Industry 4.0 is coming: Is digital adoption a new mechanism linking entrepreneurial ambition to business performance?

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Stephen Roper
Enterprise Research Centre and Warwick Business School
stephen.roper@wbs.ac.uk

Jane Bourke
Department of Economics, Cork University Business School, University College Cork
Jane.Bourke@ucc.ie

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ABSTRACT

The advent of Industry 4.0 emphasises the potential importance of digital adoption for sustained competitiveness. Here, based on new survey data for over 9,000 firms in the UK, Ireland and USA we consider whether digital adoption provides a new mechanism through which firms' growth ambition is realised. Our analysis emphasises the commonality of factors linked to adoption in each of the three countries. Four key conclusions emerge. First, we find strong evidence that growth ambition is associated with digital innovation. The implication is that digital innovation can operate as a mechanism through which ambition is linked to subsequent business performance. Second, network and collaborative linkages are strongly associated with digital adoption as suggested in epidemic models of technology diffusion. Third, there is strong evidence that firm-level strategic influences impact digital adoption. Micro-businesses with stronger internal resources (business plans, training, external finance) are more likely to be digital innovators, potentially reinforcing their competitive advantages over more resource-constrained competitors. Fourth, and unexpectedly, prior adoption of digital technologies is negatively linked to subsequent adoption, while prior levels of sectoral adoption are positively linked to adoption. This we interpret as an informational or perhaps competitive effect. Our results suggest the variety of factors which influence technology diffusion even in relatively small micro-businesses. In policy terms while this presents a complex challenge, developing networking and information sharing mechanisms seems an obvious policy opportunity.

Keywords: Digital adoption; micro-business; growth ambition.

CONTENTS

1. INTRODUCTION

The links between entrepreneurial ambition and small business performance have been widely explored. In their meta-analysis of longitudinal studies Levie and Autio (2013, p. 5) find ‘positive and robust effects … [and] at least some of the effect of growth intentions on realised growth may be through its effect on innovativeness’. More recent work by Rypestol and Aarstad (2018) provides further evidence of the link between entrepreneurial ambition and innovation in Norwegian firms, and suggest the conditioning role of market structure. A generation earlier, in their classic study of ambitious female entrepreneurs Gundry and Welsch (2001) also found that more ambitious entrepreneurs adopted strategies which focussed (among other things) on planning, technological change, team-based organisation and diverse sources of finance. Here, inspired by the prospect of Industry 4.0 (OECD 2017), we consider the potential importance of a new mechanism – digital adoption – which may enable ambitious entrepreneurs to drive business performance. Are firms which are more ambitious more likely to adopt digital technologies? And, does the adoption of these technologies also depend on competition?

We focus on the potential for digital adoption to mediate the link between ambition and business performance in micro-enterprises, i.e. those with 1-9 employees. Relatively little is known about digital adoption in micro-enterprises as these are often excluded from surveys of innovation such as the UK Innovation Survey and from surveys of technology adoption such as the OECD’s ‘Digital Economy Outlook’. Jones et al. (2014, p. 286) comment that: ‘a review of the existing literature points to a knowledge gap regarding ICT adoption in micro-enterprises’. Benito-Hernandez et al. (2012) do however provide some insight in the role of firms’ in-house resources in shaping innovation in Spanish micro-enterprises while Tu et al. (2014) provide particular evidence of the value of supply chain co-operation in Chinese night markets. A priori, however, we might expect resource constraints, reflected in a discussion of the liability of smallness in Carroll (1983), to influence the way in which micro-businesses develop and implement strategies for innovation and growth (Cohen and Levin 1989). For example, if R&D and innovation projects involve significant up-front costs this may disproportionately reduce innovation in micro-businesses (Cohen and Klepper 1996). Empirical evidence is provided by Baumann and Kritikos (2016) who find a lower incidence of product and process innovation among micro-businesses in German manufacturing than among larger firms. Bengtsson et al. (2007) report similar results for ICT adoption. Dorrington et al. (2016) also report the results of a small-scale survey of digital uptake among 57 micro-firms in the UK emphasising skill and financial constraints on adoption. This echoes earlier studies which emphasise the particular resource constraints (Wolcott, Kamal, and Qureshi 2008) and attitudinal barriers to ICT adoption in micro-firms (Simmons, Armstrong, and Durkin 2008) as well as a lack of awareness of the benefits of ICT adoption (Jones et al. 2011). Roper and Hewitt-Dundas (2017) suggest the potential importance of collaboration during the innovation process as a means of enabling micro-enterprises to share risk and extend their resource base.

Our analysis is based on new survey data for large, representative samples of micro-businesses (c. 9,500 firms) in the UK, Ireland and the USA collected in early 2018. These surveys provide data on the adoption of seven digital technologies (Customer relationship management (CRM), E-Commerce, Web-based Accounting Software, Computer-Aided Design (CAD), Cloud computing, Artificial Intelligence (AI) and Machine Learning) as well as indicators of personal and business ambition and business performance. We make two main contributions. First, we test whether digital adoption provides a mechanism through which business ambition is linked to organisational performance. Understanding this linkage seems important given the growing dominance of digital technologies and their increasing uptake by SMEs. Inter alia, we explore the role of ambition in shaping firms' adoption behaviour which has more typically been linked to information and awareness, the anticipated strategic advantages of adoption (Karshenas and Stoneman 1993), or past adoption behaviours (McWilliams and Zilbermanfr 1996; Bourke and Roper 2014).

The argument is developed as follows. Section 2 outlines our conceptual framework, derived from behavioural foundations related to firms' awareness of digital technologies and their assessment of the risk/reward balance. Section 3 develops related hypotheses drawing on previous studies of ambition and adoption behaviour. Section 4 describes our data and empirical approach. Sections 5 and 6 present empirical results, discussion and policy implications.

2. CONCEPTUAL DEVELOPMENT

2.1 Behavioural foundations

Decision models such as the theory of planned behaviour (TPB) envisage a two-stage decision process: awareness and evaluation. In the awareness phase, the TPB envisages that a decision maker becomes aware of the potential options – a pure informational impetus without any evaluative element. In the more analytic evaluation phase, the decision maker then compares potential choices depending on their anticipated costs and benefits. This two-stage decision model closely resembles the main themes in the research literature on technology adoption (van Oorschot, Hofman, and Halman 2018). Epidemic, or disequilibrium, models of adoption recognise that information is imperfect, and therefore that firms may simply be unaware of new technologies (Meagher and Rogers 2004). Awareness is then a necessary, if not sufficient, condition for adoption. The sufficient condition is a positive benefit-cost evaluation which, in terms of technology adoption, may reflect the technological and market position of the firm, the firm's experience of prior adoption (Bourke and Roper 2014; McWilliams and Zilbermanfr 1996), and the returns to adoption which may be themselves by influenced by others' prior adoption (Karshenas and Stoneman 1993). Individual firms' evaluation of the anticipated returns from adoption may also differ, however, depending on their level of entrepreneurial ambition.

Epidemic or disequilibrium models of diffusion emphasise firms' awareness of innovations, and the learning and informational influences on adoption (Meagher and Rogers 2004). Here, the evidence suggests that having larger numbers of connections increases the probability of accessing useful knowledge and, ultimately, the probability of adoption (McEvily and Zaheer 1999; Hansen 1999; Laursen and Salter 2006; Leiponen and Helfat 2010; Storper and Venables 2004). For any given network density, however, network structure may also be important. Choi et al. (2010), for example, compare diffusion patterns among networks with uniformly random structure, and those with areas of high and low density. Their analysis suggests that 'adoption is strongest when networks consist of cliquish sub-network[s], which consist of individuals who are interacting intensively with each other … Bridges, which connect and weave sub-networks [make] the whole system integrated' (Choi et al., 2010, p. 172). An equally important insight in the Choi et al. (2010) analysis is the dependency of any diffusion process on the network position of the initiator(s) of any diffusion process: where initiators are isolated, diffusion may fail to occur, or occur slowly at least initially;

where initiators are intensively networked diffusion will be rapid, and potentially more widespread.

Epidemic or informational explanations of innovation diffusion are, at best, partial, however. Rather, ‘the essential prediction of a theory of diffusion is that potential adopters of a new technology should have different (preferred) adoption dates, or, synonymously, that at any given date only some of the potential adopters will wish to be actual users’ (Fusaro 2009, p. 504). ‘Equilibrium’ models of diffusion which reflect firms’ characteristics and the time of adoption, make very different underlying assumptions to epidemic models. Typically, equilibrium models start from assumptions of perfect foresight (i.e. firms are able to choose when to adopt an innovation to maximise their returns), and rationality (i.e. firms’ decisions about whether and when to adopt are governed purely by the expected returns)[1]. This leads to three factors which may influence firms’ assessment of the returns from adoption – the rank, stock and order effects (Fusaro 2009). Rank effects reflect how the heterogeneous characteristics of potential adopters influence their assessment of the returns from adoption. For example, firms with an in-house R&D capability (Griffith, Redding, and Van Reenan 2003), or track record of investment in new technology (Roper and Hewitt-Dundas 2015), may place more value on digital adoption. Similarly, where a digital technology is complementary to firms’ existing technologies, this may increase the perceived value (Colombo, Grilli, and Piva 2006; Cassiman and Veugelers 2006). Firms with greater absorptive capacity, for example, may assess the returns to adoption more positively than those with weaker capabilities (Ahlin, Drnovsek, and Hisrich 2014).

The other influences on adoption envisaged in equilibrium models relate to the impact of timing on the anticipated returns to adoption. ‘Stock’ effects suggest that as the stock of adopters increases, the marginal benefits from adoption may vary. For non-network goods, first mover advantage may suggest higher returns, with returns declining as the number of adopters increases (Fusaro 2009). For network goods, however, where their value depends directly on the number of adopters, returns may increase as the number of adopters increases (Henkel and Block 2013). Competition – market stealing effects – may also increase the costs of non-adoption as the level of

[1] Information flows, fashion or bandwagon effects which may lead to adoption even when returns are not optimal are excluded.

adoption increases (Bloom, Schankerman, and Van Reenen 2013)[2].

While the epidemic and equilibrium frameworks focus on individual adoption episodes, learning-by-using models suggest the potential impact of previous adoption decisions (McWilliams and Zilbermanfr 1996). Here, the argument suggests that firms' experience of prior adoption, and the development of related management routines, may generate dynamic economies of scope reducing the costs of subsequent adoption (Stoneman and Kwon 1994; Colombo and Mosconi 1995; McWilliams and Zilbermanfr 1996; Stoneman and Toivanen 1997; Arvantis and Hollenstein 2001). Experience of prior adoption may have informational advantages, helping firms to assess more accurately the likely costs and benefits of future adoption. Such experiences may be either positive or negative depending on firms' past success in adoption and the value derived from new technology investments. Past experience of early-adoption, for example, and its implicit risks, may discourage future adoption. However, where prior early-adoption was successful in generating high returns this may encourage future adoption.

While previous studies have considered epidemic, strategic and learning by using effects, individually and together, on adoption decision-making, these empirical studies have generally not been in the context of micro-businesses. A notable exception is a series of papers that use this encompassing framework to consider adoption decision-making in small private health-care practices (Bourke 2014; Bourke and Roper 2012; Bourke and Roper 2014). As many of the health-care practices comprise solo-practitioners, they cannot strictly be considered micro-businesses. However, these studies successfully employ an encompassing framework of informational, strategic and experiential effects to empirically explain adoption decision-making, including digital and information technology, in small businesses.

2.2 Hypothesis development

Our hypotheses reflect the three main themes highlighted in the adoption and diffusion literature: epidemic or network effects, strategic effects on adoption, and learning by using effects, as well as considering the impact of ambition on adoption decisions.

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[2] Karshenas and Stoneman (1993) also discuss 'order effects', which depend crucially on the full information assumption implicit in equilibrium models, and which reflect firms' attempts to maximise adoption returns conditional on the adoption decisions of co-related firms.

Network or epidemic models of diffusion focus on the informational influences on adoption (Meagher and Rogers 2004) and the extent of firms' social and business networks. Generally, having larger numbers of connections increases the probability of accessing useful knowledge and, ultimately, the probability of adoption (Storper and Venables 2004). Econometric studies of innovation also find strong and positive relationships between the probability and extent of innovation and the extent of firms' networks of collaboration partners (McEvily and Zaheer 1999; Hansen 1999; Laursen and Salter 2006; Leiponen and Helfat 2010). As one study commented: 'an important conclusion from [diffusion] research is that knowledge about the benefits of the innovation is spread through contact with prior adopters, so network ties with prior adopters predict adoption by the focal organisation' (Greve 2011, p. 949). This suggests our first hypothesis:

H1: Network effects on adoption (Epidemic effects)

Participation in social and business networks will be positively related to adoption.

Awareness is a necessary but not sufficient condition for adoption. Firms' cost-benefit assessment of the returns to adoption also needs to be positive reflecting internal factors such as absorptive capacity and external market conditions and others' prior adoption. In terms of absorptive capacity, the recent review by Song et al. (2018) bemoans the lack of uniformity of approach of previous studies but does highlight a strong positive link between absorptive capacity and firm-level outcomes. Other studies emphasise the role of absorptive capacity in enhancing the returns to cooperative innovation, particularly when partners are distant (Badillo and Moreno 2018). As Song et al. (2018) note, however, the positive benefits of absorptive capacity are strongly contextual depending on the nature of knowledge flows, their extent and the market situation of the firm. Returns from adoption may also depend on others prior adoption – the stock effect – although empirical results here are often ambiguous (Bourke and Roper 2014).

H2: Strategic effects on adoption

H2a: Rank effects – related to firms' ability to exploit the benefits of digital adoption – will positively influence adoption.

H2b: Stock effects – related to other firms' prior adoption – will negatively influence adoption.

Firms' own experience and learning from past adoption episodes may also shape the returns to adoption, however, through learning-by-using effects (McWilliams and Zilbermanfr 1996). Bourke and Roper (2016), for example, find significant and positive learning by using effects in firms' adoption of advanced manufacturing technologies in Irish manufacturing firms while Colombo and Mosconi (1995) find similar evidence for Italian metal-working firms. Evidence for the impact of learning-by-using effects on firms' digital adoption is limited although there has been some recent discussion of the role of learning-by-using effects in educational attempts to encourage adoption (Chan et al. 2017). The balance of evidence suggests our third hypothesis

H3: Learning by using effects on adoption

Prior adoption of other digital technologies will lead to higher levels of uptake of new digital technologies.

Our fourth and fifth hypotheses relates to the potential link between ambition and adoption. Given an awareness of any new technology, behavioural models suggest that adoption decisions are based on the perceived costs and benefits (Fusaro 2009). Digital technologies vary, however, in terms of their risk/reward profiles, the maturity of the technology itself and existing levels of adoption. Technologies such as Customer Relations Management (CRM) software and E-commerce are relatively mature technologies, whose benefits are widely understood and for which adoption may involve few risks. High levels of existing adoption may also depress returns, however. Firms are less likely to be aware of the potential benefits of adopting newer technologies such as artificial intelligence (AI) or machine learning (ML). Adoption of AI or ML may therefore pose greater downside risks, but due to low current adoption may also have the potential for higher returns to adoption. Rates of adoption may therefore be related both to awareness and firms' ability to calibrate potential rates of return (Alford and Page 2015).

Standardly, behavioural models of adoption would relate the adoption decision to firms' expectation of future returns. In reality, firms' different business models suggest a more complex picture with adoption reflecting both the expected levels of return and its variability. For example, Morris et al. (2005) refer to firms' 'investment model' reflecting aspirations for sustainability and growth. Individual firms' aspirations in terms of rates of return may also differ depending on levels of entrepreneurial ambition. Higher 'ambition' may equate to an aspiration for higher returns over the planning horizon and, potentially, a greater tolerance of greater downside returns or risk. Lower levels of ambition may equate to a desire for a less extreme payoff profile which minimises downside risk and provides more predictable returns. Suppose for example that firms' anticipated utility derived from any adoption decision is given by $U=aE(y)-bVar(y)$, $a,b>0$, and that adoption is undertaken when the anticipated utility it generates $U>U^*$, where U^* is a hurdle rate of return shaped by other investment options. Ambitious entrepreneurs (high a, low b) may then make different adoption decisions to those with more of a focus on stability or sustainability (low a, high b) depending on the expectation and variability of returns. This suggests that more ambitious firms may ceteris paribus be more likely to be early adopters of newer technologies such as AI/ML where the average returns are greater but more uncertain. There may also be an indirect learning-by-using effect related to ambition if in previous periods more ambitious firms were early adopters of other digital technologies (McWilliams and Zilbermanfr 1996). Higher levels of ambition are also likely to mean that firms invest in internal resources such as staff training, team building (Gundry and Welsch 2001) and innovation (Levie and Autio 2013). These capabilities may increase firms' absorptive capacity and their ability to effectively use new technologies, increasing the benefit-cost ratio and the probability of adoption.

These arguments suggest our fourth and fifth hypotheses:

H4: Ambition and investment

Greater ambition will be associated with higher levels of digital uptake.

H5: Ambition and digital maturity

Ambition will be more strongly linked to the adoption of less mature and less widely adopted technologies

3. DATA AND METHODS

Our analysis is based on the Micro-business Britain survey. This survey aimed to build a representative picture of established micro-businesses in the UK, US and Ireland. Telephone interviews were conducted with individuals who were either the owners or managers of each business. The focus was on established micro-businesses, i.e. firms with 1-9 employees that had been established for three years or more. Firms were also excluded from the survey if they were branches, divisions or subsidiaries of larger companies, if they were charities, or if they were part of the public sector. Firms in the 5-9 size-band were over-sampled as were firms in some UK regions (Northern Ireland and Wales) to prevent particularly small sample sizes in these groups[3]. In the analysis responses are therefore weighted to obtain representative results[4]. The Micro-business Britain Survey included 9,755 interviews in total: 6,254 in the UK, 1,500 in Ireland, and 2,001 in the USA. The UK survey was undertaken by telephone using a CATI system between February and May 2018 based on a commercially sourced sampling frame and achieved a response rate of 9.3 per cent. The Irish survey was undertaken between February and April 2018 and achieved an overall response rate of 11.7 per cent. US fieldwork was conducted during March and April 2018 from a US call centre. The US response rate was 12.3 per cent. The survey asked about a number of key business characteristics and strategies, provides a detailed overview of the structure and bio-demographics of the leadership team, information on the ambition of the respondent and business and detailed information on the timing of adoption of seven digital technologies.

Dependent variables

The survey asked firms about the adoption of seven digital technologies. These were:

- **Customer relationship management (CRM) systems** use data analysis about customers' history to improve business relationships with customers, specifically focusing on customer retention.
- **E-commerce** involves selling goods and/or services through the company website.
- **Web-based accounting software** is an accounting information system which can be accessed with any device which is internet enabled.
- **Computer-aided design software** aids in the creation, modification, analysis, or optimization of a design.

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[3] Table A1 provides a breakdown of survey responses by broad sector.
[4] Weighting strategies varied slightly between countries depending on the aggregate statistics available. Details are available from the authors on request.

- **Cloud computing** involves the practice of using a network of remote servers hosted on the Internet to store, manage, and process data, rather than a local server or a personal computer.
- **Artificial intelligence** - the simulation of human intelligence processes – learning, reasoning and self-correction - by machines, especially computer systems.
- **Machine learning technologies** use statistical techniques to give computers the ability to "learn" (i.e., progressively improve performance on a specific task) with data, without being explicitly programmed.

For each technology firms were asked whether they use each of these technologies and whether they had adopted them in the last three years, 3-6 years ago or before that. Our dependent variables are binary variables reflecting whether firms adopted each technology in the last three years[5].

Figure 1 illustrates the overall level of adoption of each technology in the UK, Ireland and the US, reflecting both current and prior adoption. Levels of adoption are somewhat lower in the US than in the UK and Ireland where around 40 per cent of micro-businesses are using web-based accounting software and cloud computing. The newer technologies – AI and Machine Learning (ML) are being used by less than 10 per cent of micro-businesses. The build-up of adoption through time is illustrated in Figure 2 which reports the percentage of firms using each technology in 2012, 2015 and 2018. Table 1 provides a summary of our dependent and independent variables for the UK, Ireland and USA. Variable definitions are included in Table A1.

Measuring ambition

There are no accepted measures for business ambition and so here we use questions developed from those used in the Global Entrepreneurship Monitor study of early stage entrepreneurship. We focus on two questions which ask firms how important it is to them to 'build a national and/or international business' and or to 'keep my business similar to how it operates now'. In the survey each question is answered with a Likert scale, and in the analysis we transform these Likert scales into binary variables which take value 1 if a particular business objective is said to be 'important' or 'very

[5] Note we exclude from each adoption model prior adopters of each technology. That is the adoption model for CRM excludes firms which adopted CRM in prior periods.

important'. Overall, 21 per cent of UK micro-businesses suggested that 'building a national or international business' was important (Ireland 27 per cent, US 33 per cent; Table 1) compared to 75 per cent which emphasised the importance of 'keeping the business similar to how it operates now' (Ireland 74 per cent, US 77 per cent; Table 1).

In the analysis it is important to recognise that the two ambition variables may be interpreted differently in each of the different economies. Operating in the much smaller Irish economy the need for growing businesses to develop an international presence may be much greater than that in the US or UK. The less ambitious 'keep the business similar to how it operates now' may have a more consistent interpretation across economies (Figure 3).

Independent variables

Our first hypothesis relates to epidemic or informational effects and we use three indicators to capture firms' network position. First, we have an indication of the breadth of firms' collaboration for innovation (Laursen and Salter 2006). This is derived as a simple count variable from a question asking 'which types of partner or partners did you collaborate with over the last three years'. Seven partner types are identified so this breadth variable takes values 0 to 7[6]. Previous studies have shown a strong positive relationship – if non-linear relationship - between the breadth of firms' collaboration and innovation (Leiponen and Helfat 2010; Classen et al. 2012; Love, Roper, and Vahter 2014). On average UK micro-businesses were collaborating with 0.38 innovation partners (Table 1). Second, we construct a similar count variable for the number of different sources of business advice which firms used over the last year. Previous studies have again shown a positive relationship between innovation and firms' use of consultants (Gonzalez-Benito, Munoz-Gallego, and Garcia-Zamora 2016) and advisory programmes (Sawang, Parker, and Hine 2016). Finally, we construct a count variable for the number of formal business organisations or networks of which firms were members[7]. Previous studies have suggested that networks may matter

[6] These are: Suppliers of equipment, materials, services or software; Clients or customers; Competitors or other businesses in your industry; Other businesses not in your industry;

Consultants, commercial labs or private R&D institutes; Universities or other higher education institutions; Government or public research institutes.

[7] Network organisations differ between countries and this is reflected in the survey. Four organisations are common to all countries: Business referral networks, Chambers of Commerce, LinkedIn and Sector or Trade Associations. In the UK we add the Federation of

differently for varying types of innovation (Kim and Lui 2015). On average, UK micro-businesses had 0.46 advisory partners and were members of an average of 0.48 types of business networks (Table 1).

Rank effects relate to firms' ability to appropriate the benefits of any adoption. Potentially this relates both to the effectiveness of firms' operations as well as their market profile and we therefore reflect both aspects in our three rank effect measures. To reflect firms' operational strength we include dummy variables for whether or not a firm has a business plan and whether it provides training for employees or business managers. A third dummy variable reflects firms' export market status. Business planning (Silva, Pazmay, and Saa 2017), training (Borras and Edquist 2015; Vivarelli 2014) and exporting (Love and Roper 2015) have all been positively linked to innovation in previous studies. Here, 29 per cent of UK businesses have a business plan, 65 per cent provide training for managers and employees, and 34 per cent are exporting. Stock effects on adoption are related to competitors' prior adoption of the same technology. In our analysis this is reflected by variables which profile prior adoption (ie. before 2015) in the same region and industry within which each firm is located. Prior evidence on the importance of order effects on adoption is limited and generally inconclusive (Fusaro 2009).

While stock effects relate to the impact of other firms' prior adoption decisions on current adoption, learning by using effects relate to economies of scope resulting from firms' own earlier adoption. We capture this using firms' own prior adoption of digital technologies and develop a count variable which takes values 0 to 6 depending on how many other digital technologies were adopted by each firm prior to 2015. For CRM adoption, this learning-by-using variable suggests that UK micro-businesses had adopted an average of 0.84 digital technologies previously (Table 1).

Control variables

We include a number of other control variables in our analysis. Business vintage (measured in years), for example, has been shown to be negatively related to innovation in some other studies (Mazzarol, Reboud, and Volery 2010). Involvement of

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Small Businesses (FSB), in Ireland IBEC and the Irish SME Association (ISME), and in both the Institute of Directors (IoD). In the US we add the National Federation of Independent Businesses (NFIB) and SCORE.

the original founder, being home-based and family-owned may have a similar negative effect on innovation (Willard, Krueger, and Feeser 1992). Conversely, a larger leadership team, external finance, past growth and profitability may also create capacity for innovation (Nohria and Gulati 1996; Lee 2015). Models also include standard industry dummies.

Modelling strategy

Following previous studies we estimate an adoption function estimating the probability that a firm adopted a digital technology in the last three years (Karshenas and Stoneman, 1993; Bourke and Roper, 2014). If A_i is the probability of adoption then:

$$A_i = \beta_0 + \beta_1 EPID_i + \beta_2 RANK_i + \beta_3 STOCK_i + \beta_4 LBU_i + \beta_5 AMB_i + \beta_6 CONT_i + \varepsilon_i$$

Where: $EPID_i$ is a vector of variables designed to capture epidemic effects, $RANK_i$ and $STOCK_i$ aim to capture rank and stock effects respectively, LBU_i reflects learning by using effects, AMB_i is ambition and $CONT_i$ is a vector of controls. In each case as our dependent variable is a binary measure we estimate probit models. One issue which arises in modelling adoption is how to treat firms which have previously adopted a technology. Here, we exclude these from our estimation samples and so the reference group in each case is the group of micro-businesses which have not adopted a specific technology prior to the last three years. in any prior period. All models include standard industry dummies.

4. EMPIRICAL RESULTS

Probit estimates are presented in Tables 2, 3 and 4 for UK, Irish and US firms respectively and highlight the factors associated with the probability that a micro-enterprise will adopt an individual digital technology. Table 5 provides a symbolic summary of the country estimates.

Three variables are used to measure possible epidemic or informational effects: breadth of partner types involved in collaborative innovation, breadth (number) of sources of advice and breadth (number) of networks and formal organisations of which the firm is a part. All three variables have positive, and often significant, associations with digital adoption. In particular, there is a consistent and strong positive association between the number of partner types micro-enterprises collaborate with for innovation and the probability they will adopt new digital technologies (Tables 2, 3 and 4). This finding is consistent across all seven technologies examined in the UK and also evident in the US and Irish data. Engagement with more sources of business advice and formal business organisations or networks are also positively associated with adoption in each of the countries (Table 5). This evidence provides strong support for our first hypothesis which relates to epidemic effects and suggests that the extent of micro-business networking and collaboration is strongly linked to digital adoption.

Next, we look at our findings in relation to strategic behaviour. Rank effects, i.e. a micro-businesses' ability to exploit the benefits of digital adoption, are measured by whether they have a business plan, exporting and training variables, and all are expected to positively influence adoption. Across all seven technologies examined, and in each of the countries, having a business plan is strongly linked to technology adoption (Table 5). Interestingly, this effect is consistent across the more established, as well as the emerging technologies (AI and ML). In addition, we identify a positive link between the probability that a firm is participating in employee or managerial training and adoption. In the UK, exporting is also positively associated with digital adoption. These results suggest strong support for the importance of rank effects and Hypothesis 2a.

The returns from adoption may also be influenced by other firms' prior adoption and we capture this stock effect by a variable measuring the proportion of prior adopters (before 2015). A priori, we expect the stock effect to negatively impact adoption as returns decrease the more extensive is prior adoption. Contrary to expectations, however, the coefficients on the stock effect variables across all seven digital technologies in the UK are positive, i.e. the greater the stock of prior adopters, the more likely micro-enterprises are to adopt a new technology (Table 2). The implication is that any negative effect on returns is dominated by positive influences from others' prior adoption. At least two possibilities are evident here. First, there may be a competitive explanation if adoption becomes a defensive response to prior adoption by market rivals. This is perhaps unlikely, however, given that we find strong positive coefficients on the stock effect term in the UK even for those technologies where adoption remains atypical, particularly AI and ML (Table 2). Second, the extent of prior adoption may be acting as a signal to firms of the value of a specific technology within their sector. This informational effect is similar in nature to the strong epidemic effects noted earlier. Evidence on stock effects proves weaker and less consistent in our Irish and US data (Tables 4 and 5). We therefore find little support for the negative stock effect envisaged in Hypothesis 2b.

We also consider if a firms' prior adoption of other digital technologies (prior to 2015) leads to higher levels of uptake of new digital technologies (i.e. learning-by-using effects). We expect (Hypothesis 3) that experiential learning through previous adoption and use of technologies will positively impact subsequent adoption decisions. However, our analysis reveals the opposite to be the case; prior adoption of other technologies negatively impacts the probability that a micro-enterprise adopting a new technology in the current time period. This finding is strong and statistically significant in the UK and across all of the technologies examined and although less consistent is also evident in the Irish and US data. Therefore, our analysis does not support Hypothesis 3 that learning-by-using effects lead to higher uptake of new digital technologies. A number of different mechanisms may be generating this negative connection between prior and current adoption. One explanation relates to the substitutability of the different digital technologies in firms' operations: having adopted a digital technology in the past there may be no operational need for further adoption. Embracing E-commerce may, for example, make adopting web-based accounting less important if cash-flow management is already transparent. Competitive factors may also be important. If past adoption of a digital technology has given a firm a competitive advantage this may mean further (and potentially costly) digital adoption is not necessary. Alternatively, there may be a negative learning effect where prior adoption of digital technologies has proven difficult or led to disappointing returns. Either might generate the observed negative effect.

Finally, we consider if firms' growth ambition influences digital technology adoption. We use two variables to do so. These binary variables capture whether a micro-enterprise considers it important to: (i) build a national and/or international business; or, (ii) keep the business similar to how it operates now. A priori, we expect that stronger ambition will be associated with higher levels of digital uptake (Hypothesis 4). In relation to building a national and/or international business, our analysis reveals a significant positive relationship with adoption for six of the technologies in the UK (Table 2). Confirmatory evidence is suggested by the negative coefficients on the variable which measures a 'lack' of ambition in UK firms, i.e. keeping the business similar to how it operates now (Table 2). Therefore, our UK analysis supports H4 with confirmatory evidence from Ireland and the US. We also hypothesised that growth ambition will be more strongly linked to the adoption of less mature and less widely adopted technologies. However, our analysis in relation to the two ambition variables does not reveal a clear distinction with respect to the ambition-adoption relationship for mature versus emerging technologies. Therefore, we find little support for H5.

Three control variables are also strongly associated with levels of adoption. Firm size and the use of external finance are both positively linked to the probability that micro-businesses will undertake digital adoption in the UK (Table 2). Conversely, firm vintage is negatively associated with the probability of adoption in each of the countries considered (Tables 2, 3 and 4). The involvement of the original founder, being home-based and family-owned have little consistent association with digital adoption. Top management team size has little consistent relationship with digital adoption in the UK and Ireland but is negatively associated with adoption in the USA (Table 4).

5. DISCUSSION AND CONCLUSION

Diffusion of digital technologies among micro-businesses has been rapid over the last decade with around 40 per cent of micro-businesses in the UK now reportedly using both web-based accounting and cloud-based computing (Figure 1). Adoption of E-commerce and CRM software remains less common but has also increased significantly over the last decade (Figure 2). For the first time our analysis sheds some light on the factors associated with digital adoption among micro-businesses and provides a benchmark comparison with the US and Ireland. Very similar factors prove important in shaping digital adoption in each of the three countries with operational, informational, market and ambition related factors all proving important. Four key findings emerge.

First, we find strong evidence that ambition is strongly associated with the probability of digital innovation. This proves to be the case both for digital technologies which are well established (e.g. CRM, Ecommerce) as well as emerging technologies such as AI or ML and across all three countries covered by the Micro-business Britain survey data. The implication is that digital innovation can be a mechanism through which ambition is linked to subsequent business performance. Given the advent of Industry 4.0 recognising this linkage seems important if ambitious micro-businesses are to be able to translate aspiration into real growth.

Second, network and collaborative linkages are strongly associated with digital adoption as suggested in epidemic models of technology diffusion (Rogers, 1983). Advisory networks, business networks and innovation collaborations can all provide micro-businesses with information and understanding of the value of digital technologies and are positively linked to digital adoption. The significance of these networks provides an indication of the potential value of policies designed to build or strengthen inter-firm networks and collaborative innovation such as the Knowledge Transfer Network[8]. It also suggests the value of diverse sources of advisory support – both public and private in encouraging firms to adopt new digital innovations.

Third, there is strong evidence that firm-level strategic influences impact digital adoption. Micro-businesses internal resources (business plans, training, external finance) are more are strongly associated with digital innovation, potentially reinforcing their competitive advantages over more resource-constrained competitors. This reflects arguments made in recent OECD publications which suggest that a stronger impetus towards innovation in 'frontier' firms and a failure of diffusion towards 'laggards' may be exacerbating disparities between high and lower productivity firms (OECD 2015). Network initiatives which build connectivity and information flows between firms may be one way of addressing such diffusion failures.

Fourthly, we find unexpected relationships between prior adoption (both by individual firms and in the sector in which firms are operating) and the probability of adoption. Prior adoption of digital technologies is (unexpectedly) negatively related to subsequent adoption. This may reflect either implementation challenges or increased competitive advantage. Prior levels of sectoral adoption are, however, positively linked to adoption. This we also interpret as an informational or perhaps competitive effect.

More generally our results suggest the variety of factors which are associated with technology diffusion even in small micro-businesses. In policy terms while this presents a complex challenge, developing networking and information sharing mechanisms seems an obvious policy opportunity. In more strategic terms, evidence from elsewhere suggests the importance of digital adoption and the effective use of digital technologies for sustained competitiveness.

[8] See https://ktn-uk.co.uk/.

Figure 1: Adoption among micro-businesses: UK, Ireland and the USA

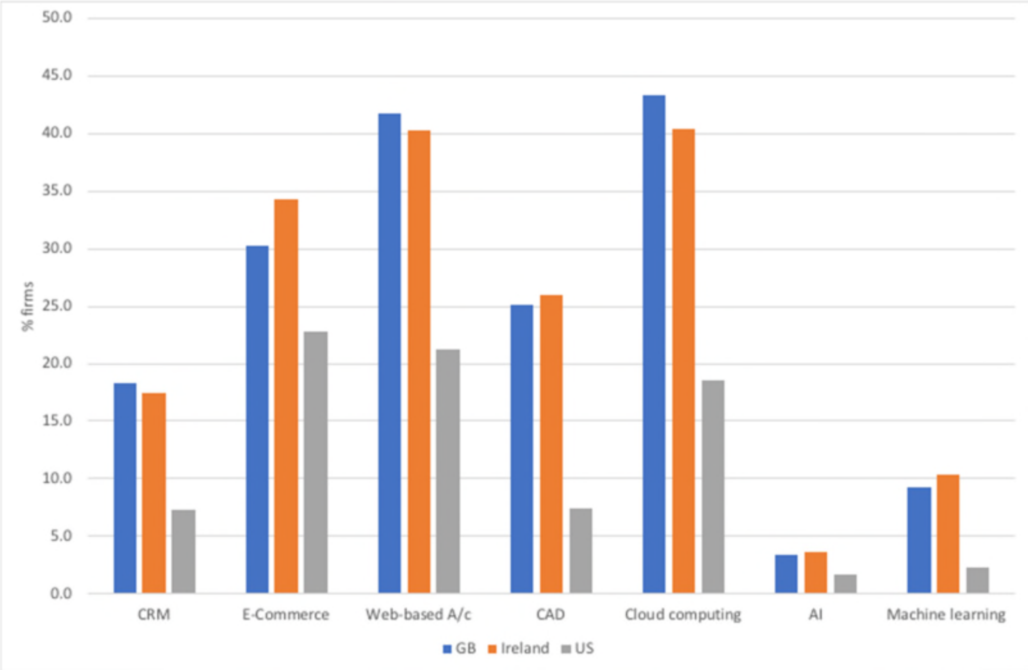
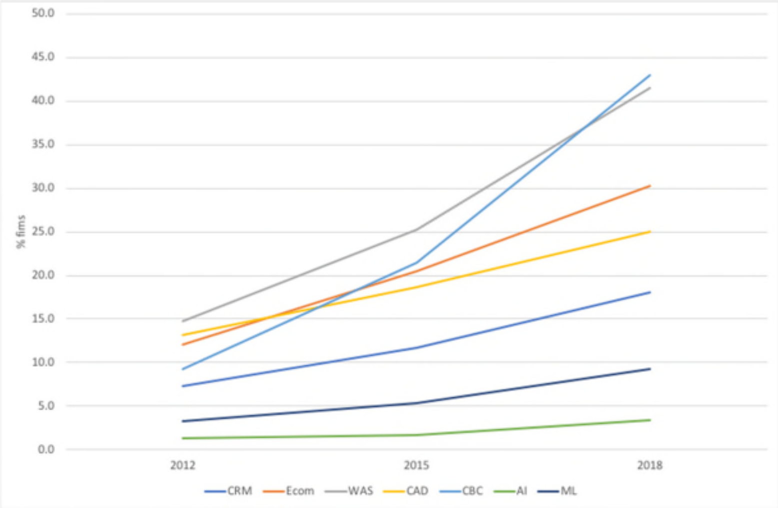
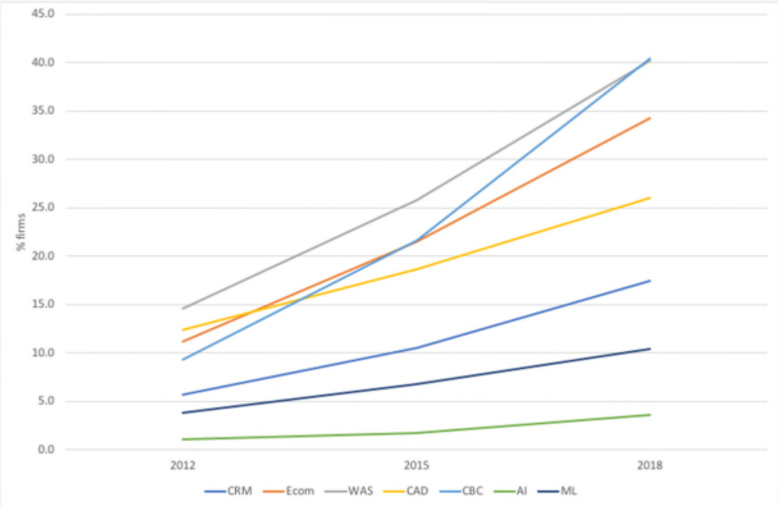


Figure 2: Adoption curves in the UK, Ireland and US

(a) UK



(b) Ireland



(c) USA

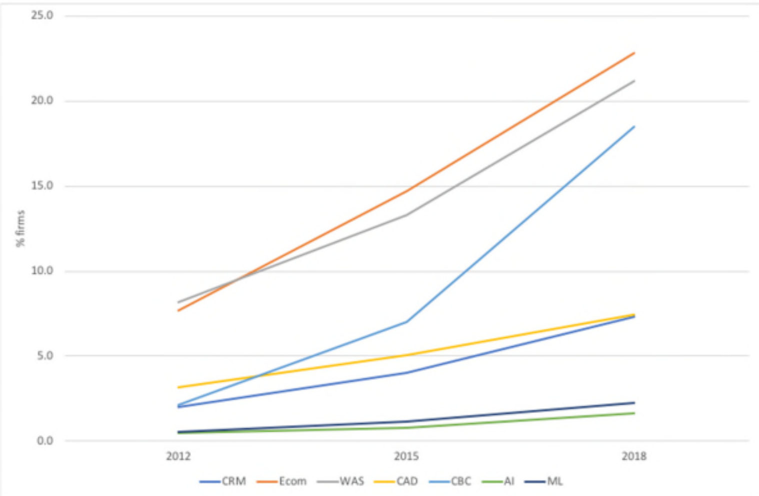


Figure 3: Ambition measures by country

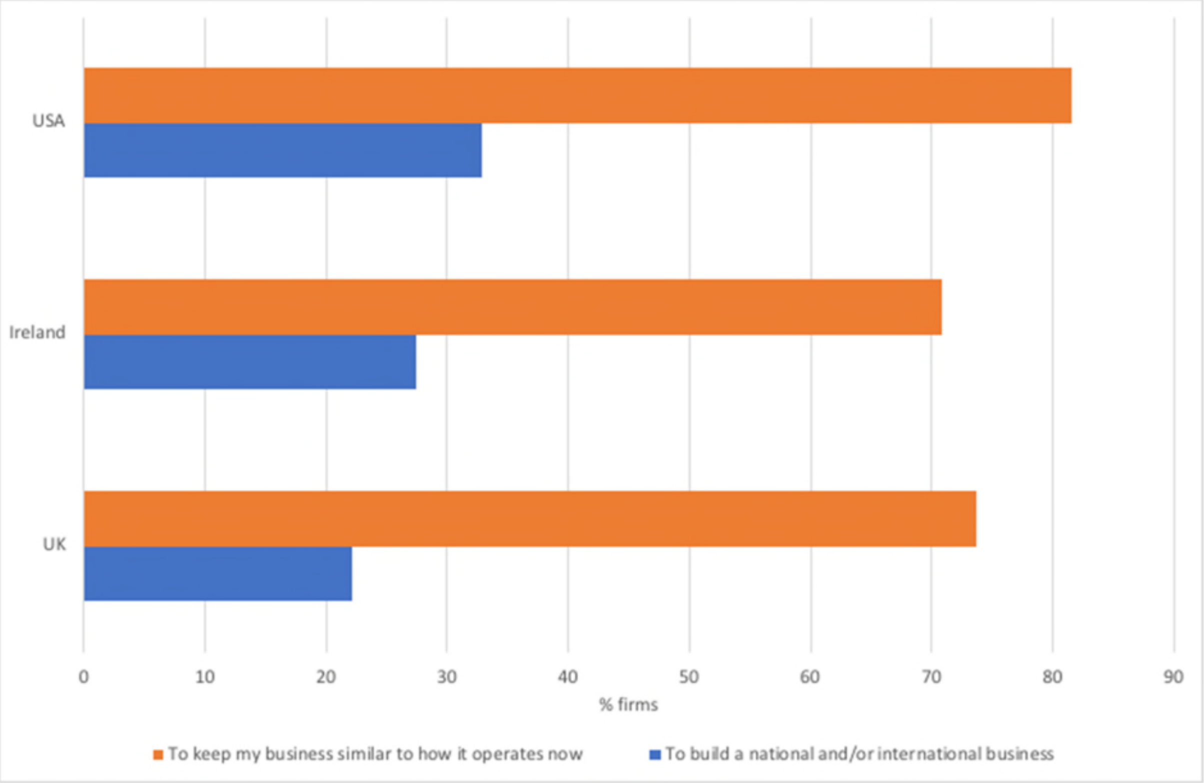


Table 1: Descriptives by country

	UK N=5046		IRELAND N=1227		USA N=1850	
Variable Name	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables (Adoption in Current Time Period)						
CRM	0.08	0.27	0.08	0.27	0.05	0.22
CBC	0.22	0.41	0.22	0.42	0.13	0.34
E-Commerce	0.11	0.31	0.14	0.34	0.08	0.28
WAS	0.17	0.37	0.17	0.37	0.09	0.29
CAD	0.07	0.25	0.08	0.27	0.02	0.14
AI	0.02	0.12	0.02	0.12	0.01	0.10
ML	0.04	0.20	0.05	0.21	0.02	0.13
Ambition variables						
Build National/Int. Business	0.21	0.41	0.27	0.44	0.33	0.47
Keep business the same	0.75	0.43	0.74	0.44	0.77	0.42
Epidemic effects						
Breadth: Partners	0.38	1.04	0.44	1.09	0.35	0.88
Breadth: Advice	0.46	0.95	0.56	1.12	0.70	1.35
Breadth: Networks	0.48	0.63	0.50	0.64	0.43	0.77
Rank effect measures						
Business Plan	0.29	0.46	0.31	0.46	0.28	0.45
Training	0.65	0.48	0.71	0.45	0.43	0.50
Exporting	0.34	0.47	0.42	0.49	0.34	0.47
Stock effect measures						
Stock_CRM	0.12	0.08	0.12	0.08	0.05	0.03
Stock_CBC	0.21	0.08	0.22	0.07	0.08	0.04
Stock_Ecom	0.21	0.04	0.23	0.06	0.17	0.07
Stock_WAS	0.26	0.05	0.30	0.05	0.14	0.03
Stock_CAD	0.20	0.11	0.21	0.10	0.06	0.03
Stock_AI	0.02	0.01	0.02	0.01	0.01	0.00
Stock_ML	0.06	0.02	0.08	0.03	0.01	0.00
LBU effect measures						
LBU_CRM	0.84	1.07	0.95	1.13	0.43	0.69
LBU_CBC	0.67	0.88	0.76	0.94	0.36	0.61
LBU_E-Comm	0.66	0.91	0.75	0.96	0.27	0.54
LMU_WAS	23.98	18.77	25.44	19.16	18.84	12.63
LBU_CAD	0.54	0.50	0.55	0.50	0.47	0.50
LBU_AI	0.71	0.46	0.74	0.44	0.65	0.48
LBU_ML	0.81	0.39	0.84	0.37	0.95	0.22
Control variables						
Vintage	23.98	18.77	25.44	19.16	18.84	12.63
Home based	0.54	0.50	0.55	0.50	0.47	0.50
Family owned	0.71	0.46	0.74	0.44	0.65	0.48
Founder still involved	0.81	0.39	0.84	0.37	0.95	0.22
TMT size	2.00	1.12	1.92	1.04	1.98	1.57
External Finance	0.40	0.49	0.50	0.50	0.30	0.46
Size of firm (employ.)	3.86	2.21	4.07	2.43	3.86	2.67

Notes: See Annex 1 for variable definitions. Observations are weighted to give representative results.

Table 2: Probit estimations for adoption of individual digital technologies: UK firms

	CRM	CBC	E-Comm	WAS	CAD	AI	ML
Vintage	-0.002***	-0.002***	-0.001	-0.002***	0.0000	0.0000	-0.000**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Home-based	0.009	0.046***	0.009	0.050***	-0.01	0.002	-0.008
	(0.006)	(0.015)	(0.010)	(0.014)	(0.008)	(0.003)	(0.005)
Family-owned	-0.015**	-0.003	0.013	0.002	-0.005	-0.004	-0.009*
	(0.007)	(0.016)	(0.010)	(0.015)	(0.009)	(0.003)	(0.005)
Founder	-0.003	0.009	0.002	-0.002	0.006	0.003	0.007
	(0.009)	(0.020)	(0.013)	(0.018)	(0.010)	(0.004)	(0.006)
TMT	0.003	0.009	0.005	0.001	0.005	0.001	0.004**
	(0.002)	(0.007)	(0.005)	(0.007)	(0.003)	(0.001)	(0.002)
External Finance	0.018***	0.047***	0.032***	0.052***	0.014*	-0.002	0.010**
	(0.006)	(0.015)	(0.011)	(0.014)	(0.008)	(0.003)	(0.005)
Size	0.004***	0.007**	0.003	0.011***	0.002	-0.001	0.002
	(0.001)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.001)
Breadth: Partners	0.013***	0.037***	0.015***	0.032***	0.011***	0.003***	0.006***
	(0.002)	(0.008)	(0.004)	(0.007)	(0.003)	(0.001)	(0.002)
Breadth: Advice	0.002	0.021**	-0.003	0.020***	0.003	0.001	0.005**
	(0.003)	(0.008)	(0.005)	(0.007)	(0.004)	(0.001)	(0.002)
Breadth: Networks	0.009**	0.052***	-0.005	-0.001	-0.004	0.000	0.000
	(0.004)	(0.012)	(0.008)	(0.011)	(0.006)	(0.002)	(0.004)
Business Plan	0.027***	0.030*	0.037***	0.056***	0.027***	0.008**	0.015**
	(0.008)	(0.017)	(0.012)	(0.016)	(0.009)	(0.004)	(0.006)
Training	0.008	0.074***	0.01	0.042***	0.027***	0.004	0.022***
	(0.006)	(0.016)	(0.011)	(0.015)	(0.008)	(0.003)	(0.005)
Exporting	-0.004	0.002	0.024**	0.011	0.021**	0.002	-0.001
	(0.006)	(0.017)	(0.012)	(0.015)	(0.010)	(0.003)	(0.005)
Stock Effect	0.319***	1.276***	0.133	1.508***	0.912*	0.426	4.448
	(0.113)	(0.386)	(0.440)	(0.453)	(0.540)	(0.442)	(10.519)
Learning-By-Using	-0.015***	-0.032***	-0.043***	-0.058***	-0.033***	-0.002*	-0.013***
	(0.003)	(0.009)	(0.006)	(0.008)	(0.004)	(0.001)	(0.002)
Build National/Int. Business	0.043***	0.086***	0.081***	0.058***	0.033***	0.013***	0.007
	(0.010)	(0.021)	(0.016)	(0.019)	(0.012)	(0.005)	(0.006)
Keep business the same	-0.035***	-0.066***	-0.031***	-0.050***	-0.006	-0.003	-0.008
	(0.008)	(0.018)	(0.012)	(0.016)	(0.009)	(0.003)	(0.006)
N	5229	4645	4695	4398	4772	5849	5606
Chi-squared	342.328	417.185	214.678	309.054	168.815	97.445	177.269
p - value	0	0	0	0	0	0	0
R-squared	0.182	0.104	0.078	0.088	0.076	0.102	0.089
BIC	2444.292	5103.84	3370.862	4404.379	2580.081	1107.744	1949.013

Notes: Models exclude prior adopters of each technology. Reference groups are therefore non-adopters of each technology. Models include industry dummies. Observations are weighted to give representative results.

Table 3: Probit estimations for adoption of individual digital technologies: Irish firms

	CRM	CBC	E-Comm	WAS	CAD	AI	ML
Vintage	-0.001**	-0.004***	-0.002**	-0.002**	-0.001*	0.0000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Home-based	0.004	-0.006	0.041	0.031	-0.008	0.002	-0.005
	(0.013)	(0.031)	(0.030)	(0.033)	(0.019)	(0.005)	(0.011)
Family_ owned	-0.016	0.003	-0.006	0.014	-0.014	-0.002	-0.007
	(0.016)	(0.035)	(0.031)	(0.031)	(0.024)	(0.007)	(0.014)
Founder	0.007	-0.085*	-0.098**	-0.061	0.009	-0.02	0.012
	(0.016)	(0.051)	(0.048)	(0.052)	(0.026)	(0.016)	(0.012)
TMT	-0.001	0.007	-0.005	0.006	0.013*	0.003	0.003
	(0.005)	(0.015)	(0.013)	(0.016)	(0.008)	(0.002)	(0.004)
External Finance	-0.009	0.028	0.03	0.053*	0.021	-0.004	-0.003
	(0.012)	(0.030)	(0.026)	(0.029)	(0.018)	(0.005)	(0.009)
Size	0.003	0.023***	0.004	0.012*	0.002	-0.002	0.002
	(0.002)	(0.006)	(0.005)	(0.006)	(0.004)	(0.001)	(0.002)
Breadth: Partners	0.015***	0.041***	0.037***	0.029*	0.021**	0.003*	-0.004
	(0.005)	(0.014)	(0.011)	(0.015)	(0.008)	(0.002)	(0.004)
Breadth: Advice	-0.003	0.048***	0.008	0.021*	-0.001	-0.003	0.004
	(0.004)	(0.014)	(0.009)	(0.012)	(0.007)	(0.002)	(0.006)
Breadth: Networks	0.005	0.063**	-0.007	0.008	-0.01	0.002	0.005
	(0.009)	(0.026)	(0.022)	(0.024)	(0.015)	(0.003)	(0.009)
Business Plan	0.046***	0.056	0.074**	0.124***	0.052**	0.026***	0.026**
	(0.017)	(0.036)	(0.033)	(0.037)	(0.026)	(0.009)	(0.012)
Training	0.033**	0.082***	0.038	0.088***	-0.017	-0.005	0.022**
	(0.013)	(0.031)	(0.028)	(0.032)	(0.025)	(0.006)	(0.011)
Exporting	-0.007	0.014	0.060**	0.016	0.001	0.000	-0.005
	(0.013)	(0.031)	(0.030)	(0.034)	(0.019)	(0.005)	(0.010)
Stock Effect	0.644	2.362**	0.327	1.188***	0.112	-1.941	-1.493
	(0.707)	(1.018)	(0.284)	(0.412)	(0.249)	(1.715)	(1.790)
Learning-By-Using	-0.026***	-0.016	-0.078***	-0.074***	-0.041***	0.000	-0.003
	(0.007)	(0.015)	(0.016)	(0.017)	(0.010)	(0.002)	(0.005)
Build National/Int. Business	0.059***	0.017	0.009	0.039	0.062**	0.007	0.019
	(0.022)	(0.037)	(0.030)	(0.039)	(0.027)	(0.006)	(0.014)
Keep business the same	-0.004	-0.046	-0.027	-0.039	0.011	-0.006	-0.003
	(0.013)	(0.037)	(0.029)	(0.035)	(0.019)	(0.006)	(0.013)
N	1255	1123	1110	1010	1140	1302	1275
Chi-squared	115.608	143.973	100.237	90.94	68.617	93.692	59.614
p - value	0	0	0	0	0	0	0
R-squared	0.24	0.157	0.14	0.132	0.129	0.175	0.097
BIC	703.206	1215.84	1023.022	1044.752	779.538	381.318	569.246

Notes: Models exclude prior adopters of each technology. Reference groups are therefore non-adopters of each technology. Models include industry dummies. Observations are weighted to give representative results.

Table 4: Probit estimations for adoption of individual digital technologies: USA firms

	CRM	CBC	E-Comm	WAS	CAD	AI	ML
Vintage	-0.001***	-0.001	-0.002***	0.000	0.000	0.000	0.000
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Home-based	0.002	-0.02	-0.015	0.003	0.002	-0.003	-0.002
	(0.004)	(0.016)	(0.019)	(0.015)	(0.004)	(0.002)	(0.002)
Family-owned	0.004	-0.024	0.000	-0.006	-0.002	0.001	-0.001
	(0.004)	(0.017)	(0.017)	(0.019)	(0.005)	(0.001)	(0.002)
Founder	0.002	0.039*	0.007	0.026		-0.001	0.003**
	(0.006)	(0.023)	(0.028)	(0.025)		(0.004)	(0.001)
TMT	-0.003**	-0.015***	-0.012**	-0.004	-0.004**	0.000	-0.001
	(0.001)	(0.006)	(0.005)	(0.005)	(0.002)	(0.000)	(0.001)
External Finance	-0.002	0.073***	0.024	0.019	0.014**	0.004	0.003
	(0.004)	(0.022)	(0.018)	(0.016)	(0.007)	(0.003)	(0.002)
Size	0.003***	0.011***	0.011***	0.010***	0.001*	0.0000	0.001**
	(0.001)	(0.003)	(0.003)	(0.003)	(0.001)	(0.000)	(0.000)
Breadth: Partners	0.003	0.030***	0.020***	0.017**	0.002	0.001	-0.002*
	(0.002)	(0.010)	(0.007)	(0.007)	(0.002)	(0.001)	(0.001)
Breadth: Advice	0.004**	0.015**	0.006	0.014***	0.0000	0.0000	0.001**
	(0.001)	(0.006)	(0.005)	(0.004)	(0.001)	(0.000)	(0.001)
Breadth: Networks	0.007**	0.023**	0.020*	0.005	0.006**	0.002**	0.003***
	(0.003)	(0.012)	(0.011)	(0.008)	(0.003)	(0.001)	(0.001)
	0.011**	0.029	0.083***	0.043*	0.020**	-0.001	0.003
	(0.005)	(0.022)	(0.028)	(0.023)	(0.010)	(0.001)	(0.003)
Training	0.005	0.035*	0.022	0.038**	0.012	0.002	0.002
	(0.005)	(0.020)	(0.018)	(0.016)	(0.008)	(0.002)	(0.003)
Exporting	-0.001	-0.017	-0.007	-0.016	0.005	0.002	0.003
	(0.004)	(0.016)	(0.017)	(0.014)	(0.006)	(0.002)	(0.002)
Stock Effect	0.507**	-1.273*	-3.195	-0.17	0.428	0.293	-0.187
	(0.244)	(0.696)	(4.445)	(0.598)	(0.432)	(0.437)	(0.567)
Learning-By-Using	0.003	0.014	-0.051***	-0.024*	-0.003	0.001	-0.001
	(0.003)	(0.012)	(0.015)	(0.013)	(0.003)	(0.001)	(0.001)
Build National Int. Business	0.006	0.001	0.003*	0.001	0.000*	0.004	0.0000
	(0.005)	(0.001)	(0.001)	(0.001)	(0.000)	(0.003)	(0.000)
Keep business the same	-0.003	0.007	-0.017	0.004	0.001	-0.002	-0.004
	(0.005)	(0.022)	(0.024)	(0.021)	(0.006)	(0.002)	(0.003)
N	1852	1797	1617	1690	1761	1552	1800
Chi-squared	213.56	228.735	158.107	114.075	102.496	162.961	187.384
p - value	0	0	0	0	0	0	0
R-squared	0.24	0.149	0.169	0.118	0.237	0.371	0.234
BIC	610.397	1339.279	1033.295	1096.421	510.988	311.947	357.421

Notes: Models exclude prior adopters of each technology. Reference groups are therefore non-adopters of each technology. Models include industry dummies. Observations are weighted to give representative results.

Table 5: Summary of estimation results by country

	UK	IRL	USA
Rank effects			
Business Plan	++	++	+
Training	+	+	+
Exporting	+		
Stock effects	+	+	
Epidemic effects			
Breadth: partners	++	++	+
Breadth: advice	+	+	+
Breadth: network	+		++
Learning-by-Using effects	--	-	-
Ambition			
Build nat/ int. business	++	+	+
Keep business the same	-		

Note: '+' indicates a positive and significant effect across 2-4 technologies; '++' a positive and significant effect 5-7 technologies; '–' and '—' indicate similar negative effects.

Annex 1: Variable definitions

Variable Name	Definition
Dependent Variables	
CRM, CBC, Ecommerce, WAS, CAD, AI, ML	Binary variables which take value 1 if the firm has adopted the technology in the previous three years
Ambition Variables	
Build National/Int. Business	Binary variable taking value 1 where the firm said this objective was either important or very important
Keep business the same	Binary variable taking value 1 where the firm said this objective was either important or very important
Independent Variables	
Vintage	Age of the business measured in years
Home-based	A binary variable taking value 1 where the business was home based
Family-owned	A binary variable taking value 1 where the business was family owned
Founder	A binary variable taking value 1 where the business founder was still involved
TMT	Number of members of the senior management team
External Finance	A binary variable taking value 1 where the business is a user of external finance
Size	Size of the business measured by employment
Breadth: Partners	Average number of partner types with which the firm is collaborating for innovation
Breadth: Advice	Average number of partner types from which the firm has sought advice over the previous year.
Breadth: Networks	Average number of business networks of which the firm is a member
Business Plan	A binary variable taking value 1 where the business has a business plan
Training	A binary variable taking value 1 where the business provides training for employees or managers
Exporting	A binary variable taking value 1 where the business is exporting
Stock_CRM, Stock_CBC, Stock_Ecom, Stock_WAS, Stock_CAD, Stock_AI, Stock_ML	Stock of prior adopters: the proportion of previous adopters of each technology (by 2015) in the firms' industrial sector
LBU_CRM, LBU_CBC, LBU_E-Comm, LMU_WAS, LBU_CAD, LBU_AI, LBU_ML	Learning by using: The number of digital technologies previously adopted by each firm (by 2015)

Annex 2: Sectoral and size-band overview of survey data

	UK			Ireland			USA		
	1-4	5-9	Total	1-4	5-9	Total	1-4	5-9	Total
ABDE - Primary	255	114	369	41	17	58	51	60	111
	6.50%	4.90%	5.90%	4.50%	2.80%	3.90%	4.40%	7.20%	5.50%
C - Manufacturing	334	258	592	87	63	150	80	116	196
	8.50%	11.20%	9.50%	9.60%	10.60%	10.00%	6.90%	13.80%	9.80%
F - Construction	424	226	650	68	57	125	71	75	146
	10.70%	9.80%	10.40%	7.50%	9.50%	8.30%	6.10%	8.90%	7.30%
G - Retail, wholesale	697	402	1099	162	111	273	242	151	393
	17.70%	17.40%	17.60%	17.90%	18.60%	18.20%	20.80%	18.00%	19.60%
HI - Transport, accommodation, food	376	293	669	132	90	222	51	102	153
	9.50%	12.70%	10.70%	14.60%	15.10%	14.80%	4.40%	12.20%	7.60%
JKL - Information, finance, real estate	506	287	793	123	65	188	170	131	301
	12.80%	12.40%	12.70%	13.60%	10.90%	12.50%	14.60%	15.60%	15.00%
M - Professional, scientific	682	356	1038	143	112	255	213	85	298
	17.30%	15.40%	16.60%	15.80%	18.80%	17.00%	18.30%	10.10%	14.90%
N - Administrative services	333	174	507	70	34	104	129	60	189
	8.40%	7.50%	8.10%	7.80%	5.70%	6.90%	11.10%	7.20%	9.40%
PQRS - Other services	340	197	537	77	48	125	155	59	214
	8.60%	8.50%	8.60%	8.50%	8.00%	8.30%	13.30%	7.00%	10.70%
Total	3947	2307	6254	903	597	1500	1162	839	2001
	100%	100%	100%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%

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Centre Manager
Enterprise Research Centre
Warwick Business School
Coventry, CV4 7AL
CentreManager@enterpriseresearch.ac.uk

Centre Manager
Enterprise Research Centre
Aston Business School
Birmingham B4 7ET
CentreManager@enterpriseresearch.ac.uk