_i, is linear , so that

$$\varepsilon_i = (\rho\, \sigma_\varepsilon/\sigma u_i)\, (u_i-\mu_u) + v_i$$

and

$$E(v_i | u_i)=0 \text{ and } Var(v_i | u_i) =\sigma^2_\varepsilon (1-\rho^2).$$

This allows one to derive the corrected expected current level of use of the new technology conditional on the decision to adopt or to have adopted the technology by 1993.

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[4] In this section, for clarity of presentation, the subscript j is omitted from the specification of the variables

Given that the current use (y_{ij}) is observed only when the firm has decided to become an adopter ($z_{ij}>0$), then the corrected expression for the reduced sample becomes:

$$E[y_i| z^*_i>0] = E[y_i| \psi'w_i>u_i] = \beta'x_i + E[\varepsilon_i/u_i>- \psi'w_i]$$
$$= \beta'x_i + \beta_\lambda \lambda_i(s_i)$$

where $\beta_\lambda = \rho\, \sigma_u$, s_i is the normal score of y_i ($y \sim N(\psi'w;\sigma^2)$ evaluated at zero, i.e. $s_i = -w_i\, \psi/\sigma_u$, and λ_i is the truncated mean $E(y_i|u_i< \psi'w_i)$. The latter is usually called the Inverse Mill's Ratio –IMR- (see Greene 1993 and Maddala 1994 for more details). More in general, the first part on the RHS, i.e. $x_i\beta$, accounts for the determinants of technology replacement, while the second, i.e. $\beta_\lambda \lambda_i(s_i)$, accounts for the sample selection of users among the total population of firms. Furthermore, just assuming that $\mu_u=0$ and that $\sigma_\varepsilon=1$, and that the conditional expectation of ε_i given u_i is linear, the original TR equation corrected for the sample selection bias (6.1) can be rewritten as:

$$y_i \mid z_i^* > 0 = \beta'x_i + \beta_\lambda \lambda_i(s_i) + v_i \qquad (6.2)$$

(6.2) indicates that the level of use of a new technology (y_i) conditional on the choice of becoming an adopter ($z_i^* > 0$) is determined by the level of exogenous factors (w_i), via a parameter β, and by the level of sample selection (λ_i) via the parameter β_λ.

The statistical distribution of the Sample Selection Equation

This far no assumption has been made with respect to u_i, except that its mean is zero and its variance equals unity. The assumption about its distribution is a crucial one as

it determines the specification of the sample selection equation and allows one to estimate the correction factor λ in the second step of the model.

From an economic point of view the empirical evidence based upon the inter -firm diffusion literature suggests that over time the cumulative number of adopters, i.e. the probability to be an adopter, follows a sigmoid path, such as a logistic or a Gompertz density function, rather than a Normal distribution (see Chapter 2 for more details). However, the model in (6.2) is a snapshot of the firm behaviour at one specific point in time, i.e. 1993, and not over time. Consequently, the traditional theory on time dependent patterns of technology adoption is of little use.

Given the cross-sectional nature of the sample, it is quite reasonable to assume that the probability distribution across a heterogeneous sample of firms at a specific point in time is symmetric and bell shaped, such as the Normal or the Logistic probability distribution. The Logistic curve is very similar to the Normal except that its tails are much thicker.

In statistical terms, assuming that u_i is Normally distributed then it is quite straightforward to prove that λ_i in equation (6.3.) equals the ratio of the density and the distribution function evaluated at $\psi' w_i/\sigma_u$:

$$\lambda_i(s_{ui}) = \phi(\psi' w_i/\sigma_u) / \Phi(\psi' w_i/\sigma_u).$$

This is the exactly the result one would get if the sample selection equation were modelled by a Probit model. However, the assumption that u_i is normal is a strong one because, as Goldberg (1980) has proved, to assume Normal selection-bias adjustment can be quite sensitive to departures from Normality.

Lee (1982b, 1983) has presented an alternative to the Probit method. He suggests that whatever the distribution of u_i and ε_i, it is possible to apply a general transformation to Normality such that:

$$\varepsilon_i^* = J_1(\varepsilon_i) = \Phi^{-1}[F(\varepsilon_i)]$$

$$u_i^* = J_1(u_i) = \Phi^{-1}[G(u_i)]$$

where ε_i^* and u_i^* are the new standard normal random variable N(0,1) after the transformation of the distribution function of the original 'u_i' ($G(u_i)$) and ε_i ($F(\varepsilon_i)$). For the rest the procedure is the same as for the Probit model in the two-stage estimation except that now ψw is substituted by $J_1(\psi' w_i)$, so that:

$$z_i = 1 \quad \Leftrightarrow \quad u_i < \psi' w_i \qquad \Leftrightarrow J_1(u_i) < J_1(\psi' w_i)$$

and

$$\text{Prob}(z_i = 1) = F\,[\,J_1(\psi' w_i)] = F(\psi' w_i).$$

Thus, conditional on $z_i = 1$, the final estimating equation corrected for selectivity bias and with distribution of u_i equal to $F(u_i)$ is:

$$y_i \mid z_i^* > 0 = \beta' x_i + \beta_\lambda \lambda_i(s_i) + v_i$$

where $\lambda_i = \phi_1\,[(\psi' w_i)]/F(\psi_i' w)$ and $s_{ij} = F(\psi' w_i)$. This means that if one believes that u follows a Logistic curve then the <u>Logit model</u> is the best specification of the selection criterion equation with the corresponding correction factor being $\lambda^L_i(s^L_i)$:

$$s^L_i = \phi^{-1}[P_{logit}] = \phi^{-1}[e^{-\psi w} / (1 + e^{-\psi w})]$$

$$\lambda^L_i = \phi(s^L_i)/\Phi(s^L_i)$$

Whatever the probability distribution, the parameters of the sample selection model could be estimated by ML. However, this can be quite cumbersome and the alternative Heckman's two step estimation method (Heckman 1979) is used instead. The former is efficient whereas the latter is consistent and based on the method of moments[5] (see also Greene 1995 'Limdep7- User Manual'). In summary the Heckman's procedure (Heckman 1979) used in this study consists of:

i. Use the selection equation to estimate ψ_i and for each observation calculate the corresponding λ_i.

ii. Linearly regress y_i on w_i and λ_i to estimate β and $\beta_\lambda=\rho\sigma$

iii. Adjust the standard errors and the estimate of σ^2_ε, which are inconsistent.

This procedure allows one to correct the coefficient estimates of the final Technology Replacement model for the sample selection bias arising when selecting the sample of adopters from the total population of eligible firms in the sample (i.e. truncation).

However, this approach takes into account only the first step of the sample selection problems. The theoretical model is also defined only for those adopters which are currently using the technology. This means that one has to estimate the probability to observe an adopter who is also a *current user* (with the exclusion of non users and total users).

The following section details how the left and right censoring of the subsample of current users can be modelled within the conditional probability of having adopted the technology, leading to the corrected technology replacement equation.

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5 More details about this approach can be found in Maddala (1994), Heckman (1979), Greene (1981), etc.

6.2.2. Censoring and the multinomial selection rule.

The results of the previous section suggest that the model of technology replacement should be specified via a two step procedure. The first step defines the probability for a firm i to become an adopter in or by 1993 (Selection Criterion equation):

$$z^*_i = \psi' w_i + u_i \qquad u_i \sim \text{Normal/Logistic} \qquad (6.1.)$$

$$z_i = 1 \quad \text{if Adopter in/by 1993}$$

$$z_i = 0 \quad \text{if Non-Adopter in 1993}$$

The second step defines the Technology Replacement (TR) equation corrected for the selection of the sub-sample of adopters, assuming a Logit (L) or a Probit (P) specification:

$$[y_i \mid z^*_i > 0] = \beta' x_i + \beta_\lambda \lambda^{P/L}_i (s^{P/L}_i) + v^{P/L}_i \qquad y_i \in]0; 1[\qquad (6.2)$$

For both theoretical and mathematical reasons, the Technology Replacement equation is defined only for those firms that are currently using both technologies. Consequently, those firms that are no longer using the new technology ($y=0 \rightarrow k_n=0$) and those who own all the technology ($y=1 \rightarrow k_n=100\%$) must be excluded from the second step of the two stage sample selection procedure.

This is equivalent to first partitioning the sample of eligible firms in two categories, adopters and non adopters (6.1), and then, among the adopters, select the sub-group of users that are currently using both old and new technology (6.2) as seen in Figure 6.1. However, the elimination from the second step of the analysis of the extreme values of 0 and 100% use of a technology can cause left and right censoring that can seriously invalidate the coefficient estimates.

This section presents three alternative routes that could be followed in order to overcome this type of problems, namely: visual inspection, Tobit model and multinomial selection rule.

Visual Inspection

A measure of the magnitude of the error committed by ignoring the censoring in the second step of the analysis can be preliminarily investigated by visual inspection, that is by comparing the estimates with and without the inclusion of the censored firms also from the first step of the analysis (i.e. from the Sample Selection equation).

This type of rudimentary test can give us an idea of the size of the misspecification and the different parameter estimates but does not provide corrected coefficients.

Tobit Model

A less arbitrary approach would be to use in the second step equation (6.2) the Tobit model (see Tobin, 1958 and also, Amemiya, 1984 and 1994) rather than the standard regression model, as it would account for the left and right censoring. In order to do so the left hand side of the original intra firm model ($\ln[\, k_n / (100-k_n)]$) must be specified differently, as the current variable is observable over a range of negative and positive values whose censoring points are not estimable:

$y_i = \ln(0) = -\infty$ if $k_n = 0$;

$y_i = \ln(\infty) = +\infty$ if $k_n = 100\%$

The specification suitable to the censoring requirements of non negative observations Ln(LHS)>0 would imply rewriting the TR equation, corrected for sample selection (6.2) as:

$$\ln(k_n) = \beta_\kappa \ln(100-k_n) + \beta X + \beta_\lambda \lambda + v_i \qquad \text{if } 0<k_n<1$$

$$\ln(k_n) = 0 \qquad \text{otherwise}$$

The above equation would satisfy the Tobit model except for the simultaneity problems arising from the existing proportion of old capital stock ($\ln(100-k_n)$) in the RHS of the equation. As this amount is complementary to k_n it would not satisfy the exogeneity requirement of independent variables.

To overcome this problem would require an instrumental variable approach. This can be done by simply introducing the lagged value of $\ln(100-k_n)$. Unfortunately, this possibility is ruled out by the lack of data on k_n before 1993.

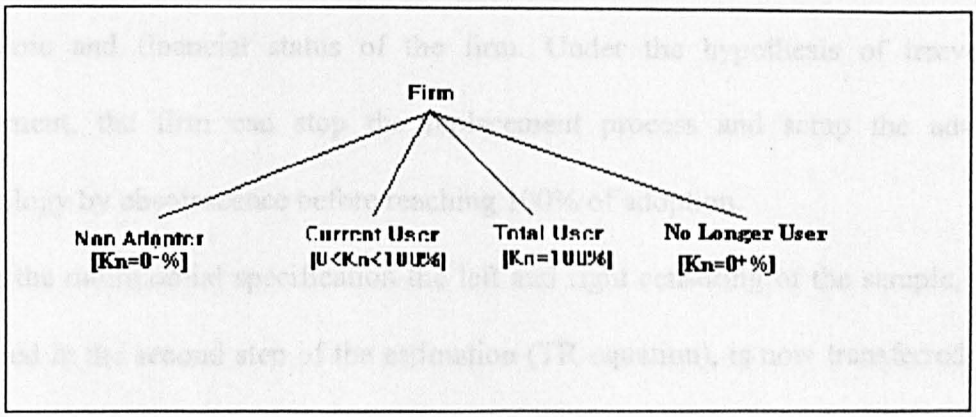
For these reasons the Tobit model approach has been abandoned.

Multinomial probability model

Another approach that provides the parameter estimates corrected for the censoring problem is the multinomial probability model.

Instead of dealing with the censoring of the sub-sample of adopters in the second step of the estimating procedure (Technology Replacement equation) it assumed that the firm faces a multiple choice in the first step of the model (Selection Criterion equation) and chooses where it wants to position itself. As suggested by the equilibrium approach, the extreme cases are just one of the possible mutually exclusive choices the firm can make (see Figure 6.2.). The probability to be a *current user* is then straightforward and can be used to correct the TR equation for sample selection.

Figure 6.2 The Multinomial selection rule



Classifying the firms in terms of their possible choices is equivalent to partition the original sample into 4 different categories:

Choice	*Status*	
0	non adopter	if $k_n=0^-$
1	current user	if $0<k_n<100\%$
2	total user	if $k_n=100\%$
3	no longer	if $k_n=0^+$

According to this classification, both non adopters and no longer users use 0% of the new technology. However, the corresponding probability to adopt the technology for the first time or the chance to end its use are quite different. In one case, one might deal with an innovative firm while in the second with a firm averse to changes. For this reason, they have been classified into two different categories.

The multinomial model has been chosen as an alternative to the ordered choice model as the disequilibrium model would suggest. The ordered choice model would implicitly assume that a firm moves from lower to higher levels of adoption up to saturation (i.e. sequentially from 1 to 4). On the contrary, the Multinomial Selection rule is path free and the firm can decide, under both technological and financial constraints, what is the best in the short and medium run. This is in line with the equilibrium model that allows the adoption path to be discontinuous and non-strictly

(or weakly) monotonous. One adopter can just temporarily suspend the adoption or dismiss the use of the technology due to current market conditions and the current economic and financial status of the firm. Under the hypothesis of irreversible investment, the firm can stop the replacement process and scrap the advanced technology by obsolescence before reaching 100% of adoption.

Using the multinomial specification the left and right censoring of the sample, which occurred in the second step of the estimation (TR equation), is now transferred to the first step of the model (SC equation) where it is explicitly modelled by the positioning of the firm among a set of possible choices. In this way, both 0% and 100% of use of the technology become simply part of the decision as to whether to use the technology.

The Selection Criterion equation is here modelled by the multinomial Logit / Probit model giving the conditional probability for a firm to belong to one of the mutually exclusive status. In the second step, the resulting Inverse Mills Ratio is then used as a correction factor in the Technology replacement equation which is now, for obvious reasons, uncensored.

In statistical terms, let's assume that the possibilities for firm i with respect to the technology j, can be classified as: 0=decision not to adopt; 1=decision to use; 2= decision to fully use; 3=decision to no longer use the technology. The multinomial probabilistic model attributes a set of probabilities for the s+1 choices for a firm with characteristics W, and it is specified as:

$$z^*_i = \psi' w_i + u_i \qquad u_i \sim \text{Normal}$$

$$\begin{array}{lll} z_i = 0 & \text{if } k_n = 0^- & \text{(Non Adopter)} \\ z_i = 1 & \text{if } 0 < k_n < 100\% & \text{(Current User)} \\ z_i = 2 & \text{if } k_n = 100\% & \text{(Total User)} \\ z_i = 3 & \text{if } k_n = 0^+ & \text{(No Longer User)} \end{array} \qquad (6.3)$$

(6.3) defines the Multinomial Selection Criterion Equation (accounting for previous sample selection and censoring) while the resulting Corrected Technology Replacement equation will be:

$$[y_i \mid z_i=1] = \beta' x_i + \beta_\lambda \lambda^M (s_i^M) + v_i^M \qquad (6.4)$$

As for the binomial model, the multinomial selection criterion equation (6.4.) defines the probability that the firm belongs to the in the s-th sample and u_i determines the type of probabilistic model.

For ease of presentation let's assume that the firm faces three alternatives instead of four[6] and also that u_i is normally distributed, N(0,1); then the Multinomial Probit model for the s-th sample, can be specified as[7]:

---

6 For most of the technologies the number of firms belonging to 2 is very small, sometimes accounting for less than 1% of the adopters. Moreover, the presence of missing values in their record can further reduce their presence in the estimating sample. This causes insufficient variation in the classification variable to be used for the estimation. For most technologies, 2 and 3 had to be merged one category, i.e. 2=completed substitution or, not being significant, (2) has been completely omitted from the analysis and a dummy variable used instead.

7 For the three probabilities the marginal effects of changes in the regressors would be:

$\partial \text{Prob}(z_i = 0)/ \partial w = -\phi(-\psi' w_i)\, \beta$

$\partial \text{Prob}(z_i = 1)/ \partial w = (\Phi(-\psi' w_i) - \phi(\mu - \psi' w_i))\, \beta$

$\partial \text{Prob}(z_i = 2)/ \partial w = \phi(\mu - \psi' w_i)\, \beta$

It is worth emphasising that with this specification the interpretation of the marginal effects is not straightforward. The impact of an increase in one of the W on s=2 does have the same sign of β upon the corresponding probability while the opposite sign upon the probability of s=0. The interpretation of the coefficients of the middle range is however ambiguous as it depends on the combination of the shift in the other two probabilities. Moreover if a dummy variable is specified the standard marginal effects are no longer meaningful. The right procedure would be to compare the probabilities that result when the variable takes its two different values with those that occur with the other variables held at their sample means.

$\text{Prob}(z_i = 0) = 1 - \Phi(-\psi' w_i)$

$\text{Prob}(z_i = 1) = \Phi(\mu - \psi' w_i) - \Phi(-\psi' w_i)$

$\text{Prob}(z_i = 2) = 1 - \Phi(\mu - \psi' w_i)$

If u_i in (6.3) follows a logistic distribution the extension of the Probit to the Logit probability model is straightforward and requires very little change in the previous procedure.

Once the Selection Criterion Equation has been estimated it is possible to estimate the Corrected Technology Replacement Equation as:

$$
\begin{aligned}
[y_i \mid z_i=1] &= \beta' x_i + (\rho_1\sigma_1)\, \phi[H_1(\Psi_1' w_i)] / \Phi\, [H_1(\Psi_1' w_i] + v_i^M \\
&= \beta' x_i + (\rho_1\sigma_1)\psi_1^M + v_i^M \\
&= \beta' x_i + \beta_{1\lambda}\psi_1^M + v_i^M
\end{aligned}
$$

The two-step estimating technique used to test this model is detailed in Lee (1983) and the Limdep7 User's manual (see Greene, 1995). In the first step the estimates of the Multinomial model (i.e. coefficients and the estimated asymptotic covariance matrix and predicted probabilities) are obtained by Maximum Likelihood.Then for the selcted observation for which z_i equals the desired value, λ_i^M is computed by: (i) selecting the predicted probability, P_1 (ii) calculating the inverse of the standard normal (or logit) cumulative density function (H) evaluated at P_1, i.e. $H_1 = \phi^{-1}(P_1)$; and (ii) using this information to calculate the IMR , i.e. $\lambda_1^M = \phi[H_1]/\Phi[H_1]$.

In the second step the consistent estimates of β and $\beta_{1\lambda}$ are derived by least squares regression of y_1 on x and λ_1.

The next sections define the corrected variable specification of the two step sample selection model.

6.3. THE SELECTION CRITERION EQUATION SPECIFICATION

The estimating model discussed in the previous section considers the decision to further use a new technology in time t via a two stage model: the selection criterion equation accounting for firm i's probability to have adopted the technology j sometime before or during time t (6.1); and the technology replacement equation, defining the determinants to further use a technology in time t (6.2). The two can be defined as follows:

Selection Criterion equation: $$z^*_{it} = \psi' w_{it} + u_{it} \quad (6.1)$$

Corrected Technology Replacement equation:

$$[y_{it} \mid z^*_{it}] = \beta'_t x_{it} + \beta_\lambda \lambda_i(\alpha_i) + v_{it} \quad (6.2)$$

This indicates that the decision as to how much to use the technology (6.2) is conditional on the decision of the firm to be an adopter (6.1).

The selection criterion equation can be modelled via a binary or a multinomial selection rule (see section 6.1 for a full discussion) and it is a function of the determinants of first adoption.

The existing literature upon inter firm diffusion has widely explored the possible factors (w_t) leading a firm to adopt a technology for the first time and these can be classified as: rank, stock, epidemic and order effects (see Chapter 3). They reflect the market and firm specific characteristics at time t, and as they change over time, so does the probability to adopt.

Part of these effects, with the exception of the order effect, also affect the determinants of technology replacement (x_t) in time t (see equation 6.2)[8]. Consequently, given the cross-sectional nature of the model specification, a large part of the variables determining both adoption (w_t) and the level of use of a new technology (x_t) at time t affect simultaneously the Selection Criterion Equation and the Technology Replacement equation.

Common to many economic studies, the lack of variability between the two steps of the model and the simultaneity problems might cause possible *spurious significance of sample selection effects.*

Not much can be done with respect to the choice of the dependent variables, but the simultaneity problem due to the time specification of the two sets of regressors (w_t and x_t) can be overcome.

According to (6.1.), z_{it} defines the probability that a firm has reached the status of adopter by 1993 as a function of the determinants of adoption in 1993. However, by definition, a firm becomes an adopter as soon as it adopts for the first time at least one unit of the new technology and the firm remains an adopter even if subsequently decides to no longer use the new technology. This is because the decision to first adopt is irreversible and thus the innovator's characteristics and experience will always be different from a non-adopter, which has never used the new technology.

Consequently the total sample of adopters, i.e. when $z_{it}=1$, is made up not only of <u>first</u> adopters in 1993, but also of firms that have adopted before 1993 (<u>earlier</u> adopters).

For those earlier adopters that have adopted the technology between say 1970 and 1992, it is more likely that the explanatory variables in 1993 are the effect rather than the determinants of first adoption, as defined by the Selection Criterion equation in

8 see Chapter 5.6 for the specification of the determinants of intra firm adoption

equation 6.1. To ignore this might cause serious *problems of endogeneity* in the selection criterion equation.

A better specification would use a different set of variables measuring the probability to be an adopter by 1993 as a function of the variables at the time of first adoption ($t=\tau_i$), when the decision is actually taken.

Given the cross-sectional nature of the model, the introduction of this type of time dependent variables is not straightforward.

The statistical details of the time dimensional Selection Criterion Equation is given in the following session.

6.3.1. The Statistical Derivation of the Time Vs Space Specification of the SC Equation

The Selection Criterion equation (6.1) defines the probability to be an adopter in or by 1993 as the unconditional probability to observe an adopter in or by 1993:

$$P_{iT}\,(z_{iT}=1)= F\,(z_{iT}=1) \qquad \text{where } T=1993 \qquad (6.7)$$

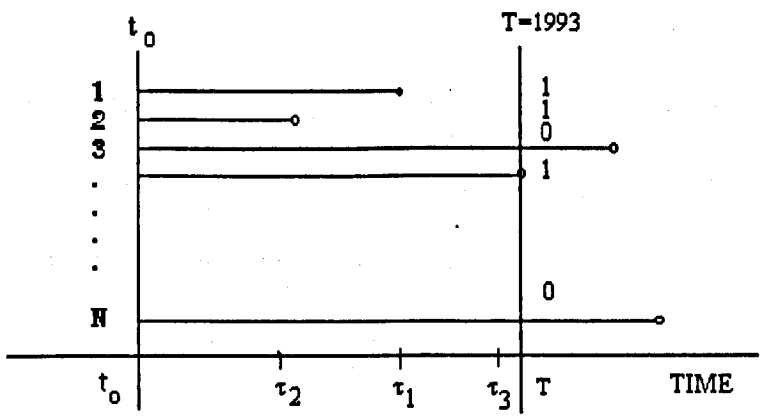
However, this is too restrictive as it does not take into account the characteristics and the timing of the decision process to first adopt a new technology.

The corrected conditional probability to observe an adopter in or by 1993 is represented in figure 6.3. The two vertical axes delimit the observation interval from when the technology first appeared on the market ($t=t_o$) up to 1993 ($t=T$). Each

horizontal line represents one firm in the sample (i=1..N) and its length determines the time of first adoption by the firm (τ_i)

The labels on the right axis define the status of adoption in 1993, where the firm's probability to become an adopter in or by that date is specified as $z_{ij}=1$ and $z_{ij}=0$ otherwise.

Figure 6.3. Intertemporal probability to become an adopter



Given that the adoption time is heterogeneous, the corrected conditional probability to be an adopter by 1993 should take into account that:

- The number of adopters in or by 1993 ($z_T=1$ where $z_T=\sum_{i=1}^{N} z_{it}$) reflects the decision to first adopt in 1993 plus the decision taken some time in the past by those firms which have first adopted before 1993. This is equivalent to saying that the current number of adopters in 1993 is given by the sum of those who adopted before 1993 and those who adopted in 1993:

$$P_T[z_T=1]: \{\sum [i / z_{it}=1 \text{ for each } \tau_i < T] + \sum [i / z_{it}=1 \text{ for each } \tau_i = T]\}$$

- To become an adopter is an irreversible decision (but not to be a user) due to the different characteristics that might differentiate an ex-user from a firm that has

never adopted the technology. The firm becomes an adopter as soon as it adopts at least one unit of the new technology and it remains in that status thereafter. Although the firm might discontinuously use the technology the change in the status from non-adopter to adopter occurs only once, at the time of first adoption ($t=\tau_i$):

$$P_{iT}\,[z_{iT}=1/z_{i\,\tau_i}=1 \quad \text{where } \tau_i \leq T]$$

and is conditional to not having used the technology before first adoption:

$$P_{iT}\,[z_{iT}=1/\,z_{i\tau o}=0 \;\; \text{for each } \; t_o \leq \tau\,]$$

- The probability to be an adopter by time T is conditional on the sample of potential adopters and must be corrected for those firms eligible for first adoption who might first adopt the technology after 1993. Consequently one has to face the problem of truncation in the sample of users.

$$P_{iT}\,[z_{iT}=1/\,z_{\phi t}=0 \;\; \text{for each } t<T \text{ and } \varphi= 1,...N-\varphi]]$$

In summary, defining $z_{it}=1$ as the condition for a firm i to be an adopter at time t and $z_{it}=0$ if the firm has not yet adopted the technology, the total probability to be an adopter BY 1993, i.e. t=T, is given by the two <u>conditional composite probabilities</u>:

a) the probability for a firm i to be an adopter by and in time T=1993 conditional on having first adopted sometime before or in time T=1993 ($\tau_i \leq T$) and to have not adopted before the date of first adoption, τ_i , i.e. uniqueness of the event (*time dimension for firm i*):

a1) $P_{iT}[z_{iT}=1/\,(z_{i\tau_i}=1)]$ where $\tau_i \leq T$

a2) $P_{iT}[z_{iT}=1/\,(z_{it}=0)]$ where $t \leq \tau_i$

yielding:

$$P_{iT}[z_{iT}=1/\ \{z_{i\tau_i}=1 \cap z_{it}=0\}] \quad \text{where } \tau_i \leq T \text{ and } t \leq \tau_i$$

b) The probability to be an adopter by or in time T=1993 conditional on the sample of potential adopters at that time . This is equivalent to correcting the RHS for the right truncation of the sample of non adopters at time T (Z_T=0) who might decide to first adopt the technology after time T (*cross-sectional or space dimension*):

$$P_{iT}[z_{iT}=1/\ Z_T=0]$$

where $Z_T = \Sigma_{i=1}^{N} z_{iT}$.

Condition (a) can be rewritten as the Cumulative probability (P_{iT}) given by the sum of the probabilities to have not adopted before τ_i (P') plus the conditional probability to have adopted at time τ_i (P'') plus the conditional probability to adopt after τ_i (P'''):

$$\begin{aligned} P_{iT}[P_{iT}[z_{iT}=1/\ \{z_{i\tau_i}=1 \cap z_{it}=0\}] \quad = \quad & P'_{i\,\tau-}\,[z_{it}=0 \text{ for each } t_o \leq t < \tau_i] + \\ & P''_{i\,\tau}\,[z_{i\tau i}=1/z_{i,\tau i-\varphi}=0 \text{ where } \varphi=(\tau_i - t_o),...] + \\ & P'''_{i\,\tau+}\,[z_{i,\tau i+1}=1/\ z_{i,\tau i}=0 \text{ where } \tau_i \leq T] \qquad (6.8) \end{aligned}$$

The probability in (6.8) is simply the sum of the probabilities of adoption over time, where: z_{it}=0 before first adoption ($t<\tau i$) and z_{it}=1 at the date of first adoption ($t=\tau_i$) conditional on not having used the technology before τ_i. After that date ($t>\tau_i$) the probability to adopt for the first time is zero, the decision to first adopt already being taken and not repeatable ($P'''_{i,t}\,[\phi] = 0\ \forall\ t<\tau$).

This allows one to rewrite (6.8.) as:

$$P_{iT}[z_{iT}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\} \text{ where } \tau_i \leq T \text{ and } t<\tau_i] = P'_{it}[z_{it}=0 \text{ for each } t_o \leq t < \tau_i] + P''_{it}[z_{i\tau t}=1/z_{i,\tau-\varphi}=0 \text{ where } \varphi=(\tau_i - t_o),..]$$

Or equivalently as (6.9):

$$P_{iT}[z_{iT}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\} \text{where } \tau_i \leq T \text{ and } t<\tau_i] = \sum_{t=1}^{\tau} p_{it}[z_{i\tau}/z_{it}=0 \text{ for each } t_o \leq t \leq \tau_i] \quad (6.9)$$

From (6.9.) condition (a) can be simply rewritten as the conditional cumulative probability distribution at time of first adoption ($t=\tau$):

$$P_{iT}[z_{iT}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\}] = P_{i\tau t}[z_{i\tau_i}=1] / P_{i\tau}[z_{i,\tau-\varphi}=0] \quad (6.10)$$

Under the assumption of continuous probability, (6.10) is equivalent to:

$$P_{iT}[z_{iT}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\}] = F_{i\tau} / [1- F_{i\tau}] \quad (6.11)$$

In (6.11), F is the cumulative probability function of adopting by 1993, which is equivalent to the conditional probability to adopt at time τ_i , while the denominator reflects the probability not to have adopted before first adoption and can be written as one minus the probability to have adopted before that date:

$$P_i[z_{i,\tau-\varphi}=0]= [1-F_{i\tau}]$$

The intuition behind this can be better grasped by looking at figure 6.4. where the probability of adoption by time t is represented by a tree diagram. At each moment in time the decision of the firm is conditional on the decision taken in previous years. This implies that the conditional probability of not having adopted by 1993 can be written as:

$$P_i[z_{i,\tau-\varphi}=0] \quad = [1-p_{i,to}]^* [1-p_{i,t1}]^* \ldots =$$

$$= 1 - p_{i,to} - p_{i,t1} + (p_{i,to}\, p_{i,t1}) + \ldots$$

The equilibrium approach also suggests that this decision is independent of the decision taken in the past, consequently all the cross products equal zero yielding:

$$P_i[z_{i,\tau-\varphi}=0] \quad = 1 - \Sigma_t\, p_{it}$$

$$= [1-F_{i\tau}]$$

From (6.10) it is now straightforward to show that for a firm the probability to be an adopter by time T equals the conditional probability to adopt at the time of adoption.

$$P_{iT}[z_{iT}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\}] = P_{i\tau}[z_{i\tau}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\}]$$

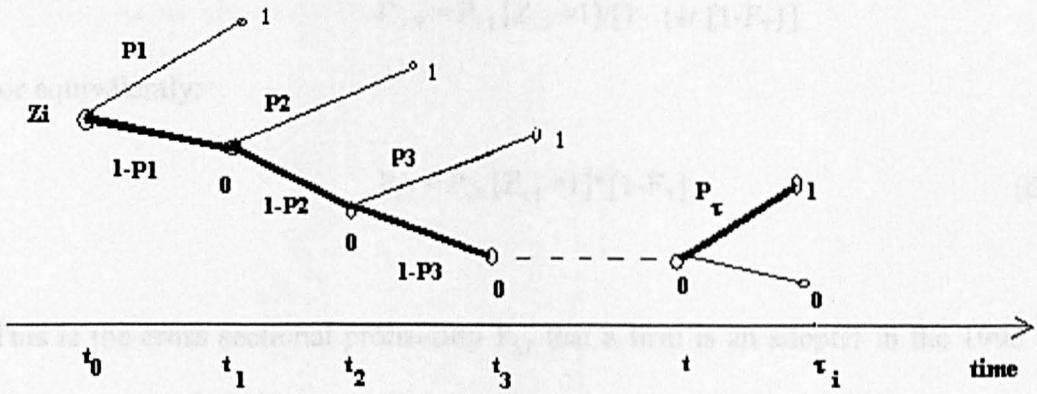
where $\tau_i \leq T$ and $t \leq \tau_i$.

This also implies that for a firm i:

$$F_{iT} / [1 - F_{iT}] = F_{i\tau_i} / [1 - F_{i\tau_i}] \qquad (6.12)$$

The conditional probability to be an adopter by or in 1993 (T) therefore equals the probability of becoming an adopter at the time of adoption (τ_i).

Figure 6.4. Conditional probability of adoption at time $t=\tau_i$



The cross-sectional dimension probability (b) takes into account that the decision to adopt is truncated at time T. This implies that the total probability to adopt at time T should be adjusted to account for those potential adopters that might adopt the technology sometimes after T. This is equivalent to correcting the probability of being an adopter at time T for the presence of non-adopters or future potential adopters:

$$P_T[Z_T=1/z_{it}=0\ \forall t_o \leq t \leq T \text{ and } i=1...N] = P_T[Z_T=1] / P_T[Z_t=0\ \forall t_o \leq t \leq T \text{ and } i=1....N] \tag{6.13}$$

where $P_T = \sum_{i=1}^{N} P_{iT}$.

The denominator of the RHS of (6.13) defines the cumulative probability that the sub-sample of firms has not adopted the technology by time T and can be rewritten as one minus the cumulative density probability to have adopted in or by 1993

$$P_T = P_T[Z_T=1] / [1-\sum_{i=1}^{N} P_{it}\ [z_{iT}=1/\{z_{i\tau_i}=1 \cap z_{it}=0\} \text{ where } \tau_i \leq T \text{ and } t < \tau_i] \tag{6.14}$$

After substitution of (6.11) and (6.12) in the denominator of (6.14) the probability to adopt of a single firm becomes:

$$P_{i,T} = P_{i,T}[Z_{i,T}=1]/[1-\{1/[1-F_T\}]$$

or equivalently:

$$P_{i,T} = P_{i,T}[Z_{i,T}=1]*[1-F_T] \qquad (6.15)$$

This is the cross sectional probability $P_{i,T}$ that a firm is an adopter in the 1993 cross-section. $[1-F_T]$ is the correction factor for the sample of those firms that might adopt at a later stage.

The probability $P_{i,T}$ is firm i cumulative conditional probability of adoption by T=1993 (condition a). But again from (6.11) and (6.12), $P_{iT} = F_{iT}/(1-F_{iT})$. This implies that at sample level (i.e. $P_T = \sum P_{i,T}$ i =1..N), this probability becomes:

$$P_T = [F_T/(1-F_T)]*[1-F_T] = F_T \qquad (6.16)$$

where from (6.11)

$$F_T = \sum_{i=1}^{N} F_{\tau_i}$$

and

$$F_{i,\tau_i} = f(x_{i,\tau}\,;\,\beta) \qquad (6.17)$$

This shows that for a sample of firms the probability of adoption by or in time T equals the probability of adoption at the time of first adoption. This result justifies why in the Sample Criterion Equation it is better to use the determinants of adoption at time of adoption rather than the state of the variables at time T.

This finding gives rise to a different specification of the two step sample selection procedure. The TR equation remains unchanged while the Selection Criterion Equation in the first step of the model is specified as (6.18):

$$z^*_{ijt} = \psi' w_{i\tau_i} + u_{it} \qquad (6.18)$$

where $w_{i\tau_i}$ defines the set of regressors at time of adoption.

The variables used in the corrected time dependent specification are presented in the following session.

6.3.2.The Time Dependent Determinants of the SC Equation

The results of the previous session (see equations 6.16. and 6.17.) indicate that the probability to be an adopter in or by 1993 is a function of the determinants of adoption at the time the decision is taken (w_τ), the corresponding selection equation having being specified as (6.18):

$$z^*_{ijt} = \psi' w_{i\tau_i} + u_{ijt} \qquad (6.18)$$

(Time Dependent Selection Criterion Equation)

Contrary to the specification of the technology replacement equation (see Chapter 5) the Selection Criterion equation refers to the decision to become an adopter, rather than to extensively use the new technology. The factors that can affect the decision to first use a new technology have been extensively looked by the inter firm literature. This turns out to be very useful as its predictions can be used to specify of the RHS

variables of the Sample Criterion Equation[9]. The inter-firm literature, indicates that what determines the first adoption of a new technology are rank, stock, order and epidemic effects at the time the decision is taken.

Most of the technologies in the CURDS sample are quite old, appearing on the market between 1950 (NC) and 1970 (CNC, Microprocessors in processes). Consequently not all the information in the 1993 sample is available from the date of first adoption. This has lead to some reduction in the set of variables that could be used for the testing of the model. They are summarised as follows.

Rank Effect (characteristics of the firm)

The inter firm literature predicts that (potential) adopters do differ in some important dimensions determined by the characteristics of the firm (David, 1969, 1991; Davies, 1979, etc). As such they are firm specific they can be approximated by:

- *Number of employees* (LE) at the time just before or nearest to first adoption (data are available for 1970, 1975, 1980, 1986, 1991, 1993). As a further test the size variable can be split, by multiplicative dummies, into three different size categories: less than 50 (LEsmall), between 50 and 500 (LEmedium) and more than 500 employees (LElarge). Their predicted sign is positive (see for empirical evidence on

9 It is worth noticing that those factors have also been used as a guideline in the derivation of the possible intra firm effects (see Chapter 5) and in the preliminary empirical exploration of the intra-firm diffusion (see preliminary analysis in Chapter 3). However, in the former cases they have been used as a categorizer for the intra firm effects, while it is only in the SS equation that their original specification, i.e. inter firm effects, is used straightaway.

relationship between firm size and speed of adoption, Mansfield, 1968, Romeo, 1975, Davies, 1979, etc. and more recently Colombo and Mosconi, 1995).

-*Age of the establishment at time of first adoption*, i.e. the difference between the date of start up and the date of first adoption (LAGE). This is included on the basis that the age of the establishment might influence adoption. However, the impact is dubious. The accumulated experience of a firm might have a positive impact upon adoption, but at the same time older firms might be less flexible than young firms in adopting new technologies (Baldwin, 1998). Empirical studies do yield contrasting results. Dunne (1994) has found that diffusion is independent of the age of the establishment, while Little and Triest (1996) have found a negative relationship between the number of new technologies adopted by the firm and the firm age. On the contrary, Noteboom (1993) has found that age is significant and with a positive coefficient. For this reason its sign and significance will be left to the empirics.

-*Industry dummy* (D_I , i=1,..n-th industrial sector)

D_{Ii} is a dichotomous variable taking value one if firm i belongs to the i-th industrial sector and zero otherwise. Fifteen sectors (according to the SIC classification) are initially specified in the model. However, in order not to lose too many degrees of freedom some of the industries have been grouped based upon the significance of an equal parameter restriction. This variable takes into account that each firm faces different markets for its products and different input costs depending upon the sector it belongs to. It is here implicitly assumed that the within sector market demand and supply, as well as market concentration, can lead to (faster or slower) adoption patterns. Reinganum (1981) suggests that greater market power would speed the

diffusion process. Similar result were found by Götz (1999) indicating that high competition often promotes diffusion. On the contrary Quirmback (1986) suggests that in a more concentrated industry a small number of users could slow down the pace of diffusion. More recently, the empirical studies of Karshenas and Stoneman (1993) found a positive relationship between market structure and technology diffusion, while Colombo and Mosconi (1995) found no significant impact of the Herfindahl index on the speed of adoption. For this reason sign and significance are left to the empirics.

-Characteristics of the management at time of first adoption.

These are specified as dummy variables that take the value of 1 if a managerial innovation had already been introduced at the time of first adoption of the advanced technology, and zero otherwise. The innovations are : Computer Aided Production Management system (CAPM), Just in time production (JIT), Total Quality Management principles (TQM), and whether the firm possess the BS575/ISO 9000 accreditation (BS575). These variables are introduced on the grounds that managerial practices, managerial innovations and organisational innovations might generate complementarities from the use of other existing technologies and speed up technology extent of use (see Colombo and Mosconi, 1995 as well as Cainarca et al, 1990 on the adoption of flexible automation systems). Given that these variables are plant and technology specific their sign will be determined empirically.

-Characteristics of the firm production system at time of first adoption.

This is defined by a dummy variable that takes the value 1 if, at the time of first adoption, the firm was already using other technologies, and 0 otherwise. The set of

technologies is: Numerically controlled (NC) and Computerised numerically controlled (CNC) machinery, Microprocessors incorporated into manufacturing production processes (MICRO) , Coated Carbide or ceramic tools or inserts for metal cutting (CoT), Programmable Robot (ROBOT) and Computer Aided Design/draught system with graphics (CAD). This variable should account for any substitutability and complementarity arising from the interaction with the existing production capital goods.

Previous studies in the area have supported this hypothesis. For example Karshenas and Stoneman (1993) and Stoneman and Kwon (1994), using the CURDS data set found that the adoption of a technology is not only affected by variables related to the technology itself but also by variables relating to other technologies. Moreover, the degree of complementarity can affect the probability of simultaneous adoption, e.g. CoT and CNC. Other evidence can be found in Colombo and Mosconi (1995), that suggests that previous adoption of certain technologies can reduce the initial training and installation costs, i.e. retooling and set up time, of the new technology. Also Cohen and Levinthall (1989) (implicitly) suggest that there might be positive complementarities between technology generation and technology adoption. However, the opposite can also happen. The characteristic of the firm's existing production system might require radical changes in the production line making adoption of an innovative technology too expensive. Consequently the sign of these variables will depend upon the technology used and it is left to the empirics to determine its value.

The Stock and Order effects

The traditional inter firm literature would suggest the existence of stock effects such that the incremental profit gains from adoption decrease with the number of rival firms already using the technology (Reinganum 1981a/b). Moreover, the order effect predicts that the returns to a firm from the adoption of a new technology depend upon the position of the firm in the order of adoption, so that first mover advantages make early adoption more attractive (Funderberg and Tirole, 1985 Stoneman and Ireland , 1985). Both effects should be unambiguously negative. Following Stoneman and Kwon (1994), the stock effect can be proxied by the within industry cumulative number of adopters in 1993, while the order effect by the (total or within industry) cumulative number of users at date of installation (τ). However, the cross sectional specification of this model assumes that the determinants of adoption are the variables at time of adoption, so both order and stock effects will be proxied by the same variable at time of firm first adoption: LSH_I, the series of within industry I (I=1..15) number of users, or LUSERS, its pulled version.

Epidemic effect

-Number of years between first appearance of the technology and technology adoption (LY*tech*)

This variable should account for learning and spillovers from other firms' adoption On the basis that as time proceeds, either more potential users become aware of a technology, or firms in general become more aware of the characteristics of the technology, the information spreading mechanism is assumed to have a positive impact upon adoption. Epidemic or learning effects have been investigated in a number of studies and empirical applications have confirmed their predictions (see for

examples Mansfield, 1968, Hannah and McDowell, 1984, Karshenas and Stoneman, 1993, etc.)

Table 6.1. Time dimension specification ($t=\tau_i$) of the Selection Criterion equation: Label, variable definition and whether log transformed

			Expected sign
DEPENDENT VARIABLE at time $t=t_I$			
D'j	•	'Binomial variable (D'j' = 1 Adopted ; D'j'=0 Non Adopted)	
Multi	•	Multinomial variable (Multi ∈ [0,1,2,3])	
RANK variables			
	•	***Employees at time near to time $t_{\tau i}$ (log)***	
$LE_{\tau i}$		Number of employees	+
	or		
$LEsmall_{\tau i}$		le_t if number of employees less than 50 ; 0=otherwise	+
$LEmedium_{\tau i}$		le_t if number of employees between]50,200[; 0=otherwise	+
$LElarge_{\tau i}$		le_t if number of employees greater than 50; 0=otherwise	+
$Lage_{\tau i}$	•	***age of the establishment*** at time of adoption (log)	?
Group	•	***Establishment part of group (1=yes; 2=No)***	+
	•	***Managerial Innovation at time t***	
$DCAPM_{\tau i}$		Dummy -CAPM adoption (1=Yes ; 0= No)	+/_
$DJIT_{\tau i}$		Dummy -JIT adoption (1=Yes ; 0= No)	+/_
$DTQM_{\tau i}$		Dummy -TQM adoption (1=Yes ; 0= No)	+/_
$DBS575_{\tau i}$		Dummy -BS575 –ISO9000 adoption (1=Yes ; 0= No)	+/_
	•	***Complementary and/or substitute technologies at time t***	
$DNC_{\tau i}$		Dummy -CN adoption (1=Yes ; 0= No)	+/_
$DcoT_{\tau i}$		Dummy -CoT adoption (1=Yes ; 0= No)	+/_
$Dmicro_{\tau i}$		Dummy –Microprocessors adoption (1=Yes ; 0= No)	+/_
$Drobot_{\tau i}$		Dummy -Robot adoption (1=Yes ; 0= No)	+/_
$DCAD_{\tau i}$		Dummy -CAD adoption (1=Yes ; 0= No)	
	•	***Industrial sector***	
D_{it}	•	Dummy (1= firm belongs to industry I, 0= otherwise), i=1,...,15 - SIC classif.	+/-
INTER FIRM EPIDEMIC variables at time t (skills, learning within firm and spillovers from adoption of other firms)			
LY_{Tt}	•	Within industry i number of years since the first firm adopted the new technology*(log)*	+
Ly_t	•	Years from first appearance of the technology and adoption by the firm*(log)*	+
INTER FIRM STOCK variables			
$Lusers_{\tau i}$	•	Share of adopters at time of firm first adoption*(log)*	-
$Lshi_{\tau i}$	•	Within industry i share of adopters, i.e. Lshar*Di i=industry 1, ..., 15 *(log)*	-

The information set of the time dimension Selection Criterion equation is smaller than for its space dimension version. This is due to the fact that some of the 1993 variables

are not available in the year of the firm's first adoption. Despite the theoretical time inconsistency of the determinants of first adoption, as a further check the space specification will be tested empirically, and its performance compared to the time dimensional specification.

The full set of variables used in the time and space dimensional specification is summarised in Tables 6.1 and 6.2 respectively.

Table 6.2. Space dimension specification (t=1993) of the Selection Criterion equation: Label, variable definition and whether log transformed

DEPENDENT VARIABLE at time T=1993			
$D'j_t$	•	Binomial variable (D'j' = 1 Adopted ; D'j'=0 Non Adopted)	
Multi	•	Multinomial variable (Multi ∈ [0,1,2,3])	
			Expected sign
RANK variables			
	•	***Employees at time near to time t (log)***	
Le_T		Number of employees	+
	or		
$LEsmall_T$		le_t if number of employees less than 50 ; 0=otherwise	+
$LEmedium_T$		le_t if number of employees between]50,200[; 0=otherwise	+
$LElarge_T$		le_t if number of employees greater than 50; 0=otherwise	+
$Lage_T$	•	***age of the establishment*** at time of adoption (log)	?
	•	***Managerial Innovation at time t***	
$DCAPM_T$		Dummy -CAPM adoption (1=Yes ; 0= No)	+/_
$DJIT_T$		Dummy -JIT adoption (1=Yes ; 0= No)	+/_
$DTQM_T$		Dummy -TQM adoption (1=Yes ; 0= No)	+/_
$DBS575_T$	•	Dummy -BS575-ISO9000 adoption (1=Yes ; 0= No)	+/_
	•	***Complementary and/or substitute technologies at time t***	
DNC_T		Dummy -CN adoption (1=Yes ; 0= No)	+/_
$DcoT_T$		Dummy –CoT adoption (1=Yes ; 0= No)	+/_
$Dmicro_T$		Dummy –Microprocessors adoption (1=Yes ; 0= No)	+/_
$Drobot_T$		Dummy –Robot adoption (1=Yes ; 0= No)	+/_
$DCAD_T$		Dummy –CAD adoption (1=Yes ; 0= No)	
	•	***Industrial sector***	
Di	•	Dummy (1= firm belongs to industry I, 0= otherwise) , I=1,...,15	+/-
INTER FIRM EPIDEMIC variables at time t			
(skills , learning within firm and spillovers from adoption of other firms)			
$LinY_T$	•	Within industry i number of years since the first firm adopted the new technology*(log)*	+ +
Ly_t	•	Years from first appearance of the technology and adoption by the firm*(log)*,	
	•	Otrher	
INTER FIRM STOCK/ordwer variables			
$Luser_T$	•	Share of adopters in 1993 *(log)*	-
Sh_T	•	Within industry i share of adoption in 1993, i.e. Lshar*DI I=1,15	-

6.4. Conclusion

One of the problems associated with the testing of the intra firm equilibrium model derived in Chapter 5, is that it is defined only for a restricted sample of firms, i.e. those currently using the technology, with the exclusion of ex adopters (using 0% of kn) and full users (using 100% of kn).

However, the decision to currently use the technology is just one of the possible outcomes of an irreversible conditional choice made sometime in the past to become an adopter.

In the CURDS data set the variable accounting for intra firm diffusion is available only for 1993, restricting the testing of the model to a single cross section of firms.

To model only the current status of the firms in 1993 might cause serious truncation in the probability distribution, as it would not consider that some of the firms might adopt the technology sometime in the future, while to look only at some of the possible outcomes generates sample censoring.

The probability of using a technology, conditional on the irreversible choice of adopting it, and the selection of possible outcomes (i.e. the current level of use) should be used instead. If ignored, this might cause serious bias in the parameter estimates.

The solution proposed in this chapter is to use the Heckman's two step procedure (Heckman, 1979). This specification allows one to model, in the first step, the decision to be an adopter in or by 1993 via the specification of a selection criterion equation (see section 6.2.2).

In the second step the actual intra firm estimating equation is corrected for the truncation of the sample (using the information in the first step of the analysis) yielding the corrected technology replacement equation.

This chapter has also discussed different ways of dealing with the censoring of the sample caused by the exclusion of the 'extreme users'. It has also proposed a multinomial two step selection rule capable of accounting for all types of problems, namely: a) the sample selection of the eligible unit whose choice is observable; b) the truncation caused by the unobservable future choice; c) the censoring in each specification of the subset of outcomes (see section 6.2.3.).

Whatever specification is used, the arguments of the SC equation can be outsourced from the inter firm literature, that has extensively explored the factors that lead a firm to first adopt a new technology (see section 6.3). The determinants of the TR equation are specified according to the prediction of the intra firm model presented in chapter 5 (see section 5.6). However, one of the problems, common to several applications of this type of model, is that the determinants of both steps are often defined over the same information set and several variables are used in both steps of the specification. The simultaneity of their impact upon the sample selection and the final model specification, can easily yield spurious and insignificant sample selection correction factors (Inverse Mill's Ratio).

A further problem is that the current level of the dependent variables in the modeling of the decision to become an adopter can be the consequence rather than the determinant of the status of the unit, generating endogeneity and misspecification problems.

By means of probabilistic tools, this chapter has derived an alternative specification of the Selection criterion equation, showing how the cross sectional nature of the model can be combined with the time specification when the dependent variable is observable only at one specific point in time (see section 6.3.2).

In summary, this chapter has presented different ways to deal with the sample selection, truncation and censoring problems that might arise in the estimation of the intra firm model of technology replacement. It has also shown how the time dimension can be combined with the space dimension when the dependent variable is available at only one specific point in time. Once all these factors are taken into account in the model specification one can proceed with the testing of the firm's decision to extensively invest in a new technology, under uncertainty and conditional to having in the past used at least one unit of the new technology and not having completed the replacement process (i.e.100% use).

The next chapter presents the results of the empirical estimates of the intra firm model for the technologies available in the CURDS data set for the cross section of UK engineering and manufacturing firms in 1993.

Chapter 7.

TESTING OF THE INTRA FIRM DIFFUSION MODEL: EMPIRICAL RESULTS

7.1. Introduction

This chapter aims at testing the validity of the intra firm diffusion model of technology replacement whose predictions indicate that the firm's optimal level of technology ownership is determined by technological (α_o/ α_n) and economic factors (c_{nt}/c_{ot}):

$$K_{nt} / (K_{nt}+K_{ot}) = 1/ (1+ (\alpha_o/ \alpha_n) (c_{nt}/c_{ot}) \qquad (5.17)$$

By the means of econometric tools, the model will be tested for the technologies available in the CURDS data set for the cross section of UK engineering and manufacturing firms in 1993.

However, three main problems associated with the original derivation of the model, have to be solved:

1) its non-linear nature makes it difficult to handle econometrically;

2) its aggregate nature does not allow one to directly measure the impact of some of its determinants, e.g. price expectations and uncertainty;

3) some of its determinants (i.e. relative productivities) are not available in the CURDS data set;

4) the model is defined only for those firms currently using the technology, with the exclusion of ex users and the 'extreme users', using respectively 0% and 100% of the new technology.

The first three problems have already been discussed in chapter 5 and how they have been overcome is summarised below.

The first problem has been overcome by applying a simple log linearization yielding the linearized version of the model, which can be easily estimated by OLS:

$$\log(Kn_{it}/ Ko_{it})) = \log(\alpha_{ni}/\alpha_{oi}) + \log(c^*_{ot}/c^*_{nt})] \qquad (5.35)$$

The second type of problem has been overcome by substituting the user cost of capital specification into (5.17) and explicitly modelling[1] the price effect, on the right hand side of (5.34), yielding:

$$\log[Kn_t/(Ko_t)] = \log(\alpha_n/\alpha_o) + \log(-dq_{ot}) - \log(-dq_{nt}) - [(r + \delta + 1/2\,\sigma^2\,\beta_1)(q_{nt}/dq_{nt} - q_{ot}/dq_{ot})]$$

The final parameterisation being:

$$\log[k_{nt}/(100-k_{nt})] = \kappa_1 \log(\alpha_n/\alpha_o) + \gamma_1 \log(-dq_{ot}) - \gamma_2 \log(-dq_{nt}) - \gamma_3 (q_{nt}/dq_{nt} - q_{ot}/dq_{ot}) \qquad (5.39)$$

where $\gamma_3 = (r + \delta + 1/2\,\sigma^2\,\beta_1)$

(5.39) is the final estimating equation of the intra firm model, where k_n is the proportion (%) of capital stock incorporating the advanced (new) technology; k_o -or equivalently $(100-k_n)$- is the percentage of capital stock incorporating the existing (old) technology.

1 See Chapter 5 section 4 for the intermediate steps in this derivation.

In the intra firm model α_n and α_o are taken to be constant and firm specific. They reflect the core competencies of the firm i.e. a rank effect $-\kappa$ with a coefficient equal to one, ($|\kappa|=1$). On the contrary (c^*_{ot}/c^*_{nt}) does not change across firms but does change over time (price effect-γ). It is a function of changes in capital good prices, corrected for uncertainty about future profitability of the investments (via the significance and the size of the parameter γ_3) and under rational expectations (via the assumption that $\gamma_1=1$ and $\gamma_2=-1$)[2].

The impact of uncertainty reduces the probability of further adopting a new technology via an increase in the waiting option value and it will affect the size of γ_3. Given that uncertainty is not known a priori it will be estimated empirically after subtracting from γ_3 the interest rate, outsourced from the NIS publications, and the depreciation factor used by Jorgenson (1965) in his empirical estimates (i.e. $r_{(t=1993)}+\delta = 0.05+0.025$).

The assumption of rational price expectations can be tested empirically, looking at the significance of γ_1 and γ_2. If they are significantly different from one (in absolute value) then the hypothesis of rational expectations cannot be accepted. This means that the expected prices are different from observed prices, and that the firm forecasting error will be reflected in the size of $\gamma_{1/2}$.

In Chapter 5, epidemic (ζ) and inter firm stock effects (ξ) have also been allowed to enter the model. There are no theoretical reasons to justify their presence but it has been shown elsewhere they significantly affect the speed of first adoption among firms. Their expected signs should be opposite ($\zeta>0$ and $\xi<0$) but insignificant.

2 See previous Chapter for more details about the derivation of the estimating equation and the assumption of the model.

The third problem was that not all the variables specified in (5.39) are available in all or any of the three CURDS surveys.

The CURDS data set contains data upon the level of technology adoption for different technologies, i.e. NC, CNC, and Micro, as well as other firm characteristics. This is rare information and allows one to test the theoretical model. However, the question relating to the intra firm level of ownership is present only in the 1993 questionnaire . This constrains the testing to a cross section of firms at a specific moment in time, i.e. 1993.

The intra firm model basically specifies the determinants of adoption as a function of the productivity parameters (α_n/α_o) and the price or user cost effects (c^*_{no}/c^*_{nt}). The relative productivity of the two types of capital inputs is not directly observable, but each being firm specific, they can be approximated by several firm specific characteristics present in the CURDS data set. This adds a cross sectional or *space dimension* to the diffusion phenomena and can explain the reason why different firms show different level of ownership at each point in time.

The *time dimension* of the study is given by the price effect. However, given that the final model specification is restricted to a cross section of firms, c^*_{jt} would be constant. The lack of cross sectional variation has been overcome by defining the relative price change in terms of its change since the firm's first adoption (see section 5.6 for a discussion).

The last type of problem arising with the testing of the model is that equation (5.39) is defined only for those firms that have started the process of technology transfer currently owning at least 1% of k_n with exclusion of those firms that are saturated with the new technology, i.e. owning 100% of k_n. This condition imposes some

constraints on the estimating procedure as the decision to use a new technology is conditional on the irreversible choice of having adopted it in the past and not using it at 'extreme' levels, i.e. 0 and 100%. This has yielded to the specification of a two step estimating equation accounting for the possible misspecification of the model arising from the selection and the truncation of the sample (see Chapter 6).

A summary of the main variables used to test the time dimension and cross sectional specification of the Selection Criterion Equation, is given respectively in Table 6.1 and Table 6.2 (Chapter 6, pp. 239-240).

More details of the variables specification of the final TR Equation can be found in Table 5.2 (Chapter 5, pp.202) while their summary statistics can be found in Appendix D.

This chapter presents the empirical estimates of the intra firm diffusion model and aims to model the firm's decision to extensively invest in a new technology, under uncertainty and conditional on having in the past used at least one unit of the new technology and not having completed the replacement process (i.e.100% use).

Section 7.2. summarises the final estimating equation of the intra-firm Technology Replacement equation corrected for both truncation and censoring. Section 7.3. discusses the empirical results for the three technologies. A final section summarises the finding of the study.

The econometric package used for the testing of the model is Limdep7 while all the manipulations of the data set are carried out using Stamp5 and SPSS.

7.2 The Two Steps Estimating Equation: Testing procedure

The two-stage testing procedure derived for the intra firm model implies the specification of a latent factor model accounting for the determinants of sample selection (6.1) plus a second regression equation (6.2), corrected by the sample selection factor λ derived in the first step of the analysis:

$$z^*_{ijt} = \psi' w_{it} + u_{it} \tag{6.1}$$

(Selection Criterion equation)

$$[y_{ijt} \mid z^*_{ijt}] = \beta' x_{it} + \beta_\lambda \lambda_{it}(\alpha_i) + v_{it} \tag{6.2}$$

(Corrected Technology Replacement equation)

The Selection Criterion Equation (6.1) defines the state of the firm in 1993 via a latent (binary or multinomial) variable (z_{ijt}). In the case of binary choice models (Logit or Probit) it takes value 1 if the firm has adopted the technology and 0 otherwise (z=1 adopter and z=0 non-adopter). If the binary case is extended to the multinomial or ordinal case then the latent variable is specified as a discrete variable ranging from 0 to *s*, where *s* is the number of possible mutually exclusive choices.

The determinants of the decision to first adopt the technology (w) are the traditional inter firm effects such as rank, stock, order and epidemic effects. They can be modelled using the time or the space dimension of first adoption determinants (see Section 6.2. and Table 6.1.). The first one assumes that the chance to be an adopter by 1993 has to be related to the determinants of adoption at the time when the decision to buy the first unit of the new technology $t=\tau_i$ is taken (time dimensional specification

of w_τ), i.e. $z^*_{it}=\psi' w_{i\tau i} + u_{it}$. The second one assumes that what determines the number of adopters in T=1993 is simply the observed value of the independent variables in 1993 , i.e. w_{iT} (space dimension specification of w_υ), i.e. $z^*_{iT} = \gamma\, w_{iT} + u_{iT}$. This is the best specification that can be determined empirically.

The Technology Replacement equation (6.2) defines the determinants of the level of use of a technology by a firm, corrected for the conditional choice to be an adopter. It is made up by two parts: the determinants of intra firm diffusion (x) and a sample selection correction factor (λ) derived from the Selection Criterion equation (6.1).

The variables used to model the intra firm effects include rank, price effect (subject to uncertainty and price rational expectations) as well as inter firm epidemic and stock effects (see for a full discussion section 5.6.4 and Table 6.3).

Once the correction factor (λ) is introduced among the list of independent variables of the technology Replacement equation, the model can be estimated by simple Least Squares regression. However, the LHS of (6.2) is the log of the ratio of the new over the existing technology ($y_{ij}=\ln(k_{ij}/(100-k_{ij}))$. It is defined over the sample of adopters currently using the technology, with the exclusion of ex users (those that in the past have adopted the technology but have dismissed its use in 1993) and extreme users (those that have reached the maximum of the diffusion process and use 100% of the new technology). This means that the empirical estimates must be corrected also for the censoring caused by the further selection from the sample of adopters.

The different model specifications used to overcome both sample selection bias and sample censoring of the eligible firms are summarised in Table 7.1.

Table7.1. Econometric models of the equilibrium intra-firm technology replacement

TWO STAGES PROCEDURE		
	$z^*_{ij} = \psi' w_i + u_i$ (Selection Criterion equation)	
	$[y_{ij} \mid z_{ij}] = \beta' x_i + \beta_\lambda \lambda_i(\alpha_i) + v_i$ (Technology Replacement equation)	
i) Binary Probit/Logit Selection Equation (sample selection)		
Selection Criterion equation:	$z^*_{ij} = \psi' w_i + u_i$ zi=1 If Adopter in 1993 zi=0 if Non-Adopter in 1993	$u_i \sim$ Normal or Logistic
Technology Replacement equation:	$[y_{ij} \mid z^*_{ij}>0] = \beta' x_i + \beta_\lambda \lambda^{P/L}_i(\alpha^{P/L}_i) + v^{P/L}_i$	
Censoring *by visual inspection (total sample of firms with and without exclusion of no longer and total users)*		
ii) Multinomial Selection Equation (sample selection + censoring)		
Selection Criterion equation:	$z^*_{ij} = \gamma w_i + u_i$ $z_i = 0$ if $k_n = 0^-$ $z_i = 1$ if $0<k_n<100\%$ $z_i = 2$ if $k_n = 100\%$ $z_i = 3$ if $k_n = 0^+$	$u_i \sim$ Normal (Non Adopter) (User) (Total User) (No Longer User)
Technology Replacement equation:	$[y_{ij} \mid z_{ij}=1] = \beta' x_i + \beta_\lambda \lambda^M_i(\alpha^M_i) + v^M_i$	

The selection criterion equation refers to the decision to adopt a technology in/by 1993 which has been modelled via:

i) Binary Probit/Logit selection model

ii) Multinomial selection model

For both models the determinants of the choice of adopting the technology can be specified using the time ($w_{i\tau_i}$) versus space (w_{iT}) dimension of the Selection Criterion Equation.

The corresponding Inverse Mills Ratio (LAMBDA) is then used in order to correct the replacement decision due to the exclusion from the sample of both potential adopters and those firms that might decide to invest in the new technology after 1993, i.e. when the last survey was carried out.

The main difference between i) and ii) lies in the specification of the possible outcomes of the firm choice and the impact of censoring.

With the use of the binary approach only two outcomes (adopt/non adopt) are modelled via the Logit or Probit probability distribution, depending upon the technology under consideration. The impact of the extreme users exclusion (censoring) in the second step of the model is done by visual inspection, comparing the estimate obtained from (i) with and without the inclusion of the no longer users and those firms that have completely replaced 100% of their existing capital stock with the new technology.

Model ii) combines both censoring and sample truncation in a series of mutually exclusive choices for which the technology replacement equation must be corrected.

The model specification that best fits the behaviour of the firm will be tested empirically. The testing procedure can be summarised in the following steps:

1a) Sample selection criterion: Probit Vs Logit Model Specification;

1b) Censoring of current users: visual inspection of the restricted and unrestricted model, i.e. with and without extreme users;

2) Multinomial two stages sample selection approach;

3) Time versus space specification of the Selection Criterion Equation;

The theoretical intra firm technology replacement model is tested on the sample of firms in the CURDS data set for three technologies: NC, CNC, and Micro[4]

Given the complexity of the testing procedure, the results will be presented step by step for each model specification and for each technology.

The main findings are summarised in the following section.

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[4] Other technologies had to be excluded due to the lack of data on some of the determinants of adoptions, i.e. price of CoT.

7.3. EMPIRICAL ESTIMATES

7.3.1 The Replacement Process of CNC technology

CNC technology is a relatively young technology which appeared on the market in 1970. Its spread of use has increased very quickly over the years and has overtaken the spread of ownership of NC (the previous generation, non-computerised version, of CNC).

In 1993 about 80% of the eligible firms in the sample have introduced CNC into their production process. The proportion of the machine tool stock that incorporates CNC is on average less than 20 % for 52 % of the firms, while only 7 % of the firms have a proportion in excess of 70 %. The determinants of the observed heterogeneity of the current level of current use of CNC are discussed below.

The Selection Equation: Probit vs Logit Model Specification

The first step in testing the theoretical model of technology replacement is to establish the probability distribution for the Selection equation, i.e. the probability for a firm to have adopted the new technology by or in 1993. Dealing with a cross section it seems reasonable to assume that the population of firms is Normally distributed. However to allow for departure from Normality, the hypothesis that the distribution is Logistic, i.e. with higher probability to observe extreme cases, has also been tested. In both cases the specification of the technology replacement equation remains the same, except for the correction term LAMDA derived from the first step equation.

Table 7.2.a, columns one and two, shows the empirical estimates of the Probit model over the unrestricted total sample of firms and the restricted sample of users. In both

cases the Normality assumption can explain most of the variability of the model (pseudo R_u^2=0.91; R_r^2=0.92)[5]. Using the Logistic distribution does not improve the explanatory power of the model. The predictions of both Logit and Probit specifications are exactly the same for all observations except one. Also the marginal effects of the two models, not explicitly reported here[6], are not significant.

The Selection Criterion equation of the unrestricted sample of firms (Table 7.2.a. column 1) indicates that the determinants of first adoption of a new technology before or in 1993 are directly related to firm size (LEsmall=E≤50, LEmedium=E≤500, LElarge=E>500), and the smaller the firm the more likely is to adopt it. The other factors which are inversely related to first adoption, are: age of the establishment at time of adoption (LAGE), whether the firm had adopted Computer Aided Production Management system (DCAPM) and whether it had received the BS5750/ISO9000 (DBS575) accreditation at time of first adoption. It also shows that the within industry share of adopters at time of firm' first adoption (LSH) exerts a significant but, unexpected, negative influence upon the decision to become an adopter of a new

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5 The pseudo R^2 is calculated as : R^2=var(yf)/(1+var(yf)), where yf=β'x +lambda (see Zavonia and McKelvey, 1975)

6 The parameters reported in Table 7.2.a are not the marginal effects one is accustomed to analysing but they are the coefficients dE(y)/dx =f(β'x)β, where f(.) is the density function of the specific probability distribution (Greene, 1993). Given the presence of dummy variables in the sample criterion equation, the marginal effects (or partial derivatives) defined at the regressors means may not be meaningful. This also explains why the size of the coefficients does not lie between zero and one, as it should be in the case of marginal effects. However, the significance of each regressor remains unchanged whether one uses the coefficient or the slope (marginal effect) of the variables. In this section the discussion is limited to the significance and not to the size of the variables.

technology. Contrary to expectations none of the technologies used by firms in 1993 is significant.

Table 7.2.a. Time dimensional specification of the SC equation: CNC

	1	2	3	4	5	
Variable/Model	Probit	Probit	Logit	Logit	Multi-SS	
Sample	Total firms	Current Users	Total firms	Current users	Current users	Total & ex-users
Choice	z=1	z=1	z=1	z=1	z=1	z=2
n	*153*	*149*	153	*149*	150	150
Constant	-6.52	*-7.41*	-12.40	-15.04	19.71	-
	(2.981)	*(3.145)*	(6.06)	(6.732)	(7.010)	
LAGE	-0.61	-	-	-	-	-
	(.372)					
$LEsmall_t$	3.69	*3.73*	6.76	7.10	9.28	-
	(.927)	*(.953)*	(1.928)	(2.11)	(2.746)	
$LEmedium_t$	3.21	*3.25*	5.86	6.14	7.99	-
	.774	*(.801)*	(1.615)	(1.771)	(2.302)	
$LElarge_t$	2.39	*2.39*	4.34	4.47	5.67	-
	(.551)	*(.559)*	(1.141)	(1.220)	(1.584)	
$DMICRO_t$	-	-	-	-	-	-
$DCAPM_t$	-2.09	-	-4.24	-	-	-
	(1.195)		(2.269)			
$DBS575_t$	-2.12	*-3.35*	-3.88	-6.27	-7.81	-
	(.828)	*(1.354)*	(1.525)	(2.763)	(3.650)	
$DJIT_t$	-	-	-	-	-	-
$DCOT_t$	-	-	-	-	-2.30	-
					(1.220)	
DNC_t	-	*1.02**	-	2.08	2.28	-
		(.353)		(1.222)	(1.265)	
$LSH2_t$	-0.70	*-0.64*	-1.20	-1.06	-1.27	-
	(.254)	*(.249)*	(.533)	(0.52)	(.552)	
$LSH3_t$	-0.79	*-0.71*	-1.48	-1.29	-1.58	-
	(.273)	*(.270)*	(.581)	(.580)	(.627)	
$LSH5_t$	-1.79	*-1.76*	-3.28	-3.25	-3.98	-
	(.581)	*(.564)*	(1.22)	(1.214)	(1.329)	
$LSH678_t$	-1.05	*-0.99*	-1.95	-1.82	-2.34	4.73*
	(.289)	*(.282)*	(.608)	(.590)	(.727)	(2.547)
$LSH9_t$	-1.28	*-1.20*	-2.44	-2.26	-3.14	-4.52*
	(.363)	*(.353)*	((.751)	(.720)	(.896)	(2.38)
$LSH10_t$	-1.11	*-1.02*	-2.03	-1.83	-2.67	-3.87
	(.313)	*(.303)*	(.632)	(.597)	(.805)	(1.766)
$LSH12_t$	-0.56	*-0.52*	-1.06	-	-1.12	-
	(.313)	*(.311)*	(.626)		(.665)	
$LSHGROUP_t$	(-0.43)**	-	n.s.	n.s.	n.s.	-
	(.261)					
$LSH1_t$	n.s.	*n.s.*	-	-	-0.69	n.s.
					(.580)	
$LSH4_t$	n.s.	*n.s.*	-	-	-	n.s.
$LSH15_t$	n.s.	*n.s.*	-	-	-	n.s.
$LSH13_t$	n.s.	n.s.	n.s.	n.s.	n.s.	n.s.
Log-Lik	*-26.88*	*-24.22*	-26.14	-23.50	-27.86	
L-ratio (χ^2)	*124.10*	*124.91*	125.57	126.36	152.62	

NOTE: variables without star, all significant between 0 and 5% significant level; * significant between 6% and 7%; ** significant between 8% and 9%; standard errors in brackets; n.s. not specified; χ^2 = calculated Likelihood ratio test that all the coefficients equal zero.

These results would indicate that young small firms are more likely to adopt CNC while the opposite happens for those firms using CAPM and with BS5750/ISO9000 quality accreditation. Moreover, the within order/stock effect (LSHi i= industry1,2,3,..) highly affects the adoption of a new technology , while the latter is independent of other technologies in use.

The Technology Replacement Equation with Probit sample selection correction factor

The information provided by the SC specification is only related to the determinants of first adoption and the firm probability to become an adopter by and in 1993.

The next step of the model is to use this type of information in the second step of the estimating procedure, via the Inverse Mill's Ratio (LAMBDA).

In Table 7.2.b. column 1 the Technology Replacement equation, corrected for the Probit sample selection (LAMBDA/Probit) shows that both prices (stock effect), and firm characteristics (rank effects) are highly significant.

The empirical estimates of the price variables coefficients [7] suggest that the use of the new technology increases the higher is the reduction in its real price (β_{dqcnc}=-2. 46)

[7] All the price variables show the expected sign. In fact the original specification of the stock effect (see 5.39) was such that:

$$\ln(c_{old}/c_{cnc}) = \gamma_1 \log(-dq_{ot}) - \gamma_2 \log(-dq_{nt}) - \gamma_3 (q_{nt}/dq_{nt} - q_{ot}/dq_{ot})$$
(DQold) (DQcnc) (QNQTOT)

where $q_{j,t}$ is the price of technology j at time t. The first term of the RHS is expected to have a positive sign being the relative change in the price of the old or existing technology from the date of the firm first adoption [$dq_{old}= q_{old}(\tau) - q_{old}(1994)$]. The second term has a negative expected sign and is the relative change in the price of the new technology [$dq_{cnc}= q_{cnc}(\tau) - q_{cnc}(1994)$]. The last term is the differential of the inverse of the relative reduction (RR) between the existing and the new technology [$(q_{cnc}/dq_{cnc})- (q_o/dq_o)$]= [$(1/RR_{cnc})-(1/RR_{old})$]. Its expected sign is negative as it is expected that the relative reduction in the price of the new technology is higher than for the old technology ($RRcnc>RRo \Rightarrow RRcnc^{-1}<RRo^{-1}$).The parameter of QnQtot, reflect

and its impact is higher than the existing technology price reduction impact (β_{dqtot} =1.78). The Wald test of the hypothesis that (in absolute value) they equal one, cannot be rejected for the price of the old technology (χ^2=0.618), while the contrary happens for the price of CNC (χ^2=23.69). This indicates that prices are highly significant. Moreover, the firms seem to hold expectations about the change in the price of CNC. The price change of the existing set of technologies is not affected by any expectations. The latter indicates that the firm can access the whole information set on the existing technologies to correctly predict the change in price of the set of old technologies, while for the new technology it holds incomplete information. In a broader sense this finding would also be similar to the Bayesian learning approach used by Stoneman (1981). In fact, Stoneman (see Chapter 3) assumes the expected performance of the old technology is known by the firm with certainty and it equals its expected value, while the advanced technology, being new to the firm, is subject to an approximation degree that reduces over time as the firm accumulates experience. The empirical estimates also show that the higher the differential in relative price change of the new over the existing technology the more likely is for the firm to use the new technology extensively (β_{qnqcnc}= -0.51). The hypothesis that β_{qnqcnc} equals only depreciation and devaluation rates ($r+\delta$=0.075) cannot be accepted indicating that the uncertainty about future profits ($1/2 .\sigma^2 \beta_1$) perceived by the firms in the sample, on average, does affect the investment decision of the firms (and equals 0.435). In this case, as predicted by the theory, uncertainty does (negatively) affect the firm's decision to further invest in the new technology.

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the impact of interest rate, depreciation rate and uncertainty $\gamma = \{\rho - \lambda^{\wedge} + 1/2 .\sigma^2 \beta_1\}$ whose magnitude is uncertain depending upon the size of uncertainty ($1/2 .\sigma^2 \beta_1$).

The j-test for the joint significance of the price effect (H_o: $\beta_{dqcnc}=\beta_{qntot}=\beta_{qnqcnc}=0$) cannot be rejected at 0% significance level (t=3.237). Their inclusion improves the goodness of fit (R^2) from 0.63 to 0.72.

The rest of the variables indicates that the rank effects do affect the intra-firm diffusion process, especially for those firms doing in house R&D ($\beta_{R\&D93}$=1.68) and belonging to an industrial group ($\beta_{Group93}$ =0.53). However, those firms which are export oriented use the technology less extensively than those exporting less than 20% of their output (β_{ex20}=-0.86). Among the rank effects the size effect does not seem to be very significant except for small firms with less than 50 employees ($\beta_{LEsmall}$=0.45), which are slightly more likely to use the new technology extensively than other firms. There is no evidence of significant financial liquidity constraints like the average real turnover/profit ratio of the previous six years (LTURNOVER2Y)[8]. It is instead highly significant if, prior to the date of first adoption of CNC, the firm has introduced technological innovations like: Computer Aided Design/Draughting system with graphics (β_{DCAD}=1.38); Microprocessors incorporated in any of the Products manufactured in the factory ($\beta\delta_{DMICRO}$ -0.80); Programmable robot (β_{DRobot} = 0.1.08) and microprocessors incorporated in manufacturing processes (other than CNC) for controlling, monitoring or inspection ($\beta_{DM\text{-}Prod}$ = -0.69).

The most dignificant production system is make/assemble to order, relative to Engineering to order (β_{PS2}=0.88). It also appears that those firms which have met high quality standards via accreditation with BS575 or ISO 9000, are the most likely to extensively use the new technology (β_{DBS575}=0.64)

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8 We have also tested the significance of the Profit-loss variable for 1981, 1985 and 1991 as an indicator of financial position of the firm but it was not significant.

Contrary to expectations the adoption of substitute technologies, like NC, is not significant in the extent of use of CNC technology. This indicates a possible lack of flexibility in shifting from early technology generations to later, due to the irreversibility of investments.

Moreover, none of the variables accounting for the epidemic effect are relevant.

The within Industry 10 share of adopters seems to be the only industry dummy effect significantly different from zero (χ^2=1.705). Industry 10 is the Electrical Machinery Sector where almost 81% of the firms have adopted CNC and are currently producing an average of 16% of their output on the new technology. However, when the industry and the share effects are specified separately, the current number of adopters at time of adoption is no longer significant. This confirms the prediction of the intra firm equilibrium model about the insignificance of the level of adoption by other firms (SHI where I=1,...15), due to the fact that intra firm stock effects are already indirectly picked up by the intra firm model specification.

The sample selection factor (β_{Lambda}) derived from the first step of the model does not exert any *direct impact* upon the level of use of the new technology. This would suggest that the decision to become an adopter does not directly affect the current optimal level of use of the new technology. This is coherent with the equilibrium theory suggesting that, in each moment in time, the optimal level of use of a new technology is firm specific and it is determined by the current environment and as such changes over time. Consequently, the decision to first adopt a new technology is a necessary but not sufficient condition to extensively using that technology[9].

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9 As a further check the technology replacement equation has also been estimated using the correction factor (lambda), derived from a Logit sample selection equation (see table.7.2.b column 3). However, also in this case the sample selection factor is insignificant.

Table 7.2.b. Time dimensional specification of the TR equation: CNC

	1	2	3	4	5
Model	Probit SS	Probit SS	Logit SS	Logit SS	Multi-SS
Sample	*Total firms*	*users*	Total firms	Users	Total
Choice	$z_{it}=1$	$z_{it}=1$	$z_{it}=1$	$z_{it}=1$	$z_{it}=1$
N	*69*	*69*	*69*	*68*	*68*
Constant	-	-	-	-	-
LDCNC	-2.46	*-2.47*	-2.46	-2.47	-2.45
	(.656)	*(.653)*	(.655)	(.649)	(.640)
LDTOT	1.78	*1.79*	1.79	1.64*	1.60*
	(1.024)	*(1.02)*	(1.02)	(.971)	(.973)
QNQTOT	-0.51	*-0.51*	-0.51	-0.42	-0.42
	(0.112)	*(0.112)*	(0.112)	(.137)	(.135)
LBATCH	-	-	-		-
GROUP93	0.53	*0.53*	0.53	0.56	0.56
	(.253)	*(.252)*	(.253)	(.257)	(.257)
R&D93	1.69	*1.69*	1.68	1.66	1.65
	(.356)	*(.356)*	(.358)	(.358)	(.356)
DLEsmall	0.44	*0.46*	0.45*	0.51	0.50
	(.250)	*(.247)*	(.248)	(.221)	(.220)
DLEmedium	(0.21)**	(0.22)**	(0.21)**	0.24*	0.24
	(.144)	(.143)	(144)	(.131)	(.130)
DLElarge	(-0.12)**	(0.13)**	(0.12)**		-
	(.120)	(.148)	(.147)		
EX20	-0.86	*-0.85*	-0.86	-0.72	-0.73
	(.299)	*(.299)*	(.299)	(.292)	(.286)
TURNOVER2Y	-	-	-		-
DCAD	1.32	*1.32*	1.38	1.44	1.44
	(1.316)	*(.298)*	(.298)	(.279)	(.315)
DCAPM	-	-	-		-
DM-PROD	-0.67	*-0.68*	-0.69	-0.73	-0.71
	(.288)	*(.289)*	(.286)	(.292)	(.288)
DJIT	-	-	-		-
DTQM	-	-	-		-
DBS575	0.63	*0.64*	0.64	0.70	0.68
	(.628)	*(.338)*	(.338)	(.340)	(.331)
DMICRO	0.87	*0.87*	0.80	0.79	0.80
	(.323)	*(.322)*	(322)	(345)	(.353)
DCOT	-	-	-	-0.771*	-0.74
				(.456)	(.441)
DNC	-	-	-		-
DROBOT	1.01	*1.02*	1.01	1.11	1.08
	(.477)	*(.477)*	(.476)	(.398)	(.494)
PS5	-	-	-		-
PS2	0.93	*0.93*	0.92	0.91	0.91
	(.304)	*(.304)*	(.305)	(.310)	(.308)
PS3	-	-	-		-
PS4	0.89*	-	-		-
	(.557)				
PS1	n.s.	n.s.	n.s.	n.s.	n.s.
LAGE	-	-	-		-
Liusers93	n.s.	*n.s.*	n.s.	n.s.	n.s.
LCNCY	n.s.	n.s.	n.s.	n.s.	n.s.
LTCNC	n.s.	n.s.	n.s.	n.s.	-
LIFOUT93	n.s.	n.s.	n.s.	n.s.	n.s.
LAMBDA	-	-	-	-	-
sh1	n.s.	-	-	n.s.	*n.s.*
sh2	-	-	-	-	-
sh3	-	-	-	-	-
sh4	n.s.	*n.s.*	n.s.	n.s.	*n.s.*
sh5	-	-	-	-	-
sh6	n.s.	*n.s.*	n.s.	n.s.	*n.s.*
sh7	n.s.	*n.s.*	n.s.	n.s.	*n.s.*
sh8	n.s.	*n.s.*	n.s.	n.s.	*n.s.*
sh9	-	-	-	-	*n.s.*
sh10	6.04	*6.02*	6.05	6.03	*6.07*
	(2.249)	*(2.243)*	(2.250)	(2.260)	*(2.256)*
sh11	-	*n.s.*	n.s.	n.s.	*n.s.*
sh12	-	-	-	-	-
sh13	n.s.	*n.s.*	n.s.	n.s.	*n.s.*
sh15	n.s.	*n.s.*	n.s.	n.s.	*n.s.*
sh678	-	-	-	-	-
shgroup	-	-	-	-	-
R2	0.72	*0.72*	0.72	0.72	0.72
R2c	0.40	*0.40*	0.40	0.39	0.39
Log-L	-44.48	*-44.49*	-44.48	-43.42	-70.16
F	2.27 (1%)	*2.27 (1%)*	2.18 (1%)	2.21 (1%)	2.21 (1%)

NOTE: variables without star all significant between 0 and 5% significant level; * significant between 6% and 7%; ** significant between 8% and 9%'; standard errors in brackets; n.s. stands for not specified

In summary , the two stage binomial specification confirms the prediction of the intra firm diffusion model, that is: price and rank effects do affect the replacement of the old with an advanced technology. Moreover, the investment decision has been proved to be affected by uncertainty and price expectation about the future CNC price level. Contrary to the disequilibrium approach to technology diffusion there are no epidemic effects driving the within firm spread of use of a new technology.

This model also hints that the inter-firm stock effects do not affect the firm decision to extensively use a new technology. This has to be related to the fact that stock effects are already picked up by the intra firm model in other ways. Moreover, the insignificance of the sample selection factor indicates that the current level of technology adoption is independent of the decision to first adopt that technology.

Censoring of current users: visual inspection of the restricted model

In the two-stage sample selection model, those firms currently using 0 or 100% level of technology were excluded from the TR regression equation (6.2) on account of both theoretical assumptions and mathematical constraints. In order to have an idea of the magnitude of the left and right censoring this might cause, the whole analysis has been replicated excluding the non-eligible firms also from the first step of the analysis. This means that the Selection Criterion equation (6.1) is now estimated over the sample of adopters /non-adopters with the exclusion of the no longer users and fully users, reducing the sample to current users and non-adopters. The specification of the Corrected Technology Replacement equation remains the same.

The different estimates of the restricted sample Probit model can be found in column two of Table 7.2.a and 7.2.b. for the SC and the corrected TE equation respectively.

They are quite similar to the unrestricted case in column one, except that most of the significant variables do show a slightly higher coefficient.

According to the Selection Criterion equation, it is more likely that a firm that had adopted NC in the past, is now an adopter and a current user of the technology (DNC). Contrary to the full sample estimates it also appears that the impact of intra industry effects (LSHi i=industry 1,2,3,..) is weaker while the size effects are stronger, especially for small and to a less extent also for medium sized firms (LEsmall and LEmedium).

In the second step of the model, the TR regression equation corrected for to the Sample selection of the censored sample, shows a weaker impact of the price effects (LDTOT, QnQtot), R&D and export level (Ex20), while showing a higher impact of rank effects. The test of the joint significance of the price effects can be rejected (j-test: t=3.82). As in the previous model, the price effect is highly significant and they significantly contribute to explain the total variability of the model[10].

It also indicates that firms do choose the current level of advanced technology ownership based upon expectations on its change in prices (H_o:β_{LDCNC}=-1, χ^2= 4.929). The forecasting error between the observed (β_{LDCNC} = -2.5) and the expected price being almost 1.50, i.e. $dq_{CNC} = \gamma . d\ q^e_{CNC}$, where $\gamma = \beta_{LDCNC} - 1$ (see chapter 5 for more details). We are not able to reject the hypothesis of rational expectations for the existing technologies (H_o:β_{LDTOT}=1, χ^2= 0.5997).

[10] The J-test (Davidson and McKinnon, 1981) is here used to compare the forecasts of the price effects (d_P^*) against those of the Other effects (say d_O^*) on the basis that their combination should produce a level of technology ownership (y) with smaller forecast error. The compound model being $y = (1-\psi)\ d_O^* + \psi\ d_P^*$ This model is estimated by OLS and if ψ is not significantly different from zero, then the model does not add anything to the explanation of y. If it is significant then the price effects significantly contributes to the explanation of y.

The testing for the presence of an uncertainty effect has led us to accept the hypothesis that it does affect the investment decision (H_o:$\beta_{LDQnQtot}$=0.075, χ^2= 18.66) and equals 0.435.

The sample selection of the group of adopters (LAMBDA) does not exert any significant impact upon the intensity of the new technology use.

Despite these differences, the magnitude of the parameter estimates of the restricted and unrestricted model and the explanatory power of the two models is almost the same. This is mostly because only 4 firms are no longer using the technology or have reached the saturation level. By visual inspection this would suggest that their exclusion, does not significantly change our results and the impact of censoring is negligible.

Censoring of current users: Multinomial two stages sample selection approach

The visual inspection approach does not provide us with the final estimates corrected for censoring. A more statistically grounded approach to account for censoring and sample selection is provided by the Multinomial two stage sample selection approach. Estimates are produced in column 5 of Table7.2.a/b.

According to this formulation, the dependent variable in the Sample Selection equation in the first step of the model is specified such that:

Selection Criterion equation:

$$z^*_{ij} = \psi' w_i + u_i \qquad u_i \sim \text{Normal}$$

$$\begin{array}{lll} z_i = 0 & \text{if } k_n = 0^- & \text{(Non Adopter)} \\ z_i = 1 & \text{if } 0 < k_n < 100\% & \text{(User)} \\ z_i = 2 & \text{if } k_n = 100\% \text{ and } 0^+ & \text{(Total User)} \\ z_i = 3 & \text{if } k_n = 0^+ & \text{(No Longer User)} \end{array}$$

and

Technology Replacement equation:

$$[y_{ij} \mid z_{ij}=1] = \beta'X + \beta_\lambda \lambda^M_i(\alpha^M_i) + v^M_i$$

In the first step, due to the very small sample size, the group of Users and No Longer Users has been pulled together into one category[11].

The empirical estimates of the SS equation and the TR equation can be found in Table 7.2.a and 7.2.b column 5 and 6.

The impact of the regressors upon the probability to become an adopter still using the technology in 1993, is highly significant (see Table 3a column 5 for $z_i=1$)[12]. The intensity of the impact of the regressors upon the decision to be a current user is much stronger than in the binary case. This is true for all the variables except for the age of the establishment (LAGE) and the adoption of the CAPM management innovation, that are no longer significant. Another difference is that now the presence of CoT and NC (complementary and substitute technologies), is highly significant even if with a sign opposite to predictions.

On the contrary the probability to be an 'extreme user' (fully or not currently using the technology but having used it in the past), with respect to the probability not to be an

11 Dummy variables have been used to pick up the different impacts of each of the two groups to but none of them was significant.

12 It is worth emphasising that with this specification the interpretation of the marginal effects of (j=1) is not straightforward. In fact the impact of an increase in one of the w_i on s=2 does have the same sign of β upon the corresponding probability while the opposite sign upon the probability of s=0. The interpretation of the coefficients of the middle range is however ambiguous as it depends on the combination of the shift in the other two probabilities.

adopter is significantly affected only by a few intra industry share effects (see Table 7.2.a column 5 for z_i=2).

This result suggests that none of the factors leading to first adoption exert a significant impact either upon those firms that have decided to dismiss the use of a new technology or those that are fully using the technology.

The TR equation, corrected for the sample selection of the current users provides results intermediate but not significantly different from the Probit specification with and without the 'extreme' users. The explanatory power of the model is good (R^2=0.72 ; R^2 corrected=0.39) and the residuals are well behaved. In this case, as well, sample selection (LAMBDA) does not significantly affect the level of use of the new technology.

Similar to the Probit two stages approach rank, price and inter firm stock effects do significantly affect the intra-firm diffusion process. None of the epidemic effects exerts a significant impact upon diffusion.

The Time versus space specification of the Selection Criterion Equation

As a further test of the validity of the time dimensional specification of the SS equation, the same exercise has been repeated for the space dimensional specification and the corresponding corrected technology replacement equation.

As in the cross sectional case, the estimates of both the Probit and Logit specification are very similar and with the same predictive capability (i.e. yielding the same predicted probabilities). For this reason, also in this case the hypothesis of Normality cannot be rejected.

The estimates of the binary Selection Criterion equation in Table 7.2.c . (column 1,2) suggest that in 1993 the probability to observe an adopter is mostly determined by the financial position of the firm before first adoption (LTURNOVER2Y) and whether the firm is export oriented (EX20). The significant characteristics of the production system are: whether the firm has already adopted CAD and the average batch size of its production. Also the within industry 10 effect (LSH10) turns out to be significant.

The predictions of the Corrected Technology Replacement equation are robust across the bivariate Logit, Probit (see Table 7.2.c. column 4,5). The size and significance of the variables confirm the predictions of the time dimensional model Table 7.2.b. that is: the price and rank effects but not the epidemic effects, nor the stock/order effects are significant in the process of technology replacement and in none of the cases is the sample selection significant (LAMBDA)

The cross sectional specification of the multinomial selection criterion equation indicates that only the average batch size (Lbatch) is significant at 5%. This leads one to conclude that, overall, in 1993, very few factors seem to affect the probability to currently use the technology. This result is difficult to accept and indicates that there might be a misspecification problem possibly due to the nature of the variable definitions. The space dimension specification basically assumes that the probability to be an adopter in/by 1993 is related to the level of factors in 1993 while it is more likely that those factors are the consequence rather than the cause of first adoption (see Chapter 6.3 for a discussion of this issue). On this ground, the space dimensional specification is abandoned in favour of the time dimensional specification of the CNC model.

Table 7.2.c. Cross Sectional dimension of SC and TR equation: CNC

Sample Criterion Equation					*Technology Replacement Equation*			
	1	2	3			4	5	6
	Logit	Probit	Multi-SS	Multi-SS	Model	Logit SS	Probit SS	Multi-SS
Sample	All	All	All	All	Sample	All	All	All
Choice	z_i=1	z_i=1	z_i=1	z_i=2	Choice	z_i=1	z_i=1	z_i=1/2
n	131	131	*131*	131	*n*	*69*	*69*	68
Constant	-	-	-	-	Constant	-	-	-
-					LDCNC	-2.73	-2.66	*-2.46*
						(.671)	(.672)	*(.657)*
-					LDTOT	1.84**	1.80**	*1.90***
						(1.05)	(1.060)	*(1.05)*
-					QNQTOT	-0.44	-0.42	*-0.44*
						(.142)	(.143)	*(.138)*
LBATCH,	2.135	1.23	*2.76*	-	LBATCH	-	-	-
	(.967)	(.577)	*(1.364)*					
GROUP93,	-	-	-	-	GROUP93	-0.48**	0.47*	*0.52*
						(.260)	(.264)	*(.265)*
R&D93,	-	-	-	-	R&D93	1.74	1.74	*1.65*
						(.365)	(.371)	*(.360)*
le93,	-	-	-	-	DLEsmall	0.48	0.43	*0.42**
						(.240)	(.239)	*(.235)*
-					DLEmedium	-	-	-
-					DLElarge	-	-	-
EX20,	-4.49	-2.56	-	-	EX20	-0.88	-0.92	*-0.80*
	(2.206)	(1.277)				(.329)	(.324)	*(.304)*
LTURNOVER2y,	1.94*	1.13**	-	-	LTURNOVER2Y	-	-	-
	(1.137)	(.661)						
DCAD,	6.38	3.66	*5.69**	-	DCAD	1.44	1.50	*1.43*
	(2.744)	(1.584)	*(3.102)*			(.328)	(.325)	*(.333)*
DCAPM,	-	-	-	-	DCAPM	-	-	-
DMPROD,	-	-	-	-	DM-PROD	-0.67	-0.71	*-0.71*
						(.298)	(.298)	*(.286)*
DJIT,	-	-	-	-	DJIT	-	-	-
TQM,	-	-	-	-	DTQM	-	-	-
DBS575,	-	-	-	-	DBS575	-	-	*0.65*
								(.326)
DMICRO,	-	-	-	-	DMICRO	0.77	0.83	*0.80*
						(.343)	(.343)	*(.355)*
DCOT,	-	-	-	-	DCOT	-	-	-
DRobot,	-	-	-	-	DNC	-	-	-
-					DROBOT	-	-	*1.14*
								(.500)
-					PS1	n.s.	n.s.	*n.s.*
-					PS2	0.79	0.85	*0.90*
						(.321)	(.318)	*(.308)*
-					PS3	-	-	-
-					PS4	-	-	-
-	-	-	-	-	PS5	-	-	-
LAGE,	-	-						
Lyiad,	-	-	-	-	LAGE	-	-	-
-					Liusers93	n.s.		
-					LCNCY	n.s.		
-					LTCNC	-	-	-
-					LIFOUT	n.s.	n.s.	*n.s.*
-					LAMBDA	-	-	-
d1	-8.96	-5.27	-	-	sh1	-	-	-
	(4.594)	(2.76)						
d2	n.s	n.s.	n.s.	n.s.	sh2	-	-	-
d3	-	-	-	-	sh3	-	-	-
d4	n.s.	n.s.	*n.s.*	*n.s.*	sh4	n.s.	n.s.	*n.s.*
d5	n.s.	n.s.	*n.s.*	*n.s.*	sh5	-	-	-
d45	-	-	-	-	sh6	n.s.	-	-
d6	n.s.	n.s.	*n.s.*	*n.s.*	sh7	n.s.	-	
d7	n.s.	n.s.	*n.s.*	*n.s.*	sh8	n.s.	-	
d8	n.s.	n.s.	*n.s.*	*n.s.*	sh9	-	-	-
d678	-	-	-	-	sh10	-	5.88	*5.69*
							(2.331)	*(2.512)*
d9	-	-	-	-	sh11	-	n.s.	*n.s.*
d10	-11.3	-6.68	-	-	sh12	-	-	-
	(4.851)	(2.92)						
d11	-	-	-	-	sh13	n.s.	n.s.	n.s.
d12	-	-	-	-	sh15	n.s.	n.s.	n.s.
d13	n.s	n.s.	-	-	Sh678	-	-	-
d15	n.s	n.s.	-	-	Shgroup	-	-	-
					R2	*0.74*	*0.73*	*0.72*
					R2c	*0.41*	*0.41*	*0.38*
Log-Lik	-17.78	-17.53	*-16.57*		Log-L	-40.04	-41.59	-69.96
L-ratio (χ^2)	86.86	86.68	*125.09*		F (prob)	2.25 (1%)	2.30 (0%)	2.10 (1%)

NOTE: variables without star significant between 0 and 5% significant level; * significant between 6% and 7% . ** significant at 8%; standard errors in brackets; n.s. not specified

In summary, this study suggests that the probability to first adopt CNC in/by 1993 is fairly Normally distributed and the time dimensional specification better models the determinants of first adoption. Among the determinants of adoption of CNC, the significant variables are age (with negative coefficient) and size of the establishment, and in particular smaller firms seems more likely to first adopt than bigger firms. Other technologies in use do not play a significant impact upon adoption, except when the sample is restricted to the current users, in which case, those firms that are currently using also NC seem to be more prone to further invest in CNC. These result seems to be in line with the evidence found by Rees, Briggs and Oakey (1984) over a sample of Canadian firms, indicating that there might be contagious effects in the use of NC and CNC machines for small plants or single-establishment firms, but not for the entire sample. It also seems that those firms that use Computer Aided Production Management System are less likely to adopt CNC in favour of other type of production methods. In the time dimensional specification to have received the BS575/ISO9000 accreditation shows a negative sign. However, in the cross sectional specification it shows the right (positive) sign. Confirming that firms with high quality standards are more likely to adopt than other firms.

Some of the results of the Selection Criterion equation are contrary to expectations. This might be because the specification used defines the probability to adopt the new technology in 1993, conditional on not having adopted it in the past. In this respect some of the predicted effects are less intense or show the wrong sign. In fact in 1993 only about 80% of the firms in the sample had already adopted the new technology and only a small proportion of the potential adopters might end up adopting it. However, it is, in a certain way, reassuring that the impact of the decision to first

adopt never turns out to significantly affect the ownership level of the new technology.

Despite the several specifications of the selection criterion equation, the persistent insignificance of the sample selection correction factor (LAMBDA) indicates that the decision to first adopt a new technology is a necessary but not sufficient condition to extensively using CNC. In fact, whether one uses a time or a (improper) space definition of the selection Criterion equation neither the truncation nor the censoring of the sample significantly affects the level of use of the CNC technology.

The estimates of Technology Replacement are consistent across the different specifications, confirming the prediction of the intra firm diffusion model. Both rank and price effects are highly significant in the process of technology substitution. The price effects are all significant and show the correct sign. Uncertainty about future profits seems to significantly slow down the decision to further invest in a new technology, via the increase of the negative slope of the price effect ($1/2\sigma^2\beta \sim 0.4$). It has also been shown that the firm reacts to expectations about future prices (or expected threshold price) of CNC, while it seems to operate under rationality for the price of the old technologies. The latter, being old and known to the firm, can be correctly forecasted, contrary to the advanced technology, that is only partially known by the firm. This result, seem to be in line with to the prediction of the Stoneman (1981) model, where it is assumed that the firm knows with certainty , some of the properties of the old but not of the new technology.

The rank effect indicates that CNC is a technology used mostly by small and medium firms, not export oriented, with 'make to order' production system, and that belongs to

an industrial group. Moreover users do use, among other technologies, microprocessors incorporated in their products, robot, and Computer aided design machines. They also carry out a significant amount of R&D confirming the production of Cohen and Levinthall (1989) who illustrate that firms which spend upon R&D are more easily able to assimilate new technologies. It also appear that whether they have received the BS5750/ISO9000 accreditation, plays a significant role in the extent of use of the new technology.

Epidemic effects do not affect the intra-firm diffusion of the technology, while inter-firm stock effects are significant only in one sector, but are not significant when the industry effect is separated from the stock effect. This is in line with the prediction of the model indicating that the intra firm stock effect is already picked up by the technology replacement equation.

7.3.2. THE REPLACEMENT PROCESS OF NC TECHNOLOGY

NC technology is a very old technology which first appeared in 1955. Among the sample of adopters almost 31% are no longer using NC and only 3.3% of the firms in the sample claim that NC represents more than 50% of the machine tool stock of the establishment.

Moreover, none of the firms is fully using 100% of the technology.

The rational for this is going to be related to the appearance on the market of CNC, the computerised advanced version of NC. As one might expect, as soon as CNC technology is adopted, it replaces NC technology. CNC appeared on the market in 1971 and since then the NC replacement process (by obsolescence as assumed by the

economic intra-firm theory) has been taking place. As shown below, the empirical estimates of the theoretical replacement model do reflect the obsolescence of NC technology.

The Selection Equation: Probit vs Logit Model Specification

For NC technology the assumption of a normal probability distribution of the Selection Criterion equation does not hold. The Normality assumption causes lack of convergence of the estimator. This is because the distribution is very skewed and with a high number of adopters (z_{ijt}=1) with only few firms having still to adopt NC technology (z_{ijt}=0). The Logit specification better models the distribution of adopters in 1993.

In Table 7.3.a. column 1, the Logit SC equation indicates that in 1993 very few factors still exert a significant impact upon first adoption of NC. Their joint significance is rejected at almost 15% probability (Likelihood ratio(χ^2)= 87.2).

In 1993 among the significant rank effects, the size of the firm at time close to first adoption (LEsmall,LEmedium, LElarge) indicates that the smaller is the firm the higher is the probability to have adopted the technology by that date. Similar to CNC, to be awarded the BS575/ISO9000 quality accreditation reduces the chances to adopt the technology by/in 1993. None of the other technological characteristics of the firm are significant.

On the contrary the within industry number of users (LSHi i=industry1,2,3,4,etc.) is highly significant. It negatively influences the spread of adoption of NC providing evidence of inter firm stock/order effects, predicting that there are decreasing profits gains from the increasing number of adopters of a new technology. This is particularly

true for the probability of adoption of NC that has been on the market for nearly 30 years and it is now considered almost an obsolete technology.

Table 7.3.b shows the results for the Technology Replacement equation adjusted for the sample selection via the IMR (LAMBDA).The results for the TR equation with Logit time dimensional sample selection correction (LAMBDA/LOGIT) are shown in column 1. According to this specification, those firms extensively using NC do a significant amount of R&D ($\beta_{R\&D93}$=1.36) and have received the BS5750/ISO9000 quality accreditation (β_{B575}=1.48). They have also already introduced CNC (β_{DCNC}=1.73) as well as microprocessors ($\beta_{M\text{-}prod}$=2.28) in their production processes. This result hints that those firms are highly innovative and willing to adopt and extensively use a new technology. However, perhaps due to the irreversibility of investments, they find it more difficult to subsequently convert their production system once a superior technology appears on the market. Despite the significance of the rank effects, none of the price effects significantly affect the investment decision of the firm[13].

Contrary to the determinants of first adoption, at intra-firm level the within industry number of users at time of adoption exerts a positive impact upon intra-firm diffusion.

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13 The quality adjusted price series of NC shows increasing values over time, reflecting the obsolescence of NC (particularly with respect to CNC, its computerized version. Consequently, ($q_{NC,t}$-$q_{NC,t-1}$) is positive and the price change log (-$q_{NC,t}$) , as specified in (5.39), is undetermined. Purely as an empirical exercise the price change ($q_{NC,t}$) rather than (-$q_{NC,t}$) has been used in the specification of this price covariate. Even if it is not what the theory would predict, this variable has been thought to be able to pick up some of the variability of the price change over time (even if of the wrong sign). However, as it will be seen later in the discussion, none of the price effects , as well as the whole model specification, is not appropriate for this machine tool.

However, when the industry effects are separated from the share of adopters at time of adoption, the predictive capability of the model remains unchanged, while the share effects are no longer significant.

This result can be interpreted in three different ways. It might pick up some underlying epidemic effects (whose predicted sign is positive). It might pick up the general trend leading to dismissal (by depreciation) of the use of the technology or, more likely, it simply suggests that the intra firm inter stock/order effects are not significant as they are already implicitly accounted for by the theoretical model. In the latter case the significance of the Industry dummies simply indicates that the extent of use of NC is related to the market and to the properties of the final product sold on that market.

Common to CNC none of the variables, specifically designed to pick up epidemic effects, nor the sample selection effect (LAMBDA) do significantly affect the extent of use of the technology.

Censoring of current users: visual inspection of the restricted model

If we exclude from the testing of the selection criterion equation those firms that no longer own NC, the sample size reduces of about one third as the technology dismissal rate is quite high. The variables significant in the previous model are still significant (see Table 7.3.a column 2), and with slightly higher coefficients. This happens for both steps of the model, with the exception of the within industry share effects in the corrected technology replacement equation (see Table 7.3.a/b column 1 and 2). The latter suggests that the intra industry effects are stronger in determining the decision to dismiss the use of the technology than it is to extensively use it, or alternatively that

the inter firm stock effects affect the probability of first adoption but not the intensity of the use soon after first adoption.

Contrary to the previous specification, the sample selection correction factor does slightly but not significantly affect the technology replacement equation at 7% ($\beta_{LAMBDA/LOGIT}$=1.08).

The Multinomial two stages sample selection approach

The Multinomial Logit model should measure the exact impact of the determinant of adoption on those firms currently undertaking the process of technology substitution.

The Sample Selection equation seems to indicate that the factors affecting the chance to adopt and currently use the technology are the same as those leading to the dismissal of the technology(see Table 7.3.a column 3 and 4). This result is not surprising, given the obsolescence of NC.

The size and the significance of coefficients confirms the results of previous specifications indicating that the only significant factors are size and stock/order effects.

In the corrected TR equation (see Table 7.3.b column 3) only the growth rate in the price of the alternative technologies seems to exert a marginal significant impact.

This suggests, once again, that in 1993 the technology replacement of NC is no longer significantly affected by the current economic and technological characteristics of the firm. The most innovative firms, which have in the past used NC, have already undertaken the process of technology replacement. What has driven this decision is mostly the change in the quality adjusted price of the alternative technologies (β_{LDTOT}=1.23), which should make their adoption more profitable than NC. However,

even if its sign is the right one, its significance can be rejected only at the 8% significance level. The theory would also predict that, its coefficient, in absence of price expectations, should equal 1. This hypothesis cannot be rejected (χ_2 =0.58), suggesting that the firm operates under perfect foresight and knows exactly what prices of the existing technologies are from one period to the other. This model also indicates that uncertainty plays no role upon further adoption of NC.

The determinants of the corrected Technology Replacement equation are reported in the last column of Table 7.3.b showing that the relative change in the price (β_{LDNC}=1.51) of NC does weakly affect the level of use of NC. Moreover, the firm is more likely to extensively use NC having already started the process of technology replacement with the most advanced technology CNC (β_{DCNC}=1.81) and being export oriented (β_{ex}= 0.50), although the latter are significant at 7%. There is also some evidence of intra industry stock effect for Industries 5,7 and 10, although only one of them shows the right sign (β_{SH5}=0.48, β_{SH7}= 0.30, β_{SH10}=-0.48). Moreover, similar to CNC, when the number of users is separated from the industry effect their significance disappear, indicating that these variables are only picking up some residual intra industry effects. The extent of use of NC is inversely related to the time since first adoption (β_{LNCY}=-2.05) and use 'make to order' production

Using this specification there is no significant evidence of sample selection effects (LAMBDA/MULTI).

Table 7.3.a. The selection criterion equation : NC

Time dimensional specification of the SC equation					*Cross-sectional specification of the SC equation*				
	1	*2*	3	4		5	6	7	8
Model Sample	*Logit* *Total firms*	*Logit* *Current users*	MULTI-SS		Model Sample	Logit *(Users& Non adopters)*	Logit *current user*	MULTI-SS	
	z=1	z=1	z=1	z=2	z=1	z=1	z=1	z=1	z=2
n	*169*	*101*	166	166	n	140	140	*136*	*136*
Constant	-9.22 (2.835)	*-11.97* *(4.599)*	-5.69 (2.64)	-6.70 (2.84)	Constant	-	-	-	-16.72 (7.183)
$LAGE_{\tau i}$	-	-	-		$LAGE_t$	-	-	-	
$LEsmall_{\tau i}$	4.12 (.993)	*4.98* *(1.625)*	4.24 (1.055)	4.44 (1.038)	$le93_t$	-	-	-	0.25* (1.345)
$LEmedium_{\tau i}$	3.08 (.724)	*3.62* *(1.122)*	3.21 (.762)	3.22 (.756)					
$LElarge_{\tau i}$	2.62 (.588)	*3.35* *(.992)*	2.69 (.614)	2.72 (.612)					
$DMICRO_{\tau i}$	-	*-4.23* *(1.72)*	-	-	$DMICRO_t$	-	-	-	-
$DCAPM_{\tau i}$	-	-	-	-	$DCAPM_t$	-	-	-	-
$DBS575_{\tau i}$	-2.44 (.946)	*-2.65** *(1.54)*	-2.03* (1.134)	-2.68 (1.151)	$DBS575_t$	-	-	-	-
$DJIT_{\tau i}$	-	-	-	-	$DJIT_t$	-	-	-	-
$DCOT_{\tau i}$	-	-	-	-	$DCOT_t$	-	-	-	-
$DCNC_{\tau i}$	-	-	-	-	$DCNC_t$	2.43 (1.027)	-	*5.29* *(1.901)*	-
-					$DCAD_t$	-	-	-	-
-					$DM\text{-}PROD_t$	-1.86 (0.728)	-	-	-
-					$R\&D93_t$	-	-	*4.71* *(2.729)*	5.88 (2.746)
-					$GROUP93_t$	-1.43 (0.620)	-	-	-
-					$lBATCH_t$	-	-	-	-
					$PS1_t...PS5_t$	n.s.	-	*n.s.*	*n.s*
$EX20_{\tau i}$	-	-	-	-	$EX20_t$	-	-	-	-
					$lcncsh_t$	-	-	-	-
$lSH1_{\tau i}$	n.s.	n.s.	n.s.	n.s.	$SH1_t$	-	-	*n.s.*	*n.s.*
$lSH2_{\tau i}$	-0.79 (.378)	-	-2.07 (.641)	-1.82 (0.654)	$SH2_t$	-	-	*-1.67* *(0.682)*	-
$lSH3_{\tau i}$	-0.75* (.399)	-	-2.16 (.656)	-1.75 (.667)	$SH3_t$	-	-	-	-
$lSH4_{\tau i}$	-1.01* (.460)	-	-2.12 (.838)	-	$SH4_t$	-	-	*n.s.*	*n.s.*
$LSH5_{\tau i}$	-0.81 (.382)	*-1.01* *(.529)*	-2.05 (.638)	-1.80 (.640)	$SH5_t$	-	-	-	-
$LSH6_{\tau i}$	-1.01 (.460)	*-1.45* *(.628)*	-2.26 (.684)	-1.97 (.698)	$SH6_t$	-	-	*n.s.*	*n.s.*
$LSH7_{\tau i}$	-		-2.01 (.620)	-1.48 (.627)	$SH7_t$	-	-	-	-
$LSH8_{\tau i}$	-0.95 (.401)	*-1.25* *(.580)*	-2.38 (.666)	-1.86 (.665)	$SH8_t$	-	-	-	-
$LSH9_{\tau i}$	-0.65* (.373)	-	-1.92 (.618)	-1.62 (.625)	$SH9_t$	-	-	-	-
$LSH10_{\tau i}$	-1.00 (.422)	*-1.31* *(.644)*	-2.31 (.673)	-1.96 (.668)	$SH10_t$	-	-	-	-
$LSH11_{\tau i}$	n.s.		-1.62 (.612)	-1.26 (.623)	$SH11_t$	-	-	-	-
$LSH12_{\tau i}$	-	-	-1.25 (.633)	-	$SH12_t$	-	-	-	-
$LSH13_{\tau i}$	-0.94 (.472)	*-1.24* *(.620)*	-2.30 (.708)	-1.92 (.720)	$SH13_t$	-	-	-	-
$LSH15_{\tau i}$	-	-	n.s.	n.s.	$SH15_t$	-	-	*n.s.*	*n.s*
Log-Lik	*-44.25*	*-25.67*	-123.22		Log-Lik	-53.40	-	*-68.49*	
L-ratio(χ^2)	*81.20*	*77.70*	104.85		L-ratio(χ^2)	85.45	-	*137.38*	

NOTE: The variables without star are significant between 0 and 5% significant level; * significant between 6 and 7%; standard errors in brackets; n.s. not specified; χ^2 is the calculated Likelihood ratio test that all the coefficients are zero

Time Versus Space Dimension of the Determinants of Adoption

Using the cross-sectional dimension (t=1993) instead of the time ($t=\tau_i$) dimension specification of the SC equation, the results are quite different. First of all the model only converges if the total sample is restricted to the sample of current users and non adopters, with the exclusion of those firms that, despite having in the past adopted the new technology, are no longer using it in 1993[14]. Column 4 in Table 7.3.a shows the results of the binary choice Logit model specification.

None of the effects significant in the previous time dimension specification are significant. In 1993 the probability to be an adopter is inversely related to the probability of belonging to an industrial group (GROUP93) and to have introduced micro-processors into the production processes (DMICRO). In 1993 none of the epidemic, while only a few stock variables, with opposite signs, are significant. Moreover, the number of firms that are still using NC have already adopted also CNC (DCNC) . This is a clear indicator that the adopters of NC are independent establishments that are slowly undertaking the process of technology substitution of NC with CNC and microprocessors.

Table 7.3.b. column 4, shows the estimates of the corresponding technology replacement equation. Contrary to the estimate of the probability to first adopt the new technology, the introduction of microprocessors ($\beta_{DM\text{-}PROC}$=0.91) and CNC (β_{DCNC}=1.81) in the production system of the firm does increase the probability to use NC, as it does whether the firm is export oriented (β_{EX20}=1.01).

14 In the sample there are no firms owning 100% of the technology. So the sample of extreme users is restricted only to the no longer user of the technology.

Intra-industry stock effects are significant but of the 'wrong' sign via the level of current users in Industry 5 and 7 , i.e. Mechanical Handling equipment and Agricultural Machinery and contractors plant and machinery (β_{SH5}=0.52 and β_{SH7}=0.47).

The model also shows the significance of epidemic effects, such as the years from the 'within industry' date of first adoption (β_{LNCSH}=1.19) and the years between first appearance of the technology and first adoption (β_{LYNC}=-4.44). However, its coefficient shows the wrong sign indicating that later adopters of NC use the technology less extensively than early adopters (moreover, their joint significance is only accepted at a 6% significance level (χ^2=5.473)).

It also emerges that old firms are less likely to extensively use NC (β_{LAGE}=-1).

Within the price effect only the impact of the growth rate of the price of NC technology is slightly significant (β_{LDNC}=1.77*). The theory would predict that β_{LDNC} should equal minus one. This hypothesis cannot be accepted (χ^2 = 8.057) contrary to the hypothesis that β_{LDNC}=1 (χ^2 =0.622). The explanation for this is that contrary to other technologies whose quality adjusted price decreases over time, the price of NC increases due to the obsolescence of the product. NC machines require cards , rather than computerised control as in the advanced version CNC. Moreover, as pointed out by Geoff Noon from the UK Technology Machine Tools Association, NC is now only available in the second hand market and its (quality adjusted) price increase reflects the obsolescence of the technology[15]. This is also reflected by the insignificance of the price of NC with respect to the existing technologies (QNQTOT) as well as the

[15] see footnote 1

absence of uncertainty related to further investments in NC. A further test on the relative contribution of price effect upon the total variability of the model (i.e. J-test for subset of coefficients) leads one to reject the hypothesis that prices significantly affect the spread of adoption on NC (estimated fitted values t=0.76).

From this model specification one would conclude that what affects technology replacement are mainly rank effects related to the technological characteristics of the production system of the firm. Those firms export oriented (EX20) and young firms (LNCY) that have recently adopted NC are more likely to extensively use NC. The only other significant factors are the technological characteristics of the production system and a few within industry share of users and epidemic effects. In none of the models presented so far, the variables accounting for prices significantly affect the intra firm diffusion of NC.

The cross-sectional dimension of the SC specification has yielded coefficients significantly different from the time dimensional specification. This is due to the different specification of the latent variable and to the different samples used in testing the models. This makes it impossible to compare the two models.

The process of NC technology replacement is difficult to model as it represents an obsolete technology at the end or close to the end of the diffusion process. Most of the problems are the consequences of the high number of adopters and the marginal level of use of the new technology leading to lack of robustness of the estimates.

The several steps of the testing procedure, it has emerged that the probability to adopt NC follows the Logistic curve (with Normality assumption the estimators do not converge). However, it is very difficult to determine what are the determinants of intra firm adoption. They cannot be uniquely defined as they change with the model specification and with the definition of the variables.

Table 7.3.b. The Technology Replacement Equation: NC

Time dimensional specification of the SC equation (t=τl)				*Cross-sectional specification of the SC equation (t=T)*			
	1	*2*	3		4	5	6
Model	*Logit*	*Logit*	**MULTI-SS**	**Model**	**Logit**	**Logit**	**MULTI-SS**
Sample	*Total firms*	*Current users.*	**Total Users**	**Sample Choice**	*Total Users*	*Current Users*	**Users**
Choice	z_{ti}=1	z_{ti}=1	z_{ti}=1		z_{ti}=1	z_{ti}=1	z_{ti}=1/ z_{ti} =2
n	*47*	*47*	*59*	*n*	*62*	*62*	59
Constant	-	-	-	**Constant**	-	-	-
$LDNC_{ti}$	-	-	-	**$LDNC_t$**	1.77* (.976)	-	*1.51 (.719)*
$LDTOT_{ti}$	-	-	1.23* (.915)	**$LDTOT_t$**	-	-	-
$QNQTOT_{ti}$	-	*-0.004 (.024)*	-	**$QNQTOT_t$**	-	-	-
$LBATCH_{ti}$	-	-	-	**$LBATCH_t$**	-	-	-
$GROUP93_{ti}$	-	-	-	**$GROUP93_t$**	-	-	-
$R\&D93_{ti}$	1.36 (.550)	*1.22 (.531)*	-	**$R\&D93_t$**	-	-	-
$LE93_{ti}$	-	-	-	**$LE93_t$**	-	-	-
$DLEsmall_{ti}$	n.s.	*n.s*	n.s	**$DLEsmall_t$**	n.s.	-	-
$DLEmedium_{ti}$	n.s.	*n.s*	n.s	**$DLEmedium_t$**	n.s.	-	-
$DLElarge_{ti}$	n.s.	*n.s*	n.s	**$LElarge_t$**	n.s.	-	-
$EX20_{ti}$	-	-	-	**$EX20_t$**	1.01 (.329)	-	*0.50* (.014)*
$LTURNOVER2Y_{ti}$	n.s.	*n.s*	-	**$LTURNOVER2Y_t$**	n.s.	-	-
$PL9091_{ti}$	-	-	-	**$PL9091_t$**	n.s.	-	-
$DCAD_{ti}$	-	-	-	**$DCAD_t$**	-	-	*-0.828 (.341)*
$DCAPM_{ti}$	-	-	-	**$DCAPM_t$**	-	-	-
$DM\text{-}PROD_{ti}$	2.28 (.376)	*2.31 (.643)*	-	**$DM\text{-}PROD_t$**	0.91* (.485)	-	-
$DJIT_{ti}$	-	-	-	**$DJIT_t$**	-	-	-
$DTQM_{ti}$	n.s.	n.s.	-	**$DTQM_t$**	n.s.	-	-
$DBS575_{ti}$	1.48 (.598)	*1.73 (.555)*	-	**$DBS575_t$**	-	-	-
$DMICRO_{ti}$	-	-	-	**$DMICRO_t$**	-	-	-
$DCOT_{ti}$	-	-	-	**$DCOT_t$**	-	-	-
$DCNC_{ti}$	1.73 (.974)	-	-	**$DCNC_t$**	1.81 (.878)	-	*1.61 (.216)*
$DROBOT_{ti}$	-	-	n.s.	**$DROBOT_t$**	n.s.	-	*n.s.*
$PS1_{ti}$	-1.39* (.843)	-	-	**$PS1_t$**	n.s.	-	-
$PS2_{ti}$	-	*-1.50* (.795)*	-	**$PS2_t$**	-	-	*1.096* (.614)*
$PS3_{ti}$	-	-	-	**$PS3_t$**	-	-	-
$PS4_{ti}$	-	-	-	**$PS4_t$**	-	-	-
$PS5_{ti}$	n.s.	n.s.	n.s.	**$PS5_t$**	-	-	-
$LAGE_{ti}$	-	-	-	**$LAGE_t$**	-1.00 (.363)	-	-
$LNCSHR_{ti}$	-		n.s.	**$LNCSHR_t$**	1.19* (.649)	-	-
$LNCY_{ti}$	-	-	n.s.	**$LNCY_t$**	-4.44 (1.987)	-	*-2.05 (.878)*
$LTNC_{ti}$	-	-	n.s.	**$LTNC_t$**	n.s.	-	-
$LIFOUT93_{ti}$	n.s.	n.s.	n.s.	**$LIFOUT93_t$**	n.s.	-	-
LAMBDA	-	*1.08* (.629)*	-	**LAMBDA**	-	-	-
$sh1_{ti}$	-	*1.19* (.795)*	*n.s.*	**$sh1_t$**	-	-	*n.s.*
$sh2_{ti}$/ $sh3_{ti}$	-	-	-	**$sh2_{ti}$/ $sh3_{ti}$**	-	-	-
$sh4_{ti}$	n.s.	*n.s.*	*n.s.*	**$sh4_t$**	n.s.	-	*n.s.*
$sh5_{ti}$	1.01 (.361)	*0.99 (.299)*	-	**$sh5_t$**	0.52* (.302)	-	*0.48*
$sh6_{ti}$	-	*n.s.*	-	**$sh6_t$**	-	-	-
$sh7_{ti}$	1.07 (.444)	*0.96 (.399)*	-	**$sh7_t$**	0.47 (.217)	-	*0.30*
$sh8_{ti}$	-	-	-	**$sh8_t$**	-	-	-
$sh9_{ti}$	0.85 (.328)	*0.73 (.254)*	-	**$sh9_t$**	-	-	-
$sh10_{ti}$	-	-	-	**$sh10_t$**	-	-	*-0.48*
$sh11_{ti}$	1.16 (.457)	*1.05 (.375)*	-	**$sh11_t$**	-	-	-
$sh12_{ti}$	1.05 (.400)	*0.88 (.354)*	-	**$sh12_t$**	-	-	-
$sh13_{ti}$	'0.69* (.404)	*0.60* (.344)*	-	**$sh13_t$**	-	-	-
$sh15_{ti}$	-	-	*n.s.*	**$sh15_t$**	-	-	*n.s.*
R2	0.89	*0.91*		*R2*	0.55	-	*0.70*
R2c	0.15	*0.28*		*R2c*	-0.13	-	*0.24*
Log-L	27.06	*30.80*	-67.58	Log-L	-44.07	-	-58.58
F	1.21	*1.44*	1.02	F	0.80	-	1.52

NOTE: variables without star significant between 0 and 5% significant level; * significant between 6% and 7% . ** significant at 8%; standard errors in brackets; n.s. not specified

However, as one would expect from an obsolete technology, the price effects are no longer the main determinants of adoption. They are rarely significant and if they are, they show the 'wrong' sign. The same applies to the stock effects. In same cases, some technological conditions are significant. However, this results should not be so surprising as NC is an obsolete technology that is slowly moving (by obsolescence) towards its post diffusion stage.

In fact, the joint significance of the variables cannot be rejected in any of the models presented so far (F-test in table).

7.3.3. The Replacement Process of Microprocessors Incorporated into Processes

Microprocessors incorporated into processes (Micro-p) appeared on the UK market at the beginning of the seventies. By 1993, similar to CNC, it has been adopted by about 76% of the British engineering and manufacturing firms in the CURDS sample.

However, the spread of use of Micro-p has occurred at a slower and more constant rate than CNC and it has been differently affected by the market and firm technological conditions. About 66% of the current users report that the proportion of the machine tool stock incorporating CoT technology is less than 30%. Only 7 % have a proportion in excess of 70 %, among them only 2% are using 100% of the technology.

<u>The Selection Criterion equation: Probit vs Logit Model Specification</u>

The first model specification looks at the shape of the probability for a firm to be an adopter in/by 1993. The time dependent specification of the SC equation indicates that both Logit and Probit specification model the data equally well (pseudo R_u^2=0.70

and R_r^2=0.68). In fact, the predicted probability of the two models is exactly the same, except for two observations. Consequently, the assumption of Normality cannot be rejected. The joint significance of all the coefficients of the Probit specification are highly significant (L-ratio (χ^2)= 77.37)

The parameter estimates of the Probit specification (see column 1 in table 7.4.a) show that among the rank effects, what determines the decision to first adopt Micro are: size, age and both technological and managerial characteristics of the establishment.

In particular the smaller is the firm at years just before adoption the less likely is to use Micro-p (LEsmall) while medium firms (LEmedium) are more likely than large firms (LElarge) to adopt Micro-p in their production processes.

The older is the establishment at time of adoption the less likely is to adopt the technology (YmicST). Among the adoption of the other technologies, it is significant whether, at time of first adoption, the firm has already introduced NC tools. Moreover, firms that have already introduced COT tools (DCoT) and have adopted TQM management innovation (DTQM) are less likely to adopt Microprocessors in their production processes.

The within share of adopters at time of adoption, i.e. stock/order effect, is significant only for two industrial sectors: sector 5 and 9 which are respectively mechanical Handling Equipment and Industrial Plants and Machinery.

The Technology Replacement Equation with Probit sample selection correction factor

The estimates of the TR equation corrected for the Selection Criterion effect are presented in Column 1 of Table 7.4.b. The empirical estimates show that both price and rank effects do affect the speed of technology replacement. The introduction of a new technology is higher the greater is the change (reduction) in its price (β_{LDQM} =-

0.24) and the lower is the reduction in the cost of the existing technology (β_{LDQTOT}=2.69). The intra firm model would indicate that in the absence of price expectations the coefficient of both prices equals, in absolute value, 1. This hypothesis cannot be rejected for the price of the existing technologies (β_{LDQTOT}: χ^2=2.249) while it is rejected for the price of Micro (β_{LDQM}: χ^2=4.369). This would indicate that the firm formulates its investment decision upon expectations about future prices of the new technology, but not for the existing set of technologies.

The difference between the relative rate of change in its price and the price of the existing technology (β_{QDTM}= -0.29) is significant. Its coefficient reflects the impact of uncertainty, interest and devaluation of the existing capital stock, i.e. ($r+\delta+1/2\sigma^2\beta_1$). This means that in absence of uncertainty β_{QDTM} should equal ($r+\delta$), i.e. 0.075. This hypothesis cannot be accepted (χ^2=14.4) implying that uncertainty affects the investments decision. One can further calculate the marginal impact of uncertainty ($1/2\sigma^2\beta_1$) after subtracting from β_{QDTM} the estimate of the interest rate and depreciation, ($r+\delta$). This yields an estimate average uncertainty ($1/2\sigma^2\beta_1$) of 0.215.

The joint significance of the price effect (J-test: β_{QDTM} =β_{QDTot} =$\beta_{QM\text{-}TOT}$=0) would also indicate that it significantly contributes to the explanation of the total variability of the model (t=7.992) and its inclusion leads to an increase in the goodness of fit (R^2) from 0.68 to 0.78.

As in the decision to become an adopter the younger is the establishment the more likely it is to use Micro-p extensively (LYSTURTUP=-2.07).The size effect is significant only for small firms ($\beta_{DLEsmall}$ =-0.53) and its sign is negative.It is also significant whether the firm does in house R&D ($\beta_{R\&D}$=-3.07) and whether it belongs

to a group ($\beta_{GROUP93}$=1.09). Also the financial position in years just before 1993 plays a significant role ($\beta_{LTURNOVER2Y}$ = 0.42). Among the other rank effect the characteristics of the production system play a relevant role such as: the dimension of the average batch size (β_{BATCH}= -0.19), whether the firm has introduced technological innovations (β_{DCoT}=-1.48, β_{DCNC}=2.14, β_{DCAD}=1.59) , managerial innovations (β_{DJIT}=-0.91; β_{DTQM}=2.44; β_{DBS575}=-0.92) and whether the firm has the production system characteristics Make to stock (β_{PS3}=-1.58), Job shop (β_{PS4}=3.14) and Mixed systems (β_{PS5}=-1.33).

The within industry share of users , i.e. stock effect is significant only for sector 6 and 12, which are respectively General Mechanical Engineering and Electrical Machinery. However, if the industry effects are specified separately from the within industry number of users, the first are still significant while the second are totally insignificant.

The sample selection effect , i.e. LAMBDA, is not significant.

In summary, one can conclude that what determines the extensive use of this new technology are rank and stock effects via the relative cost of the technology, while epidemic effects are absent.

Censoring effects in the TR equation.

The preliminary investigation of the magnitude of the censoring is carried out by visual inspection, comparing the previous results for the total sample of firms with those obtained using only the sample of current users (excluding from the SS equation those firms that are using 0% and 100% of the new technology).

The parameters of the reduced sample estimates of the corrected TR equation do show slightly lower but not significantly different values than in the unrestricted case (see Table 7.4.a column 1). This is confirmed by the plotting of the predictive value of the two models which yield exactly the same result and by the goodness of fit of the Sample Criterion (R_r^2=0.7 and R_u^2=0.68) and Technology Replacement equation (R_r^2=R_u^2=0.78).

Table 7.4.a. Time dimension specification of the SC equation: Micro-Processors

	1		2		3	
Model	**Probit**	**Probit**	**Logit**	**Logit**	**Multi-SS**	
Sample	*Total firms*	*Current Users*	*Total firms*	*Current Users*	*Total firms*	
Choice	z_{it}=1	z_{it}=1	z_{it}=1	z_{it}=1	z_{it}=1	z_{it}=2
N	158	*138*	158	*138*	158	158
Constant	3.46	*2.86*	5.93	*4.84*	5.09	5.27
	(.981)	*(1.051)*	(1.756)	*(1.84)*	(1.809)	(2.993)
	-0.79	*-0.72*	-1.34	*-1.21*	-1.21	-1.87
LYSTURTUP$_{ti}$	(.264)	*(.283)*	(.460)	*(.450)*	(.472)	(.604)
LEsmall$_{ti}$	-0.13	*-0.12*	-0.22	*-0.21*	-0.21	-
	(.044)	*(.048)*	(.078)	*(.084)*	(.080)	
LEmedium$_{ti}$	0.26	*0.26*	0.44	*0.44*	0.45	0.63
	(.070)	*(0.071)*	(.129)	*(.128)*	(.129)	(.369)
LElarge$_{ti}$	0.13	*0.12*	0.21	*0.21*	0.20	-
	(.044)	*(.048)*	(.078)	*(.084)*	(.670)	
DCAPM$_{ti}$	-	-	-	-	-	
DBS575$_{ti}$	-	-	-	-	-	-
DJIT$_{ti}$	-	-	-	-	-	-
DTQM$_{ti}$	-1.03	-	-	-	-	-
	(.623)					
DCOT$_{ti}$	-0.63	*-0.62**	-1.05	*-1.04**	-1.10	-
	(.360)	*(.372)*	(.624)	*(.642)*	(.640)	
DNC$_{ti}$	0.78	*0.82*	1.27	*1.36*	1.34	-
	(.387)	*(.411)*	(.677)	*(.721)*	(.701)	
DCNC$_{ti}$	-	0.60*	-	-	-	-
		(.370)				
lsh2$_{ti}$	-	-		-		
lsh3$_{ti}$	-	-		-		
Lsh5$_{ti}$	-0.30	-	-0.53	-	-0.61	-
	(.183)		(.312)		(.345)	
Lsh678$_{ti}$	-	-	-	-	-	-
Lsh9$_{ti}$	-0.38	*-0.37*	-0.65	*-0.61*	-0.65	-
	(.142)	*(.142)*	(.253)	*(.249)*	(.345)	
Lsh10$_{ti}$	-	-	-	-	-	-
Lsh12$_{ti}$	-	-	-	-	-	-
Lshgroup$_{ti}$	-	*-0.26*	-	*-0.43*	-	-
		(.150)		*(.261)*		
Log-Lik	-60.69	*-54.94*	-61.26	*-55.49*	-101.01	
L-ratio (χ^2)	77.37	*71.93*	76.24	*70.82*	99.81	

NOTE: variables without star significant between 0 and 5% significant level; *significant at 6%; standard error in brackets. n.s. not specified; χ^2 = calculated Likelihood ratio test that all the coefficients are zero.

From this preliminary intuitive approach, one could say that the impact of censoring is not significant as almost no firms are using extreme values of micro-p.

The multinomial selection rule allows one to explicitly modelling the censoring in the first step of the model (i.e. SC Equation). This specification shows a higher explanatory power of the total variability of the model (R^2=0.79 -R^2_c= 0.26) (see Table 7.4.a. column 5).

The censoring correction shows that, in 1993, the probability of extensively using the technology is determined by the same factors as in the binomial model. However, the size of the coefficients of those firms that decide to currently use the technology in 1993 are slightly higher than in the binomial case. Also in this case the significant positive effects are the size of the firm and whether the firm uses NC, and significant negative effects are related to the age of the establishment and whether the firm has already adopted CoT. There is also evidence of stock/order effects within Industry 5 (i.e. Mechanical Handling equipment) and 9 (industrial (including process) plant and steelworks).

The Sample selection criterion hints that those firms more likely to currently using the new technology are relatively young and medium sized firms. The adoption of Micro is only affected by whether the firm already owns NC and CoT.

The correction for censoring also shows that the probability to move to the extremes of the technology adoption (i.e. 0% or 100%) is significant only for medium size firms ($\beta_{lEmedium}$=0.63) and it is inversely related to age (β_{LAGE} =-1.87). This would suggest that the technology is still widely in use and few factors affect its dismissal.

The technology replacement equation yields results consistent with the previous model specifications. What determines the further extent of use of a new technology is

both rank and price effects. Among the rank effects the significant variables are: composition of the existing set of technologies, average batch size, managerial innovation, characteristics of the production system, financial position of the firm in years before 1993 and whether the firm belongs to a group. It also shows that size is not relevant except for small firms that are less likely to extensively using the new technology.

The variables accounting for the price effect are also significant and their joint significance can be rejected (Ho: $\beta_{LDMicroo}=\beta_{LDTOT}=\beta_{LDM\text{-}TOT}=0$, J-test:t=11.53). Moreover, they joint specification in the technology replacement equation increases the goodness of fit of the model (R^2) from 0.72 to 0.78 and lowers the max likelihood from –28.71 to –16.67.

The price effects also indicate that there exist expectations about the price of the new technology (H_o:β_{LDQM}=-1, χ^2=0.042) but not about the price of the existing technologies (H_o:β_{LDTOT}=1, χ^2=2.216). Also uncertainty, even if not as large as for CNC, does significantly affect (H_o:$\beta_{LM\text{-}TOT}$=-0.075, χ^2=14.23) the decision to further invest on Micro and equals 0.185.

Finally, the model predicts that Industry effects are significant for industry 6 and 12, while the hypothesis of stock effects has been rejected, given the insignificance of the separate estimate of Industry and share of adoption effects.

In none of the specifications the epidemic effects or the Sample Criterion\Effect (lambda) turn out to be significant.

Table 7.4.b . Time dimension specification of the TR equation: Micro-Processors

	1		2		3		4		5	
	Probit SS *Total firms* $z_{it}=1$		Probit SS *Uses* $z_{it}=1$		Logit SS Total firms $z_{it}=1$		Logit SS Users $z_{it}=1$		Multi-SS Total firms $z_{it}=1$	$z_{it}=2$
n=54										
Constant	-	-	-	-	-	-	-	-	n.s.	n.s.
LDQM	-0.24	-0.24	-0.23	-0.23	-0.24	-0.24	-0.23	-0.23	-0.36	-0.36
	(.122)	(.122)	(.115)	(.115)	(.206)	(.206)	(.116)	(.116)	(.116)	(.116)
LDQTOT	2.69	2.69	2.67	2.67	2.71	2.71	2.69	2.69	2.66	2.66
	(.122)	(.122)	(1.125)	(1.125)	(1.140)	(1.140)	(1.135)	(1.135)	(1.01)	(1.01)
QDM-TOT	-0.29	-0.29	-0.29	-0.29	-0.29	-0.29	-0.29	-0.29	-0.31	-0.31
	(2.709)	(2.709)	(.083)	(.083)	(.084)	(.084)	(.084)	(.084)	(.084)	(.084)
LBATCH	-0.19	-0.19	-0.19	-0.19	-0.19	-0.19	-1.91	-1.91	-0.18	-0.18
	(.085)	(.085)	(.083)	(.083)	(.085)	(.085)	(.083)	(.083)	(.264)	(.264)
GROUP93	1.09	1.09	1.07	1.07	1.10	1.10	1.08	1.08	1.13	1.13
	(.322)	(.322)	(.309)	(.309)	(.322)	(.322)	(.315)	(.315)	(.304)	(.304)
R&D93	-3.07	-3.07	-3.06	-3.06	-3.09	-3.09	-3.09	-3.09	-3.21	-3.21
	(.663)	(.663)	(.658)	(.658)	(.663)	(.663)	(.668)	(.668)	(.644)	(.644)
LEsmall	-0.52	-0.52	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	-0.54	-0.54
	(.253)	(.253)	(.250)	(.250)	(.253)	(.253)	(.253)	(.253)	(.234)	(.234)
LEmedium	(-0.10)	(-0.10)	(-0.09)	(-0.09)	(-0.11)	(-0.11)	(-0.10)	(-0.10)	(-0.11)	(-0.11)
	(.133)	(.133)	(.129)	(.129)	(.133)	(.133)	(132)	(132)	(.120)	(.120)
LElarge	(0.08)	(0.08)	(0.10)	(0.10)	(0.08)	(0.08)	(0.09)	(0.09)	(-0.07)	(-0.07)
	(.149)	(.149)	(.144)	(.144)	(.149)	(.149)	(.147)	(.147)	(.144)	(.144)
EX20	-	-	-	-	-	-	-	-	-	-
Lturnover2y	0.42	0.42	0.41	0.41	0.42	0.42	0.41	0.41	0.39	0.39
	(.206)	(.206)	(.201)	(.201)	(.206)	(.206)	(.202)	(.202)	(.204)	(.204)
CAPM	-	-	-	-	-	-	-	-	-	-
MPROD	-	-	-	-	-	-	-	-	-	-
JIT	-0.91	-0.91	-0.87	-0.87	-0.92	-0.92	-0.90	-0.90	-0.96	-0.96
	(.386)	(.386)	(.362)	(.362)	(.386)	(.386)	(.315)	(.315)	(.347)	(.347)
TQM	2.44	2.44	2.41	2.41	2.46	2.46	2.44	2.44	2.50	2.50
	(.419)	(.419)	(.406)	(.406)	(.419)	(.419)	(.668)	(.668)	(.407)	(.407)
DBS575	-0.92	-0.92	-0.93	-0.93	-0.93	-0.93	-0.95	-0.95	-0.97	-0.97
	(.394)	(.394)	(.403)	(.403)	(.394)	(.394)	(.407)	(.407)	(.388)	(.388)
DCAD	1.59	1.59	1.55	1.55	1.61	1.61	1.58	1.58	1.69	1.69
	(.525)	(.525)	(.506)	(.506)	(.525)	(.525)	(.514)	(.514)	(.504)	(.504)
DCNC	2.14	2.14	2.10	2.10	2.17	2.17	2.13	2.13	2.41	2.41
	(.873)	(.873)	(.842)	(.842)	(.873)	(.873)	(.860)	(.860)	(.783)	(.783)
DCOT	-1.48	-1.48	-1.49	-1.49	-1.47	-1.47	-1.47	-1.47	-1.39	-1.39
	(.412)	(.412)	(.412)	(.412)	(.412)	(.412)	(.417)	(.417)	(.397)	(.397)
DNC	-	-	-	-	-	-	-	-	-1.45	-1.45
									(.736)	(.736)
ROBOT	-	-	-	-	-	-	-	-	-	<-
PS2	-	-	-	-	-	-	-	-	-	<-
PS3	-1.58	-1.58	-1.56	-1.59	-1.59	-1.59	-1.57	-1.57	-1.70	-1.70
	(.578)	(.578)	(.571)	(.578)	(.578)	(.578)	(.576)	(.576)	(.504)	(.504)
PS4	3.14	3.14	3.14	3.16	3.16	3.16	3.17	3.17	3.22	3.22
	(.749)	(.749)	(.750)	(.749)	(.749)	(.749)	(.756)	(.756)	(.738)	(.738)
PS5	-1.33	-1.33	-1.31	-1.35	-1.35	-1.35	-1.34	-1.34	-1.42	-1.42
	(.725)	(.725)	(.719)	(.725)	(.725)	(.725)	(.729)	(.729)	(.700)	(.700)
LAGE	-2.07	-2.07	-2.09	-2.08	-2.08	-2.08	-2.08	-2.08	-1.74	-1.74
	(.347)	(.347)	(.346)	(.347)	(.347)	(.347)	(.348)	(.348)	(.821)	(.821)
Liusers	-	n.s.	-	n.s.	-	n.s.	-	n.s.	-	n.s.
D5	-2.69	n.s.	-2.62	n.s.	-2.70	n.s.	-2.64	n.s.	n.s.	-2.92
	(.958)		(.931)		(.958)		(.944)			(.878)
D6	-5.84	n.s.	-5.82	n.s.	-5.86	n.s.	-5.87	n.s.	n.s.	-6.38
	(1.416)		(1.426)		(1.42)		(1.432)			(1.355)
D9	-1.47	n.s.	-1.46	n.s.	-1.48	n.s.	-1.44	n.s.	n.s.	-1.57
	(.736)		(.722)		(.736)		(.730)			(.714)
D10	-1.54	n.s.	-1.55	n.s.	-1.54	n.s.	-1.55	n.s.	n.s.	-1.72
	(.691)		(.686)		(.963)		(.691)			(.686)
D11	-2.76	n.s.	-2.66	n.s.	-2.76	n.s.	-2.72	n.s.	n.s.	-3.05
	(.963)		(.939)		(.963)		(.956)			(.928)
D12	-7.11	n.s.	-6.99	n.s.	-7.11	n.s.	-7.09	n.s.	n.s.	-7.60
	(1.586)		(1.564)		(1.586)		(1.59)			(1.500)
LAMBDA	-	-	-	-	-	-	-	-	-	-
sh6	n.s.	-1.47*	n.s.	-1.43	n.s.	-1.48	n.s.	-1.45	-1.75	n.s.
		(.842)		(.829)		(.842)			(1.506)	
sh12	n.s.	-1.83	n.s.	-1.78	n.s.	-1.85	n.s.	-1.81	-2.12	n.s.
		(.844)		(.827)		(.844)			(1.509)	
R2	0.78	<-	0.78	<-	0.78	<-	0.78	<-	0.79	<-
R2c	0.23	<-	0.24	<-	0.24	<-	0.23	<-	0.26	<-
Log-L	-16.62	<-	-16.41	<-	-16.58	<-	-16.62	<-	-50.08	<-
F	2.42		2.42				2.42		2.50	

NOTE: variables shown are all significant between 0 and 5% significant level; standard error in brackets; n.s. not specified

Time Vs space specification of the Sample Selection model specification

The time versus space specification does not yield good results.

Whether the SC equations are binomial or multinomial, the coefficients are hardly significant, except for the adoption of CAD (β_{CAD}=0.35) and the possession of BS5750/ISO9000 accreditation (β_{DBS575}=0.20). Moreover, in the second step of the model, none of the lambda's (selection correction factors) are significant. For this reason the results are omitted. Thus in this case as well, the time dimension specification has been shown to be superior to the space dimension specification of the determinants of first adoption.

In summary, the testing of Micro-p has shown that the probability to become an adopter is Normally distributed. The model estimates are consistent across specifications and what determines the replacement of the old with the new is mostly driven by Rank and price effects. There is no evidence of Epidemic or other stock effects and the extent of use of a technology is independent of the decision to adopt a new technology. As for CNC, the intra firm technology replacement model has been shown to reasonably well explain the heterogeneity in the level of use of Microprocessors for a sample of UK British and manufacturing firms.

7.4. Summary of the results

The technology replacement model has been used to model the adoption pattern of three technologies available in the CURDS data set (CNC, NC, Micro-p). The final empirical estimates indicate that the theoretical intra firm model can explain the

process of technology substitution of the old with the new technology, for two out of three technologies. They are Computerised Numerically Controlled and Microprocessors incorporated into processes.

The testing of the Numerically Controlled tool machine case is very problematic. It often yields inconsistent parameter estimates, wrong sign for the coefficients and most importantly never explains a relevant proportion of total variability (see joint significance of the coefficients). This has to be related to the fact that NC appeared on the market in 1955 and in 1993, after about 40 years, only few firms are still using it. Being an obsolete technology, most of the current users are dismissing its use in their production system and introducing more advanced technologies, like for example CNC. Consequently NC can no longer be considered an advanced technology as required by the intra-firm model. NC is rather a technology that has reached its post diffusion stage and is no longer sold on the market (except the second hand market). The high presence of ex-users has in fact led to the rejection of the hypothesis of Normality of the probability of adoption. Also the overall extremely low level of ownership has created several problems in the testing of the model, such as the non-convergence of the estimators or parameters inconsistent across the different model specifications. This is mostly because we were trying to model the introduction of further technology instead of its dismissal, which, given the irreversibility of the investments, occur in the theory only by obsolescence. Moreover, NC machines are out of production. They can be bought only in the second hand market. That is probably why none of the variables accounting for the stock, or price effects, are relevant. It also explains why the determinants of adoption were not consistently significant.

In the case of CNC and Micro-p the empirical results are very satisfactory. For both technologies the probability to become an adopter (i.e. the sample selection criterion) is Normally distributed, and using the time or space specification of the independent variables does not significantly affect the estimates of the corrected technology transfer equation. In fact, the sample selection correction factor (LAMBDA) is never significant , whatever specification of the sample selection model is used. This suggests that the extent of use of the new technology is independent of the decision to first adopt the new technology. Confirming the prediction of Chapter 2, to become an adopter does not necessarily imply to be an extensive user (even if both effects are necessary to the spread of the use of a new technology).

Table 7.5. The determinants of the Intra Firm Technology Replacement

	CNC	Micro in processes
Rank effect:		
-Adoption of other technologies	Micro in processes (+) Micro in products (-) CAD (+) , Robot (+)	Micro in products (-) CAD (+), CNC(+), COT(-)
-Managerial innovation	-	Just in time (-) Total quality management (+) BS575 Quality Accreditation (-)
-Production system	Make to order	All but Make to order (various) Average batch size (+)
- Liquidity	-	Average Turnover
- Size	Small firm (E<50) (+)	Small firm (E<50) (-)
- Within industry effects	I10	I5, I6, I9,I10,I11,I12
- Other	R&D (+), Group (+), Export(-)	R&D (-), Group (+), Age (-)
Price effect:		
-growth rate (dq_o)	significant (+)	significant (+)
- growth rate (dq_n)	significant (-)	significant (-)
- relative difference[q_n/dq_n-q_n/dq_n]	significant	significant
- Uncertainty ($\frac{1}{2}\sigma^2\beta_1$)	significant (0.4)	significant (0.2)
- Expectations (γ_3=forec. error)	new technology γ_n=1.5 old technology γ_o=0	new technology γ_n= −0.8 old technology γ_o=1.66
Epidemic effects	-	-
Inter firm Stock effects	(sh10)	(sh6 , sh12)
Sample selection LAMBDA	-	-

The estimates of the Technology Replacement equation confirm the predictions of the intra firm model presented in Chapter, suggesting that what determines the replacement of the old with the new technology are price and rank effects. For both technologies, in both models these two effects are highly significant. They are firm and technology specific and they are also consistent across the different specifications used in the model specification. They are summarised in Table 7.5.

The rank effects reflect the core competencies and the technological characteristics of the production system of the firm. For CNC they would indicate that extensive users are small firms, doing in house R&D, not very export oriented and with production systems that make to order.

Micro tends to be adopted more extensively by younger and larger firms, not export oriented, not doing internal R&D and without quality accreditation. Its adoption is influenced by the financial position of the firm in previous years and, contrary to CNC, is compatible with different production system.

The empirical estimates have also shown that , for both CNC and Micro, the intensity of adoption is not independent of the adoption of the other technologies, whose significance and sign are technology specific. This indicates that technological compatibility and cumulative knowledge from the experience of previous technologies play a relevant role in the extent of use of a new technology. Among the rank effects, whether the firm belongs to an industrial group has turn out highly significant and positive in both technologies. This confirms the predictions of Cainarca et al. (1990) indicating that firms belonging to large groups do show higher rates of adoption than independent firms.

Also the price effect, as predicted by the intra firm model, is highly significant in determining the current level of use of the technologies. The coefficients are all significant and of the right sign.

The hypothesis of expectations about the price of the advanced technology (CNC /MICRO) cannot be rejected, while they do not seem to hold for the prices of the existing capital stock.

Also uncertainty about future market conditions has turned out to be significant for both technologies (slowing down the diffusion of CNC and fastening the diffusion of Micro-processors). This, together with the price expectations, seems to significantly affect the process of technology replacement.

As predicted by the intra firm model, none of the epidemic effects affect the intra firm diffusion process. The same can be said for inter-firm stock effects, whose significance disappears if substituted with industry dummies effects. The reasons for this is that the stock effects are already picked up by the intra firm model. The information spreading mechanism, suggested by the epidemic effects, does not explain the dynamic of technology replacement, while the rank effects are highly significant. This confirms the hypothesis that it is the capability of the firm to process information, via its own core competencies (i.e. firm specificity), and not the amount of information, that is the right learning mechanism.

7.5. Conclusions

This chapter has tested the new intra firm model of technology replacement presented in this thesis. The estimating procedure has required some statistical caveats due to the characteristics of both model specification and the data set.

The intra firm model looks at the determinants of technology replacement from a point immediately after first adoption until the diffusion is completed for the firm . This implies that it is defined only for the current users of the new technology, with the exclusion of non adopters and extreme users, (i.e. those using 0%, but having used higher levels in the past) and 100% of the new technology). Consequently the model must be modified to take into account both the sample selection due to the exclusion of non adopters , as well as the censoring due to the exclusion of extreme users.

The first type of problem has been overcome using the two step Heckman procedure (Heckman 1979) , the first step modelling the probability to be an adopter in/by 1993 , the second modelling the final estimating equation corrected by the sample selection factor derived in the first step of the model. One of the problems in using this approach is that both steps are defined simultaneously over the same information set, causing overparametrization and endogeneity, and spurious significance of the sample selection correction factor and final parameters estimates. For this reason an alternative 'time dimensional' specification has been proposed based upon the fact that the adoption decision is irreversible and is determined by the market and firm condition at the time the decision is taken. The second type of problem, i.e. the censoring, has been overcome using a multinomial specification for the selection criterion equation in the first step of the model.

After a meticulous testing of each step of the model specification, the empirical estimates have shown that the prediction of the new equilibrium intra firm model are correct and what determines the extensive use of a new technology are rank and price effects. The former are firm specific and reflect the core competencies of the firm such as: technological characteristics of the existing production system; management ; production organisation; size; whether the firm do R&D, etc. The second is a function of price reduction, uncertainty and price expectations about the new technology.

Contrary to the inter firm literature, this model suggests that epidemic type of learning does not effect the intra firm diffusion of a new technology.

Among the other inter firm effects, the order effect does not apply to intra firm diffusion, while inter-firm stock effects, as expected, do not influence the process of technology substitution. In fact, as a further cross check, they were specified into the empirical model. However, when industry dummies are introduced, the effect of the stock variable vanishes.

Chapter 8.

CONCLUSION

In the economy one can observe many examples of the spread of new technology (where, by new technology we mean here a process innovation or an advanced cost-reducing technology incorporated into capital goods). In most firms and for most technologies the time period between first use of a technology and 100 percent use of that technology, is often many years (see Stoneman and Karshenas (1995) for a survey). If one believes that technological progress is the key to success or in some cases survival for firms, why do they not immediately transfer all their production to the new technology, but instead wait? Why does the firm's replacement of old by the new technology take so long (and sometimes not even reach full completion)?
This thesis is aimed at answering such questions by looking into the black box of the almost unexplored process of technology transfer at the firm level.

The process by which the use and/or ownership of a new technology spreads over time has been the major interest of a specific research area traditionally referred to as technology diffusion. However, most of this literature is concerned with the inter-firm diffusion of innovations, that is the process that leads firms to first adopt innovative technologies (See for example the game theoretical approach of Reinganum (1981), or Funderberger and Tirole (1985), also the empirical evidence provided by Colombo and Mosconi (1985) on the spread of ownership of flexible automative technologies, the several studies of Stoneman and various co-authors (1994, 1995, 1997,etc) on the spread of NC, CoT and CNC, etc.). Intra-firm diffusion, that is the process determining the time path of use of a technology within a firm from

a point immediately after first use until diffusion is complete for that firm, has been almost completely ignored.

The paucity of suitable data for analysing the diffusion of this phenomenon is one of the main reasons why intra firm diffusion has been relatively ignored in the literature. The CURDS data set used in this thesis is one of the rare data sets that provides information on intra firm diffusion, in this case for a sample of 343 establishments in the UK Engineering and metalworking sector on the pattern of ownership and use over time of four technologies: Numerical control of metal cutting, forming or joining tools (NC); Computerised numerical control of metal cutting forming or joining tools (CNC); Coated Carbide or Ceramic Tools or Inserts for metal cutting (CoT); and Microprocessors incorporated in processes (MICRO).

In *Chapter two* of this thesis it has been shown that if one is interested in the *extent of use* of a new technology in an industry then it is just as important to understand the development of technology use within the firm after first use (intra-firm diffusion) as it is to understand the pattern of first use across firms (inter-firm diffusion). Using the information in the CURDS data set, the differences between these two aspects of technology spreading has been shown. Inter-firm diffusion has been represented by the distribution of the number of firms that have adopted the new technology, with intra-firm diffusion by the extent of use of the new technologies by each firm in 1993. The main findings indicate that: i) the diffusion path across firms over time is technology specific and occurs at different speeds; ii) at each moment in time the level of new technology ownership across firms is quite heterogeneous. Consequently, if one wants to measure the industry benefits from a new technology, to look only at the number of adopters (inter firm diffusion) could be highly misleading (as each firm might produce only a very small proportion of its output with the new technology).

What determines the total industry output produced with the new technology (and thus the industry benefits from adoption) is a combination of both the number of adopters (inter firm diffusion) and the proportion of output produced on the new technology by the adopters (intra firm diffusion).

This chapter has also shown that in the early years of technology spreading, the inter firm effects exert a slightly greater impact on diffusion than intra firm effects, while the opposite is true for the remaining period. The impact of intra-firm diffusion on total industry output produced on the new technology is persistently greater than the inter firm level of adoption and its importance also greatly increases over time. For these reasons, and because the intra firm effect has been widely overlooked, this thesis has concentrated on the spread of the new technology within firms rather than the spreading across firms.

Chapter three has looked at the limited literature upon intra firm diffusion where there are only two principle pieces of work: the Mansfield (1968) and the Stoneman (1981) models. As in many inter-firm diffusion studies, the Mansfield Model assumes that the spread of use of a new process embodied in a new capital good follows an S-shaped curve and what determines the spread of adoption over time is information acquisition about the true performance of the technology. This is basically a disequilibrium process driven by passive information acquisition. Stoneman (1981) presents an alternative equilibrium learning model showing that diffusion is faster the greater is the true profitability of the new technology. However, despite the sophisticated theory, the Stoneman Model is intractable empirically.

Using the information in the CURDS data set, the predictions of the milestone Mansfield model have been tested empirically. The results reported in chapter 3 have shown that there is little support for the predictions of this seminal disequilibrium

model and that information spreading explains only a small part of the observed diffusion pattern. This, together with other theoretical and empirical weaknesses, has led us to abandon this type of approach in favour of an alternative equilibrium approach incorporating the intra firm version of rank, stock, and epidemic effects. Those effects have been determined for inter-firm studies (see Davies 1979, David 1991, Reinganum 1981, Stoneman and Kwon 1998, Mansfield 1995, etc) but have never been applied before to intra firm studies. A preliminary empirical approach is based around the use of a Tobit model (Tobin, 1957) which takes into account the role of technology complementarities; it better exploits the information in the CURDS sample and the censoring due to observations with zero use of technology (i.e. ex users). The empirical estimates indicate that diffusion does not strictly follow a Logistic curve as suggested by Mansfield. Information spreading, it seems, is not the main determinant of the spread of adoption. The replacement of old with the new technology is better explained by an equilibrium approach, the factors that drive the intra-firm diffusion process of a new technology being basically time since first adoption, firm size, and other technologies in use. The results also suggest that as newer technologies are introduced, older technologies will be used less extensively.

In essence this preliminary analysis suggests that what is significant in the determination of the use of a new technology within the firm are rank effects while there is some ambiguity as to whether epidemic effects also pick up stock effects. So, even if the Mansfield type epidemic effects are significant they are not the only determinants of adoption.

The stock effect plays a major role in inter-firm studies and predicts that it is mainly profitability considerations and changes in the returns from adoption over time that determines the adoption of a new technology (see for example Reinganum, 1981a, 1981b, 1983, Quirmbach, 1986,etc.). Similarly, one would expect that at the intra firm

level, for a given cost of the technology, what leads the firm to further invest in a new technology are mainly the expected profit gains from its extended use. If the expected benefits from adoption decrease with the within firm extent of use, they may be a disincentive to immediately replace all the existing capital with the more advanced type. On the contrary, if profits are unbounded, i.e. increase with the extent of use of a new technology, the firm might want to extensively use the new technology right from the start. This could explain why firms do not immediately switch to the new technology but wait. Moreover, if it were assumed that profit gains are firm specific and that some firms might find it profitable to switch only when costs reach a certain level, this approach could also explain the heterogeneity of technology ownership across firms and over time. This aspect of technology transfer has been neglected by the existing intra-firm literature.

Chapter four has explored this possibility via a model based upon 'intra firm stock effects'. The derivation of the model was not straightforward. Basically, two types of approaches have been used to model the shape of the relationship between profit gains (and the total production costs) and the adoption of a new technology. These are the cost function approach and the multiple technology approach. The former defines the impact from the extended use of a new technology via a reduction in total production costs, the latter via its impact upon the total capacity of the firm. However, neither of the two specifications allows one to determine whether profits gains are decreasing or increasing with the level of adoption of a new technology. In particular the shape of the profit-cost curve has been proved to depend upon the type of demand function for the firm's final output. In the case of constant elasticity of demand, profit gains are unbounded, whereas when using a linear demand function, profits are bounded. Moreover, while following the cost approach it was not possible to define the optimal

combination of the new and the existing technologies, the multiple technology approach has resulted being independent of the shape of the demand curve and yielding the same results in both the monopolistic and the competitive case.

In summary, neither of the approaches followed in chapter 4 provides a rationale as to why it is rational for a firm not to immediately switch to a new technology but wait. The results indicate that there may well exist stock effects, but their impact is not consistent across different specifications and in particular depend upon the shape of the demand curve. However, the models consistently suggest that the decision of the firm to increase the proportion of more advanced machinery in use is mostly driven by: a) the relative reduction in the price of the technology over time and b) the higher productivity of the new technology with respect to the existing. What these models neglect is that a reduction in costs might itself have a cost. In fact, neither of the specifications takes into account the investment cost of buying the new technology. In this respect the inter firm literature would suggest that not only the acquisition cost of a new technology but also relative price expectations (see for example Stoneman and Karshenas, 1994 and Stoneman and Kwon, 1996), will play an important role in diffusion. Moreover, given the long time path of adoption of a new technology, a model of intra firm diffusion should take into account that the firms operate under different scenarios at each point in time and this may generate uncertainty about the outcome of any investment decision.

Chapter 5 presents a new theoretical equilibrium intra-firm model that overcomes some of the limitation emerged in previous chapters. This model is built upon the standard neo-classical economic theory of investment and can be considered an extension of the milestone Jorgenson model (1970 and 1965). The innovative contribution with respect to the neo-classical model is that: a) the investment decision

is derived under different market scenarios and not just under perfect competition; b) the total capital stock of the firm is no longer treated as homogeneous and unique but it is explicitly modelled as a stock incorporating new, K_n, and old technology K_o, each characterised by different productivity, α_o and α_n respectively. This has involved using a three rather than a two factor production function, such that $Y=f(L, K_o, K_n; \beta, \alpha_o, \alpha_n)$, where $\alpha_n > \alpha_o$ due to the advanced property of K_n with respect to K_o.

This modelling, by the means of optimal control theory, shows that there exist stock effects in intra firm diffusion. Their influence depends upon the expected profit gains from further adoption which, in turn, are a function of the type of demand curve the firm faces for its product (market conditions). This model also shows that the spread of new technology is driven by changes in costs of the two types of capital (economic condition) and relative productivity of the new and the existing capital stock at the plant level (technical conditions). The higher are both the performance characteristics of the advanced technology and the reduction in its relative price, the faster will be the replacement process of the old with the new technology. This model also indicates that the extent of use of a new technology is not independent of the firm's level of ownership of existing technology and is influenced by complementary and substitutes technologies in use by the firm. Moreover, while the cost effect is exogenous, the technological characteristics is endogenous and reflects the *core competencies* of the firm in processing information and combining and efficiently using the inputs in its production system. This result shows that the role of information acquisition is important. However, the firm is neither a passive recipient of information, as in the Mansfield (1968) approach, nor a simple processor of information about the true profitability of the firm, as in the Stoneman model (1981). It is rather a processor of

information about how to efficiently organise its production, implement its plant and how to efficiently use the new technology. In this framework, the speed of adoption reflects the firm's speed of learning from its own experience. This would explain why, even if firms can access the same amount of information (especially after decades from the appearance of a new technology), they own different levels of new technology. In this model the impact of the market position of the firm (monopoly, competition) is endogenised via the demand curve.

This model is basically an equilibrium model where the firm decides upon the combination of inputs according to their technological characteristics and their prices, via the user cost of capital, at the time the decision is made. It also implicitly assumes that the firm holds rational expectations and decides how much to invest in the new technology based upon perfect information about the characteristics of the market and the technology itself. However, given that investments are irreversible once the firm decides to invest, it cannot just disinvest should the market conditions change adversely. Consequently, the firm might find it more profitable to wait for new information about prices, costs and other market condition before it commits its resources. In this light, following the Dixit and Pindyck (1994) approach to irreversible investments, the intra firm investment model presented in Chapter 5 has been further modified to allow for the inclusion of uncertainty.

Given that the replacement process takes several years, there are several elements of uncertainty that might affect the investment decision. They are not necessarily technology specific but concern uncertainty about: future demand or input (or competitive output) prices, interest rates, performance of the new technology, etc. To select only one factor would have yielded biased results while to include too many would have made the mathematical derivation of the model too complicated. For these reasons, following Bertola (1988), the intra firm model has been modified

introducing a generic specification of uncertainty: uncertainty about the firm's future revenue. Under this assumption the model remains basically unchanged except that uncertainty acts as a smoothing factor for the economic variables affecting the decision to invest, i.e. the relative change in the shadow cost of capital. Consequently, the higher is the volatility of future revenue the higher is the value of the option of waiting. In the absence of uncertainty the option value of waiting is zero and the value of the investment simply equals its shadow cost of capital at the moment the investment decision is taken. This result indicate that, further to uncertainty, the decision to invest in a new technology is also influenced by the relative reduction of acquisition costs over time, i.e. changes in the user costs of capital. One might assume that the firm has perfect information and formulates its investment decision under prefect foresight about future changes in input prices; as such the firm operates under 'rational expectations' and knows exactly what prices will be from one period to another. This assumption is quite strong. In fact, it is more likely that the firm does not know exactly the price of the technology from one period to another and it bases its investment decision upon partial information, so that its decisions are based upon 'price expectations'. Furthermore, under the assumption of irreversible investments, the profit maximising firm is more likely not to respond instantaneously to changes in price but rather adjust its current level of use of each capital stock to the desired optimal level based upon expected future price changes. This is an important aspect of the model as it directly affects the intra-firm level of use of the existing technologies via the changes in the user cost of each type of capital. This implies that the type of price extrapolation the firm bases its decision upon may be a crucial element in the derivation of the optimal intra firm level of use of a new technology. In other words, acquisition prices are important and expectations about future (quality adjusted) prices might have a role in the decision to further invest in a new technology. Chapter 5

section 5 presents a series of alternative specifications for the firm's price expectations and how the theoretical intra firm model has been modified to explicitly account for this possibility.

In summary, the intra firm diffusion model (derived in chapter 5) is basically an equilibrium model solidly grounded in economic theory. It is built upon profitability considerations and as such can be considered an intra firm stock effect model. It predicts that the implementation of the new technology is driven by physical benefits (via firm specificity- α_n/α_o); economic costs (acquisition costs under uncertainty and rational expectations- c^*_{ot}/c^*_{nt}) and market conditions (implicitly modelled via the type of demand curve). The first determines the heterogeneous level of use across firms (rank effect), the second determines the within firm extent of further use of the new technology over time (price effect) while the third affects the expected profit gains from adoption (stock effect).

The optimal accumulation path of the new technology is in essence a function of economic, technological and market conditions. This is an important result that, contrary to Takayama's (1991) critiques to the Jorgenson model, proves that the marginal product of capital is bounded and investments cannot grow to infinity as prices decrease. However, Jorgenson did consider only the perfect competitive scenario and did not consider the technological constraint a new type of capital stock would impose. In several of his papers, he specifies the optimal capital ownership as a function only of capital productivity, current acquisition cost (user cost of capital) and the final output price. The intra firm diffusion model encompasses this specification showing that even if the demand curve were not binding (i.e. under perfect competition) optimal investment would not be unbounded, being constrained by the relative change in the acquisition price and the technological characteristics of the two

sets of technologies. This can be better seen if one uses a relative measure of intra firm diffusion such as the proportion of capital stock incorporating the new technology over the total capital stock of the firm. In this case the spread of new technology, for a given level of output, is mostly driven by the relative shadow cost (c_{nt}/c_{ot}) and the technological performance (α_o/α_n) of the new relative existing types of capital, while the demand constraint does not enter directly this expression but is implicitly modelled in the derivation of the model. This result remains unchanged whether a firm is a monopolist or it operates on a perfectly competitive market.

In summary with respect to the Jorgenson's model, the intra firm investment model is also capable of dealing with: (i) different types of capital stock, i.e. advanced and old technologies (ii) technological constraints to adoption such as the technological characteristics of the current production system and complementarities between technologies; (iii) the influence of the relative cost of the two technologies and the expectations about their future prices; (iv) uncertainty and (v) market structure, i.e. monopoly or competition between firms.

In *Chapter 6*, the capital accumulation equation derived in the new intra firm diffusion model has been rewritten in a way suitable to empirical testing. The testing procedure used to estimate the model parameters was not straightforward as the decision to currently use the technology is just one of the possible outcomes of an irreversible conditional choice made sometime in the past to become an adopter. Moreover, in the CURDS data set, the variable accounting for intra firm diffusion is available only for 1993, restricting the testing of the model only to a single cross section of firms.

The nature of the decision model and the characteristics of the data set had to be modelled in order to correct for both censoring and sample selection. These effects, if ignored, might have caused serious bias in the parameter estimates. In fact, to model only the current status of the firms in 1993 causes serious truncation in the probability distribution, as it would not consider that some of the firms might adopt the technology sometime in the future, while to look only at some of the possible outcomes generates sample censoring.

Chapter 6 has presented alternative ways to deal with this type of problems. The Heckman's two step procedure is used to correct for the sample selection of the sub-sample of firms as those that have in the past adopted the new technology and are currently using it in 1993. In the first step of the model, the decision to be an adopter in or by 1993 is modelled via a selection criterion equation. In the second step the actual intra firm estimating equation is then corrected for the truncation of the sample (using the information in the first step of the analysis) yielding the corrected technology replacement equation.

The determinants of the selection criterion equation, i.e. the probability to be a user in or by 1993, have been outsourced from the inter firm literature that has looked at the factors that lead a firm to first adopt a new technology (see section 6.3). The determinants of the corrected technology replacement equation have been specified according to the predictions of the intra firm model presented in chapter 5 (see section 5.6). However, one of the problems, common to several applications of this type of model, is that the determinants of both parts of the model are defined over the same information set and several variables were used in both steps of the specification. This could have caused simultaneity upon the sample selection and the final model specification, yielding spurious and insignificant sample selection correction factors (i.e. the Inverse Mill's Ratio). A further conceptual discrepancy was that the current

level of the dependent variables in the modelling of the decision to become an adopter can easily be the consequence rather than the determinant of the status of the units, generating endogeneity and misspecification.

By means of statistical and probabilistic tools, chapter 6 has derived an alternative specification of the probability of using a technology, conditional to the irreversible choice of adopting it, and the selection of possible outcomes (i.e. the current level of use). This has yielded to a redefinition of the Selection criterion equation as a function of the level of the variables at time of adoption. This has also shown how the cross sectional nature of a model can be combined with the time specification when the dependent variable is observable only at one specific point in time.

This chapter has also discussed different ways of dealing with the censoring of the sample, caused by the exclusion of those firms that have in the past adopted the new technology but in 1993 have completed the process of technology transfer (i.e. those firms using 0% or 100% of the technology). It has also proposed a multinomial two step selection rule capable of accounting for all types of problems, namely: a) The sample selection of the eligible unit whose choice is observable; b) The truncation caused by the unobservable future choice; c) The censoring in each specification of the subset of outcomes.

In *chapter 7* the new intra firm model of technology replacement been tested over three out of the four technologies in the CURDS data set, namely: NC, CNC and Micro (CoT being excluded due to the lack of some of the relevant variables).

After a meticulous testing of each step of the model specification, the empirical estimates have shown that the prediction of the new equilibrium intra firm model are correct for two out of the three technologies. The results for NC are very unsatisfactory and inconsistent. This is not surprising as NC is an almost obsolete

technology, available now exclusively on the second hand market. By 1993, it had reached its post diffusion stage.

For the other technologies, it is found that what determines the extent of use of a new technology is mainly rank and price effects. The former are firm specific and reflect the core competencies of the firm such as: technological characteristics of the existing production system; management ; production organisation; size; whether the firm does R&D, etc. The latter reflect price reductions, uncertainty and price expectations about the new technology. Contrary to the inter firm literature, the model indicates that epidemic learning does not effect the intra firm diffusion of a new technology.

Among the other inter firm effects, the order effect does not apply to intra firm diffusion, but stock effects, already implicitly incorporated into the model, are highly significant in the process of technology substitution. The empirical results also shows that uncertainty about future revenues reduces the impact of the changes in ratio of relative prices of the new and the old types of capital by about 75%. This means that if there exist uncertainty about the future this will lower the extent of use of the new technology.

Also price expectations of the new and old technologies turn out to significantly affect the decision on further use of Microprocessors incorporated into processes, while in the case of CNC the firm's act as if they know, with certainty, the price of the old but not the new technology.

For all technologies the sample selection correction factor (of the sub-set of adopters currently using between 1 and 99% of the new technology -IMR) is never significant. This indicates that the decision as how much to use the new technology is independent of the probability of being an adopter. This result is in line with the study carried out in Chapter two suggesting that intra and inter firm diffusion are both

important and that intra firm diffusion is independent of the inter firm diffusion of new technology.

In this model, supply side effects and the possible impact of the increasing demand for the technology upon its relative price have not been explicitly included, the latter being assumed exogenous. However, one might argue that interaction effects between inter and intra firm processes do exist, but they have been picked up by supply side effects, i.e. changes in prices. This hypothesis has not been considered here for two main reasons. Firstly, as seen in chapter 2, supply side effects can be better explained by the aggregate demand for new technology of each individual firm rather than the number of firms of the industry that have adopted the technology. The latter, despite being widely used in inter firm studies, often overestimates the demand for the new technology and would not be representative of the real demand for that good.. Secondly, in an open economy it is difficult to isolate the impact of internal demand when the technology is imported from abroad. Supply side effects are interesting area that needs further research. However, this is beyond the scope of this study.

One might be tempted to use the findings of this study to draw policy guidelines. In fact, although the diffusion of new technology is of major public policy concern, public policy has been primarily concerned with the generation of innovations (invention and R&D) rather than their spreading within and across economies. Consequently, policy relating to the application of innovations (adoption/ extent of use) has been largely overlooked even though it is key to the realisation of benefits from technological change.

This thesis has important policy implications for industrial development in that if diffusion is largely a learning phenomenon then information provision policies could affect the diffusion process. However, given that it is found that the equilibrium

effects dominate, then information stimulation will have little impact on the diffusion process and the appropriate instrument would be a subsidy to the cost of the technology. In particular we have seen that what drives the diffusion process is the relative cost of the new over the old technology. This means that price intervention and fiscal incentives together with stabilisation policies to lower uncertainty would be the most effective way to speed up technology transfer. Given that the process of technology transfer is mostly the result of intra firm effects, rather than inter firm effects, it is advisable that policies should no longer concentrate on incentives to first adoption, but instead on incentives proportional to the level of intra firm adoption by each firm.

However, is it really socially optimal to speed up the diffusion process and the rate of technological adoption? This thesis has not addressed welfare analysis, consequently such policy recommendations need to be handled with care.

Overall this thesis aimed to shed some light on the under researched process of technology adoption within the firm. Using statistical and econometric tools, this thesis has proved why it is important to look at intra firm diffusion. It has also presented a theoretical model that provides a rationale to explain why, for the firm, it is not profitable to transfer immediately all of its production to the new technology, but wait. This model determines, for a single firm, the optimal replacement path of the old with the new technology, taking into account how changes in costs, price expectations, technological constraints, existing and previous technologies, uncertainty and market structure can influence the degree of technology adoption by a firm. The impact of uncertainty, process expectations and market structure play upon the firm's investment decision in a new technology has never been explored before. Using sophisticated statistical and econometric tools, the validity of this theoretical approach has been proved across a cross section of firms in the UK engineering and

metalworking sector. The theoretical model presented in this paper can be seen as a unique contribution to the understanding of the determinants of the adoption of new technology, and the empirical analysis provides considerable insight into a area where to date, little research has previously been completed.

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APPENDIX A

A1- The CURDS data set-

A1. The CURDS data set

The main data sources used in this study are three surveys (1981, 1986, 1993) of technology adoption in nine Minimum List Headings Industries in the UK engineering and metalworking sector undertaken by the Centre for Urban and Regional Development Studies (CURDS) at the University of Newcastle upon Tyne (see Alderman et al., 1988).

CURDS contains longitudinal data for a sample of firms in the UK engineering industry on firm characteristics, first adoption dates for five different technologies, the proportion of output produced using the new technologies in 1993 and some other relevant information about the determinant of the diffusion process as well as the production system characteristics and the managerial innovations.

The 1993 survey followed on two earlier surveys in 1981 and 1986 of the same sample of firms which although they do not contain questions relating to intra firm diffusion do contain information that enables us to track the date of first adoption of new technologies by the firms in the 1993 sample.

The 1993 questionnaire has been slightly modified with respect to the other two. In addition to the other two questionnaires it contains information upon the intra-firm level of use of a new technology. The main information on intra firm diffusion relates to the percentage of the machine tool stock of the firm that in 1993 incorporated each of the four advanced technologies.

All the three surveys have been carried on every six years by the means of a postal questionnaire.

With sample attrition and non response the sample size has decreased over time from 1127 in 1980 to 814 in 1986 and 345 in 1993. However, investigation of the causes of this attrition has provided some relevant information about the diffusion process, suggesting that there is no evidence of sample selection bias in the response to the 1986 survey (see Stoneman and Kwon, 1994). Moreover, there are rather good reasons to believe that the sample restriction is due only to the low response rate typical of postal questionnaires (cfr. M.Colombo personal experience on a similar survey carried on in Italy).

The hypothesis of sample selection bias over the three surveys (up to and including 1993) has also been investigated by Silvia Sgherri in her Italina Doctoral thesis. She came to the conclusion that the sample bias is not significant and the exit of firms from the sample was random (see S.Sgherri, a.y. 1997-78, 'Empirical Models of New Technology Adoption: A Critique', Tesi di Dottorato, Scuola Superiore degli Studi Universitari e Perfezionamento S.Anna, Univerista' di Pisa, Italy)

The variable definitions and the original codification of the data set are presented below.

The data set contains information for each of the three sample dates (unless otherwise specified).

SIX-YEARLY SURVEY OF NEW TECHNOLOGY ADOPTION IN BRITISH MANUFACTURING INDUSTRY

UNIVERSITY OF NEWCASTLE UPON TYME

Centre for Urban and Regional
Development Studies
Newcastle upon Tyne
NEI 7RU
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Establishment Characteristics

ySturtUp = Year of start up (-99 = missing ; -1 = pre 1900 some dates have been stimated)

Status93 = Status change (1=Yes; 2=No)
Nstatus93= Nature of change (1= Take-over/merger; 2=management buy-out; 3=sold/spun off, 4= change in share ownership/directors, 5=bought from receivers; 6=no change)
Status86 = Status in 1986 (1 = Group establishment ; 2 = Independent)
Status81 = Status in 1981 (1 = Group establishment ; 2 = Independent)

Industry = to which the establishment belongs (1968 SIC):
1 = MLH 331 = Agricultural Machinery;
2 = MLH 332 = Metal working machine tools;
3 = MLH 333 = Pumps, Valves, compressors, fluid power equipment;
4 = MLH 336 = Construction and earth-moving equipment;
5 = MLH 337 = Mechanical handling equipment;
6 = MLH3393/4 Refrigerating machinery, space-heating, ventilating, Air-conditioning equipment, Scales and weighting machinery and portable power tools.
7 = MLH 3391/2/5/6/7/8 = Mining, Printing, bookbinding and paper goods, Scales and weighting machinery and Portable power tools; Food and drink processing and packaging machinery and bottling machinery
8 = MLH 3399 = miscellaneous (non electrical) machinery
9 = MLH 341 = industrial (including process) plant and steelworks, i.e. Boilers and boiler-house plant, constructional steelworks, fabricated iron and steelworks. ;
10 = MLH 361 = Electrical machinery;
11 = MLH 390 = Engineers small tools and gauges;
12 = Subcontractors ;
13 = MLH 349 = Ball, roller, plain, and other bearings; Precision chains and other mechanical engineering;
15 = Other mech. Engineering

Metal81= Metalworking activity at the establishment in 1981 (1 = Yes ; 0 = No)

E93 = Number of employees in 1993 (-999 = missing)
E86 = Number of employees in 1986 (-999 = missing)
E81 = Number of employees in 1981 (-999 = missing)
E75 = Number of employees in 1975 (-999 = missing)
E70 = Number of employees in 1970 (-999 = missing)

R&D93 = R&D onsite, i.e. work designed to produce new or improved product or processes in 1993 (1=Yes; 2 = No ; 0 = Missing)

R&D86 = R&D onsite, i.e. work desiged to produce new or improved products or processes in 1986 (1 = Yes ; 2 = No ; -999 = missing)
R&D81 = R&D onsite, i.e. work desiged to produce new or improved products or processes in 1981 (1 = Yes ; 2 = No ; -999 = missing)

R&Dem93 = number of employees engaged full time on R&D in 1993 (-999 = missing or not applicable, i.e.no R&D onsite)
R&Dem86 = number of employees engaged full time on R&D in 1986 (-999 = missing or not applicable, i.e.no R&D onsite)
R&Dem81 = number of employees engaged full time on R&D in 1981 (-999 = missing or not applicable, i.e.no R&D onsite)

Financial Status

T90/91= Turnover in 1990/91
T85/86= Turnover in 1985/86
T80/81= Turnover in 1980/81

P90/91= Pre tax profit in 1990/91
P85/86= Pre tax profit in 1985/86
P80/81= Pre tax profit in 1980/81

PL90/91= Profit or loss in 1990/91
PL85/86= Profit or loss in 1985/86
PL80/81= Profit or loss in 1980/81

Production System Charateristics

PRDSYSTM = Production system main characteristic (1 =Engineering/Project based 2=Make/assemble to order;3=Make/assemble to stock 4=Job shop (subcontr.))

BACTCHSIZE = Average batch size for the product or service described above (-99 missing)

Introduction of new technology/systems

Process innovations

NC = adoption of NUMERICAL CONTROL of metal cutting, forming or joining machinery (1=Yes; 2=No ; 3=not applicable; 4=planned ; 0=missing)

CNC = adoption of COMPUTERISED NUMERICAL CONTROL of metal cutting, forming or joining machinery (1=Yes; 2=No ; 3=not applicable; 0=missing)

CoT = adoption of COATED CARBIDE or CERAMIC TOOLS or INSERTS for metal cutting (1=Yes; 2=No ; 3=not applicable; 0=missing)

MICRO = adoption of MICROPROCESSORS incorporated in manufacturing PROCESSES (other than CNC) for controlling, monitoring or inspection, adoption (1= Yes; 2= No; 3= not applicable; 4= planned for 1993; 0= missing)

Robot = adoption of PROGRAMMABLE ROBOT (1= Yes; 2= No; 3= not applicable; 4= planned for 1993; 0= missing)

Other innovations

CAD = adoption of COMPUTER AIDED DESIGN/DRAUGHTING system with graphics
(1= Yes; 2= No; 3= not applicable; 4= planned for 1993; 0= missing)

M-prod = adoption of MICROPROCESSORS incorporated in any of the PRODUCTS manufactured in the factory
(1= Yes; 2= No; 3= not applicable; 4= planned for 1993; 0= missing)

INTER FIRM DIFFUSION
Year of first adoption of the advanced technology by firm i

Process innovations

yNC = Year of NC first adoption (-99=missing)
yCNC = Year of CNC first adoption (-99= missing)
yCoT = Year of CoT first adoption (-99= missing)
yMICRO = Year of MICRO first adoption (-99= missing)

Other innovations

yCAD = Year of CAD first adoption (-99= missing)
yM-prod = Year of M-prod first adoption (-99= missing)

INTRA FIRM DIFFUSION
Percentage of machine tools of the firm i that incorporates the following technologies

Process innovations

NC = Estimated proportion of machine tool stock that incorporates NC (%)(-99= missing)
CNC = Estimated proportion of machine tool stock that incorporates or uses the CNC (%) (-99= missing)
CoT = Estimated proportion of machine tool stock that incorporates or uses the CoT (%) (-99= missing)
MICRO = Estimated proportion of machine tool stock of the manufacturing processes (excluding CNC) that incorporates or uses Microprocessors for controlling, monitoring or inspection MICRO (%) (-99= missing)

Managerial innovation

CAPM = adoption of Computer Aided Production Management system (1=yes; 2=No; 0=missing)
yCAPM = timing of adoption of CAPM (-99=missing)

JIT = Adoption of Just in Time principles (1=yes; 2=No; -99=missing)
yJIT = timing of adoption of Just in Time

TQM = Total Quality Management principles (1=yes; 2=No; -99=missing)
yTQM = timing of adoption of Total Quality Management principles

BSISO= possession of BS5750/ISO9000 accreditation (1=Yes;2=No; 3 =Planned or pending)
yBSISO= Year of BSISO first awarding (-99= missing value)

APPENDIX B

B1. Relative importance of inter vs intra firm effects: weighted analysis-

B1. Relative importance of inter vs intra firm effects: weighted analysis

The analysis of the inter and intra firm effects have been carried out also taking into account the different size of the establishments. Two different weights have been used: the number of employees (w_{Eit}) and the turnover (w_{Tit}) of the firm i.

In order to do so the original equations 2.1/2, 2.3 and 2.4 detailed in Chapter 2 have been modified so that for each technology j:

Level analysis:

$$D_{rjt} = Y_{rjt} / Y_{rt} = (N_{jt}/N_t) \ (\bar{Y}_{rjt} / \bar{Y}_{rt}) \qquad (2.1/2w)$$

Relative analysis:

$$\log(Y_{rjt} / Y_{rt}) = \log(N_{jt}/N_t) + \log(\bar{Y}_{rjt} / \bar{Y}_{rt}) \qquad (2.3.w)$$

Growth rate analysis:

$$d\log D_{rjt} = [dN_{jt}/N_{jt} - dN_t/N_t] + [d(\bar{Y}_{rjt}) / \bar{Y}_{rjt} - d(\bar{Y}_{rt}/Y_{rt}] \qquad (2.4.w)$$

where:

$\bar{Y}_{rjt} = \sum_i (Y_{jit} . w_{rit}) / N_{jt}$ and $\bar{Y}_{rt} = \sum_i (Y_i . w_{rit}) / N_t$ $\qquad$ i=1..N $\qquad$ r=E,T

Table 2.2 and 2.3 reports the results for j=CNC using weights (w_{rit}) for each r= Employees, Turnover. As one can see the figures do not change significantly from the results in Table 2.1 discussed in Chapter 2.

Table B1.a. CNC inter and intra firm effects, weighted by the size of the establishment i.e. Number of employees (w_{ei})

		LEVEL ANALYSIS		LOG ANALYSIS		GROWTH RATES ANALYSIS		
	Industry Usage (D_E)	Proportion of adopters (N_j/N)	Usage per adopter ($\bar{Y}_{Ejt}/\bar{Y}_{Et}$)	INTER-firm (%) $\log(N_j/N)$	INTRA-firm (%) $\log(\bar{Y}_{Ejt}/\bar{Y}_{Et})$	Industry Usage $d(Y_{jE}/Y_E)$	INTER-firm (%) $(dN_j/N_j\text{-}dN/N)$	INTRA-firm (%) $(d\bar{Y}_{Ej}/\bar{Y}_{Ej} - d\bar{Y}_{Et}/\bar{Y}_{Et})$
1993	0.361	0.82	0.44	-0.09 **(19.49%)**	-0.36 **(80.51%)**	0.361	0.152 **(21.1%)**	0.567 **(78.90%)**
1986	0.230	0.70	0.33	-0.16 **(24.55%)**	-0.48 **(75.45%)**	0.701	0.372 **(27.61%)**	0.858 **(72.39%)**
1981	0.069	0.47	0.15	-0.33 **(28.31%)**	-0.83 **(71.69%)**	0.957	0.912 **(58.32%)**	0.651 **(41.68%)**
1975	0.003	0.04	0.07	-1.39 **(54.72%)**	-1.15 **(45.28%)**	-	1.000 **(48.58%)**	1.058 **(51.42%)**

Source: personal elaboration from CURDS data set.

Table B1.b. CNC inter and intra firm effects, weighted by the size of the establishment, i.e. Turnover (w_{Ti})

		LEVEL ANALYSIS		RELATIVE ANALYSIS		GROWTH RATES ANALYSIS		
	Industry Usage (D_T)	Proportion of adopters (N_j/N)	Usage per adopter ($\bar{Y}_{Ejt}/\bar{Y}_{Et}$)	INTER-firm (%) $\log(N_j/N)$	INTRA-firm (%) $\log(\bar{Y}_{Ejt}/\bar{Y}_{Et})$	Industry Usage $d(Y_{jE}/Y_E)$	INTER-firm (%) $(dN_j/N_j\text{-}dN/N)$	INTRA-firm (%) $(d\bar{Y}_{Ej}/\bar{Y}_{Ej} - d\bar{Y}_{Et}/\bar{Y}_{Et})$
1990	0.16	0.80	0.44	-0.10 **(12.07%)**	-0.706 **(87.93%)**	0.529	0.23 **(44.45%)**	0.288 **(40.71%)**
1985	0.054	0.62	0.33	-0.21 **(16.42%)**	-1.06 **(83.58%)**	0.754	0.439 **(40.71%)**	0.64 **(59.2%)**
1980	0.007	0.35	0.15	-0.46 **(21.30%)**	-1.698 **(78.70%)**	-	-	-
1975	-	-	-	-	-	-	-	-

NOTE: Turnover is only available for the following years: 1990/91; 1985/86; 1980/81.
The sample size reflects the missing values. Dates have been adjusted accordingly.
Source: personal elaboration from CURDS data set.

APPENDIX C

C1- Testing of Logit and Tobit models:
Variable definition

C2- Testing the Mansfield Model:
Summary of the model specifications

C.1. Variables definition

The definition of the variables used for the testing of the **Mansfield model** are:

D_{ij} = proportion of machine tool stock of establishment i that incorporates each of the three new technologies in 1993 where j = NC, CNC or COT.

T_{ij} = for each j the number of years between first adoption of the technology by the establishment and 1993

L_{ij} = for each j, the proportion of firms in the whole sample that used technology j at the date of first adoption by establishment I

$M_i(t)$ = employment level of the firm in 1993 (data also available for 1970, 1975,1981 and 1986)

$R\&Ddum_i$ = dummy variable, taking the value 1 if the establishment undertakes in house R&D and zero if it does not (data available for 1993, 1986 and 1980).

$Expdum_i$ = dummy variable, equal to 1 if the percentage of total output going for export is greater than 20% and 0 otherwise (data available for 1993, 1986 and 1980).

Further variables included in the **Tobit model**:

R_i (t)= turnover of the firm (data available for 1991, 1986 and 1980).

$ISHARE_{ij}$ = proportion of firms in the industry the firm i belongs to, that have adopted the technology j by 1993

D_jy = technology state dummies taking value 1 if the technology y (other than j), has been adopted by the firm i, i.e. NC case: DCNC (1=yes; 0=no), DCOT (1=yes; 0=no)

Table C.1. shows the descriptive statistics for the sample of firms that have adopted the technology by 1993.

Other variables not included in the CURDS data set were: the **technology real quality adjusted price series**.

Data on the prices of the technologies in the CURDS data set were not ready available.

The price series of NC-CNC, CoT, Micro have been outsourced from Ufficial Statistical Sources and ad hoc studies. They all have been adjusted to take into account of : i) changing

(decreasing) purchasing power of the sterling over the years; and ii) quality improvements in the technology.

Table C.1.a SAMPLE STATISTICS (Mansfield and Stoneman-Battisti /Tobit model)

Variables	*CNC*		*CoT*		*NC*	
	Mean (Std.dev)	*Cases*	*Mean (Std.dev)*	*Cases*	*Mean (Std.dev)*	*Cases*
D_{ij}	0.2595 (0.216)	223	0.4148 (0.3506)	222	0.0825 (0.144)	228
$D_{ij}>0$	–	*208*	–	*176*	–	*116*
$\log[D_{ij}/1-D_{ij}]$	-1.2513 (1.261)	208	-0.3124 (1.8169)	176	-2.1104 (1.269)	116
T_{ij}	12.19 (4.464)	220	15.4916 (7.052)	179	15.3452 (9.396)	168
L_{ij}	44.83 (23.65)	220	47.1554 (26.219)	179	30.999 (17.22)	168
M_i(1993)	205.81 (307.58)	237	185.08 (292.302)	264	195.1739 (300.56)	253
$RDdum_i$ (1993)	0.7657 (0.425)	239	0.7256 (0.447)	266	0.7579 (0.429)	252
$EXPdum_i$ (1993)	0.5294 (0.500)	238	0.5227 (0.500)	264	0.5320 (0.500)	250
R_i (1991)	19170.56 (89364.21)	203	17133.26 (84831.37)	226	18370.62 (87306.48)	
ISHARE	0.8556 (0.0791)	240	0.9433 (0.053)	267	0.8790 (0.768)	168
DNC	0.9750 (0.1565)	240	0.8352 (0.372)	267	–	–
DCNC	–	–	0.7865 (0.411)	267	0.9130 (0.282)	253
DCOT	0.8667 (0.341)	240	–	–	0.8656 (0.342)	253
Number of Adopters	*240*		*267*		*253*	

Notes: Sample A - all firms that have adopted the technology by 1993.
Standard deviation in parenthesis

The changing purchasing power has been eliminated by deviding the series of current producer price index i.e. output- homesales, annual averages[1]- by the purchasing power of number Index (1985-100) sourced from Economic Trends[2].

[1] Those figures are calculated taking the inverse ratio of the respective annual averages of the general index of retail price (Source:CSO 'Annual Abstract of Statistics')

The Statistical sources and the methodological caveat used to built the quality adjusted price series are summarised below for each technology.

NC-CNC

Price data of NC-CNC machine tools for the period 1969-92 were supplied by the CSO but unfortunately for a number of years the data for the two types of machines are not separately distinguished. The fundamental difference between the two technologies is that CNC is more advanced, being the computerised version of NC.

CNC first appeared on the market in 1970 and being a computer based technology should be adjusted for quality improvements over time. Following Stoneman et al. 1992, this has been done using the trend underlying the quality improvements of computers (see below the details about the series). The resulting adjusted price series has then been used to proxi the real quality adjusted CNC computer prices from 1972, the date of first firm adoption up to 1992.

NC is a very old technology appeared on the market in 1950. For this technology (non computer based) the quality improvements have been decreasing in recent years as it is slowling moving towards obsolescence. Nowadays its impact upon the CSO price series is only marginal being mainly available only in the second hand market.

By detrending the CSO price series using the quality adjusted CNC series we have derived the price series of NC. The gap between 1950 and 1969 has been covered using backward forecasts based upon the structural time series specification (see Harvey, 1989). The package used was Stamp5. However, given the small number of observations the price series of both NC and CNC must be used only as a proxi for the real unobserved prices. In order to avoid spurious results the series has also been derived using ratios of price indexes. This analysis is

[2] The Producer Price Index of output of manufactured products, could have been use instead. Both deflators account for inflation, however given that some of the technologies might be imported from

preferred as it gives more smoothed results and allows to visualise the frequency domain and some of the possible errors.

CoT Prices

Being unable to locate a published domestic price series for the price of Coated carbide tools this tool has been excluded from the testing of the intra firm model.

Computer Prices

The CSO calculates a price series for EDP equipment that does contain some corrections for quality improvement. As shown by Stoneman et al.(1992), that series considerably underestimates the extent of the improvement. In alternative to this they have produced a quality adjusted price series, for the period from Dec. 1986 - May 1992, for computers in the UK using hedonic methods. For earlier years , i.e. before 1986, there are no reliable estimates of quality adjusted computer prices in the UK. The final series were provided by Kwon and Otto Toivanen based upon the result of the considerable literature relating to the US. This literature is summarised by Triplett (1989) which also provides a series quality adjusted prices for computer systems in the US for the periods 1957-1972 and 1972-1984 (Tables 4.13A and 4.14, pp. 194 and 196). This US price series corrected for changes in the dollar/sterling exchange rate (taken from Parking and Bade, 1988, p.38-39) has been used for the period from 1957-1984. The gap between 1984 and 1986, has been covered using the CSO index. However, given that this fails to adequately take into account quality improvement it has been adjusted using the average underestimate of the fall in the quality adjusted computer price shown in the CSO series compared to the Stoneman et al. estimates for the period from 1987-1992.

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abroad the first deflator has been preferred to the second.

In summary the price series of quality adjusted computer prices has been carried out using the outcome of the study of Triplett (1989) for the period 1957-1972 and 1972-1984 (Tables 4.13A and 4.14, pp. 194-96), Stoneman et al (1992) for the years 1987-1992 and the corrected CSO index for the period 1984 and 1986.

Microprocessors in processes prices

Similar to computers the price index for Microprocessors has been adjusted for quality improvements over time and the complete time series has been outsourced from the research of Karshenas and Stoneman (1993). The series they use is based upon the average selling prices in US dollars in the US Market. These prices are translated into sterling prices via the $/£ exchange rate. Using three different data sources, for each generation, in each period in which it on the market, they calculated the cost (average selling price in S) per K of memory. For the period from 1985 - 1992 data has been taken from Tyson (1992) on the average selling price in US $ for 256K and 1M EPROMS (the data originally coming from Dataquest). For the period from 1978 - 1984 the data used in Gruber (1992) has been kindly supplied to us by the author (although again the original source is Dataquest), and covers the average selling prices of 8, 16, 32, 64, 128 and 256K EPROMS. For the period from 1973 - 1977 we have relied upon the data contained figure 2.3 (p.40) of Dosi (1984).

C.2. TESTING OF THE MANSFIELD MODEL: Summary of the model specification

Each model specification has been estimated using ad hoc statistical techniques or each each technology , i.e. NC,CNC and CoT. The statistical packages used are Limdep7 for the non linear and two stages Least Squares and Stamp for structural approach .
The testing procedure of the Mansfield model can be summarised in the following steps:

Testing the shape of the statistical distribution

a. The Logistic model (NLS –weighted / unweighted)

a.1 Fixed s.l. : $D_{ijt} = 1/ (1+\exp(-\alpha-\beta_{ij}T_{ij})+e_{ij}$

a.2. Variable s.l.: $D_{ij} = \phi_j/ (1+\exp(-\alpha- \beta_{ij}T_{ij})+ e_{ij}$

a.3. weighted logistic curve wirh weight =T

b. The Gompertz growth curve (NLS -w/n)

b.1 Univariate non linear model $D_{ijt}= \exp(-\exp(\alpha+\beta.T_{ijt})+ e_{ij}$

b.2. Linearised model with explanatory variables

$\log D =c+\beta_1\log (T^*j)+\beta_2\log (T^*R\&Ddum)+\beta_3\log(T^*Expdum)+\beta_4 \log(T^*M) + \beta_5\log (T^*jshare) + e_{ij}$

Testing the final model

c. The Mansfield Approach (Two Stages Weighted Least Squares)

$D_{ij} = e_0 / (1+\exp(-e_1-e_{2i}*T_{ij}) + e_{ij}$

$e_{2i} = g_0+ g_1*RDdum_i+ g_2*Expdum_i+ g_3*M_i+ g_4*L_{ij} + e_{ij}$

d. Multivariate Logistic with unknown saturation level (NLS approach)

$D_{ij}= b_0/(1+\exp(-b_1-(b_2*RDdum_i+b_3*Expdum_i+b_4*M_i+b_5*L_{ij})*T_{ij})) + e_{ij}$

e. Logistic linearization (OLS approach)

fixed ($\phi_{ij}=1$) or variable ($\phi_{ij}\leq 1$) saturation level

$\log[D_{ij}/(\phi_{ij}-D_{ij})] = b_1+ b_2*RDdum_i+ b_3*Expdum_i+ b_4*M_i+ b_5*L_{ij} + e_{ij}$

f. Structural approach (ML and the Kalman filter)

$\log[D_{ij}/(1-D_{ij})] = \mu_{it}^*+b_1*RDdum_i+b_2*Expdum_i+b_4*M_i+b_5* L_{ij} +b_6*T_{ij}+ \varepsilon_{ijt}$

$\mu_{it}^* = \mu_{i,t-1}^* +\beta_{i,t-1} +\eta_{it}$

$\beta_{it} = \beta_{i,t-1} + \xi_{it}$

Appendix D

Estimating the Final Technology Replacement Equation

D1. Variables definition

D2. Summary statistics

Table D.1.a The determinants of intra-firm diffusion: variable definitions[a]

Dependent Variable		
KnKo	•	(Kn/(1-Kn))
		PRICE Effect
$DTOT_t$	•	Price differential of **Ko** : Po(t+1)-Po(t) Real Index of quality adjusted Gross Domestic Fixed Capital Formation
DKn	•	Price differential of **Kn** : Pn(t+1)-Pn(t) where Kn=new technology (CNC, NC, MICRO) Real Quality Adjusted Produced Price Index of Kn
QNQTOT	•	Relative price change (Pn/(-dPn) - Po/(-dPo))
		RANK Effect
Employment		
E t	•	Average number of employees t= 1993, 1986, 1981, 1975, 1970
Age		
Age	•	Years from start-up (1993-sturtup year)
Export		
$Ex20_t$	•	Dummy -Exports in 1993 (>20%=yes ; 0=otherwise)
R&D		
RDE_t	•	In House R&D employees/Total employees in 1991; 1986;1991
$R\&D_t$	•	In House R&D dummy (yes=1, no=0) in 1991; 1986;1991
Turnover		
$turnoverNy_t$	•	N years Average Real Turnover in 1990/91; 1986/86 ; 1980/81 (deflated by RPI)
RT_t	•	Real turnover in 1990/91; 1986/86 ; 1980/81 (deflated by RPI)
Liquidity		
PT_t	•	Current Profits/Turnover in 1991; 1986; 1981
PL_t	•	Dummy - Profits or loss in 1991/1986/1981 (1= Profits ; 0= Loss)
Production System Characteristics		
PSI_t	•	Dummy – Firm Prod. System (Yes=1; 0= otherwise)
	•	I=engineering to order; Make to order, Make to stock, Job shop, Mixed
BATCH	•	Average batch size
Ownership		
Group t	•	Dummy (1 =Group establishment ; 0 = Independent) t=1993, 1986, 1981
Complementary and/or substitute technologies		
DJ_t	•	Dummy - adoption of J (1=Yes ; 0= No) of J=Cot; Micro; Robot; CAD, CNC, NC, etc
Managerial Innovation		
DJM	•	Dummy (1=Yes ; 0= No), – adoption of JM , JM=CAPM, JIT,TQM;BSISO-ISO900
		EPIDEMIC other INTER-FIRM STOCK EFFECTS
YSTUR	•	Years from startup to fisrt adoption
T J	•	Years from firm first adoption up to 1993 ('93-1stadopt) , J = new technology
J y	•	Years from first appearance of the technology to first adoption by the firm (1stadop - 1970), J = new technology
Iusers93	•	Within industry share of adopters in 1993
shI[b]	•	Within Industry I (I=1,2,...15) share of adopters at time of the firm first adoption , i.e. Iusers93*DI
IFout93	•	Average within industry *Firms* output produced on the new technology in 93 (INTRA-INDUSTRY average firm level of use)
JDIFF	•	Average industry output produced on the new technology in 93 (INTRA INDUSTRY average total level of use)

Note: a) Variables are NOT log transformed ; b) 'shI' being the product DI*Iusers93 (I=1,2 etc) is not included in the summary statistics.

Table D2.a Summary statistics: CNC (Current users)

	N		Mean	Median	Mode	Std.dev.	Variance	Min	Max	Percentile		
	Valid	Missing								25%	50%	75%
Dependent variable												
KNKO	208	1	.65	.25	.11	.17	1.36	.01	18.00	.11	.25	.67
Price effect												
DCNC	198	11.00	25.97	17.46	41.05	16.13	260.11	-.53	56.33	10.93	17.46	41.05
DTOT	198	11.00	18.40	20.58	22.37	4.42	19.57	2.27	23.96	14.40	20.58	22.37
QNQTOT	198	11.00	-2.13	1.12	-1.71	26.50	702.15	-206.43	70.47	-1.71	1.12	1.81
Rank effect												
Employment												
E93	205	4.00	220.99	90.00	25.00[a]	324.57	105346.12	10.00	2300.00	39.00	90.00	260.00
E86	205	4.00	297.22	115.00	100.00	464.27	215551.07	10.00	3500.00	46.50	115.00	340.00
E81	207	2.00	378.38	140.00	35.00[a]	633.24	400998.48	9.00	5304.00	46.00	140.00	430.00
E75	183	26.00	496.97	150.00	40.00	877.20	769484.69	2.00	6790.00	50.00	150.00	610.00
E70	165	44.00	588.86	150.00	60.00	1112.38	1237388.07	2.00	8479.00	50.00	150.00	650.50
Age												
AGE	179	30.00	50.27	54.00	50.00	19.74	389.81	.00	81.00	39.00	54.00	65.00
Export												
EX20	207	2.00	.53	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
R&D												
RDE93	163	46.00	.03	.02	.00	.04	.00	.00	.25	.00	.02	.04
RDE86	200	9.00	.02	.01	.00	.04	.00	.00	.29	.00	.01	.03
RDE81	158	51.00	.03	.02	.00	.03	.00	.00	.15	.01	.02	.04
R&D93	206	3.00	.78	1.00	1.00	.42	.17	.00	1.00	1.00	1.00	1.00
R&D 86	208	1.00	.79	1.00	1.00	.41	.17	.00	1.00	1.00	1.00	1.00
R&D 81	209	.00	.76	1.00	1.00	.43	.18	.00	1.00	1.00	1.00	1.00
Turnover												
TURNOVER3Y	175	34.00	30.45	25.95	10.52	22.32	498.34	2.93	158.41	18.44	25.95	36.55
TURNOVER2Y	121	88	34.2566	29.672	2.93	23.0140	529.6426	2.93	158.41	21.5797	29.6721	40.586
RT 91	175	34.00	14255.05	3549.77	709.95[a]	67777.87	4593839846.27	191.69	851945.38	1273.66	3549.77	9650.41
RT86	150	59.00	11010.22	3492.00	970.00	25155.70	632809210.26	242.50	192059.97	1200.37	3492.00	11349.00
RT81	130	79.00	12195.57	2889.25	1270.00	28833.49	831369966.42	254.00	209549.99	889.00	2889.25	10160.00
Liwuidity												
PT91	71	138.00	.10	.06	.10	.16	.02	.00	1.26	.03	.06	.10
PT86	72	137.00	.27	.06	.03[a]	1.69	2.85	.00	14.40	.03	.06	.10
PT81	54	155.00	.29	.07	.10	1.53	2.35	.00	11.33	.04	.07	.11
PL91	99	110.00	1.24	1.00	1.00	.48	.23	1.00	3.00	1.00	1.00	1.00
PL86	81	128.00	1.07	1.00	1.00	.26	.07	1.00	2.00	1.00	1.00	1.00
PL81	75	134.00	1.28	1.00	1.00	.51	.26	1.00	3.00	1.00	1.00	2.00
Production system												
PS1	209	.00	.33	.00	.00	.47	.22	.00	1.00	.00	.00	1.00
PS2	209	.00	.43	.00	.00	.50	.25	.00	1.00	.00	.00	1.00
PS3	209	.00	.10	.00	.00	.29	.09	.00	1.00	.00	.00	.00
PS4	209	.00	.13	.00	.00	.34	.11	.00	1.00	.00	.00	.00
PS5	209	.00	.01	.00	.00	.12	.01	.00	1.00	.00	.00	.00
BATCH	182	27.00	94.89	6.00	1.00	425.27	180853.69	1.00	5000.00	2.00	6.00	25.00

...Continue

	N		Mean	Median	Mode	Std.dev.	Variance	Min	Max	Percentile		
	Valid	Missing								25%	50%	75%
Ownership												
GROUP 86	208	1.00	.89	1.00	1.00	.31	.10	.00	1.00	1.00	1.00	1.00
GROUP 81	209	.00	.60	1.00	1.00	.49	.24	.00	1.00	.00	1.00	1.00
GROUP 93	200	9.00	.90	1.00	1.00	.30	.09	.00	1.00	1.00	1.00	1.00
Industrial sector												
INDUSTRY	209	.00	7.14	8.00	3.00	3.70	13.73	1.00	15.00	3.00	8.00	10.00
Complementary and substitute technologies												
DCOT	209	.00	.89	1.00	1.00	.32	.10	.00	1.00	1.00	1.00	1.00
DROBOT	127	82.00	.25	.00	.00	.62	.38	.00	1.00	.00	.00	.00
DCAD	199	10.00	1.01	1.00	1.00	.92	.84	.00	0.00	1.00	1.00	1.00
DM-PROD	161	48.00	.68	1.00	1.00	.67	.44	.00	0.00	.00	1.00	1.00
Managerial Innovation												
DCAPM	189	20.00	.46	.00	.00	.53	.28	.00	0.00	.00	.00	1.00
DJIT	181	28.00	.40	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
DTQM	181	28.00	.41	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
DBSISO	123	86.00	.89	1.00	1.00	.32	.10	.00	1.00	1.00	1.00	1.00
Epidemic and other inter firm effect												
YSTUR	181	28.00	43.28	40.00	43.00	20.33	413.25	12.00	93.00	28.00	40.00	55.50
TCNC	198	11.00	12.32	13.00	15.00	4.36	19.03	2.00	23.00	9.00	13.00	15.00
CNCY	198	11.00	11.68	11.00	9.00	4.36	19.03	1.00	22.00	9.00	11.00	15.00
EPID	198	11.00	4.29	4.92	4.23	1.60	2.57	.17	5.89	2.93	4.92	5.79
Iuser93	209	.00	86.24	88.12	94.04	7.24	10.34	63.76	100.00	83.35	88.76	93.02
IFOUT93	209	.00	25.69	20.00	10.00[a]	21.25	451.61	1.00	100.00	10.00	20.00	40.00
CNCDIFF	209	.00	22.17	21.21	38.15[a]	80.12	750.23	1.00	38.00	18.00	21.00	23.00

NOTE: (a) Multiple modes exist. The smallest value is shown.

Table D2.b Summary statistics: NC (Current users)

	N		Mean	Median	Mode	Std.dev.	Variance	Min	Max	Percentile		
	Valid	Missing								25%	50%	75%
Dependent variable												
KNKO	115	.00	.29	.11	.05	.52	.27	.01	4.00	.05	.11	.25
Price effect[b]												
DNC	115	.00	.11	10.31	14.32	30.25	914.86	-67.10	42.23	-33.87	10.31	26.09
DTOT	115	.00	15.86	17.10	17.20	4.55	20.73	2.27	23.96	12.37	17.10	18.39
QNQTOT	115	.00	-6.80	.33	5.63	54.65	2986.66	-547.25	32.18	-11.62	.33	5.63
Rank effect												
Employment												
E93	114	1.00	210.41	100.00	20.00	286.64	82162.00	1.00	1750.00	40.00	100.00	260.00
E86	114	0.00	316.94	125.00	65.00	474.59	225237.55	3.00	2500.00	56.00	120.00	320.00
E81	115	0.00	384.43	143.00	35.00[a]	576.87	332784.25	3.00	3550.00	50.00	143.00	550.00
E75	114	10.00	474.34	165.00	40.00	824.96	644738.01	4.00	5000.00	40.00	150.00	561.75
E70	105	10.00	528.72	141.00	.00	1001.25	1002502.76	1.00	7000.00	36.00	141.00	585.00
Age												
AGE	115	.00	50.57	44.00	100.00	25.90	670.86	12.00	100.00	31.00	44.00	63.00
Export												
EX20	113	2.00	.57	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
R&D												
RDE93	112	3.00	.15	.01	.00	.01	.00	.00	1.00	.00	.01	.04
RDE86	110	5.00	.02	.01	.00	.02	.00	.00	.08	.00	.01	.03
RDE81	85	30.00	.03	.02	.00	.03	.00	.00	.14	.01	.02	.04
R&D93	115	.00	.77	1.00	1.00	.43	.18	.00	1.00	1.00	1.00	1.00
R&D 86	115	.00	.79	1.00	1.00	.41	.17	.00	1.00	1.00	1.00	1.00
R&D 81	115	.00	.74	1.00	1.00	.44	.19	.00	1.00	.00	1.00	1.00
Turnover												
TURNOVER3Y	97	18.00	101.95	34.07	4.10	239.20	57214.42	.36	1972.20	9.90	34.07	87.51
TURNOVER2Y	96	19.00	102.87	31.02	106.50	228.18	52065.81	.36	1627.05	9.44	31.02	97.41
RT 91	97	18.00	102.79	33.16	21.30	288.60	83290.58	.36	2662.50	11.20	33.16	95.47
RT86	79	36.00	91.73	31.72	9.70[a]	233.29	54423.05	2.43	1920.60	9.70	31.72	84.34
RT81	70	45.00	125.65	30.16	25.40	319.59	102139.28	1.91	2095.50	10.00	30.16	83.19
Liwuidity												
PT91	44	74.00	.12	.06	.10	.27	.07	-.07	1.25	.01	.06	.10
PT86	33	82.00	.08	.04	.03[a]	.25	.06	-.25	1.40	.02	.04	.07
PT81	33	82.00	.06	.05	.00[a]	.06	.00	-.05	.24	.01	.05	.09
PL91	48	67.00	.88	1.00	1.00	.49	.24	.00	3.00	1.00	1.00	1.00
PL86	39	76.00	.87	1.00	1.00	.34	.11	.00	1.00	1.00	1.00	1.00
PL81	37	78.00	.92	1.00	1.00	.49	.24	.00	3.00	1.00	1.00	1.00
Production system												
PS1	115	.00	.39	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
PS2	115	.00	.37	.00	.00	.48	.23	.00	1.00	.00	.00	1.00
PS3	115	.00	.10	.00	.00	.31	.09	.00	1.00	.00	.00	.00
PS4	115	.00	.12	.00	.00	.33	.11	.00	1.00	.00	.00	.00
PS5	115	.00	.02	.00	.00	.13	.02	.00	1.00	.00	.00	.00
BATCH	106	9.00	428.44	5.00	1.00	2731.25	7459720.13	1.00	20000.00	1.00	5.00	26.25

..... Continue

	N		Mean	Median	Mode	Std.dev.	Variance	Min	Max	Percentile		
	Valid	Missing								25%	50%	75%
Ownership												
GROUP 86	115	.00	.62	1.00	1.00	.49	.24	.00	1.00	.00	1.00	1.00
GROUP 81	115	.00	.92	1.00	1.00	.27	.07	.00	1.00	1.00	1.00	1.00
GROUP 93	115	.00	.61	1.00	1.00	.49	.24	.00	1.00	.00	1.00	1.00
Industrial sector												
INDUSTRY	115	.00	7.10	8.00	3.00	3.53	12.49	1.00	15.00	3.00	8.00	10.00
Complementary and substitute technologies												
DCOT	112	3.00	.91	1.00	1.00	.29	.08	.00	1.00	1.00	1.00	1.00
DROBOT	96	19.00	.11	.00	.00	.32	.10	.00	1.00	.00	.00	.00
DCAD	112	3.00	.73	1.00	1.00	.44	.20	.00	1.00	.00	1.00	1.00
DM-PROD	100	15.00	.51	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
DCNC	112	3.00	.94	1.00	1.00	.24	.06	.00	1.00	1.00	1.00	1.00
DMICRO-pc	108	7.00	.65	1.00	1.00	.48	.23	.00	1.00	.00	1.00	1.00
Managerial Innovation												
DCAPM	106	9.00	.45	.00	.00	.50	.25	.00	1.00	.00	.00	1.00
DJIT	96	19.00	.33	.00	.00	.47	.22	.00	1.00	.00	.00	1.00
DTQM	100	15.00	.41	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
DBSISO	112	3.00	.52	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
Epidemic and other inter firm stock effects												
YSTUR	115	.00	77.60	76.00	88.00	9.16	83.93	55.00	92.00	70.00	76.00	88.00
TNC	115	.00	15.40	17.00	5.00	9.16	83.93	1.00	38.00	5.00	17.00	23.00
NCY	115	.00	27.60	26.00	38.00	9.16	83.93	5.00	42.00	20.00	26.00	38.00
Iusers93	115	0	82.62	85.29	83.33	17.04	290.53	14.29	100.00	81.40	85.29	90.91
IFOUT93	115	.00	16.28	3.6592	4.34	1.0295	1.0599	1.08	4.45	3.1215	3.6592	4.343
NCDIFF	115	.00	7.07	6.62	8.76	3.20	10.23	3.00	14.33	4.81	6.62	8.76

NOTE: (a) If multiple modes exist. The smallest value is shown; (b) The price effect for NC is measured in absolute value as the quality adjusted price of this almost obsolete technology increases over time. The reasons for this empirical exercise are detailed in chapter 8.

Table D2.c Summary statistics: MICRO (Current users)

	N		Mean	Median	Mode	Std.dev.	Variance	Min	Max	Percentile		
	Valid	Missing								25%	50%	75%
Dependent variable												
KNKO	229	51	0.65	0.11	0.11	1.976	3.87	.11	19.00	5.26e-2	0.111	0.49
Price effect												
DMICRO	257	24.00	14.36	17.13	1.12	11.34	128.54	-1.52	37.69	1.12	17.13	23.11
DTOT	257	24.00	12.66	13.89	1.01	8.03	64.50	1.01	23.61	2.27	13.89	20.58
QNQTOT	257	24.00	-0.71	-1.59	-13.58	30.716	943.47	-91.90	119.71	-13.58	-1.60	-0.59
Rank effect												
Employment												
E93	281	.00	195.75	75.00	40.00[a]	308.79	95351.09	10.00	2300.00	35.00	75.00	237.50
E86	279	2.00	270.79	99.00	65.00	484.94	235169.87	10.00	3500.00	40.00	99.00	275.00
E81	281	.00	312.98	101.00	40.00	561.42	315195.95	13.00	5304.00	40.00	101.00	355.00
E75	273	8.00	364.67	80.00	.00	748.34	560009.62	2.00	6790.00	30.00	80.00	331.50
E70	250	31.00	416.50	70.00	.00	940.63	884791.25	8.00	8479.00	22.75	70.00	330.50
Age												
AGE	280	1.00	46.80	38.00	100.00	27.65	764.62	12.00	100.00	25.00	38.00	59.75
Export												
EX20	278	3.00	.51	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
R&D												
RDE93	273	8.00	.03	.01	.00	.04	.00	.00	.25	.00	.01	.04
RDE86	274	7.00	.02	.01	.00	.03	.00	.00	.29	.00	.01	.03
RDE81	203	78.00	.03	.02	.00	.03	.00	.00	.21	.01	.02	.04
R&D93	280	1.00	.72	1.00	1.00	.45	.20	.00	1.00	.00	1.00	1.00
R&D86	280	1.00	.76	1.00	1.00	.43	.18	.00	1.00	1.00	1.00	1.00
R&D81	281	.00	.73	1.00	1.00	.44	.20	.00	1.00	.00	1.00	1.00
Turnover												
TURNOVER3Y	242	39.00	104.25	28.94	7.10	306.19	93754.05	1.68	3739.80	9.61	28.94	84.09
TURNOVER2Y	239	42.00	96.01	28.22	7.10[a]	219.84	48330.64	1.68	1627.05	8.93	28.22	81.64
RT91	242	39.00	127.46	27.34	17.75[a]	587.88	345597.21	1.42	8520.00	10.56	27.34	85.20
RT86	208	73.00	93.01	29.54	9.70[a]	219.49	48174.43	.19	1920.60	9.70	29.54	87.30
RT81	184	97.00	101.03	25.40	12.70	251.57	63289.07	1.27	2095.50	7.62	25.40	76.20
Liwuidity												
PT91	113	168.00	.09	.05	.00	.18	.03	-.10	1.25	.01	.05	.10
PT86	99	182.00	.09	.05	.03	.19	.04	-.25	1.40	.02	.05	.09
PT81	91	190.00	.09	.04	.10	.29	.08	-.31	2.10	.01	.04	.10
PL91	130	151.00	.89	1.00	1.00	.57	.33	.00	3.00	1.00	1.00	1.00
PL86	109	172.00	.94	1.00	1.00	.40	.16	.00	3.00	1.00	1.00	1.00
PL81	102	179.00	.89	1.00	1.00	.58	.33	.00	3.00	1.00	1.00	1.00
Production system												
PS1	281	.00	.35	.00	.00	.48	.23	.00	1.00	.00	.00	1.00
PS2	281	.00	.43	.00	.00	.50	.25	.00	1.00	.00	.00	1.00
PS 3	281	.00	.09	.00	.00	.28	.08	.00	1.00	.00	.00	.00
PS 4	281	.00	.12	.00	.00	.32	.10	.00	1.00	.00	.00	.00
PS 5	281	.00	.01	.00	.00	.12	.01	.00	1.00	.00	.00	.00
BATCH	249	32	372.44	5.00	1.00	2249.00	5057975.13	1.00	20000.00	1.00	5.00	25.00

..... Continue

	N		Mean	Median	Mode	Std.dev.	Variance	Min	Max	Percentile		
	Valid	Missing								25%	50%	75%
Ownership												
GROUP81	281	.00	.57	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
GROUP86	271	10.00	.90	1.00	1.00	.30	.09	.00	1.00	1.00	1.00	1.00
GROUP93	273	8.00	.60	1.00	1.00	.49	.24	.00	1.00	.00	1.00	1.00
Industrial sector												
INDUSTRY	281	.00	7.09	8.00	10.00	3.54	12.54	1.00	15.00	3.00	8.00	10.00
Complementary and substitute technologies												
DCOT	271	10.00	.80	1.00	1.00	.40	.16	.00	1.00	1.00	1.00	1.00
DROBOT	225	56.00	.12	.00	.00	.33	.11	.00	1.00	.00	.00	.00
DCAD	262	19.00	.69	1.00	1.00	.46	.21	.00	1.00	.00	1.00	1.00
DM-PROD	242	39.00	.55	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
DNC	254	27.00	.65	1.00	1.00	.48	.23	.00	1.00	.00	1.00	1.00
DCNC	273	8.00	.75	1.00	1.00	.44	.19	.00	1.00	.00	1.00	1.00
Managerial Innovation												
DCAPM	249	32.00	.40	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
DJIT	244.00	37.00	.39	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
DTQM	247.00	34.00	.42	.00	.00	.49	.24	.00	1.00	.00	.00	1.00
DBSISO	276	5.00	.51	1.00	1.00	.50	.25	.00	1.00	.00	1.00	1.00
Epidemic and other inter firm stock effects												
YSTUR	280	1.00	46.80	38.00	100.00	27.65	764.62	12.00	192.00	25.00	38.00	59.75
TMICRO	203	78.00	8.55	9.00	13.00	4.54	20.59	.00	21.00	5.00	9.00	12.00
MICROY	257	24.00	10.63	11.00	.00	6.81	46.40	.00	22.00	7.00	11.00	15.00
Iusers93	281	.00	75.31	78.26	82.93	12.24	149.71	50.00	100.00	66.67	78.26	84.21
IFOUT93	281	.00	21.67	22.32	22.32	8.09	65.41	6.00	39.67	18.20	22.32	27.07
MICRODIFF	281	.00	13.75	14.55	15.08	4.63	21.48	3.00	23.13	10.00	14.55	15.26

NOTE: (a) Multiple modes exist. The smallest value is shown