AMT adoption and innovation: An investigation of dynamic and complementary effects

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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 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. Strong complementarities between simultaneously adopted AMTs suggest the value of disruptive rather than incremental AMT implementation strategies.

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

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 the knowledge embodied in firms' capital equipment. 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 (AMH) – or the integration and optimisation of the production process - as in computer aided production management or computer integrated manufacturing (CIM) (Zammuto and O'Connor 1992). In this paper, we specifically address the question of whether, and over what period, the adoption of AMTs impacts on firms' innovation success.

Previous studies have considered the factors which shape firms' adoption of AMTs, suggesting positive links between AMT 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 employment and productivity. Bartelsman, Van Leeuwen, and Nieuwenhuijsen (1998), for example, report higher average growth rates of total factor productivity and employment for Dutch firms which employed AMT. Employment growth has also been linked to

AMT use in France, the UK and the US, while employment reductions have been noted in Italy, Norway and Denmark (Bartelsman, Van Leeuwen, and Nieuwenhuijsen 1998). Arvantis and Hollenstein (2001), in their study of AMT adoption in Switzerland, highlight the need for further analysis 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 uses forms of computerised aided manufacturing (CAM), 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. 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.

Other studies report the influence of AMT in the innovative process for low-and-medium technology firms (Santamaría, Nieto, and Barge-Gil 2009) and for small firms (Raymond, Croteau, and Bergeron 2009). Both studies 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 face 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 provides AMT adoption histories, we focus here on the relationship between innovation and the prior adoption of AMTs. Specifically, we ask whether, and over what period, the adoption of AMTs impacts on firms' innovation success. The AMTs examined include computer-aided manufacturing (CAM), automated materials handling (AMH), computer-integrated manufacturing (CIM) and robotics. Most, if not all, of the prior studies of the relationship between AMTs and innovation have been based on cross-sectional data making causality difficult to identify, and providing little information on the nature of the learning effects and lags involved in AMT adoption and the potential benefits for innovation. Our study makes three main contributions. First, it clearly highlights the temporal profile of the performance benefits of individual

AMTs, highlighting short-term disruption effects but longer-term benefits. Second, it highlights complementarities between the adoption of specific AMTs, and third it suggests the role of learning-by-using effects in the shaping of the AMT–innovation relationship (Rosenberg 1982).

The rest of the paper is organised as follows. Section 2 provides a brief overview of AMTs, and their degree of integration in the manufacturing process; a discussion of the relationship between innovation and AMTs; and, the role of complementarities learning-by-using effects in the enhancement of firms' innovation performance. Section 2 also outlines our three hypotheses relating to the potential impacts of prior AMT adoption on innovation. Section 3 describes the data used in our study. Our empirical analysis is based on a panel dataset relating to Irish manufacturing firms which were surveyed at regular intervals over the 1994-2008 period. Section 4 outlines the main empirical results and Section 5 discusses the implications of this work. Variable definitions are included in an Annex.

2. Concepts and hypotheses

2.1 AMTs and Innovation

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. We briefly describe the four AMTs studied in this paper and subsequently categorise them based on the extent to which they integrate elements of the manufacturing process.

Computer-aided manufacturing (CAM) is the use of computer software to control machine tools and related machinery in manufacturing process and would include processes such as numerically controlled machining, laser cutting, water-jet cutting and robot control. Automated Materials Handling (AMH), sometimes called automated storage/retrieval systems, involves the automated movement of items during the manufacturing process. Such systems may use high-rise stacker cranes, automated guided vehicle systems, computerized conveyors, computerized carousels, and other such systems to store and retrieve materials. Computer-integrated manufacturing (CIM) involves integrated systems of NC machines, robots, material conveyors, and other such computer-driven equipment. Robotics may involve simple pick and place robots, with 1, 2, or 3 degrees of freedom or more sophisticated robots that can handle tasks such as welding or painting on an assembly line and may also have the benefit of trajectory control (Kotha and Swamidass 2000).

Innovation is identified as a critical driver of business productivity and economic growth (Schumpeter 1934; Romer 1990). Schumpeter (1934) argued that the catalyst to innovation is the transformation of knowledge into new products or processes. The relationship between innovation output and innovation inputs has been used extensively in the literature (Crepon, Duguet, and Mairessec 1998; McCann and Simonen 2005; Griffith et al. 2008.; Roper, Du, and Love 2008). Numerous scholars have attempted to explain why some firms are more likely to innovate, with firm characteristics, such as size, sector, ownership, and location being identified as influential drivers of innovation output (Audretsch and Feldman 1996; Boschma 2005; Gordon and McCann 2005; Jordan and O'Leary 2008; McCann and Simonen 2005; Tether 1998; Romer 1990; Roper, Du, and Love 2008). The importance of R&D to innovation activity within firms has also been established by many authors (Roper, Du, and Love 2008; Freel 2003). Firms engaging in R&D activity benefit their existing stock of knowledge resulting in commercial gains from the introduction of new products, processes and/ or organisational innovations (Roper, Hewitt-Dundas, and Love 2004). There is also considerable evidence of the importance of external sources of knowledge for innovation outputs (Mansury and Love 2008). These external sources of knowledge may include linkages with customers, suppliers, competitors and/or research institutes (Roper, Du, and Love 2008). Likewise, managerial capabilities have been highlighted as an important factor in firm level innovation. Successful innovation requires that firms and managers provide clear and consistent signals to employees about the goals and objectives of the firm (Barnes et al. 2006). In addition, the technologies firms adopt and use, such as AMT, can influence innovation capabilities (Santamaría, Nieto, and Barge-Gil 2009; Raymond, Croteau, and Bergeron 2009).

In recent decades, firms have made substantial investments in AMT adoption and their diffusion across the manufacturing sector has been well documented. Factors such as firm size (Battisti et al. 2007; Karshenas and Stoneman 1993); firm vintage (Arvantis and Hollenstein 2001; Battisti and Stoneman 2005); human capital (Arvantis and Hollenstein 2001; Parhi 2007); cumulative learning from previous adoption experience (learning-by-using) (Stoneman and Kwon 1994; Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996; Stoneman and Toivanen 1997; Arvantis and Hollenstein 2001) seem influential in AMT adoption. R&D (Karshenas and Stoneman 1993; Baptista 2000) and market conditions (Arvantis and Hollenstein 2001) seem less important. To date, research has focused largely on explaining what influences and motivates AMT adoption and the relationship between manufacturing capabilities and AMT use (Spanos and Voudouris 2009). Empirical evidence in relation to AMT and flexibility (Meredith 1988; Lei and Goldhar 1990), low cost (Corbett and VanWassenhove 1993), and quality (Parthasarthy and Sethi 1992) is positive. It is generally accepted that the primary benefit of AMT use is cost-efficient flexibility in the manufacturing function (Sohal 1996). However, it is important to note that Boyer (1988) reports that manufacturing plants that emphasize low costs are also those investing more heavily in AMT.

The potential for AMTs to contribute to innovation arises 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, first, 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 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 the potential gains of AMT use 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 and 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). Santamaría, Nieto, and Barge-Gil (2009) report that the use of AMT is a critical factor in the generation of product and process innovations in low-and-medium technology (LMT) firms but is of limited importance in the case of high technology firms. Santamaría, Nieto, and Barge-Gil (2009) argue that non-R&D internal activities are important for innovation in LMT industries given the innovation process in such industries is not usually the result of the latest scientific or technological knowledge, but more likely to involve transforming the general stock of knowledge into economically useful knowledge (Santamaría, Nieto, and Barge-Gil 2009). Santamaría, Nieto and Miles (2012) examine the determinants of service innovations in manufacturers in Spain and report that advanced machinery and information technologies significantly impact the achievement of service innovations. Interestingly, an earlier study reports a non-significant association with respect to AMT use and innovation capabilities in Swiss firms (Arvanitis, Hollenstein, and Lenz 2002).

One potentially important issue in relating AMTs to innovation is that appropriating the potential benefits of AMTs may be difficult and time-consuming. 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). 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. 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). We therefore anticipate that the initial adoption and implementation of AMT is likely to have a short term disruptive effect with benefits only being realised in the medium to long term (Spanos and Voudouris 2009). This leads us to our first hypothesis:

H1a: Adoption of AMTs will lead to a short term disruptive effect on innovation performance.

H1b: Adoption of AMTs will lead to longer-term beneficial effects on innovation performance.

2.2 AMT Adoption: Complementarities and Learning-by-Using Effects

Scholars of AMT adoption and diffusion have used two models to conceptualise the trajectories of AMT adoption: the incremental and the discontinuous models (Boyer 1999). The incremental model assumes that there is a logical, sequential progression in AMT adoption from stand-alone to intermediate and finally to integrated technologies. According to the incremental model, adoption of a given technology should be deemed successful before the next, possibly more complicated, technology is adopted (Meredith and Hill 1987). In contrast, the discontinuous model of AMT adoption argues that firms move towards using an integrated system, such as CIM, in a major discontinuous leap in which all the equipment is adopted at once rather than built up incrementally over time. The discontinuous model of AMT adoption claims that successful adoption of integrated AMT systems requires considerable planning and resources and is a complex investment decision largely independent of previous adoption decisions (Meredith 1987). A common factor in these contrasting AMT adoption models is that firms do not typically adopt one AMT in isolation, but various AMTs are adopted either sequentially (incremental model of adoption) or simultaneously (discontinuous model of adoption). Our analysis extends to investigating whether complementarities arising from simultaneous adoption and learning-by-using effects from sequential adoption enhance firms' innovation performance.

Harnessing complementarities between different activities is an important aspect of firms' strategic decision-making (Milgrom and Roberts, 1990, 1995). While previous AMT studies have highlighted complementarities from adopting a suite of AMTs simultaneously; to date, there is little understanding of whether complementary AMTs benefit innovation performance. From the innovation literature, we know however that firm innovation benefits from complementary human resource management practices (Laursen and Foss, 2003) and organisational practices (Lhuillery, 2000). Therefore, any complementarities across AMTs are likely to enhance firm innovation.

In the innovation literature, there is also considerable evidence of the benefits of experiential learning from initial adoption decisions on subsequent adoption decisions. Rosenberg (1972) describes the process by which a firm increases its stock of knowledge based on its previous experience with technologies as learning-by-using. Previous studies have highlighted the benefit to firms of learning-by-using new technology with respect to subsequent adoption decision-making. For instance, Colombo and Mosconi (1995) report cumulative learning effects from AMT adoption in the Italian metalworking industry, McWilliams and Zilbermanfr (1996) report learning-by-using from the adoption of computer technology by farmers in California, and Arvantis and Hollenstein (2001) report learning-by-using effects from use of an earlier generation of manufacturing technologies on AMT adoption by Swiss firms. In a study of 392 metal-working firms, Cagliano and Spina (2000) examine the use and effectiveness of various AMTs and their computer-based integration in the context of Strategically Flexible Production (SFP). SFP comprises three principles: (i) strategic multi-focusedness, (ii) process integration across functions, and (iii) process ownership. Their examination focuses on the use of AMTs by three groups: core adopters, partial adopters and non-adopters of SFP. Cagliano and Spina (2000) report the adoption of stand-alone AMT does not provide companies with superior improvements in performance, but rather the integrated use of ATMs fosters increased time responsiveness.

In order to determine the influence of AMT complementarities and learning-by-using effects on innovation, we examine the effect of simultaneous and sequential AMT adoption on innovation performance. Two discrete activities are complementary if adding one activity increases the returns from doing the other. Therefore, we examine how adoption of one AMT may complement early adoption of another AMT, and hypothesise that simultaneous adoption of two AMTs will lead to increased returns on innovation performance.

> *H2*: – Simultaneous AMT adoption generates positive complementarities increasing the benefits for innovation

The cross-over and learning from simultaneous adoption is likely to benefit firm innovation to a greater extent than singular adoption. However, it is difficult to predict in advance where the complementarities, if any, are likely to exist between the four AMTs examined in this paper.

In relation to the sequential adoption of AMTs, previous studies have illustrated how AMT adoption benefits subsequent adoption (Arvantis and Hollenstein 2001; Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996). It is likely that as a firm increases its stock of knowledge due to learning from earlier AMT adoption, the disruptive effects of subsequent AMT adoption and implementation will be eased. Firms that sequentially adopt AMTs are likely to reap the benefits of previous ATM experience to a greater extent than firms who have no previous ATM experience. Therefore, we hypothesise that early adoption and implementation of an ATM will enhance the innovation returns from subsequent adoption decisions.

> *H3*: Early adoption of one AMT will generate learning-by-using effects increasing the innovation benefits of subsequent QIM adoption

3. 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 each conducted using similar survey methodologies and common questions. Individual survey waves were designed to be representative of the population of manufacturing plants in Ireland and Northern Ireland at the time of the survey. Sampling frames were derived either from administrative data provided by government agencies in Ireland and Northern Ireland or private sector data providers. Each survey was conducted by post with extensive telephone follow-up and was structured by plant sizeband and industry. Each survey related to the innovation activities of plants with 10 or more employees over a three-year reference period. Combining the individual surveys into the IIP results in a highly unbalanced panel reflecting plants' non-response to individual surveys but also the opening and closure of individual plants over the 1994 to 2008 period.

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, 16.3 per cent of plants' sales were derived from newly introduced products (Table 1) a figure which remained relatively constant through the different waves of the IIP (Figure 1). Variable definitions are given in Annex 1.

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. 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. Four specific AMTs are considered: Robotics, Automated materials handling, Computer aided production management, and Computer integrated manufacturing. For each of these technologies 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 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 17.5 per cent of the 1593 observations in the IIP were using Robotics with 6.3 per cent of plants adopting this in the three years prior to the date of the survey, 4.4 per cent adopting 3-6 years before the survey, and 6.4 per cent earlier than that (Table 1). Computer Integrated Manufacturing (CIM) was implemented in around a quarter of plants of which 8.6 per cent reported having adopted this technology in the previous 3 years.

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). 52.0 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 29.1 per cent of plants reported having innovation cooperation with customers, while 31.5 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 0.79 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. 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 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 in cross-sectional terms as:

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

Where: AMT_i denotes plants' adoption of AMTs, RD_i are plants' in-house R&D investments, FS_i, BS_i and HS_i are forwards, backwards and horizontal knowledge search respectively, and $CONT_i$ is a vector of other plant level controls (Annex 1). Our hypotheses suggest, however, that the innovation benefits of AMT adoption may vary depending on the time since adoption with the potential for short-term disruption (H1a) and longer-term gains (H1b). To test our hypotheses we estimate a dynamic version of equation (1) explicitly identifying AMT adoption in the current (three-year) period and in two previous periods, i.e.

$$I_i = \beta_0 + \beta_{10} AMT_t + \beta_{11} AMT_{it-1} + \beta_{12} AMT_{it-2} + \beta_2 RD_i + \beta_3 FS_i + \beta_4 BS_i + \beta_5 HS_i + \beta_6 CONT_i + \delta_i$$

(2)

Support for H1a requires $\beta_{10}<0$, with H1b requiring $\beta_{11}>0$ and $\beta_{12}>0$.

Our second and third hypotheses relate to potential complementarities and learning-by-using effects between AMTs, denoted here AMT^A and AMT^B. If $AMT^B_{t-2} = 1$ where a firm is an early adopter of AMT^B and zero otherwise we estimate:

$$\begin{aligned} I_i &= \beta_0 + \beta_{101} AMT_t^A * AMT_{t-2}^B + \beta_{111} AMT_{t-1}^A * AMT_{t-2}^B + \beta_{121} AMT_{t-2}^A * AMT_{t-2}^B \\ &+ \beta_{102} AMT_t^A * (1 - AMT_{t-2}^B) + \beta_{112} AMT_{t-1}^A * (1 - AMT_{t-2}^B) + \beta_{122} AMT_{t-2}^A * (1 - AMT_{t-2}^B) \\ &+ \beta_2 RD_i + \beta_3 FS_i + \beta_4 BS_i + \beta_5 HS_i + \beta_6 CONT_i + \delta_i \end{aligned}$$

(3)

For Hypothesis 2, which reflects the complementary benefits of simultaneous adoption we anticipate that early adoption of AMT^A in period t-2 will have greater benefits where a firm also adopts AMT^B in period t-2. Here, we test $\beta_{121}>\beta_{122}$. For Hypothesis 3 which reflects the potential learning-by-using effects from early adoption of AMT^B we test whether $\beta_{101}>\beta_{102}$ and/or $\beta_{111}>\beta_{112}$.

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.

4. Results

4.1. Dynamic Analysis

Replicating previous cross-sectional studies of the AMT-innovation relationship, we initially undertake a static analysis to determine whether AMT use benefits firm innovation (Equation 1). As presented in Table 3, only one AMT significantly impacts innovation output. Robotics has a marginally significant positive influence on firm innovation. We find no evidence of such a relationship between the CAM, AMH or CIM technologies and innovation. Our static analysis, similar to previous work in this area, therefore indicates a very weak positive relationship between AMT adoption and innovation. Arvanitis, Hollenstein, and Lenz (2002) report no significant association between AMT adoption and innovation, while a positive AMT-innovation relationship is reported in a number of studies, albeit in specific circumstances, such as small firms (Raymond, Croteau, and Bergeron 2009), firms that do not undertake R&D (Barge-Gil, Jesus Nieto, and Santamaria 2011), and LMT firms (Santamaría, Nieto, and Barge-Gil 2009).

A limitation of this static approach to the AMT-innovation relationship is that the AMT coefficients capture the effects of both current and lagged or prior adoption. Our dynamic analysis (Eqn. 2) removes this implicit restriction and allows us to test H1 which envisages a short term disruption (H1a) and a longer term beneficial (H2b) effect from AMT adoption on firm innovation. Dynamic analysis of the impact of 'early' (t-2), 'previous' (t-1) and 'current' AMT adoption on innovation performance is presented in Table 4. In relation to CAM, we see a marginally significant disruption effect in the second period and a significant long-term beneficial effect. Contrary to expectations, the disruption effects of CAM adoption last for six years before the benefits arise. With respect to AMH adoption, there is evidence of a weak disruption effect, with positive benefits experienced three or more years after adoption. A similar pattern to the CAM-innovation relationship is evident in the CIM analysis. CIM adoption results in a negative disruption effect over two periods, followed by a significantly stronger longer-term beneficial effect (Table 4). Finally, in relation to robotics, there is no evidence of a disruption effect and limited evidence of longer tem innovation benefits.

We hypothesised that AMT adoption would result in a short term disruption effect (H1a) and a longer term beneficial effect (H1b). We do find consistent but weak support for H1a. In relation to three technologies, CAM, AMH and CIM, we do find evidence of short-term disruption effects, although this finding is significant only in the case of CAM. We find stronger evidence in support of H1b, particularly in relation to CAM and CIM where there are strong longer-term innovation benefits from adoption. The short-term disruption and longer-term beneficial effects pattern for CAM, AMH and CIM adoption is not evident in relation to robotics.

Our static and dynamic estimations highlightthe different innovation effects of AMTs depending on their period of adoption. We might conclude from our static analysis, for example, that there is no positive innovation benefit from CAM, AMH and CIM adoption. This would be wrong as our dynamic analysis clearly identifies the longer-term innovation benefits which do arise from AMT adoption.

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 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 customers or 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. Firm vintage negatively influences firm innovation, whereas exporting and externally-owned firms are marginally more innovative. 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; Love, Roper, and Bryson 2011).

4.2 Complementarities and Learning-by-Using Effects

In our investigation of complementarities and learning-by-using effects, we attempt to determine if simultaneous and sequential adoption of AMTs benefit the firm (see Figure 2). We hypothesise that simultaneous AMT adoption (i.e. the adoption of more than one AMT in a given period) may generate positive complementarities increasing the benefits to innovation (H2), and that (early) adoption of one AMT will generate learning-by-using effects increasing the innovation benefits of subsequent AMT adoption (H3). We undertake four sets of analyses which examine the influence of simultaneous and sequential adoption of AMTs on innovative sales. These analyses are reported in Tables 5-8, with each Table relating to the complementarities and learning-by-using effects associated with one AMT. Table 5, for example, presents the results of our complementarity and learning-by-using analyses for CAM, and Tables 6, 7 and 8 present these analyses for AMH, CIM and robotics (Rob) respectively. In each case the structure of the table is similar with the first model in Table 5, for example, examining if early CAM adoption and early robotics adoption generate complementarities and learning-by-using effects for innovation. For our examination of complementarities, we include two variables in the first model, one of which captures whether firms were early adopters of both CAM and robotics (Early CAM * Early robotics) and another which captures those that were early CAM adopters but not early robotics adopters (Early CAM *no early robotics). In the same model we include variables which capture the potential learning-by-using effects generated by sequential adoption of AMTs. For instance, in the first model in Table 5, we examine if early adoption of robotics and subsequent CAM adoption, in both the current and previous time periods influence sales. As with the complementarities we include two variables to test each potential effect: to test for learning by using effects on the innovation benefits of current CAM adoption we include ‘Current CAM * Early robotics’ and ‘Current CAM *no early robotics’; to test for learning by using effects on the innovation benefits of previous adoption we include ‘Previous CAM *early robotics’ and ‘Previous CAM *no early robotics’. In a similar pattern, the second model in Table 5 examines if early adoption of both CAM and AMH generates complementarities for innovation and, if early adoption of AMH and subsequent adoption of CAM in the current and previous time periods generates learning-by-using benefits of innovation. The third model in Table 5 examines if early adoption of both CAM and CIM generates complementarities for innovation and, if early adoption of CIM and subsequent adoption of CAM in the current and previous time periods generates learning-by-using benefits. Each model includes the same set of control variables as those in Table 3 and 4 although for simplicity these are not reported. Full results are available on request.

Complementarities exist where the sum of the benefits of adopting AMTs separately is less than the benefit of adopting them simultaneously (Equation 3). Empirically, we are examining the influence of simultaneous early adoption of two AMTs on innovative sales. We first examine if complementarities exist between early CAM adoption and early adoption of the other three AMTs and these results are presented in the first rows of Table 5. Our analysis reveals that, in each case, early adoption of other AMTs increases the innovation value of early adoption of CAM (as is evident from the significant and larger coefficient for the first variable in each model capturing simultaneous early adoption) (Table 5). For AMH we see from Table 6 that simultaneous early adoption of AMH with CAM and with CIM enhances the innovation value of AMH; although there is no evidence that simultaneous AMH and robotics adoption has a value enhancing effect on AMH. Our complementarity results in relation to CIM (Table 7) are similar to those for CAM, i.e. we find simultaneous adoption with any of the other AMTs enhances the innovation value of CIM. In relation to robotics (Table 8), we find that simultaneous early adoption of CAM or CIM with robotics has a positive effect on the innovation value of adopting robotics, although there is no value enhancing effect from simultaneous adoption of AMH. Overall, we therefore find strong support for H2 and the idea that complementarities between AMTs increase the benefits to innovation.

Next, we investigate whether early adoption of one AMT generates learning-by-using effects increasing the innovation benefits of subsequent adoption of other AMTs. The motivation for investigating whether learning-by-using effects impact on firm innovation is that early adoption of one AMT creates the potential for learning and hence subsequent adoption and implementation of an additional AMT is likely to be less onerous. Empirically, we test for learning-by-using effects by including variables which capture sequential adoption patterns (Equation 3). For instance, in Table 5 we examine if early robotics adoption and subsequent CAM adoption, in both the current (Current CAM * Early robotics & Current CAM *no early robotics) and previous (Previous CAM *early robotics & Previous CAM *no early robotics) time periods, influence innovative sales. In the second and third columns of this table, the results for early AMH adoption and subsequent CAM adoption and early CIM adoption and subsequent CAM adoption are presented.

In relation to learning-by-using effects from early robotics adoption on subsequent CAM adoption, the direction of the insignificant coefficients is not as anticipated (Table 5). In our initial dynamic analysis (Table 4), there was a disruptive effect from CAM adoption in the t-1 (previous) period for innovation. Early AMH adoption reduced the power of the negative effect from CAM adoption in the previous period. The same is true for early CIM and robotics adoption both of which negate the disruptive effect of subsequent CAM adoption on innovation (Table 5).

Learning-by-using results for AMH, CIM and robotics adoption are reported in Tables 6, 7 and 8 respectively. Examining learning-by-using effects for AMH adoption, we find no evidence of significant learning-by-using from early adoption of CIM, CAM and robotics on subsequent AMH adoption benefitting innovation (Table 6). Similarly, there is no evidence of significant learning-by-using effects from early adoption of AMH, CAM and robotics for subsequent CIM adoption (Table 7). For robotics adoption, however, we do see evidence of learning-by-using effects from the early adoption of CAM and CIM on subsequent robotics adoption. Early adoption of CAM and CIM, positively impacts the innovation value of previous robotics adoption (Table 8). Adding robotics to a process that already has one of these AMTs is advantageous to firm innovation.

In summary, we find some support for H3 that early adoption of one AMT will generate learning-by-using effects increasing the innovation benefits of subsequent AMT adoption. In particular we find some evidence of learning-by-using effects enhancing the innovation benefits from subsequent CAM and robotics adoption, although there is no evidence of AMH or CIM adoption benefitting from learning-by-using effects from earlier AMT adoption.

4.3 Robustness Tests

We conducted two robustness tests to validate our results with an alternative measure of innovative output, and using an alternative estimation approach allowing for the potential endogeneity of the ‘treatment’ represented by firms’ AMT adoption (Maddala 1983). First, in our main analysis we use a dependent variable which reflects firms’ sales derived from new products. This reflects an emphasis on more radical innovation rather than either imitation or more incremental product change (Schnaars 1994). To consider whether our results also hold for more imitative strategies we repeated the analysis using an alternative and more broadly defined dependent variable - innovative sales from *new and improved* products. Results for the static and dynamic analysis using this broader innovation output measure were very similar to those reported in Tables 3 and 4 with estimated coefficients having identical sign patterns but slightly lower significance levels. Similarly, in terms of complementarity between the various AMTs, and in terms of the leaning-by-using effects, we find almost identical results for our main dependent variable and the broader alternative. Again, complementarity effects between AMTs prove strong but leaning-by-using effects are universally positive but almost wholly insignificant.

In a second robustness test we sought to allow for the potential endogeneity of the adoption of each of the AMTs, i.e. the possibility that the determinants of adoption may also be the determinants of innovation outcomes. We estimated two-stage models estimating first a model for the probability of adoption and then including the implied Inverse Mills Ratio (IMRs) in equations (1) to (3) (Heckman 1979). For both our main and alternative dependent variables the IMRs proved largely insignificant with the coefficients of interest remaining unchanged in sign and significance. The full robustness tests are available from the authors on request.

6. Discussion

Implications for practice

Three key findings follow from our analysis which together have implications for managerial practice. First, we find clear evidence of the dynamic profile of benefits of AMT adoption – particularly CIM, CAM and AMT - with weak short-term disruption effects but strong and significant long-term benefits for innovation. Robotics has weak but consistently positive innovation effects. Second, these longer-term innovation benefits are strongest where AMTs are adopted contemporaneously suggesting that simultaneous adoption creates complementarities between the different AMTs. Third, we find only weak evidence of any positive learning-by-using effects which may arise where AMTs are adopted sequentially. This contrasts strongly with other adoption studies which suggest, for example, strong learning-by-using effects between quality improvement measures (Bourke and Roper 2015).

In general terms our results confirm those of other studies (Barge-Gil et al., 2011; Raymond, Croteau and Bergeron, 2009) which find a positive link between AMT adoption and aspects of firm performance. In particular, as Barge-Gil et al. (2011) suggest, including AMT use and/or adoption enriches our understanding of the drivers of firms' innovation. Because of the dynamic nature of our data, however, we are also able to provide new insight into the time profile of these effects with strategic implications. Specifically, firms considering the adoption of AMTs may choose either an incremental strategy – adopting AMTs sequentially – or a discontinuous strategy – adopting AMTs simultaneously (Boyer 1999). An incremental strategy may minimise disruption and maximise the potential for organisational learning, while our results suggest that a discontinuous strategy may risk greater short term disruption but generate complementarities in implementation. Our evidence suggests that both strategies will generate innovation benefits but that a discontinuous strategy is likely to be most beneficial as the benefits of the simultaneous adoption of AMTs prove stronger than any learning-by-using effects. This is not of course to minimise the difficulties of AMT adoption – particularly where multiple AMTs are being adopted simultaneously. As Barge-Gil et al. (2011, p. 419) suggest 'skilled use of AMT is not easy to attain and depends on several contingencies'. Indeed, our evidence suggests that it may be some years after the initial adoption of AMTs before their full performance benefits are realised.

Implications for theory

Aside from suggesting the potential superiority of discontinuous AMT adoption strategies our analysis has methodological implications for those engaged in studies of AMTs and/or innovation. In terms of AMTs and adoption our results suggest the misleading implications which might be drawn from cross-sectional studies, and the need to take longer-term dynamics into account. The timing of AMT adoption appears crucial to its business benefits with coefficients in cross-sectional analyses implicitly 'averaging' opposing short-term disruption and longer-term beneficial effects. Second, as our results on the complementarities between AMTs suggest, the benefits of individual AMTs are strongly contextual, depending on the timing of adoption of other AMTs and potentially on other firm capabilities or structural characteristics (Zammuto and O'Connor 1992). In terms of innovation, our results reinforce the arguments of Barge Gil et al. (2011) and the value of considering tangible as well as intangible investments as part of any explanation of firms' innovation.

7. Conclusion

This study highlights the temporal profile of the performance benefits of individual AMTs, highlighting short-term disruption effects but longer-term benefits. In addition, we find complementarities between the adoption of specific AMTs, suggesting the value of disruptive rather than incremental AMT implementation strategies when simultaneously adopting AMTs.

Our analysis suffers from two main limitations. First, our analysis focuses on Irish manufacturing businesses only and may therefore be influenced by specific national circumstances. The 1994-2008 period considered here, however, was a period of rapidly changing institutions in Ireland as well as marked changes in the nation's economic fortunes - the Irish recovery of the late 1990s, the 2000-02 high-tech crash, and a period of rapid subsequent growth. Second, we focus here purely on the average AMT-innovation relationship and make little allowance for differences in absorptive capacity between firms. The work of Sohal and others (Hofmann and Orr 2005; Sohal 1996), however, suggests the potential importance of corporate capabilities linked to absorptive capacity for the effective implementation of AMTs. 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 Oconnor 1992). Are firms with stronger skill endowments, for example, 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. Each of these questions might provide a useful focus for future research.

Table 1: Sample Descriptives

	No. of observations	Mean	Std.Dev.
Innovative sales from new products (%)	1704	16.312	22.571
Innovative sales from new and	1700	27.612	30.515
AMT variables			
Robotics Use	1593	0.175	0.380
AMH Use	1622	0.272	0.445
CAM Use	1704	0.385	0.487
CIM Use	1625	0.214	0.410
Robotics current	1585	0.063	0.242
Robotics previous	1585	0.044	0.205
Robotics early	1585	0.064	0.245
AMH current adopter	1602	0.107	0.309
AMH previous	1602	0.064	0.244
AMH early adopter	1602	0.093	0.290
CAM current adopter	1679	0.154	0.361
CAM previous	1679	0.095	0.293
CAM early adopter	1679	0.125	0.331
CIM current adopter	1611	0.086	0.280
CIM previous adopter	1611	0.054	0.226
CIM early adopter	1611	0.067	0.250
Plant characteristics			
R&D in house	1704	0.520	0.500
Linkages with	1704	0.291	0.455
Linkages with	1704	0.315	0.465
Horizontal linkages	1704	0.793	1.387
Employment (log)	1704	3.693	1.102
Firm Vintage	1704	29.020	28.543
Externally Owned	1704	0.220	0.414
Workforce with	1704	10.330	12.893
Government support	1704	0.261	0.439
Exports (%)	1704	21.209	32.096

Source: Irish Innovation Panel– waves 2-6. Observations are weighted. Variable definitions in Annex 1.

	Table 2: Correlation Matrix	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Sales from New Products	1.00													
2	Sales from New & Improved Products	0.77	1.00												
3	Robotics Use	0.15	0.14	1.00											
4	AMH Use	0.09	0.11	0.36	1.00										
5	CAM Use	0.09	0.13	0.24	0.28	1.00									
6	CIM Use	0.09	0.09	0.35	0.35	0.45	1.00								
7	Current Robotics Adoption	0.08	0.09	0.56	0.26	0.16	0.26	1.00							
8	Previous Robotics Adoption	0.11	0.10	0.48	0.16	0.11	0.16	-0.06	1.00						
9	Early Robotics Adoption	0.05	0.05	0.57	0.16	0.11	0.14	-0.07	-0.06	1.00					
10	Current AMH Adoption	-0.01	0.03	0.17	0.55	0.16	0.21	0.28	0.03	-0.03	1.00				
11	Previous AMH Adoption	0.08	0.08	0.22	0.47	0.11	0.20	0.10	0.24	0.03	-0.09	1.00			
12	Early AMH Adoption	0.07	0.06	0.17	0.54	0.17	0.13	0.01	0.00	0.25	-0.10	-0.09	1.00		
13	Current CAM Adoption	0.04	0.08	0.22	0.24	0.57	0.37	0.25	0.09	0.02	0.29	0.07	0.00	1.00	
14	Previous CAM Adoption	-0.01	0.02	0.07	0.04	0.42	0.18	0.02	0.06	0.04	-0.04	0.05	0.06	-0.12	1.00
15	Early CAM Adoption	0.09	0.09	0.04	0.13	0.50	0.10	-0.05	0.01	0.10	-0.04	0.05	0.19	-0.15	-0.11
16	Current CIM Adoption	0.02	0.04	0.26	0.26	0.30	0.60	0.32	0.08	0.01	0.30	0.09	0.01	0.51	-0.05
17	Previous CIM Adoption	0.03	0.05	0.11	0.13	0.21	0.49	0.03	0.13	0.04	0.05	0.16	0.00	0.07	0.30
18	Early CIM Adoption	0.09	0.06	0.17	0.15	0.20	0.51	0.04	0.04	0.18	-0.05	0.08	0.21	-0.04	0.07
19	R&D in house	0.20	0.31	0.08	0.12	0.13	0.08	0.03	0.03	0.07	0.06	0.05	0.08	0.04	0.06
20	Linkages with customers	0.17	0.23	0.17	0.14	0.13	0.12	0.14	0.09	0.05	0.09	0.08	0.05	0.12	0.04
21	Linkages with suppliers	0.19	0.23	0.17	0.18	0.16	0.16	0.12	0.09	0.06	0.11	0.09	0.07	0.13	0.04
22	Horizontal linkages	0.15	0.22	0.20	0.22	0.19	0.21	0.16	0.11	0.06	0.16	0.13	0.05	0.16	0.02
23	Employment (log)	0.15	0.18	0.35	0.27	0.29	0.25	0.25	0.18	0.12	0.17	0.14	0.12	0.27	0.09
24	Firm Vintage	-0.14	-0.10	-0.03	0.03	0.00	0.00	-0.03	0.00	-0.02	0.05	-0.01	0.00	0.03	0.01
25	Externally Owned	0.13	0.12	0.23	0.14	0.16	0.14	0.16	0.14	0.08	0.08	0.09	0.05	0.19	0.05
26	Workforce with degree (%)	0.16	0.17	0.06	0.01	0.02	0.04	0.05	0.02	0.02	0.03	0.01	-0.02	0.05	-0.01
27	Government support	0.17	0.25	0.07	0.06	0.10	0.03	0.06	0.04	0.01	0.02	0.04	0.03	0.05	0.03
28	Exports (%)	0.18	0.21	0.22	0.09	0.15	0.13	0.15	0.14	0.07	0.05	0.08	0.02	0.15	0.08
		15	16	17	18	19	20	21	22	23	24	25	26	27	28

15	Early CAM Adoption	1.00													
16	Current CIM Adoption	-0.07	1.00												
17	Previous CIM Adoption	-0.03	-0.07	1.00											
18	Early CIM Adoption	0.28	-0.08	-0.06	1.00										
19	R&D in house	0.09	0.04	0.02	0.06	1.00									
20	Linkages with customers	0.03	0.09	0.04	0.05	0.23	1.00								
21	Linkages with suppliers	0.07	0.11	0.08	0.06	0.20	0.62	1.00							
22	Horizontal linkages	0.09	0.16	0.06	0.11	0.23	0.59	0.55	1.00						
23	Employment (log)	0.06	0.22	0.11	0.06	0.19	0.16	0.19	0.26	1.00					
24	Firm Vintage	-0.04	0.06	-0.02	-0.06	-0.04	-0.04	-0.01	0.05	0.09	1.00				
25	Externally Owned	-0.01	0.12	0.10	0.00	0.00	0.07	0.11	0.11	0.42	0.04	1.00			
26	Workforce with degree (%)	-0.02	0.04	-0.01	0.02	0.13	0.17	0.12	0.17	0.06	-0.01	0.16	1.00		
27	Government support	0.06	0.02	0.00	0.02	0.37	0.22	0.16	0.26	0.13	-0.03	-0.07	0.14	1.00	
28	Exports (%)	-0.02	0.11	0.09	0.00	0.11	0.13	0.11	0.16	0.35	-0.10	0.48	0.31	0.09	1.00

Source: Irish Innovation Panel – waves 2-6. Variable definitions in Annex 1.

Table 3. Static models: Tobit Models of Innovative Sales of New Products

	Model 1	Model 2	Model 3	Model 4
CAM Use	0.103			
	(-1.103)			
AMH Use		0.827		
		(-1.22)		
CIM Use			1.966	
			(-1.318)	
Robotics Use				2.806*
				(-1.446)
In-plant R&D	6.355***	5.770***	5.587***	6.174***
	(-1.167)	(-1.185)	(-1.197)	(-1.206)
Linkages with Clients	2.306	2.59	2.376	2.899*
	(-1.574)	(-1.608)	(-1.599)	(-1.624)
Linkages with Suppliers	4.246***	4.361***	4.643***	4.288***
	(-1.47)	(-1.488)	(-1.497)	(-1.504)
Horizontal Linkages	-0.186	-0.373	-0.396	-0.316
	(-0.491)	(-0.497)	(-0.501)	(-0.503)
Employment (Log)	0.105	0.265	-0.017	-0.254
	(-0.555)	(-0.562)	(-0.566)	(-0.574)
Firm Vintage	-0.072***	-0.076***	-0.066***	-0.063***
	(-0.019)	(-0.019)	(-0.02)	(-0.02)
Export Sales	0.032	0.029	0.026	0.028
	(-0.02)	(-0.02)	(-0.021)	(-0.021)
Workforce with Degree	0.148***	0.157***	0.160***	0.154***
	(-0.044)	(-0.045)	(-0.046)	(-0.046)
Government Support	3.387**	3.717***	3.735***	3.781***
	(-1.315)	(-1.327)	(-1.344)	(-1.357)
Externally Owned	2.517*	2.518*	2.894*	2.107
	(-1.502)	(-1.512)	(-1.537)	(-1.554)
Constant	3.76	3.388	3.62	4.09
	(-2.589)	(-2.609)	(-2.632)	(-2.67)
N	1704	1674	1652	1626
Chi-squared	265.944	261.718	248.948	255.126
P	0	0	0	0
Pseudo – R2	0.017	0.017	0.017	0.017

Notes: * denotes significance at 10% level; ** at 5% level and *** at 1% level. **Source:** Irish Innovation Panel – waves 2-6. Observations are weighted. All models contain industry and wave dummies. A full set of tables, which include industry and wave dummies, is available from the authors on request. Variable definitions in Annex 1.

Table 4. Dynamic models: Tobit Models of Innovative Sales of New Products

	Model 1	Model 2	Model 3	Model 4
Current CAM Adoption	-1.385			
	(-1.547)			
Previous CAM Adoption	-3.379*			
	(-1.818)			
Early CAM Adoption	5.169***			
	(-1.632)			
Current AMH Adoption		-2.119		
		(-1.746)		
Previous AMH Adoption		3.650*		
		(-2.146)		
Early AMH Adoption		2.400		
		(-1.807)		
Current CIM Adoption			-1.061	
			(-1.91)	
Previous CIM Adoption			-0.283	
			(-2.329)	
Early CIM Adoption			6.977***	
			(-2.11)	
Current robotics Adoption				2.902
				(-2.239)
Previous robotics Adoption				3.522
				(-2.564)
Early robotics Adoption				2.406
				(-2.115)
In-plant R&D	5.979***	5.807***	5.505***	6.133***
	(-1.178)	(-1.193)	(-1.196)	(-1.206)
Linkages with Clients	2.047	2.357	1.853	2.489
	(-1.591)	(-1.617)	(-1.605)	(-1.627)
Linkages with Suppliers	4.619***	4.415***	4.965***	4.610***
	(-1.479)	(-1.496)	(-1.495)	(-1.506)
Horizontal Linkages	-0.16	-0.25	-0.333	-0.275
	(-0.496)	(-0.502)	(-0.504)	(-0.503)

Employment (Log)	0.22	0.383	0.232	-0.239
	(-0.566)	(-0.572)	(-0.567)	(-0.576)
Firm Vintage	-0.069***	-0.079***	-0.067***	-0.063***
	(-0.019)	(-0.02)	(-0.02)	(-0.02)
Export Sales	0.034*	0.031	0.027	0.027
	(-0.02)	(-0.02)	(-0.021)	(-0.021)
Workforce with Degree	0.153***	0.157***	0.158***	0.133***
	(-0.044)	(-0.046)	(-0.046)	(-0.047)
Government Support	3.421**	3.481***	3.775***	4.097***
	(-1.335)	(-1.34)	(-1.347)	(-1.36)
Externally Owned	2.516*	2.291	2.717*	2.259
	(-1.509)	(-1.53)	(-1.54)	(-1.556)
Constant	3.369	2.963	3.25	4.267
	(-2.614)	(-2.635)	(-2.632)	(-2.675)
N	1679	1651	1638	1618
Chi-squared	273.795	270.695	258.286	247.654
P	0	0	0	0
Pseudo – R^2	0.018	0.018	0.017	0.017

Notes: * denotes significance at 10% level; ** at 5% level and *** at 1% level. **Source:** Irish Innovation Panel – waves 2-6. Observations are weighted. All models contain industry and wave dummies. A full set of tables, which include industry and wave dummies, is available from the authors on request. Variable definitions in Annex 1.

Table 5. CAM Adoption: Complementarities and Learning By Using Effects

	Innovation Sales		Innovation Sales		Innovation Sales
Simultaneous CAM Adoption: Complementarities					
Early CAM Adoption: w/wo early Rob		***Early CAM Adoption: w/wo early AMH***		***Early CAM Adoption: w/wo early CIM***	
Early CAM* Early Rob	12.462***	Early CAM * Early AMH	7.650**	Early CAM * Early CIM	6.444**
	(-4.075)		(-3.066)		(-2.892)
Early CAM * No Early Rob	3.470*	Early CAM * No Early AMH	4.719**	Early CAM * No Early CIM	4.234**
	(-1.873)		(-1.939)		(-1.987)
Sequential CAM Adoption: Learning By Using					
CAM Adoption: w/wo early Rob adoption		***CAM Adoption: w/wo early AMH adoption***		***CAM Adoption: w/wo early CIM adoption***	
Current CAM * Early Rob	-5.804	Current CAM * Early AMH	10.616**	Current CAM * Early CIM	-6.182
	(-5.658)		(-4.824)		(-6.740)
Current CAM * No Early Rob	-0.191	Current CAM * No Early AMH	-1.717	Current CAM * No Early CIM	-1.831
	(-1.739)		(-1.712)		(-1.675)
Previous CAM * Early Rob	-7.142	Previous CAM * Early AMH	-4.982	Previous CAM * Early CIM	3.881
	(-6.217)		(-4.479)		(-5.764)
Previous CAM * No Early Rob	-3.923*	Previous CAM * No Early AMH	-3.837*	Previous CAM * No Early CIM	-5.537***
	(-2.119)		(-2.139)		(-2.059)
CAM adoption conditional on	Rob	CAM adoption conditional on	AMH	CAM adoption conditional on	CIM
Complementarities	4.26**	Complementarities	0.71	Complementarities	0.43
LBU Current	0.94	LBU Current	6.08**	LBU Current	0.40
LBU Previous	0.25	LBU Previous	0.05	LBU Previous	2.44
Observations	1,704		1,704		1,704

Notes: * denotes significance at 10% level; ** at 5% level and *** at 1% level. **Source:** Irish Innovation Panel – waves 2-6. Observations are weighted. Models contain identical control variables as reported in initial dynamic analysis (Table 4). A full set of tables, is available from the authors on request. Variable definitions in Annex 1.

Table 6. AMH Adoption: Complementarities and Learning By Using Effects

	Innovation Sales		Innovation Sales		Innovation Sales
Simultaneous AMT Adoption: Complementarities					
Early AMH Adoption: w/wo early robotics		***Early AMH Adoption: w/wo early CAM***		***Early AMH Adoption: w/wo early CIM***	
Early AMH* Early Rob	4.033	Early AMH* Early CAM	7.774**	Early AMH* Early CIM	7.916**
	(-3.787)		(-3.07)		(-3.895)
Early AMH* No Early Rob	1.822	Early AMH* No Early CAM	1.297	Early AMH* No Early CIM	1.537
	(-2.246)		(-2.261)		(-2.187)
Sequential AMT Adoption: Learning By Using					
AMH Adoption: w/wo early AMH adoption		***AMH Adoption: w/wo early CAM adoption***		***AMH Adoption: w/wo early CIM adoption***	
Current AMH* Early Rob	1.344	Current AMH* Early CAM	1.523	Current AMH* Early CIM	1.052
	(-7.576)		(-5.448)		(-9.404)
Current AMH* No Early Rob	-2.208	Current AMH* No Early CAM	-1.864	Current AMH* No Early CIM	-1.666
	(-1.963)		(-1.883)		(-1.921)
Previous AMH* Early Rob	5.458	Previous AMH* Early CAM	2.101	Previous AMH* Early CIM	6.335
	(-7.561)		(-4.502)		(-5.217)
Previous AMH* No Early Rob	3.703	Previous AMH* No Early CAM	5.103**	Previous AMH* No Early CIM	3.825
	(-2.389)		(-2.514)		(-2.484)
AMH adoption conditional on	Rob	AMH adoption conditional on	CAM	AMH adoption conditional on	CIM
Complementarities	0.27	Complementarities	3.09**	Complementarities	2.14
LBU Current	0.21	LBU Current	0.36	LBU Current	0.08
LBU Previous	0.05	LBU Previous	0.36	LBU Previous	0.19
Observations	1,704		1,704		1,704

Notes: * denotes significance at 10% level; ** at 5% level and *** at 1% level. **Source:** Irish Innovation Panel – waves 2-6. Observations are weighted. Models contain identical control variables as reported in initial dynamic analysis (Table 4). A full set of tables, is available from the authors on request. Variable definitions in Annex 1.

Table 7. CIM Adoption: Complementarities and Learning By Using Effects

	Innovation Sales		Innovation Sales		Innovation Sales
Simultaneous CIM Adoption: Complementarities					
CIM Adoption: w/wo early Rob		***Early CIM Adoption: w/wo early AMH***		***Early CIM Adoption: w/wo early CAM***	
Early CIM* Early Rob	14.209***	Early CIM * Early AMH	7.874**	Early CIM * Early CAM	6.719**
	(-4.557)		(-3.888)		(-2.889)
Early CIM * No Early Rob	2.53	Early CIM * No Early AMH	5.136*	Early CIM * No Early CAM	2.329
	(-2.616)		(-2.744)		(-3.104)
Sequential CIM Adoption: Learning By Using					
CIM Adoption: w/wo early Rob adoption		***CIM Adoption: w/wo early AMH adoption***		***CIM Adoption: w/wo early CAM adoption***	
Current CIM * Early Rob	-7.749	Current CIM * Early AMH	-0.043	Current CIM * Early CAM	6.569
	(-6.483)		(-6.197)		(-8.833)
Current CIM * No Early Rob	-0.18	Current CIM * No Early AMH	-0.509	Current CIM * No Early CAM	-2.215
	(-2.192)		(-2.177)		(-2.015)
Previous CIM * Early Rob	-7.306	Previous CIM * Early AMH	-0.479	Previous CIM * Early CAM	-6.241
	(-7.876)		(-6.185)		(-7.258)
Previous CIM * No Early Rob	1.891	Previous CIM * No Early AMH	0.303	Previous CIM * No Early CAM	0.409
	(-2.703)		(-2.679)		(-2.493)
CIM adoption conditional on	Rob	CIM adoption conditional on	AMH	CIM adoption conditional on	CAM
Complementarities	5.13**	Complementarities	0.35	Complementarities	1.13
LBU Current	1.26	LBU Current	0.01	LBU Current	0.95
LBU Previous	1.24	LBU Previous	0.01	LBU Previous	0.76
Observations	1,704		1,704		1,704

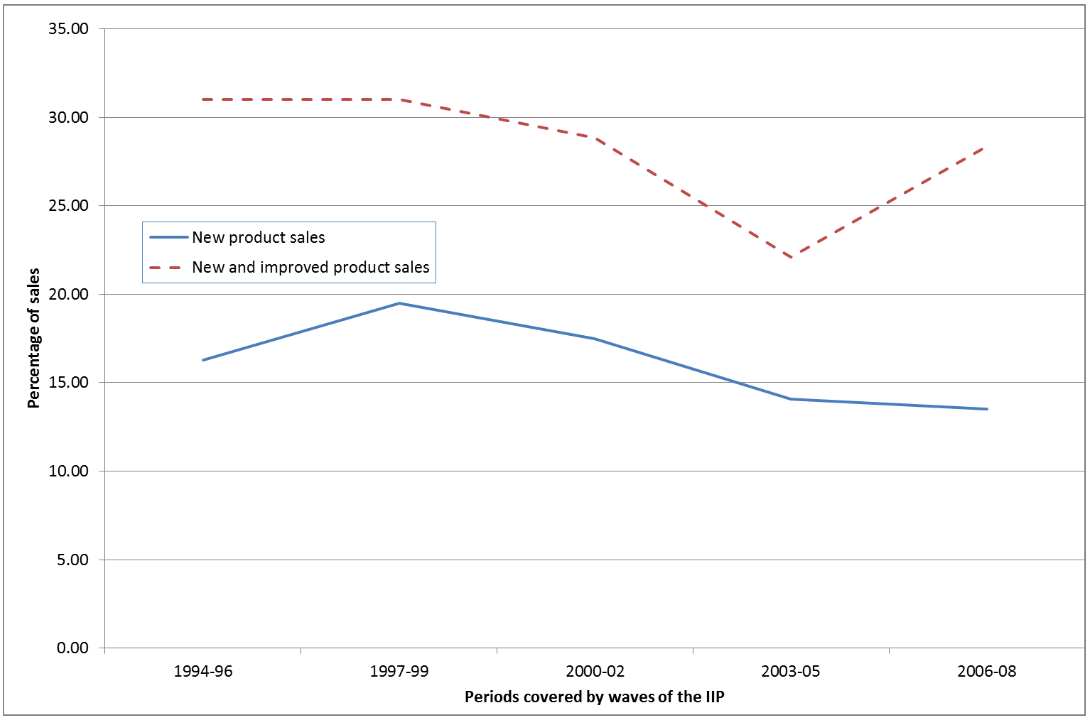
Notes: * denotes significance at 10% level; ** at 5% level and *** at 1% level. **Source:** Irish Innovation Panel – waves 2-6. Observations are weighted. Models contain identical control variables as reported in initial dynamic analysis (Table 4). A full set of tables, is available from the authors on request. Variable definitions in Annex 1.

Table 8. Robotics Adoption: Complementarities and Learning By Using Effects

	Innovation Sales		Innovation Sales		Innovation Sales
Simultaneous AMT Adoption: Complementarities					
Early Robotics Adoption: w/wo early AMH		***Early Robotics Adoption: w/wo early CAM***		***Early RoboticsAdoption: w/wo early CIM***	
Early Rob* Early AMH	4.351	Early Rob * Early CAM	13.059***	Early Rob * Early CIM	14.514***
	(-3.771)		(-4.059)		(-4.552)
Early Rob* No Early AMH	4.03	Early Rob * No Early CAM	-0.013	Early Rob* No Early CIM	0.694
	(-2.787)		(-2.588)		(-2.566)
Sequential AMT Adoption: Learning By Using					
Robotics Adoption: w/wo early AMH adoption		***Robotics Adoption: w/wo early CAM adoption***		***Robotics Adoption: w/wo early CIM adoption***	
Current Rob* Early AMH	13.403	Current Rob * Early CAM	-0.641	Current Rob * Early CIM	2.935
	(-8.66)		(-7.518)		(-6.252)
Current Rob* No Early AMH	-0.165	Current Rob * No Early CAM	3.24	Current Rob * No Early CIM	1.345
	(-2.431)		(-2.434)		(-2.534)
Previous Rob * Early AMH	12.702	Previous Rob * Early CAM	16.567**	Previous Rob * Early CIM	15.658**
	(-8.299)		(-6.833)		(-7.539)
Previous Rob * No Early AMH	2.439	Previous Rob * No Early CAM	1.35	Previous Rob * No Early CIM	3.177
	(-2.863)		(-2.913)		(-2.933)
Robotics adoption conditional on	AMH	Robotics adoption conditional on	CAM	Robotics adoption conditional on	CIM
Complementarities	0.00	Complementarities	7.65***	Complementarities	7.21***
LBU Current	2.33	LBU Current	0.25	LBU Current	0.06
LBU Previous	1.39	LBU Previous	4.29**	LBU Previous	2.42
Observations	1,704		1,704		1,704

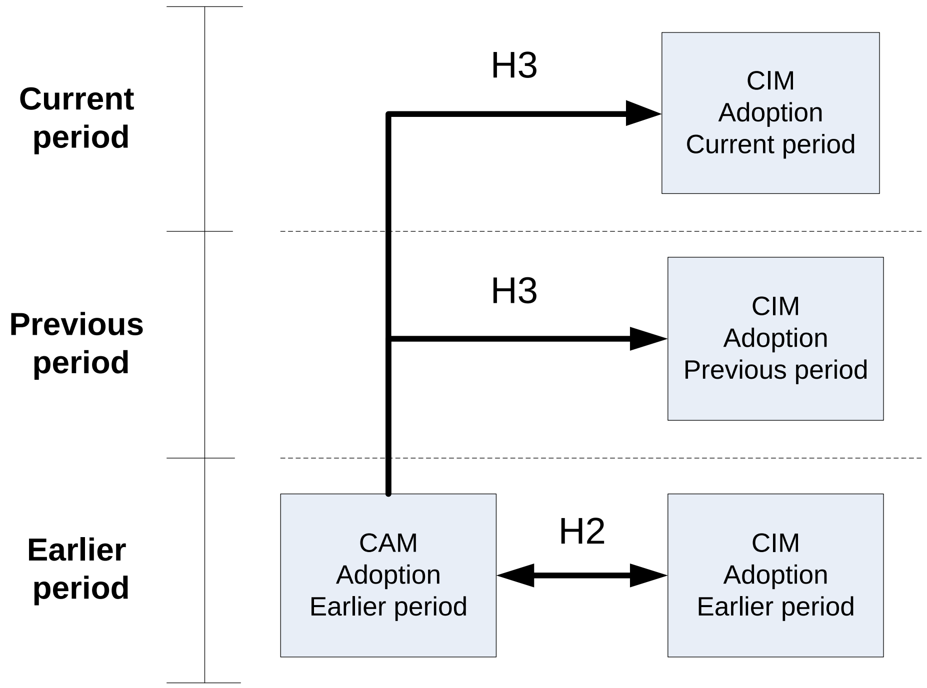
Notes: * denotes significance at 10% level; ** at 5% level and *** at 1% level. **Source:** Irish Innovation Panel – waves 2-6. Observations are weighted. Models contain identical control variables as reported in initial dynamic analysis (Table 4). A full set of tables, is available from the authors on request. Variable definitions in Annex 1.

Figure 1: Innovative sales by Irish manufacturing plants: by period



Source: Irish Innovation Panel – waves 2-6. Observations are weighted. Variable definitions in Annex 1.

Figure 2: Overview of complementarity and LBU hypotheses



Annex 1: Description of Variables

Table A1.1: 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	
Use	A binary variable taking value one if the plant uses the AMT
Current adopter	A binary indictor taking value one if the plant had first introduced the AMT in the previous three years and zero otherwise and is currently using the technology.
Early adopter	A binary indictor taking value one if the plant had first introduced the AMT in the previous six years and zero otherwise and is currently using the technology.
Previous adopter	A binary indictor taking value one if the plant had introduced the AMT at any time and is currently using the technology.
Plant characteristics	
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.
Client Linkages	A binary indicator taking value one if the plant is co-operating with customers as part of its innovation activity.
Supplier Linkages	A binary indicator taking value one if the plant is co-operating with suppliers as part of its innovation activity.
Horizontal 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.
External ownership	A binary indicator taking a value of one if the firm is owned outside Ireland.
Firm vintage	The age of the firm in years.
Export sales	Percentage of sales outside the British Isles

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