Paper to be presented at the

DRUID Society Conference 2014, CBS, Copenhagen, June 16-18

Creating value from embodied knowledge ? lags, learning and contingency: The case of AMTs and innovation

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Abstract

The ability to innovate successfully is a key corporate capability, depending strongly on firms? access to knowledge capital: proprietary, tacit and embodied. Here, we focus on one specific source of embodied knowledge ? advanced manufacturing technologies or AMTs ? and consider its impact on firms? innovation success. AMTs relate to a series of process innovations which enable firms to take advantage of numerical and digital technologies to optimise elements of a manufacturing process. Using panel data for Irish manufacturing plants we identify lengthy learning-by-using effects in terms of firms? ability to derive innovation benefits from AMT adoption. Disruption effects are evident in the short-term while positive innovation benefits occur six-plus years after adoption. Contrary to expectations we find no evidence that AMT adoption influences resource-efficiency in the production of innovation.

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Keywords: Advanced manufacturing technology; Innovation; Learning-by-using; adoption

JEL Codes: O31, O33, O34

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1. Introduction

The ability to innovate successfully is a key corporate capability, depending strongly on firms' access to knowledge capital: proprietary, tacit and embodied (Al-Laham, Tzabbar, and Amburgey 2011; Wu and Shanley 2009; Tzabbar et al. 2008; Kyriakopoulos and de Ruyter 2004). The relationship between proprietary knowledge (e.g. patents) and innovation has been widely explored (Artz et al. 2010; Mansfield 1986), as has the relationship between innovation and tacit or un-codified knowledge (e.g. workforce skills) (Knockaert et al. 2009; Ichijo and Kohlbacher 2008). Less attention has been paid to the impact on innovation of knowledge embodied in firms' acquisitions and implementation of new capital equipment, although more recently see Barge Gil et al. (2011). Here, we focus on one specific source of embodied knowledge – advanced manufacturing technologies or AMTs – and consider its impact on firms' innovation success. AMTs relate to a series of process innovations which enable firms to take advantage of numerical and digital technologies to optimise elements of a manufacturing process. These may relate to the control of individual pieces of production equipment – as in numerically controlled, computer numerically controlled (CNC) machinery or robotics – the automated movement of items during the manufacturing process – as in automated materials handling – or the integration and optimisation of the production process - as in computer aided production management or computer integrated manufacturing (Zammuto and O'Connor 1992).

Previous studies have considered the factors which shape firms' adoption of AMTs, suggesting positive links between adoption and firm size, skill levels and more flexible organisational cultures (Zammuto and O'Connor 1992). A limited number of studies have also attempted to quantify the impact of AMT use on firm employment and productivity. Bartelsman, Van Leeuwen, and Nieuwenhuijsen (1998) report higher average growth rates of total factor productivity and employment for Dutch firms which employ AMT. Employment growth has also been reported in France, the UK and the US by firms using AMT, whereas employment declines have been noted in Italy, Norway and Denmark (Bartelsman, Van

Leeuwen, and Nieuwenhuijsen 1998). Arvantis and Hollenstein (2001), in their study of AMT adoption, highlight the need for further analysis to gain a greater understanding of the relationship between technology diffusion and economic growth. In terms of the relationship between AMTs and innovation, research is limited. However, Barge-Gil et al. (2011) consider the impact on innovation where a firm has used forms of computerised controlled equipment, robotics or CAD/CAM. In their data for Spain, adoption of AMTs is strongly correlated with firm size but only weakly correlated with other firm characteristics such as R&D intensity or design use. AMT adoption then has a positive and significant effect on the probability of product innovation only for non-R&D performers but a positive impact on probability of process innovation for both R&D performers and non-performers.

The results of Barge-Gil et al. (2011) suggest the potential value of considering in more detail the factors which may condition the effects of AMTs on innovation. Other studies have also suggested the difficulties which firms may have in the effective implementation of AMTs, creating the potential for disruption effects, learning-by-using effects and time-lags in the effect of AMTs on innovation (Tyre and Hauptman 1992). Using panel data for Irish manufacturing firms, which provide AMT adoption histories, we are able to model the time profile of the AMT adoption-innovation relationship, and to consider how this relationship is contingent on other firm characteristics. As we are able to build in appropriate lags our study provides causal evidence on the AMT-innovation relationship, providing clear evidence of short-term disruption and longer-term beneficial effects.

The rest of the paper is organised as follows. Section 2 provide a brief overview of previous research focussing on the determinants of AMT adoption and learning-by-using effects and the relationship between innovation and AMTs. Section 3 introduces our hypotheses and Section 4 our data and methods. Section 5 outlines our empirical results and Section 6 concludes. Variable definitions are included in an Annex.

2. Background to the study

This section presents a brief synopsis of the determinants of technology adoption at the firm level. A limited number of empirical studies have identified factors which shape AMT adoption and these are discussed also. Next, we discuss the potential for disruptive effects with respect to AMT implementation. Finally, we discuss how AMT capabilities are likely to influence firm innovation.

2.1 Technology Adoption

The study of technology adoption has made considerable progress both theoretically and empirically. Earlier research based on the seminal work of Griliches (1957) and Mansfield (1968), highlighted information asymmetries as the key influences on adoption decisions (Rogers 2003). Later approaches (in particular, the equilibrium models reflecting organisational characteristics and strategic interactions as outlined by Karshenas and Stoneman (1993)) emphasised that adoption was based on the perceived benefits of adoption relative to its costs, i.e. the profitability associated with technology adoption. More recently, learning-by-using models reflecting cumulative learning from previous adoption decisions have been used to explain technology adoption (McWilliams and Zilbermanfr 1996).[1]

Next, we discuss some empirical work examining the factors which affect technology adoption (including AMT adoption). Numerous studies have reported that firm size has a significant and usually positive influence on adoption behaviour (Battisti et al. 2007; Karshenas and Stoneman 1993). Arvantis and Hollenstein (2001) report a positive and

[1] The basic hypothesis of the epidemic model is that non-adopters are more likely to adopt a new technology, the more widespread adoption by other member of their social system (Rogers, 2003). Empirically, epidemic effects have been measured in many forms, but in essence they are designed to capture knowledge and information gathering. Equilibrium models consider that potential users of a new technology differ from each other in important dimensions so that some firms obtain a greater return from the new technology than others do. Thus, firms who expect to receive a greater return from technology adoption are more likely to adopt it earlier (Karshenas and Stoneman, 1993). In empirical studies, variables which capture firm heterogeneity have been used to model equilibrium effects. Learning-by-using captures experiential learning within the firm. In adoption studies, learning-by-using has been measured as learning from the use of complementary technologies, complementarities between various functional groups of the same technology and the use of previous technology vintages (Stoneman and Kwon 1994; Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996; Stoneman and Toivanen 1997; Arvantis and Hollenstein 2001).

significant relationship between firm size and AMT adoption. It is likely that firm size captures firm-specific characteristics such as financial resources and range of activities which may explain why larger firms are in a position to adopt new technologies earlier that their smaller counterparts. A number of studies have examined whether year of establishment influences technology adoption; although empirical results are inconclusive (Arvantis and Hollenstein 2001; Battisti and Stoneman 2005). This may be as a result of two opposing effects: a positive effect reflecting the specific experience of older firms versus a negative effect due to lower adjustment costs due to a more modern capital stock and more openness of managers in newer firms (Parhi 2007).

Cohen and Levinthal (1990) illustrate how firms which engage in R&D activities are more easily able to assimilate new knowledge. A firm's R&D effort may provide a measure of the firm's capability of processing new technological information at a minimum cost (Baptista 2000). Investment in R&D contributes to firms' absorptive capacity. Surprisingly, empirical studies have found little evidence of R&D positively influencing adoption. For example, Karshenas and Stoneman (1993) and Baptista (2000), in examinations of CNC adoption, report insignificant results with respect to R&D.

In relation to the influence of human capital on technology adoption, Battisti et al. (2007) report that employee education levels positively influence the adoption of Information and Communication Technology (ICT). Similarly, Arvantis and Hollenstein (2001) report the positive influence of qualified personnel on AMT adoption. A skilled and educated workforce will enhance firms' absorptive capability which in turn influences technology adoption. It is generally accepted in the innovation literature that external linkages (with customers, suppliers, govt. institutions, etc.) generates synergies which foster firm innovation. Parhi (2007), in a study of AMT adoption in the Indian automotive industry, reports that the diversity and intensity of firms' external resources positively influence AMT use.

Demand and market conditions have also been considered with respect to adoption decision-making. Interestingly, Arvanitis and Hollenstein (2001) find market conditions are of limited importance in explaining AMT adoption; although, they find a higher probability of AMT adoption in high-tech sectors.

Finally, empirical studies report cumulative learning effects influencing technology adoption: AMT adoption in the Italian metalworking industry (Colombo and Mosconi 1995), the adoption of computer technology by farmers in California (McWilliams and Zilbermanfr 1996), use of an earlier generation of manufacturing technologies on AMT adoption by Swiss firms (Arvantis and Hollenstein 2001). This embodied knowledge in firms' acquisitions and implementation of new technologies is described as learning-by-using. Rosenberg (1972), for example, described how firms can learn from experience with technologies, and categorised this learning based on whether the firm was producing or using the technology. For instance, producers of a new technology may learn over time how to make the technology more cheaply and/or to improve the quality of technology. Rosenberg (1972) described this type of learning as 'learning by doing' which explains the supply of this technology. Rosenberg (1972) also describes how users of a given technology may increase their productivity over time as they learn how to better use this new technology. He terms this category of learning 'learning by using'.[2] Previous studies have highlighted the benefit to firms of learning-by-using new technology with respect to subsequent adoption decision-making (Stoneman and Kwon 1994; Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996; Stoneman and Toivanen 1997; Arvantis and Hollenstein 2001).

In summary, empirical studies have highlighted the influence of internal resources and absorptive capacity of the firm, demand and market conditions, external linkages and learning-by-using on firm decision-making with respect to technology adoption.

[2] McWilliams and Zilbermanfr (1996) highlight how economists use 'learning by doing' and 'learning by using' interchangeably, however, there is a clear supply and demand side distinction between the two (Rosenberg 1972). Given the supply side nature of 'learning by doing', it is not pertinent to this study. McWilliams and Zilbermanfr (1996) highlight both types of "learning" as playing an important role in the adoption of new technologies, as well as the 'traditional' form of learning which involves potential adopters gathering information about the performance of the new technology. These epidemic 'learning' effects capture a firm's ability to absorb knowledge from external sources and exploit it for its own innovative activities.

2.2 Implementation of AMTs and Learning-By-Using Effects

In recent decades, firms have made substantial investments in AMT adoption and their diffusion across the manufacturing sector has been well documented. The primary benefit of AMT use is cost-efficient flexibility in the manufacturing function (Sohal 1996) (a more detailed discussion of the benefits of AMTs is presented in the next section). However, AMT adoption is not without its difficulties. Sohal (1996) explains that expectations of AMT use will only be brought to fruition if a holistic approach is taken in relation to the various stages of AMT adoption and use: planning, acquiring, implementation and exploitation. Difficulties identified in implementing AMTs include: a lack of in-house programming skills, inter-departmental conflicts as responsibilities change, issues with controlling quality and stock at the sub-contractors, poor communication between management, departments and IS support, insufficient staff buy-in, and insufficient up-skilling and training provided (Sohal, 1996). Previous research has suggested the need for changing practices in order to fully assimilate AMTs within the company (Barge-Gil, Jesus Nieto, and Santamaria 2011).

The difficulties of implementing AMTs indicate that there may be a lag in firms' ability to derive the benefits of adoption. It is reasonable to assume that given these difficulties there is a period of adjustment within which firms build up knowledge and experience from using these new technologies. Essentially, firms are learning-by-using AMTs. In relation to learning-by-using effects, the innovation literature has focused on how cumulative learning and embodied knowledge influence adoption decision-making (Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996; Arvantis and Hollenstein 2001). However, little attention has been given to investigating how the disruptive elements and learning-by-using potential of AMTs may influence firm performance and innovation. Next, we discuss previous studies which have examined the relationship between AMT use and firm innovation.

2.3 AMTs and Innovation

The potential for AMTs to contribute to innovation arise from the ability of AMTs to generate economies of scope, i.e. 'the capacity to efficiently and quickly produce any of a range of parts within a family' (Zammuto and O'Connor 1992, p. 702). AMTs may, for example, enable firms to adopt more flexible production systems allowing smaller batch sizes and enabling firms to cope better with perceived environmental uncertainty (Hofmann and Orr 2005). Having more flexible production systems may also allow firms to adopt more complex innovation strategies with potentially higher returns (Hewitt-Dundas 2004). AMTs may also facilitate more radical innovation strategies as firms seek to create market turbulence by engaging in disruptive innovation in order to establish a position of market or technological leadership (Anthony et al. 2008; Hang, Chen, and Subramian 2010). Second, AMTs may lead to efficiency advantages, reducing the cost of innovations and increasing post innovation returns. Ceteris paribus this will mean that firms would be more likely to innovate or increase their level of innovative activity (Levin and Reiss 1984; Calantone, Harmancioglu, and Droge 2010). Third, AMTs may also lead to improvements in product quality and reliability reducing the potential technical uncertainty of innovation, and again having positive effects on post-innovation returns. Quality improvements may also have a negative impact on the commercial uncertainty of innovation (Astebro and Michela 2005). Both are likely to contribute positively to firms' incentive to innovate.

Despite these potential gains there have been relatively few studies of the role of AMTs in shaping firms' innovation activities. Hewitt-Dundas (2004) explores the role of AMTs in shaping small firms' innovation strategy choices, indicating that firms which have adopted AMTs are more likely to adopt 'complex' strategies involving the production of new products for new markets. Raymond, Croteau, and Bergeron (2009) also focus on small firms and demonstrate a relationship between AMT adoption on innovation outputs in Spanish small firms. Also in the context of Spain, Barges-Gil et al. (2011) argue that AMTs may contribute to explaining innovation outcomes in firms which do not undertake R&D. They argue that including AMTs as part of the explanation of firms' innovation achievements may help to broaden the relevance of research findings: 'If the role of activities closer to daily routines were highlighted as sources of innovation, however, managers may be more likely to enter the innovation process. From the perspective of innovation policy, the majority of measures to foster innovation has focused on R&D activities and has therefore been limited to a subset of innovators' (p. 416).

One potentially important issue in relating AMTs to innovation is that accessing the potential benefits of AMTs may be difficult and time-consuming involving learning-by-using.

Previous research has highlighted the many difficulties experienced by firms with respect to implementation and exploitation of AMTs (Sohal 1996). Zammuto and O'Connor (1992), for example, summarise the results of a number of studies which illustrate both the difficulties of implementing AMTs and the contingencies which may influence their effective implementation. As Barges-Gil et al. (2011) remark: 'skilled use of AMT is not easy to attain and depends upon several contingencies. It triggers many changes and success depends upon the ability of a firm to assimilate them and upon changing practices in order to afford a better fit with the AMT' (Barge-Gil, Jesus Nieto, and Santamaria 2011, p. 419)[3]. Training may, for example, contribute to enhance individual capabilities and firms' abilities to take advantage of the innovation benefits of AMTs (Barge Gil et al 2011). Similarly, more flexible – less hierarchic – management structures and cultures may also make AMT implementation more effective (Zammuto and O'Connor 1992).

The above literature informs the development of our hypotheses concerning learning-by-using effects, the positive relationship between AMT use and firm innovation, and the potential contingencies of that relationship on other firm factors. Our hypotheses are presented in the next section.

3. Hypotheses Development

Firms that adopt AMTs expect their use to generate economies of scope and cost-efficient flexibility. However, research suggests that AMTs can be disruptive and their implementation is not always seamless. Previous research on the adoption of technologies highlights that firms learn from using new technologies (Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996; Arvantis and Hollenstein 2001). We argue that this learning-by-using effect suggests that the benefit from AMT adoption is likely to increase as the time since adoption increases. In other words, we expect a time-lag with respect to the benefits of AMT adoption. For instance, a firm that invests in AMT will not necessarily see the benefits of their investment immediately; but at a later stage, when initial difficulties in its

[3] The process of AMT implementation itself, however, may also have positive benefits for innovation by stimulating new innovation as firms go through the process of learning-by-using the new technology.

implementation are ironed out, their investment in AMT is likely to bear fruition with respect to firm output. This leads us to our first hypothesis:

H_1: As time since AMT adoption increases, the impact of AMT use on firm innovation performance increases.

There is considerable evidence that firm characteristics, such as R&D, graduate workforce and backward (supplier) linkages, positively influence firm innovation. Previous studies have also established the positive relationship between firm characteristics and technology adoption, including AMT adoption (Parhi 2007; Arvantis and Hollenstein 2001). Given the influence of firm characteristics on technology adoption and firm innovation, it is likely that AMT use may increase the contribution of these factors to firm innovation. In other words, it is possible that AMTs may enhance the efficiency of the innovation input-output relationship. For example, the benefit of R&D on firm innovation may be intensified for those firms which have adopted AMT. AMT adoption may enable firms to more readily translate new knowledge gained through the R&D process into new product innovations. Similarly, AMTs may enable firms to exploit knowledge gained from interactions with suppliers for new product development more easily. The benefit of a skilled workforce to firm innovation may be intensified for those firms with AMT capabilities. The next series of hypotheses illustrate how we expect AMT use to moderate the innovation input-output relationship.

H_3: AMTs enhance the impact of R&D on firm innovation

H_4: AMT use increases the contribution of a skilled workforce to firm innovation

H_5: The positive influence of backward linkages on firm innovation is enhanced by AMT use

Our hypotheses essentially test the learning-by-using effects of AMT use on firm innovation and the efficiency-enhancing effects of AMT use on firm innovation.

4. Data and methods

Our empirical analysis is based on the Irish Innovation Panel (IIP) which provides data on the innovation activity and AMT use of manufacturing plants in Ireland and Northern Ireland over the period 1994 to 2008. More specifically, this element of the IIP comprises five surveys or waves conducted using similar survey methodologies and common questions. Each of the five surveys covers the innovation activities of plants with 10 or more employees over a three-year reference period.[4] The resulting panel is highly unbalanced reflecting non-response in individual surveys but also the opening and closure of plants over the period covered.

Plants' innovation activity in the IIP is represented by the standard Community Innovation Survey indicator: the proportion of plants' total sales (at the end of each three-year reference period) derived from products newly introduced during the previous three years. This variable has been widely used as an indicator of plants' innovation output (Laursen and Salter 2006; Roper, Du, and Love 2008; Love, Roper, and Du 2009), and reflects not only plants' ability to introduce new products to the market but also their short-term commercial success. Across those elements of the IIP used in the current analysis, 13.7 per cent of plants' sales were derived from newly introduced products (Table 1).[5]

One rather unusual feature of the IIP is that alongside plants' innovation activity it also provides information on the use and adoption of AMTs by manufacturing plants.[6] Five specific AMTs are considered: NC or CNC machinery, Robotics, Automated materials handling, Computer aided production management, and Computer integrated manufacturing. For each technology survey respondents were asked to indicate whether or not they used the technology and, if so, whether they had first introduced this technology in the three year period covered by the survey, the previous three years, or prior to this. For each respondent

[4] Individual survey response rates were: 1994-96, 32.9 per cent; 1997-99, 32.8 per cent; 2000-02, 34.1 per cent; 2003-05, 28.7 per cent; 2006-08, 38.0 per cent (Roper 1996; Roper and Hewitt-Dundas 1998; Roper and Anderson 2000; Hewitt-Dundas and Roper 2008).

[5] Variable definitions are given in Annex 1 and correlations in Annex 2.

[6] While this data is helpful one important limitation of the IIP is also worth noting. The structure of the survey questionnaire means that this adoption data is only collected for plants which reported undertaking some process innovation during the previous three years. Plants need not, however, have undertaken product innovation.

this provides an indication of whether they are using each technology and an indication of the length of time in which it has been in use in the plant. For example, around 49 per cent of the 2952 observations in the IIP were using CNC/NC machinery with 11 per cent of plants adopting this in the three years prior to the date of the survey, 16 per cent adopting 3-6 years before the survey, and 22 per cent earlier than that (Table 1). Computer integrated manufacturing was less common being used by around a quarter of plants of which only around 5 per cent reported having adopted this technology in the previous 3 years. See Figure 1 for AMT adoption curves.

The IIP also provides information on a number of other plant characteristics which previous studies have linked to innovation outputs. For example, plants' in-house R&D activities are routinely linked to innovation performance in econometric studies with suggestions that the innovation-R&D relationship reflects both knowledge creation (Harris and Trainor 1995) and absorptive capacity effects (Griffith, Redding, and Van Reenan 2003). 44 per cent of plants were conducting in-house R&D at the time of the IIP surveys (Table 1). Reflecting recent writing on open innovation (Chesbrough 2007; Chesborough 2006) external innovation relationships have also been shown to play an important role in shaping innovation outputs (Oerlemans, Meeus, and Boekema 1998; Ritala et al. 2013), complementing plants' internal capabilities (He and Wong 2012; Cassiman and Veugelers 2006; Arora and Gambardella 1990; Belderbos, Carree, and Lokshin 2006; Cassiman and Veugelers 2006). Here, we include three separate variables representing plants' external innovation co-operation with customers, suppliers and other organisations outside the supply chain. Around 22.5 per cent of plants reported having innovation cooperation with customers, while 24.0 per cent had backwards innovation cooperation with suppliers (Table 1). Links outside the supply chain could be with a variety of different types of organisation (e.g. universities, consultants) and here we construct a count variable representing the number of types of partner with which a plant was cooperating. On average, plants were cooperating with around 0.6 organisations outside the supply chain (Table 1). We also include in the analysis a variable reflecting the proportion of each plant's workforce which have a degree level qualification to reflect potential labour quality impacts on innovation (Freel 2005; Leiponen 2005) or absorptive capacity. Finally, studies of the impact of publicly funded R&D have, since Griliches (1995), repeatedly suggested that government support for R&D and innovation can have positive effects on innovation activity both by boosting levels of investment (Hewitt-Dundas and

Roper 2009) and through its positive effect on organisational capabilities (Buiseret, Cameron, and Georgiou 1995). Here, we therefore include a dummy variable where plants received public support for innovation.[7]

Our empirical approach focuses on the innovation or knowledge production function which represents the process through which plants' intellectual capital is transformed into innovation outputs (Griliches 1995; Love and Roper 2001; Laursen and Salter 2006). If I_i is an innovation output indicator for plant i the innovation production function might be summarised as:

$$I_i = \beta_0 + \beta_1 RD_i + \beta_2 FS_i + \beta_3 BS_i + \beta_4 HS_i + \beta_5 SK_i + \beta_6 GS_i + \delta_i \quad (1)$$

Where: RD are plants' in-house R&D investments, FS, BS and HS are forwards, backwards and horizontal knowledge search respectively, SK represent human capital inputs to innovation, and GS is the level of government support.

Our initial hypothesis suggests that AMTs might increase the flexibility of plants' production system increasing the efficiency of the process by which plants' intellectual capital is transformed into innovation outputs (Thomke 1997). Moreover we argue that due to learning-by-using effects the impact of AMTs on the innovation input-output relationship is likely to increase as the time since adoption increases. Let AMT_{it} indicate AMT adoption in the current period, then for the innovation production function:

$$\begin{aligned} I_i = \beta_0 + \beta_1 RD_i + \beta_2 FS_i + \beta_3 BS_i + \beta_4 HS_i + \beta_5 SK_i + \beta_6 GS_i + \\ \beta_7 AMT_{it} + \beta_8 AMT_{it-1} + \beta_9 AMT_{it-2} + \delta_i \end{aligned} \quad (2)$$

Evidence of learning-by-using effects for AMTs and Hypothesis 1 would then require $\beta_9 > \beta_8 > \beta_7$.

[7] Elsewhere we profile the range of public support initiatives for innovation in Ireland and Northern Ireland over the period covered by the IIP (Meehan 2000; O'Malley, Roper, and Hewitt-Dundas 2008).

Our remaining hypotheses investigate the potential for efficiency-enhancing effects suggesting that AMTs might increase the contribution of specific elements of firms' knowledge capital to innovation. For example, AMTs may allow plants to more readily translate knowledge gained from external linkages into new product innovations enhancing the innovation value of plants' external relationships. This type of contingency effect is reflected in Hypotheses 2 - 4 and evaluated empirically using interaction effects. For example, if AMTs enhance the impact of backwards search on innovation we would expect $\gamma_j > 0$ in the following model:

$$\begin{aligned} \mathrm{I_i} &= \beta_0 + \beta_1 \mathrm{RD_i} + \beta_2 \mathrm{FS_i} + \beta_3 \mathrm{BS_i} + \beta_4 \mathrm{HS_i} + \beta_5 \mathrm{SK_i} + \beta_6 \mathrm{GS_i} + \beta_7 \mathrm{AMT_{it}} + \beta_8 \mathrm{AMT_{it-1}} \\ &+ \beta_9 \mathrm{AMT_{it-2}} + \sum_j \gamma_j \mathrm{BS_i} \times \mathrm{AMT_{it-j}} + \delta_i \end{aligned} \tag{3}$$

In fact, depending on our test of Hypothesis 1 – learning by using effects in AMTs – we might have a more specific expectation that $\gamma_2 > \gamma_1 > \gamma_0$.

Our choice of estimation method is dictated largely by the fact that we are using plant-level data from a highly unbalanced panel and that our dependent variables are percentages. We therefore make use of tobit estimators, including in each model a set of sector controls at the 2- digit level and a series of time dummies to pick up any secular differences between the waves of the IIP. Observations are also weighted to provide representative results and take account of the structured nature of the IIP surveys.

5. Results

5.1 Learning-by-using

Our initial hypothesis suggests that due to learning-by-using effects the impact of AMT adoption on innovation outputs will increase as the time since adoption increases. We explore this hypothesis in Table 2 which reports estimates of the innovation production function (equation 2) including variables reflecting the time since adoption for the five AMTs. Models also include a series of plant-level controls, sectoral and wave dummies. As anticipated, we see strong contrasts between the innovation benefits of recent and earlier AMT adoption. In four of the five models (CNC, Robotics, CAM and CIM), we find evidence of positive and significant innovation benefits from the early adoption of AMTs, i.e. where the AMT was first implemented more than six years ago. No consistent or significant innovation-AMT relationship is evident where firms adopted any of the AMTs more recently. Where these is any significant effect from AMT adoption within the last 6 years this is actually negative, suggesting that AMT adoption is actually impacting negatively on firms' innovation performance. It is difficult to interpret this negative effect directly from the econometric evidence but it is consistent with a disruption effect: the ability of firms to innovate is impacted negatively during the period when they are implementing AMTs (Tyre and Hauptman 1992). What is perhaps more surprising is the apparent duration of this disruption or negative effect on innovative outputs before firms gain the economies of scope anticipated from AMTs. See Table 3 for a symbolic summary of the AMT learning-by-using effect on innovation.

Other factors also prove important in determining firms' innovation outputs. For example, R&D has a consistently positive and significant effect on firm innovation performance. This finding is in line with previous studies (Harris and Trainor 1995; Griffith, Redding, and Van Reenan 2003). We also find that interactions with suppliers and customers have a positive influence on firm innovation performance. Many studies have also reported the positive influence of external relationships on firm innovation outputs (Oerlemans, Meeus, and Boekema 1998; Ritala et al. 2013; He and Wong 2012; Cassiman and Veugelers 2006; Arora and Gambardella 1990; Belderbos, Carree, and Lokshin 2006; Cassiman and Veugelers 2006).There is no evidence of a relationship between interactions with competitors and firms' innovation performance. Firm size, measured by number of employees, does not influence firm innovation performance. We do, however, find a positive relationship between a graduate workforce and firms' innovation performance. Firms with increasing proportions of graduates on their workforce report an increasing percentage of sales from new products. We also find that Government support for innovation has a consistently positive and statistically significant influence on firm innovation performance. Thus, firms who receive government support for innovation report a higher percentage of sales from new products relative to those firms who do not receive such support. This finding is in line with earlier studies (Buiseret, Cameron, and Georgiou 1995).

5.2 Efficiency enhancing effects of AMTs

We next test a series of hypotheses that AMT adoption may contribute to the efficiency of the innovation process, increasing the innovation benefits of specific innovation inputs. Our learning-by-using results suggest that any such benefits are only likely in the longer term when the adoption of AMTs is having the positive effect anticipated in Hypothesis 1. We therefore test the efficiency-enhancing role of AMTs by including interaction effects in our baseline models relating only to early adoption of AMTs. In Table 4, we include an interaction effect variable for early adopter and R&D in all five models. The R&D coefficient remains consistently positive and significant in all five models. The early adopter coefficient in all five models remains positive, although the significance levels change somewhat and the AMH early adopter coefficient reaches significance in this model. The interaction effect variables are insignificant in the five models.[8] Therefore, we find little evidence in support of Hypothesis 2, i.e. that AMT adoption enhances the contribution of R&D to innovation output.

In Table 5, we include an interaction term for early AMT adopters and the proportion of graduates in the workforce. The proportion of graduates' coefficient remains consistently positive and significant in all five models. The early adopter coefficient in all five models remains positive, although the significance levels change somewhat. The AMH early adopter coefficient reaches significance in this model, whereas the robotics early adopter coefficient is no longer significant. The interaction effect variables are insignificant in the five models. Again, therefore we find little evidence that AMT adoption enhances the impact of a highly qualified workforce on innovation output.

Finally, we include an interaction term for early AMT adopters and backward (supplier) linkages to reflect the possibility that AMT adoption may enhance the value of supplier linkages on innovation (Table 6). The backward linkages coefficient remains consistently positive and significant in all five models. The early adopter coefficient in all five models

[8] The sign and significance of the other variables are consistent with the baseline models. This is the case in all the models in which we test interaction effects.

remains positive, the significance levels change slightly. The AMH early adopter coefficient reaches significance in this model, whereas the robotics early adopter coefficient is no longer significant. The interaction effect variables are negative and significant in two of the models; the interaction effect for early AMH adoption and early CAM adoption are negative and significant. Contrary to expectations this suggests that early AMT reduces (or substitutes for) the value of supplier linkages on innovation outputs. One possibility here is that co-operation with equipment suppliers as part of the implementation of AMTs is acting as a substitute for more specific co-operation with suppliers as part of firms' innovation activity. Therefore when both co-exist, the innovation benefit of each is reduced. The sign and significance of the other variables are consistent with the baseline models.

6. Discussion and conclusions

Our results suggest both the positive and negative impacts of the adoption of AMTs for innovation. On the positive side, and in the longer term, each of the AMTs we consider have strongly positive and generally significant effects on firms' innovation outputs. Achieving these positive results, however, seems difficult with little evidence of short-term innovation benefits from AMT adoption and some significant negative effects. These we interpret as disruption effects as firms seek to implement AMTs. This type of learning-by-using process – marked by short-term negative effects but longer-term positive outcomes – is well recognised in the literature on AMT adoption. Sohal (1996), for example, in his examination of AMT adoption by seven manufacturing companies identified a number of advantages achieved through AMT adoption including improved flexibility, reduced process time, reduced unit costs and improvements in product quality. Problems during implementation arose from a lack of in-house programming skills, communication between departments and management, and the trade-off between short-term production targets and the disruption involved in AMT implementation. Other studies have emphasised the importance of organisational culture as a pre-condition for successful AMT implementation (Zammuto and O'Connor 1992). Unfortunately Sohal (1996) gives little indication of the time periods over which the companies in his study were able to obtain the benefits of AMTs and so a direct comparison with our results here is difficult.

The work of Sohal and others (Hofmann and Orr 2005; Sohal 1996) points to the importance of corporate capabilities linked to absorptive capacity for the effective implementation of AMTs. Sohal (1996) also reports the benefits of AMTs in enhancing the resource efficiency of firms' production operations. It is perhaps surprising therefore that we find no evidence of any resource enhancing role from AMTs in terms of innovation either in terms of labour inputs, R&D or external linkages to suppliers. The implication – with the learning-by-using effect described before – is that in the longer-term AMTs do have innovation benefits but that these benefits are related directly to the implementation of the technology itself, not any related efficiency effects.

Our initial results suggest the complexity of the relationship between AMT adoption and innovation. For example, One other possibility – which to date we have only partially explored – is the potential for firms' absorptive capacity to shorten the learning cycle for AMT adoption. Are firms with stronger skill endowments able to accelerate the process of effective AMT implementation? How does this influence innovation outputs and competitive outcomes? Similar questions might also be posed in terms of R&D or other in-house resources such as production engineering capabilities. Adoption of one specific AMT may also be helped by prior adoption of other AMTs, a learning process which may also accelerate effective implementation. This too we have yet to explore. It may also be of value to also consider the role of AMTs in shaping the nature of firms' innovation activity. Hewitt-Dundas (2004) for example, is able to demonstrate a link between the adoption of AMTs and the complexity of innovation strategies among smaller firms.

Table 1: Sample Descriptives

	Mean	Std.Dev.
Innovative sales (% sales)	13.720	21.536
AMT variables		
CNC current adopter	0.110	0.313
CNC previous adopter	0.160	0.366
CNC early adopter	0.220	0.415
Robotics current adopter	0.036	0.186
Robotics previous adopter	0.061	0.240
Robotics early adopter	0.100	0.299
AMH current adopter	0.062	0.242
AMH previous adopter	0.100	0.301
AMH early adopter	0.156	0.363
CAM current adopter	0.087	0.282
CAM previous adopter	0.141	0.348
CAM early adopter	0.212	0.409
CIM current adopter	0.051	0.220
CIM previous adopter	0.082	0.274
CIM early adopter	0.121	0.327
Plant characteristics		
R&D in house	0.441	0.497
Forwards linkages	0.225	0.417
Backwards linkages	0.240	0.427
Horizontal linkages	0.577	1.202
Employment	70.655	168.752
Workforce with degree (%)	9.992	13.647
Government support	0.220	0.414

Notes: Variable definitions in Annex 1. N=2952. Observations are weighted to give representative results.

Table 2: Determinants of Innovation Sales (Baseline Models)

Dependent Variable: Innovative sales (% sales)					
	CNC	Robotics	AMH	CAM	CIM
Adoption Vintage					
Current adopter	-1.802	-1.755	-6.813***	1.704	-1.848
	-2.007	-3.014	-2.391	-2.018	-2.67
Previous adopter	-2.09	1.227	2.247	-8.543***	-6.573**
	-2.239	-2.98	-2.455	-2.101	-2.795
Early adopter	3.569**	3.814**	2.574	6.535***	7.255***
	-1.583	-1.944	-1.634	-1.467	-1.911
Firm Resources					
R&D	7.505***	7.591***	7.529***	7.384***	7.538***
Interaction	-0.851	-0.848	-0.853	-0.85	-0.849
Graduate	0.136***	0.137***	0.137***	0.137***	0.135***
Workforce	-0.029	-0.029	-0.029	-0.029	-0.029
Govt. Support	4.193***	4.307***	4.179***	4.132***	4.150***
for Innovation	-1.006	-1.003	-1.004	-1.001	-1.004
Backward	6.235***	6.230***	6.235***	6.175***	6.237***
Linkages	-1.161	-1.157	-1.158	-1.157	-1.158
Forward	2.605**	2.449**	2.723**	2.804**	2.596**
Linkages	-1.235	-1.235	-1.233	-1.231	-1.231
Horizontal	-0.131	-0.238	-0.179	-0.24	-0.247
Linkages	-0.409	-0.409	-0.413	-0.409	-0.41
Employment	0.004	0.001	0.003	0.004	0.003
	-0.004	-0.004	-0.004	-0.004	-0.004
Empl - squared	-0.004	0	-0.002	-0.004	-0.003
	-0.01	-0.011	-0.01	-0.01	-0.01
Constant	-0.045	-0.23	-0.114	-0.03	0.123
	-1.433	-1.427	-1.442	-1.43	-1.432
N	2952	2952	2952	2952	2952
Chi-squared	476.566	480.14	481.304	493.484	485.969
p- value	0	0	0	0	0
BIC	26894.925	26891.351	26890.187	26878.007	26885.522

Notes: Each model includes a specific technology adoption vintage variable; otherwise explanatory variables are the same. Models include industry and wave dummies.

Table 3: Symbolic Summary: AMT Learning-by-Using Effect on Firm Innovation

AMT:	CNC	Robotics	AMH	CAM	CIM
Current adopter	(-)	(-)	-***	(+)	(-)
Previous adopter	(-)	(+)	(+)	-***	-**
Early adopter	+**	+**	+	+***	+***

Table 4: Determinants of Innovation Sales – R&D & Early Adopter Interaction

Dependent Variable: Innovative sales (% sales)					
	CNC	Robotics	AMH	CAM	CIM
Adoption Vintage					
Current adopter	-1.685	-1.615	-6.805***	1.797	-1.789
	-2.003	-3.012	-2.39	-2.015	-2.67
Previous adopter	-2.46	0.925	2.11	-8.844***	-6.702**
	-2.237	-2.98	-2.459	-2.1	-2.796
Early adopter	7.340***	7.605***	3.856*	9.833***	8.965***
	-1.903	-2.493	-2.125	-1.834	-2.382
Interaction Variable					
Early Adopter	-6.432***	-6.129**	-1.999	-5.535***	-2.777
*R&D	-1.811	-2.527	-2.118	-1.852	-2.312
Firm Resources					
R&D	8.925***	8.174***	7.831***	8.530***	7.871***
Interaction	-0.939	-0.881	-0.911	-0.932	-0.892
Graduate	0.132***	0.136***	0.136***	0.133***	0.134***
Workforce	-0.029	-0.029	-0.029	-0.029	-0.029
Govt. Support	4.314***	4.365***	4.158***	4.103***	4.138***
for Innovation	-1.005	-1.002	-1.004	-1.000	-1.004
Backward	6.199***	6.190***	6.228***	6.100***	6.201***
Linkages	-1.158	-1.156	-1.158	-1.155	-1.158
Forward	2.445**	2.511**	2.713**	2.947**	2.614**
Linkages	-1.234	-1.234	-1.232	-1.23	-1.231
Horizontal	-0.071	-0.234	-0.157	-0.206	-0.241
Linkages	-0.409	-0.409	-0.414	-0.408	-0.41
Employment	0.004	0.001	0.003	0.004	0.004
	-0.004	-0.004	-0.004	-0.004	-0.004
Empl – squared	-0.004	0	-0.002	-0.004	-0.003
	-0.01	-0.011	-0.01	-0.01	-0.01
Constant	-0.614	-0.395	-0.213	-0.373	0.018
	-1.439	-1.428	-1.446	-1.433	-1.434
N	2952	2952	2952	2952	2952
Chi-squared	489.155	486.019	482.195	502.402	487.411
p- value	0	0	0	0	0
BIC	26890.326	26893.462	26897.286	26877.08	26892.07

Notes: Each model includes a specific technology adoption vintage variable; otherwise explanatory variables are the same. Models include industry and wave dummies.

Table 5: Determinants of Innovation Sales – Graduate Workforce & Early Adopter Interaction

Dependent Variable: Innovative sales (% sales)					
	CNC	Robotics	AMH	CAM	CIM
Adoption Vintage					
Current adopter	-1.815	-1.749	-6.705***	1.837	-1.802
	-2.007	-3.015	-2.394	-2.019	-2.676
Previous adopter	-2.204	1.229	2.283	-8.485***	-6.603**
	-2.244	-2.98	-2.455	-2.1	-2.797
Early adopter	3.081*	3.904*	3.235*	7.541***	7.513***
	-1.717	-2.209	-1.836	-1.618	-2.155
Interaction Variable					
Early Adopter	0.065	-0.009	-0.074	-0.104	-0.024
*Graduates	-0.088	-0.102	-0.093	-0.071	-0.095
Firm Resources					
R&D	7.518***	7.589***	7.506***	7.317***	7.527***
Interaction	-0.851	-0.849	-0.854	-0.851	-0.85
Graduate	0.130***	0.138***	0.144***	0.155***	0.137***
Workforce	-0.031	-0.03	-0.03	-0.032	-0.03
Govt. Support	4.191***	4.306***	4.173***	4.105***	4.147***
for Innovation	-1.006	-1.003	-1.004	-1.001	-1.004
Backward	6.203***	6.228***	6.229***	6.228***	6.247***
Linkages	-1.162	-1.157	-1.158	-1.157	-1.158
Forward	2.624**	2.451**	2.698**	2.745**	2.593**
Linkages	-1.236	-1.235	-1.233	-1.231	-1.231
Horizontal	-0.144	-0.238	-0.17	-0.208	-0.244
Linkages	-0.41	-0.409	-0.413	-0.409	-0.41
Employment	0.003	0.001	0.003	0.004	0.004
	-0.004	-0.004	-0.004	-0.004	-0.004
Empl - squared	-0.004	0	-0.002	-0.005	-0.004
	-0.01	-0.011	-0.011	-0.01	-0.01
Constant	0.001	-0.232	-0.144	-0.226	0.092
	-1.434	-1.428	-1.443	-1.436	-1.437
N	2952	2952	2952	2952	2952
Chi-squared	477.103	480.148	481.926	495.641	486.035
p- value	0	0	0	0	0
BIC	26902.378	26899.333	26897.555	26883.84	26893.45

Notes: Each model includes a specific technology adoption vintage variable; otherwise explanatory variables are the same. Models include industry and wave dummies.

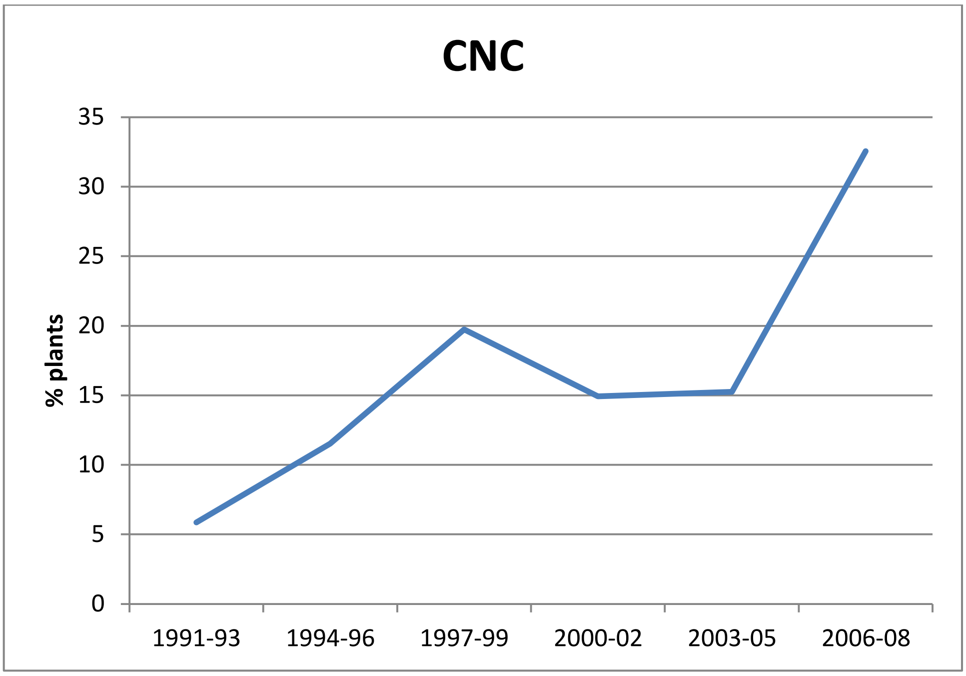
Table 6: Determinants of Innovation Sales – Backward Linkages & Early Adopter Interaction

Dependent Variable: Innovative sales (% sales)					
	CNC	Robotics	AMH	CAM	CIM
Adoption Vintage					
Current adopter	-1.803	-1.839	-6.788***	2.063	-1.829
	-2.01	-3.017	-2.389	-2.019	-2.67
Previous adopter	-2.089	1.132	2.369	-8.612***	-6.597**
	-2.239	-2.983	-2.454	-2.098	-2.795
Early adopter	3.565**	3.146	4.075**	8.342***	7.958***
	-1.698	-2.171	-1.789	-1.596	-2.145
Interaction Variable					
Early Adopter	0.015	1.751	-4.417**	-5.535***	-1.69
*Suppliers	-1.93	-2.537	-2.152	-1.943	-2.344
Knowledge Sourcing					
R&D	7.505***	7.609***	7.450***	7.295***	7.504***
Interaction	-0.852	-0.849	-0.853	-0.85	-0.85
Graduate	0.136***	0.138***	0.134***	0.137***	0.135***
Workforce	-0.029	-0.029	-0.029	-0.029	-0.029
Govt. Support	4.193***	4.315***	4.187***	4.040***	4.127***
for Innovation	-1.006	-1.003	-1.003	-1	-1.004
Backward	6.231***	6.002***	7.103***	7.642***	6.494***
Linkages	-1.292	-1.203	-1.232	-1.265	-1.211
Forward	2.605**	2.450**	2.622**	2.933**	2.584**
Linkages	-1.236	-1.235	-1.233	-1.23	-1.231
Horizontal	-0.131	-0.259	-0.056	-0.147	-0.209
Linkages	-0.411	-0.41	-0.417	-0.41	-0.414
Employment	0.004	0.001	0.003	0.004	0.003
	-0.004	-0.004	-0.004	-0.004	-0.004
Empl - squared	-0.004	0	-0.002	-0.004	-0.003
	-0.01	-0.011	-0.01	-0.01	-0.01
Constant	-0.044	-0.154	-0.279	-0.299	0.067
	-1.437	-1.431	-1.444	-1.431	-1.434
N	2952	2952	2952	2952	2952
Chi-squared	476.566	480.617	485.516	501.591	486.488
p- value	0.018	0.018	0.018	0.018	0.018
BIC	26902.916	26898.864	26893.966	26877.89	26892.99

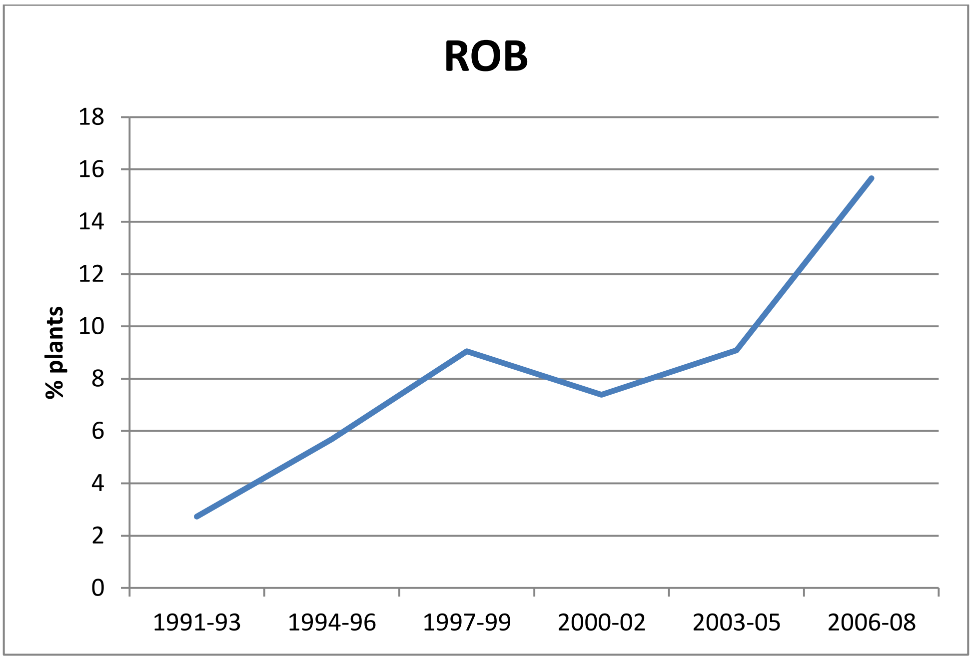
Notes: Each model includes a specific technology adoption vintage variable; otherwise explanatory variables are the same. Models include industry and wave dummies.

Figure 1: Adoption Curves

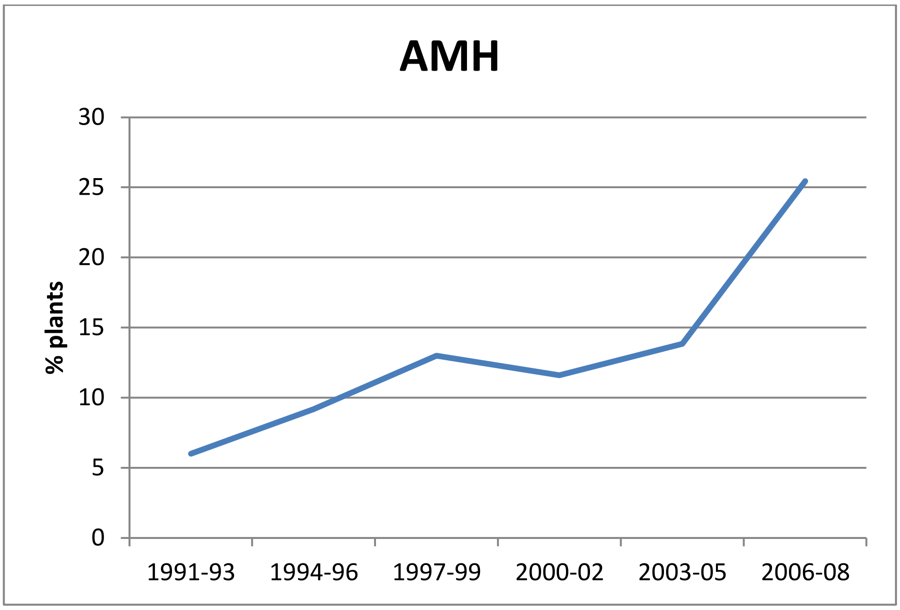
(a) CNC/NC equipment



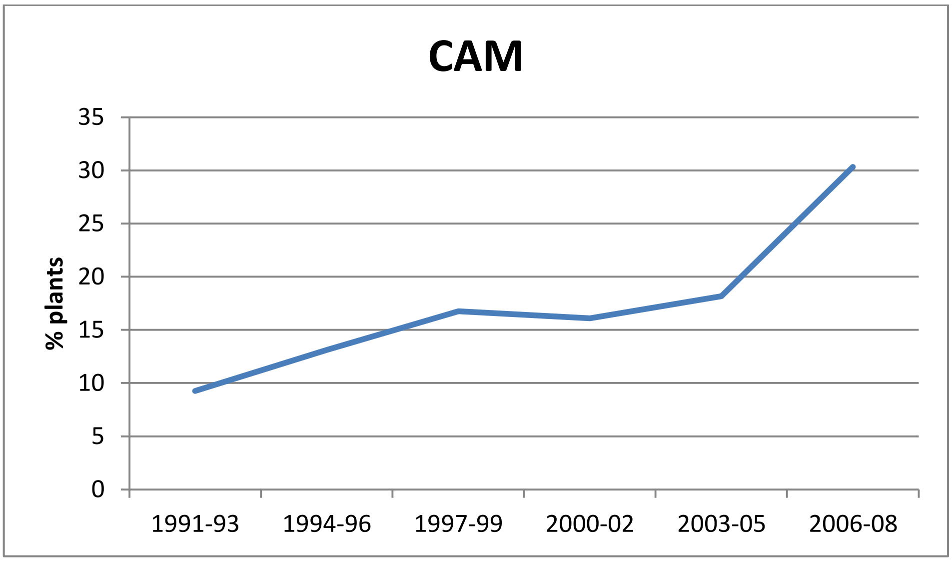
(b) Robotic equipment



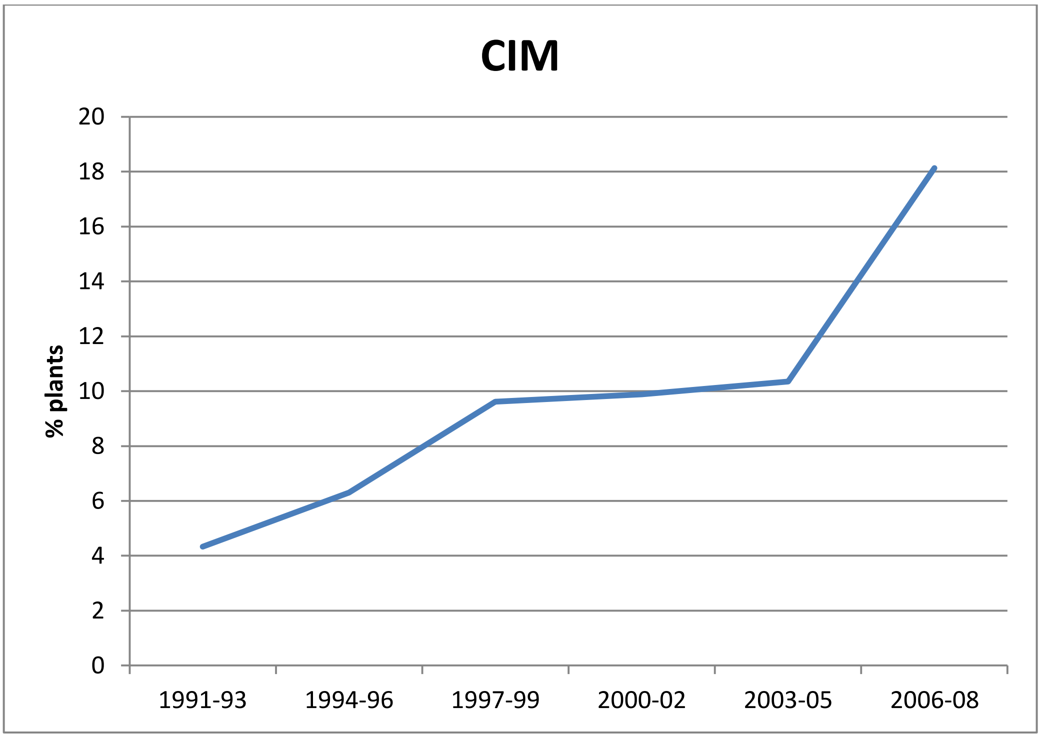
(c) Automated materials handling



(d) Computer aided manufacturing



(e) Computer integrated manufacturing



Annex 1: Variable Definitions

Innovation	
Innovative sales (new) (% sales)	An indicator representing the percentage of firms' sales at the time of the survey accounted for by products which had been newly introduced over the previous three years.
AMT variables	
Current adopter	Binary variable taking value 1 if the plant had first introduced the AMT in the previous three years and zero otherwise and is currently using the technology.
Early adopter	Binary variable taking value 1 if the plant had first introduced the AMT in the previous six years and zero otherwise and is currently using the technology.
Previous adopter	Binary variable taking value 1 if the plant had introduced the AMT at any time and is currently using the technology.
Firm Resources	
In plant R&D	A binary indictor taking value one if the plant has an in-house R&D capacity
Percentage with degree	Percentage of the workforce with a degree or equivalent qualification
Public support for product innovation	A binary indicator taking value one if the plant had received government support for product innovation over the previous three years.
Forwards Linkages	A binary indicator taking value one if the plant is co-operating with customers as part of its innovation activity.
Backwards Linkages	A binary indicator taking value one if the plant is co-operating with suppliers as part of its innovation activity.
Other Linkages	A count indicator of the breadth of plants' other innovation partnering activity. Takes values 0 to 7 depending on how many different types of partner the plant is working with: consultant, competitor, joint venture, government laboratory, university, private laboratory, industry research centre.
Employment	Employment at the time of the survey.

Annex 2: Correlations

Table A2a: Dependent variable and AMT variables (N=2952)

	|	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	isucc1	1.000															
(2)	Cncnow	0.058	1.000														
(3)	Cncnowprev	0.081	0.811	1.000													
(4)	cncnowprev~y	0.108	0.674	0.831	1.000												
(5)	Robnow	0.075	0.262	0.246	0.207	1.000											
(6)	Robnowprev	0.125	0.287	0.332	0.289	0.744	1.000										
(7)	robnowprev~y	0.141	0.258	0.332	0.320	0.570	0.767	1.000									
(8)	Amhnow	0.013	0.272	0.241	0.197	0.299	0.260	0.211	1.000								
(9)	Amhnowprev	0.063	0.262	0.301	0.260	0.297	0.368	0.314	0.752	1.000							
(10)	amhnowprev~y	0.104	0.242	0.291	0.314	0.259	0.330	0.385	0.583	0.775	1.000						
(11)	Camnow	0.061	0.324	0.315	0.241	0.240	0.242	0.216	0.302	0.286	0.263	1.000					
(12)	Camnowprev	0.058	0.350	0.368	0.309	0.219	0.254	0.255	0.250	0.272	0.283	0.766	1.000				
(13)	camnowprev~y	0.118	0.310	0.350	0.377	0.185	0.232	0.276	0.224	0.272	0.356	0.603	0.787	1.000			
(14)	Cimnow	0.032	0.277	0.254	0.206	0.272	0.256	0.234	0.297	0.290	0.258	0.480	0.397	0.319	1.000		
(15)	Cimnowprev	0.051	0.294	0.309	0.272	0.240	0.270	0.259	0.286	0.341	0.308	0.436	0.491	0.405	0.775	1.000	
(16)	cimnowprev~y	0.102	0.284	0.319	0.325	0.242	0.290	0.331	0.234	0.321	0.362	0.370	0.443	0.483	0.628	0.810	1.000

Table A2b: Dependent variable and controls (N=2952)

	|	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1)	isucc1	1.000								
(2)	rdplan	0.261	1.000							
(3)	lkclient	0.203	0.245	1.000						
(4)	lksupp	0.213	0.226	0.624	1.000					
(5)	lkhorz	0.176	0.266	0.585	0.559	1.000				
(6)	emp3	0.111	0.112	0.084	0.143	0.200	1.000			
(7)	emp2	0.046	0.035	0.005	0.055	0.101	0.808	1.000		
(8)	pdegree	0.152	0.174	0.131	0.114	0.155	0.097	0.042	1.000	
(9)	gaprodd	0.205	0.406	0.217	0.185	0.281	0.090	0.043	0.133	1.000

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