From latent to emergent entrepreneurship: The role of human capital in entrepreneurial founding teams and the effect of external knowledge spillovers for technology adoption

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Abstract

Building on the latent-emergent entrepreneurship framework, we investigate how different type of skills and combination of skills within entrepreneurial founding teams (EFTs) affect the adoption of latent vs emergent technologies (ICTs). We also examine the role of knowledge spillovers on the firm's adoption of different types of technologies and how their effect is moderated by the set of skills that are present within the EFT. We contribute by showing that latent and emergent entrepreneurs decide differently when it comes to whether they should adopt a latent or an emergent version of a technology, by identifying what type or combinations of skills differentiate between latent and emergent entrepreneurs when it comes to ICT adoption, and finally by showing how entrepreneurs, depending on their set of skills, are able to take advantage of the knowledge gathered from external spillovers to adopt different types of technologies.

Keywords

Latent-emergent entrepreneurs; Knowledge spillover creative constructive circle; Entrepreneurial human capital; External knowledge spillovers; Technology adoption

1. Introduction

Existing literature (Caiazza et al., 2020; 2016; Cunningham and Link, 2020; Gohmann, 2012) on latent and emergent entrepreneurship focuses on why some firms, despite having developed or being aware of a specific technological opportunity, decide not to (or cannot) take advantage and exploit that opportunity commercially. Relevant studies have also concentrated on why other firms can do so, even if the specific technology was not developed internally, but firms only became aware of its existence through external knowledge spillovers. In such scenarios, firms that cannot exploit technological knowledge for commercial purposes behave as (and have the profile of) *latent entrepreneurs*; whereas those that can do so, even via external spillovers, adopt the behavior of *emergent entrepreneurs* (Cunningham and Link, 2020).

One of the main reasons behind firms not being able to exploit a technology even if it is developed internally, relates to the perception of risk and level of uncertainty (Agarwal et al., 2010; 2007) that entrepreneurs (or managers) have regarding its success and the potential benefits that their firms can draw from its commercialization. These traits are in turn linked to the type and level of skills and related abilities that entrepreneurs or managers possess (Caiazza et al., 2016; 2015), which is the focus of this study.

Most latent and emerging entrepreneurship studies focus on the potential commercialization of product or service innovation. However, Caiazza et al. (2016) emphasized that the Oslo Manual (2005) includes process, marketing, and organizational innovations in its definition of innovation[1] (Kim and Lui, 2015; Tavassoli and Karlsson,

[1] Innovations can be new to the market (when a focal firm is first to develop it), but it can also be new to the firm when a firm adopts innovations that have been initially developed by other firms.

2015). Opportunity identification literature (Dew, 2009; Shane, 2000) further emphasizes that innovations also relate to new ways of sourcing materials and organizing methods that allow outputs to be sold at more than their cost of production (Casson, 2005; Shane, 2000). In this study we focus on the adoption of a certain ICT that allows firms to achieve exactly this; that of E-Commerce[2] (EC).

A firm can adopt EC for two purposes: purchasing (procurement) or selling products and services online. EC can therefore be considered as an innovative opportunity because if adopted, it can enhance procurement efficiency by increasing the speed and quality of goods and services acquired while reducing the cost of sourcing. It can also enhance the efficiency of distribution channels (Molla and Licker, 2005; Popa et al., 2018), as well as sales or marketing activities by boosting sales volume while lowering transaction costs related to establishing trade terms (price, time to delivery, product information, and availability).

When EC is used only for purchasing, we suggest that the technology is adopted in its latent form; whereas when it is used for sales, even if it is also used for purchasing, it is adopted in its more advanced or emergent form. EC for sales requires a higher level of investment for developing and maintaining the process in relation to purchasing. It also requires more extensive changes to organizational practices regarding how products are marketed and distributed, how communication with customers takes place, and how payments are received (Giotopoulos et al., 2017; Hong and Zhu, 2006; Petlier et al., 2012). Thus, although EC adoption for sales might enhance firms' transaction volume

[2] EC is defined as any business (purchasing or selling of products or services) conducted over the Internet (both B2B and B2C); however, it excludes sending and receiving text-based e-mail messages (Jeon et al., 2006).

and profitability, it is often perceived as riskier or more complex (Jones et al., 2014). Hence, it is less likely to be adopted.[3]

We argue that latent entrepreneurs are those that adopt the simple (latent) rather than advanced version (emergent) of the technology. Although such entrepreneurs are aware of the possibility of using EC for sales (as employing the simple one for procurement exposes them to how suppliers use EC for sales), their "knowledge filter" or gap (Acs et al., 2013; Audretsch et al., 2020; Audretsch and Keilbach, 2007) and lack of appropriate skills renders them uncertain of whether the potential benefits of adoption justify the related costs (Caiazza et al., 2020; Cunningham and Link, 2020), especially given the potential for organizational disruption its implementation will bring (Giotopoulos et al., 2017; Zhu et al., 2006). Hence, transitioning from EC for purchasing to selling is a shift toward a more sophisticated use of EC, distinguishing between latent and emergent entrepreneurs.

This study focuses on the skills entrepreneurial founding teams[4] (EFTs) possess, which are the main elements that separate latent from emergent entrepreneurs regarding their ability to take advantage of knowledge developed internally or via external spillovers (Caiazza et al., 2020; 2015). Therefore, it seeks to answer the following research questions: (1) Do different types of skills that EFTs possess influence the adoption of EC for latent and advanced purposes differently? (2) Which types of skills and *combination* of skills are needed for EFTs to be willing and able to move from adopting a latent EC

[3] This is characteristically reflected in official statistics regarding e-commerce usage by UK SMEs. For instance, only 19.3% of SMEs and 7.9% of micro firms in the UK adopted EC for sales, whereas 50.3% of SMEs and 31.1% of micro firms used EC for more basic purposes, such as purchasing (ONS, 2017).

[4] Defined as those individuals that own part of a firm's equity at the time of founding and are responsible for making strategic decisions (Ucbasaran et al., 2003)

version (for procurement) to an advanced EC version (for selling); that is, what skills are needed for latent entrepreneurs to become emergent entrepreneurs? (3) What type of skills allows EFTs to identify and take advantage of knowledge spillovers regarding (a) latent or (b) advanced uses of EC technology and adopt it at those levels respectively?

By answering the first two questions this study aims at contributing to the literature on emergent and latent entrepreneurship (Caiazza et al., 2020; 2016; Cunningham and Link, 2020; Gohmann, 2012) by theorizing and showing empirically that EFTs at different stages of the entrepreneurial continuum (latent to emergent) make different choices regarding the adoption of a latent or advanced technology. Further, we contribute to the literature by showing what types or combination of skills are necessary for latent EFTs to gain the decision-making abilities of emergent EFTs and, thus, exploit advanced EC technology.

Finally, by answering our last question we aim to contribute to the literature by exploring how the effect of external knowledge spillovers (information regarding the use of latent or advanced EC by other entrepreneurial firms operating in the same industry) on opportunity identification varies, depending on whether entrepreneurs are latent or emergent (determined by the type and level of human capital that EFTs possess). This aspect has largely been ignored by relevant literature (Marvel et al., 2014; Unger et al., 2011). Hence, we further enhance existing research by adapting and extending the knowledge spillover creative construction cycle (Caiazza et al., 2020) for the case of EC technology adoption.

2. Theory and hypotheses

2.1. EC adoption by latent and emergent entrepreneurs

The theoretical basis for examining the skills necessary for entrepreneurs to be either latent and adopt the latent version of EC technology rather than not adopting it at all, or emergent and adopt the advanced rather than latent version, is furnished by integrating the human capital theory (Becker, 1964) with the knowledge spillover creative constructive circle of latent and emergent entrepreneurship (Caiazza et al., 2020). According to the human capital theory, entrepreneurs with higher levels of human capital are more effective in decision-making, opportunity identification, and exploitation (Kato et al., 2015; Ucbasaran et al., 2008) that includes technology (e.g., EC) adoption opportunities (Fillis and Wagner, 2005). Thus, when entrepreneurs actively seek opportunities, which ones they are able to identify and exploit depends on (varies according to) the type of skills that they possess (Gruber et al., 2015; Kato et al., 2015; Marvel, 2013; Shane, 2000).

However, entrepreneurs identify opportunities from not only their initiative but also through spillovers (i.e., the information they receive from their external environment). Accordingly, Caiazza et al. (2020) developed a theoretical model suggesting that entrepreneurs with an appropriate set of skills and abilities can identify opportunities that hinge on existing technologies found in other firms and manage to exploit them for commercial gain. These technologies can then be further diffused to other organizations assuming entrepreneurs or top managers of those organizations can overcome the knowledge barriers that can constrain their adoption (Caiazza et al., 2016; 2015). Thus, they will be able to recognize an opportunity from relevant knowledge spillovers if they possess the appropriate prior set of skills to assimilate the external knowledge effectively (Caiazza et al., 2015; Dew, 2009; Shane, 2000).

This discussion, when applied to the adoption of EC technology, first suggests that whether a firm adopts a latent or advanced version of EC or any other technology should be influenced by the type and level of skills that entrepreneurs possess that in turn determine whether entrepreneurs have a latent or emergent mindset. It further suggests that when entrepreneurs receive different types of knowledge spillovers from the external environment regarding the opportunities or benefits different versions of a technology can deliver, they will interpret more effectively and be able to assimilate information that is more closely related to their set of skills. Integrating human capital theory and the constructive circle of latent and emergent entrepreneurship, in the next sections we develop working hypotheses regarding the effect that specific skills EFTs possess have on the ability of firms to move from (a) non-adopting EC to adopting it in its latent form and (b) latent to more advanced applications. We then develop hypotheses that consider how EFT skills moderate the effect that different types of external knowledge spillovers (i.e., information regarding EC usage by other entrepreneurial firms in the same industry) have on the actual technology adoption at different levels of sophistication.

2.2. *Hypotheses*

Rogers (1995) identified two types of specific human capital characteristics linked with technology adoption: (1) “principles” (i.e., the theoretical underpinnings of the technology) and (2) “how to” knowledge (i.e., knowledge of the applications of, or “how to use,” the technology). Regarding EC adoption, the former refers to education and experience in information technology (IT), while the latter, to education and experience in business[5] (Jean et al., 2006; Simmons et al., 2011; West and Noel, 2009).

Entrepreneurs' IT skills are an important determinant of ICT and EC adoption (Jean et al., 2006; Simmons et al., 2011). Research shows that earlier adopters of Internet-related applications were organizations with personnel qualified to understand ICT technologies (Mehrtens et al., 2001), and that entrepreneurs with IT skills are more likely to have a positive predisposition toward ICT usage (Quaddus and Hofmeyer, 2007; Peltier et al., 2012).

IT-educated entrepreneurs are more likely to act as technology champions for ICT-related innovations (Lee et al., 2006) and are more willing to provide resources and managerial support for implementing ICT projects (Kawakami et al., 2015). Moreover, because entrepreneurs with a higher level of IT skills have a better understanding of the technology (Mehrtens et al., 2001), they have a lower perception of the technological risks involved in EC adoption (Mehrtens et al., 2001; Fillis and Wagner, 2005) and are more likely to trust it regarding issues related to the security of transactions and the protection of personal details (Fillis and Wagner, 2005). Such trust and managerial support then increase the likelihood of adopting both latent (purchasing) and more advanced (selling) EC technology, given that IT skills help overcome the main barriers restricting such usages. These barriers include lack of technical knowledge and skills, concerns regarding security, reliability of payment systems, legal frameworks, and increased costs associated with ICT equipment, network infrastructure, and staff training

[5] IT education relates to formal IT education gained at a tertiary level, business education to formal education at a tertiary level at a general management or marketing discipline. IT and business experience refer to prior working experience at an IT or marketing-sales role, respectively.

(Gunasekaran et al., 2009; Jeon et al., 2006; Teo et al., 2009; Zhu et al., 2006; Zhu and Kraemer, 2005).

Although IT skills may help entrepreneurs adopt both EC technology versions along the entrepreneurial continuum (from latent to emergent), EFTs that possess a higher level of business skills are more likely to adopt EC technology for more advanced use (i.e., selling). Business skills (derived from relevant education or experience) help entrepreneurs identify market opportunities, associate them with the current development of products and services in their firms, and identify new means of organizing and distributing products and services (Jones et al., 2003; Shane, 2000). Such skills also help entrepreneurs to better understand the potential benefits that complex ICTs can deliver to a firm's marketing efforts (Simmons et al., 2008) and respond more effectively to pressures imposed by trading partners for adopting more sophisticated or advanced versions of the technology (i.e., EC for selling) (Kalakota and Robinson, 2001).

Furthermore, EFTs with a higher level of business skills tend to be more market-oriented (Atuahene-Gima and Ko, 2001; Peltier et al., 2012), which enhances the likelihood of adopting ICT technologies to increase sales. Market-oriented firms tend to seek new means of increasing sales by collecting market intelligence on customer needs and by then disseminating such information across a firm's functions to better fulfill those needs (Kohli and Jaworski, 1990; Pelham, 2000). Advanced websites, including those that promote online sales, assist in this effort by providing direct access to customers and wider market intelligence that can help firms meet future customer needs (Elia et al., 2007; Simmons et al., 2008). Hence, market-oriented entrepreneurs may view such websites as important marketing tools (Simmons et al., 2008) and realize that they can assist their firms in gaining a competitive advantage in marketing. Further, market-oriented entrepreneurs are more determined to overcome potential barriers that prevent the adoption of complex ICTs, such as perceiving them as overly complicated or time-consuming to implement (Jeon et al., 2006; MacGregor and Vrazalic, 2005).

By contrast, research shows that entrepreneurs with a higher level of technical skills, including IT skills, tend to be characterized with a lower level of commercial awareness (Ganotakis, 2012; West and Noel, 2009). Moreover, because the benefits derived from using EC for selling are of a marketing or sales nature (Simmons et al., 2008), IT-qualified entrepreneurs may not be able to fully understand or weigh the adoption benefits against the costs.

Finally, we expect no causal relationship (positive or negative) between business skills and EC adoption for purchasing because entrepreneurs with business skills are expected to focus more on marketing and sales (collect market intelligence and expand market share) (Ganotakis, 2012; Atuahene-Gima and Ko, 2001; Keskin, 2006) rather than other functions, such as those related purchasing.

Though we acknowledge that it is hard to draw a line when it comes to the skills that characterize latent and emergent entrepreneurs for the purposes of EC adoption, we argue that although IT skills can potentially increase the chances of adopting both EC versions and be a characteristic of both latent and emergent entrepreneurs, the main differentiating factor between the respective entrepreneurs is the level of business skills within an EFT. Business skills (‘how to’ skills) help entrepreneurs gain a better understanding of the benefits involved in adopting EC for sales and are vital in reducing uncertainty regarding its adoption, which is suggested to be a crucial factor for the non-exploitation of a technology (Caiazza et al., 2020; Cunningham and Link, 2020). Thus,

Hypothesis 1(a): High levels of skills derived from IT education and IT experience (principles knowledge) within an EFT increase the likelihood of adopting EC for both the latent (procurement) and advanced usage (selling).

Hypothesis 1(b): High levels of skills derived from business education and business experience (how to skills) within an EFT are the main differentiating factor between emergent and latent entrepreneurs and, therefore, between the adoption of a technology such as EC at an advanced rather than at a latent level.

We also propose that the interaction between IT and business skills within an EFT will further increase the chances of adopting EC for selling, i.e., the more advanced usage. This means that when both types of skills exist in an EFT, the chances of that team being emergent rather than latent are greater than when those skills exist in isolation.

Colombo and Grilli (2005), for example, suggest that the interaction between heterogeneous skills within a firm’s EFT improves opportunity exploitation. This is because the co-existence of heterogeneous skills increases the pool of the EFT’s cognitive resources (Ensley et al., 1998), which assists in generating diverse ideas. This diversity stimulates constructive conflict (Eisenhardt and Schoonhoven, 1990; Henneke and Lüthje, 2007; Vanaelst et al., 2006) that improves strategic decision-making and the efficient evaluation of innovative alternatives (Amason et al., 2006; Ensley et al., 1998; Kristinsson et al., 2016).

In the case of EC adoption, as entrepreneurs with different backgrounds possess different capabilities, they assist in different ways in the adoption of EC for selling. Specifically, IT education can provide entrepreneurs with the technical skills required to adopt and use EC for selling and with an understanding of the IT infrastructure required (Al-Somali et al., 2015; Mata et al., 1995). Thus, IT education can allow entrepreneurs to have a realistic perception of the costs and risks involved in adopting EC for selling. However, due to their technical nature, IT-qualified entrepreneurs might lack knowledge of how firms compete and sell products and services in the market (Oakey, 2003). Availability of skills derived from business education within the EFT provides knowledge about marketing research and enables entrepreneurs to develop a commercially oriented mindset geared towards the adoption of strategies that enhance sales. This can improve understanding especially regarding the benefits involved in EC adoption.

Similarly, entrepreneurs with IT experience have a better awareness of the firm's managerial practices and structures from an IT perspective (Zhu et al., 2006), have prior experience in the installation of different types of ICTs (Cragg et al., 2013), and are able to work with individual functional managers to develop appropriate IT applications (Mata et al., 1995). Entrepreneurs with business experience have a greater understanding of the strategic fit between ICT applications and their firms' business models and are more able to mutually adapt, align, and integrate EC and existing business strategy (Zhu et al., 2006). This can then help overcome a major challenge regarding the adoption of advanced, complex EC systems (i.e., managing the organizational changes required to accommodate that adoption) (Roberts et al., 2003; Zhu et al., 2006). Entrepreneurs with business experience are considered to be not only more market-oriented but also more likely to have previously managed organizational changes (Zhu et al., 2006) related to the marketing and sales function.

Finally, we argue that although companies gain more when both IT and business skills exist within an EFT (Ashurst et al., 2012; Fillis and Wagner, 2005; Zhu et al., 2006), the interaction between IT and business experience will be more important than the interaction between IT and business education for the adoption of the more advanced form of EC, i.e., EC for selling.

First, via IT and business skills interactions (regardless of whether they are derived from education or experience), entrepreneurs can develop a more accurate perception of the costs, risks but also benefits involved in adopting EC for selling. However, the interaction between IT and business experience *also* allows for the effective integration of the EC solution across a firm's functions and the management of the related organizational changes, thus increasing the likelihood of adopting EC for selling. In this regard, Zhu et al (2006) found that the inability of managers to deal with the managerial challenges arising from the implementation of EC technology, such as how to change organizational structures, operational policies, and coordination mechanisms to ensure alignment and integration between EC and the firm's different functionalities, lowered the perception regarding the potential benefits that can be gained from EC. Against the backdrop of the above discussion, we propose the following hypotheses:

> *Hypothesis 2(a): Both the interaction between skills derived from IT education and business education and that between skills derived from IT experience and business experience increase the likelihood of an EFT being emergent rather than latent, hence adopting EC for advanced usage (selling).*

Hypothesis 2(b): The interaction between skills derived from experience is more important than that between skills derived from education for increasing the chances of adopting EC for advanced usage (selling).

Regarding the diffusion of technological innovations, the knowledge spillover creative construction circle (Caiazza et al., 2020) and relevant literature (Caiazza et al., 2016; 2015; Cunningham and Link 2020) suggest that as the *extent of the diffusion* of an innovation among entrepreneurial firms within a sector increases, the level of uncertainty and risk that non adopting entrepreneurs have regarding its usage lessens because they become more aware of its potential benefits. This occurs because a greater level of diffusion (measured as the percentage of entrepreneurial firms within an industry sector using the latent or advanced type of EC) (Battisti et al., 2008; Gallego et al., 2014; Hollenstein and Woerter, 2008) increases the chances that a non-adopting firm is exposed to external knowledge spillovers regarding the technology usage. This situation allows entrepreneurs to become more aware of its potential benefits; thus, the perception of risk reduces.[6] Hence, upon learning about the use of EC for latent or advanced purposes as a result of knowledge spillovers from industry peers, the chances that an entrepreneur adopts EC for the same purpose increase. Caiazza et al. (2016; 2015) also suggest that once entrepreneurs are exposed to knowledge spillovers related to the usage of a technology, they better recognize its value and assimilate it if they possess appropriate skills that allow external knowledge to be effectively integrated with internal knowledge.

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[6] As the percentage of adopters increase, the chances that a firm that has not adopted the technology interact with an existing user and receive knowledge spillovers also increase (Hollenstein and Woerter, 2008). This situation allows firms to gain more information about the benefits of that technology (Arvanitis and Hollenstein, 2001; Hollenstein and Woerter, 2008); hence, the chances of adoption increase because of reduced uncertainty regarding the potential benefits and risks of the technology (Frattini et al., 2013).

Based on the above discussion, we first posit that once entrepreneurs of non-adopting firms are exposed to external knowledge spillovers regarding the use of EC for purchasing or sales by other entrepreneurial firms in the same industry sector, the chances that the non-adopters will use EC in the future for purchasing or sales respectively increase. We also argue that the effect of different types of knowledge spillovers (purchasing or sales) on the likelihood of EC adoption can further increase if certain skill types are present within an EFT. The knowledge repertoire that entrepreneurs possess determine not only what *type* of external knowledge they are more likely to notice but also how they interpret it and, thus, how much value they assign to this information (Gruber et al., 2015; Gielnik et al., 2014; Marvel, 2013; Unger et al., 2011). Overall, entrepreneurs tend to be more sensitive and assign greater value to external information more closely related to their prior knowledge (Alvarez and Barney, 2007; Tang et al., 2012).

When entrepreneurs are exposed to external knowledge spillovers regarding the use of EC for purchasing, they receive more information on how the adoption of this version can improve the efficiency of their firm's acquisition process. This can be achieved by being able to identify cheaper suppliers, by shortening purchasing and production cycles, reducing administrative costs related to the purchasing function, and by cutting costs on stock (Gunasekaran et al., 2009). These benefits are likely to be valued more by entrepreneurs with high levels of IT skills, given that one of the main functions of individuals with IT capabilities within a firm is to develop and adopt cost-effective and reliable IT applications to support the business needs of the firm (Bhatt and Grover, 2005; Bharadwaj, 2000). Therefore, given the enhanced efficiency in the purchasing process and the relatively low investment that firms need to make to start using EC for purchasing, IT skilled entrepreneurs are more likely to assign a higher value when it comes to its adoption.

For the case of EC for sales, entrepreneurs, once exposed to external spillovers on its usage, they receive information that by adopting it they can gain instant access to worldwide markets, tap into new markets niches, gain a quick and easy way of exchanging information about products, and achieve a closer relationship with customers (Elia et al., 2007). Entrepreneurs with business skills are more likely to develop a higher perception about the value of such benefits, given that some of the main characteristics of entrepreneurs with such skills are the pursuit of market growth strategies (Finkelstein and Hambrick, 1990; Ganotakis and Love, 2012) and gathering of customer-related market intelligence (Keskin, 2006; Atuahene-Gima and Ko, 2001).

Accordingly, we hypothesize that EFTs characterized by a higher level of (1) IT or (2) business skills are more likely to assign greater value and, hence, be influenced more by information regarding the (1) latent (procurement) or (2) advanced (for sales or procurement and sales) use of EC, respectively. Therefore,

> *Hypothesis 3: The higher the percentage of firms (and, hence, level of spillovers) in an industry that use EC for (a) only procurement (latent usage) or (b) selling (advanced usage), the higher the likelihood that an EFT adopts EC for these purposes, respectively.*

Hypothesis 4(a): High levels of IT skills in an EFT increase the effect that external spillovers (regarding the benefits of the latent EC version) have on the likelihood of a firm adopting EC at the latent level.

Hypothesis 4(b): High levels of business skills in an EFT increase the effect that external spillovers (regarding the benefits of the advanced EC version) have on the likelihood of a firm adopting EC at the advanced level.

3. Methods

3.1. Data and sample

The empirical analysis is based on data from a representative (in terms of industrial sector and firm size) survey of New Technology Based Firms (NTBFs) in the UK, carried out in 2005. NTBFs are defined as firms that are independently owned, (i.e., the founders own at least 50% of the company), are less than 25 years old, and operate in a high technology sector (Colombo et al., 2016; Grilli and Murtinu, 2018). We chose to investigate EC adoption specifically for NTBFs because it provides these resource–constrained (Colombo and Grilli, 2007) but nevertheless important for economic growth SMEs (and hence worth investigating [Gohmann, 2012]) with a cost-efficient way to identify and trade with new customers, enter foreign markets, adopt market niche strategies, and source supplies from cost-effective locations (Saridakis et al., 2018; Simmons et al., 2008; Zhou et al., 2019). EC can hence reduce the switching (start-up) costs (Gohmann, 2012) of becoming an entrepreneur and allow more individuals to move into self-employment. Overall, we believe that the study of EC for the case of NTBFs represents an ideal setting for investigating the adoption of a technology in its simple (latent) or advanced (emergent) version by entrepreneurs who have different profiles (latent or emergent) according to their set of skills, that are useful for disentangling external knowledge spillovers and assist firms in the adoption of various versions of a technology (Caiazza et al., 2020).

The survey gathered important information on firms' EC adoption for different purposes, founders' background, and firm specific and environmental characteristics which allows for examining external knowledge spillovers. To identify UK high technology sectors, we used an approach similar to Butchard (1987). This includes firms with high R&D intensity (measured as R&D expenditure over the amount of sales or value added) and firms with a high proportion of scientists and engineers who spend most of their time on R&D.

A combination of official data from the office of national statistics (ONS) and data from a commercial database (Financial Analysis Made Easy) was used to arrive at a suitable population from which we extracted the sample. The population comprises all independent firms in the UK less than 25 years old and belonging to high-tech sectors; therefore, it offers a clear improvement in relation to studies that did not include the independence criterion or included only firms that were independent at their inception (Storey and Tether, 1998; Saemundsson and Dahlstrand, 2005).

The second step in the sampling involved stratifying companies per age and size for each high-tech sector. It led to an initial calibrated semi-proportional random sample of 4,000 companies selected from the high-tech sector population. Data were collected by postal questionnaire, following interviews with five entrepreneurs in order to receive feedback on the clarity of the questions included in the questionnaire, and a pilot study of 100

NTBFs. Of the original sample of 4,000 companies, 412 took part in the survey. Tables 1 and 2 present the distribution of the sampled firms per industry sector and firm size, respectively, and compare them with the distribution of the population from which they are derived.

[Insert Tables 1 and 2 here]

Regarding the firm size distribution, no significant difference was found between the sampled firms and the population of firms (chi-square: 0.59), ensuring that the sample is representative per size categories. Regarding the sample distribution according to industry sector, on initial examination a chi-square test appears to show that the distribution of the original population and the sample significantly differ (χ^2 (9) = 31.546 and p=0.000238). However, this is due to the high incidence of consultants in the lowest employment band-size of just two sectors. The ONS data do not distinguish between consultants and (genuine) R&D-intensive businesses within the software and telecommunication sectors. Consultants in these sectors could not be excluded *ex ante* from the population count provided by the ONS but were excluded from the survey. As the study concentrates exclusively on R&D intensive businesses, any comparisons between the ONS figures and the study's sample proportions for these sectors would be misleading. When they are omitted from the count, the relative distribution provided by the ONS and that of the respondents to the survey does not significantly differ (χ^2 (9)= 4.049 and p=0.77) confirming the representativeness of the study's survey in terms of sectoral composition.[7] Finally, all questionnaires were answered by one of the firms'

[7] The representativeness of the sample was also verified by conducting an ex-post analysis using a range of reports published after the survey period, including that from the ONS, regarding consultancy activity in high-tech sectors.

founders and all had decision making responsibilities (i.e. involved in the day to day running of the firm).

3.2. Measures

3.2.1. Dependent variable

This study measures EC adoption is measured as a categorical variable (0, 1, 2) in order to capture which firms were non-users (0); latent users (i.e., use EC for purchasing only) (1); and advanced users, i.e., use EC for sales (2) (Battisti et al., 2009; Hollenstein and Woerter, 2008). The categorization is based on the premise that EC for sales relative to EC for purchasing requires a higher level of investment and more substantial changes within a firm's organizational structure. These changes relate to how payment and distribution of products and communication with customers and marketing occur (Fillis and Wagner, 2005).[8]

3.2.2. *Independent variables*

Starting with the different types of education that entrepreneurs possess, following previous studies (Hmieleski et al., 2015; Rauch and Rijsdijk, 2013), we measure IT and business education (attainment) as the highest academic qualification in each of the disciplines within an EFT. Specifically, we assign a value of 0 for no higher education qualifications, 1 for Higher National Certificate, 2 for Higher National Diploma, 3 for a Degree, 4 for a Masters/MBA and 5 for a PhD. IT and business experience were measured as the percentage of the entrepreneurs in an EFT with those types of experience

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[8] From the 412 sampled firms, 403 provided details regarding their EC activity, from which 78.5% had adopted EC, and 73.26% used it for online procurement; 40.94% used it to sell products and services. Further, 35.64% used it for procurement and selling, 37.62% only for procurement, and 5.19% used it only for selling.

respectively (Ganotakis, 2012). All entrepreneurial skills have as reference point the firm's incorporation date, *hence ensuring causality*.

As a robustness test for the education variables, we re-estimated the models by using the average years of IT and business education in an EFT (Grilli and Mutrinu, 2018; Colombo and Grilli, 2010). We also estimated the models by adopting an alternative operationalization for the variables capturing IT and business experience by using dummy variables on whether at least one entrepreneur within a founding team possessed a certain type of experience (Grilli and Murtinu, 2018). Results were robust to the alternative measures of education and experience; control variables behaved consistently across all model specifications.

Given that we are also interested (Hypothesis 2) in investigating how the interaction between heterogenous but complementary skills within an EFT affect the adoption of EC for selling; following Colombo and Grilli (2005) and Ganotakis (2012) we created two variables, one through the interaction between the two specific education (IT, business) and a second through the interaction between the two specific experience (IT, business) variables: IT education x business education and IT experience x business experience.

As mentioned in the build-up to Hypothesis 3, in accordance with Battisti et al. (2009) and Hollenstein and Woerter (2008), in order to capture *the level of industry spillovers* (information that exists within a firm's external environment regarding the benefits of EC usage), we use two variables that refer to the percentage of usage of EC within a firm's industrial sector. Given that we distinguish between two different levels of EC usage, we defined (1) latent and (2) advanced users as the percentage of entrepreneurial firms within the industry in which a specific firm operates that had adopted EC (1) just for purchasing and (2) for selling or for both selling and purchasing respectively. For each firm that had adopted EC either at the latent or advanced level, we could *ensure causality* by measuring the variables a year before each firm actually adopted EC. Regarding firms that had not adopted EC at all, we used the percentage of latent or advanced EC usage in the industry that they belong to, one year prior to the survey's reference point [9]. In order to test Hypotheses 4a and 4b we interacted each of the two variables capturing IT skills (IT education and IT experience) and each of those capturing business skills (business education and business experience) with (1) the percentage of latent and (2) the percentage of advanced users within the industry a firm operates.

3.2.3. Control variables

First, we control for several characteristics of an EFT, such as the level of general human capital (Parker, 2011). Following Davidsson and Honig (2003) and Colombo and Grilli (2005), an EFT's general education and general experience were measured as the average years of education and experience within an EFT, respectively. High levels of general education are associated with higher learning and analytical capacity and greater ability to address complex scenarios (Ucbasaran et al., 2008; Parker, 2011; Robson et al., 2012). This enables entrepreneurs to understand the requirements of EC adoption and recognize its organizational value. However, high levels of general experience may limit strategic flexibility (Hitt and Barr, 1989), as they are highly associated with entrepreneurial age (Chuang et al., 2007). Older entrepreneurs may be more risk-averse and less likely to

[9] We did not use the same time to construct the latent and advanced user variables for adopting firms because we could not have inferred causality, given that the percentage of industry usage would have been measured after a firm's actual adoption date for most cases.

adopt an innovation that causes a significant change to how firms function (Peltier et al., 2012). We also controlled for EFT size, measured as the number of founding members (Ucbasaran et al., 2003). Larger EFTs are characterized by higher levels of heterogeneous skills (Ucbasaran et al., 2003), enabling more creative solutions (Aspelund et al., 2005).

Second, we control for the effects of prior technologies that a firm uses before it adopts EC. Since electronic data interchange (EDI) is a predecessor of EC, we include two dummies: EDI for purchasing and EDI for selling to control for the EDI adoption effect (1 if a firm used EDI for purchasing or selling a year before the firm adopted EC) (Hong and Zhu, 2006; Hollenstein and Woerter, 2008). Prior studies found a strong relationship between experience with earlier generations of technologies and the adoption of the latest technology (Arvanitis and Hollenstein, 2001; Hollenstein and Woerter, 2008). We also consider whether a firm had adopted two technologies prior to EC adoption that can provide the platform (infrastructure) and experience upon which EC can be built; a computer network and a CRM/ERP system (Zhu et al., 2006).

Finally, we control for several firm-specific idiosyncrasies. Relatively larger firms possess a higher level of financial resources that can be useful when implementing new technology (Lin, 2014; Simmons et al., 2008; Thong, 1999). We measured firm size by the natural logarithm of the total number of employees three years prior to the survey date. Older firms may be less likely to adopt innovations as they have more rigid organizational practices that can constrain innovation adoption (Kafouros et al., 2020) and have survived and performed reasonably well for a long period without adopting EC (Chuang et al., 2007). We, therefore, include firm age, measured as the number of years since the firm was founded to the stage of EC adoption. Group membership is expected to increase awareness of the benefits of EC while reducing its adoption risks (Bayo-Moriones and Lera-Lopez, 2007) (dummy = 1 if the firm is a member of a business group prior to EC adoption). Given that EC can improve exporting efficiency (Zhou et al., 2019), exporting firms are more likely to adopt it (Stucki, 2016; Bayo-Moriones and Lera-Lopez, 2007). We control for this effect by including a dummy on whether a firm had a consistent presence in foreign markets over the three years prior to the survey date. Firms that service niche market segments can target geographically dispersed customers, which can influence EC adoption. We, therefore, include niche markets (dummy = 1 if the firm targets specific segments (niches) of the domestic or international market) (Bamiatzi and Kirchmaier, 2014). Firms that received government support (dummy = 1 if the firm receives such support prior to EC adoption) for R&D purposes (Ilin et al., 2017) are more likely to have additional resources (Masuda, 2006) needed for EC adoption. Finally, given that firms located in some regions can take greater advantage of knowledge spillovers (Caiazza et al., 2015), we control for the existence of localized networks or clusters (Audretsch et al., 2020) by considering whether a firm was located in a science park prior to EC adoption as we expect the entrepreneurial activity density to enhance regional information flows regarding EC adoption benefits (Caiazza et al., 2015; Masuda, 2006).

Table 3 presents the definition of the independent variables and a set of summary statistics. Table 4 presents the correlations between the study variables.

[Insert Tables 3 and 4 Here]

3.3. *Empirical implementation*

The importance of ensuring causality has been highlighted in almost all technology adoption studies that have recognized the limitations of past work regarding this issue (Gallego et al., 2014; Hollenstein and Woerter, 2008). Although prior studies (e.g., Battisti et al., 2009; Hollenstein and Woerter, 2008) measure the status of technology adoption at a specific "reference" point in time and use one-year lags for the measurement of the explanatory variables, this does not ensure that the explanatory variables were measured prior to the actual time of EC adoption, as adoption could have taken place before the "t-1" period. In this study, given that we have information regarding the date sampled firms adopted EC and when other firm-level decisions occurred (e.g., when EDI, CRM/ERP, or computer network adoption occurred, when a firm moved into a science park, became a member of a group or received governmental support), we can measure almost all independent variables before EC adoption took place for each firm, ensuring causality.[10]

This allows us to construct independent variables that capture whether a firm took any decision (i.e., EDI adoption) or that measure the percentage of latent or advanced EC usage within an industry prior to the time EC adoption occurred for each firm.

To differentiate between firms that a) have not adopted EC at all, b) are latent users, or c) are advanced users, we used a multinomial logit model (for a similar application, see

[10] The only exception is the firm size, exporting and niche market strategy. However, firm size is measured three years prior to the survey date, and exporting is measured as whether a firm is a consistent exporter over three years. It still represents an improvement over previous studies that used a one-year lag (Battisti et al., 2009; Hollenstein and Woerter, 2008) because more firms have adopted EC in three years than in a year. As niche strategy is path dependent it is difficult for an SME to switch from serving a market niche to the entire market, and we can safely assume it is used consistently over the years (Greve and Seidel, 2015).

Battisti et al., 2009; Hsieh et al., 2018). This model was preferred because it helps consider the mutually exclusive choices that a firm can make (i.e., non-adopter, latent-adopter, and advanced-adopter), especially given that the EC adoption path from non-usage to more advanced or complex versions is not considered to be sequential or ordered (Simmons et al., 2008), something of which a multinomial logit allows the modeling (Greene, 2012). Further, this model allows for estimating the odds ratios of the explanatory variables and provides useful coefficient interpretations (e.g., the odds ratio of a variable can estimate the change in the odds of a firm adopting EC for selling rather than purchasing, which results from a unit change in a specific independent variable).

To avoid multicollinearity, we use two different models (Ganotakis, 2012) that consider IT and business education and IT and business experience separately. Tables 5a and 5b present the two experience variables (and the relevant interactions with the basic and advanced industry user percentage). Tables 6a and 6b present the education variables (with the corresponding interactions). All models report odds ratios and control for entrepreneurs' level of general education and experience, as well as industry sectors.

The first column of each model differentiates between being *a non-user* and a latent user,[11] and the second column, between being an *advanced* and a latent user[12] (latent usage being the base category of the multinomial logit model; the category against which the other two [non-usage, advanced usage] are compared). In both model specifications, potential endogeneity can arise between the dependent and explanatory variables that

[11] An odds ratio greater than 1 indicates a greater likelihood of being a non-user than a latent user. An odds ratio less than 1 indicates a smaller likelihood of being a non-user than a latent user.
[12] An odds ratio greater than 1 indicates a greater likelihood of being an advanced user than a latent user. An odds ratio less than 1 indicates a smaller likelihood of being an advanced user than a latent user.

capture the experience of using similar technology (i.e., EDI for sales and EDI for purchasing). This issue, however, is addressed by (1) using variables measured one year prior to the time each firm adopted EC, hence minimizing the possibility of endogeneity by design,[13] and (2) using the Hausman tests of endogeneity based on a set of carefully selected potential instrumental variables. In all cases, the test statistics indicate an absence of endogeneity between those variables and EC adoption.

[Insert Tables 5ab and 6ab here]

4. Results

Regarding Hypotheses 1(a) and 1(b), the results show that overall, education (IT or business) does not influence EC adoption (Models 5 to 8 in Tables 6a and 6b). However, experience (IT and business) that entrepreneurs possess plays an important role on the adoption of EC for both purchasing and selling. The results show that IT experience increases the likelihood of a firm adopting EC for purchasing than not adopting it at all (odds ratios lower than one and significant in the “non-users” column across Models 1 to 3).[14] Model 1 shows that a 1% increase in the IT experience variable multiplies the odds of not adopting EC at all than adopting it for purchasing by 0.975; otherwise, the odds of adopting EC for purchasing than not adopting it at all increase by 2.5%. In contrast, although business experience was not found to be a differentiating factor between not adopting EC and adopting it for purchasing, it increases the likelihood of a firm adopting EC for selling than purchasing (odds ratios larger than one in the column for “advanced

[13] Further, we re-estimated the model after omitting the two variables capturing prior EDI usage, which had no effect on the remaining variables.
[14] Model 3 also shows that IT experience increases the chances of adopting EC for purchases than sales (advanced-users column).

users" across Models 1 to 4). Model 1 shows that an increase in 1% of the business experience variable multiplies the odds of adopting EC for selling than purchasing by 1.009. In other words, the odds increase by 0.9%. Hypotheses 1(a) and 1(b) are therefore supported mainly for the experience aspects of entrepreneurial skills.

The results also show that the interaction between IT education and business education does not significantly affect EC adoption for selling (Model 8, Table 6b). However, the interaction coefficient between IT and business experiences in the advanced usage column of Model 4 is positive and significant; indicating that the interaction between the two experiences increases the likelihood of adopting EC for selling. Thus, though Hypothesis 2(a) is partially supported (for the experience interaction), we find support for Hypothesis 2(b). As a post-hoc analysis, we included interactions across the domains of experience and education (i.e., interaction between IT education and business experience and that between IT experience and business education); accordingly, both interaction terms are insignificant. This result is plausible and follows our overall logic that experience matter more than education. Thus, IT-business education interactions have a lesser effect.[15]

Regarding Hypothesis 3, the results (in all tables) indicate that the percentage of EC usage within a specific industry is not an important factor when differentiating between latent EC usage and not adopting EC at all. Nevertheless, the EC usage level within an industry becomes important when differentiating between EC adoption at an advanced level relative to latent EC. In the second column (advanced users) across all models and

[15] Results are available upon request.

all tables (Models 1 to 8), the odds ratio of industry advanced users is larger than 1 and significant, indicating that when a firm operates in an industry with a higher percentage of advanced users, it is more likely to end up using EC at an advanced, in relation to a latent level. These results support Hypothesis 3 for the case of advanced users' spillovers.

Regarding Hypotheses 4(a) and 4(b), we examine how different aspects of entrepreneurial skills change the effect that external knowledge spillovers regarding the usage of EC within a firm's industry sector has on firm level adoption. The interaction terms between the education aspects of skills and industry intensity of EC usage (percentage of EC users) were insignificant across all models. By contrast, the interaction term between IT experience and industry basic users is significant (with an odds ratio lesser than 1) for *advanced users* as against *latent users* (Table 5a, Model 2, "advanced users" column). This indicates that when firms operate in an industry characterized with a high percentage of latent users, they are more likely to adopt EC for latent usage rather than at the advanced level, if at the same time their EFTs are characterized by high levels of IT experience.

However, the interaction term between commercial experience and industry advanced users is significant (with an odds ratio larger than 1) for *advanced users* against *basic users* (Model 3, Table 5b, "advanced users" column). It indicates that in situations where a high percentage of advanced users exist within the industry a firm operates and high levels of commercial experience simultaneously exist within an EFT, firms more likely transition from adopting EC for purchasing to adopting EC for sales. Therefore, Hypotheses 4a and 4b are supported for the experience variables.

5. Discussion

Our findings show that skills derived from experience (i.e., IT experience and business experience) are more important than skills derived from education (i.e., IT education and business education) for the adoption of both the latent and advanced versions of EC. We believe that this is the case because although IT education is useful when it comes to the technological aspects of EC such as programming languages, the design and maintenance of a website and the security of transactions (Al-Somali et al., 2015) and business education provides skills that assist in marketing related issues (Fillis and Wagner, 2005) and in the identification of methods for expanding market reach (Ganotakis and Love, 2012), skills from experience are more important because the implementation of EC requires significant organizational adaptation and restructuring (Giotopoulos et al., 2017; Hong and Zhu 2006; Zhu et al., 2006). This process is believed to be aided by skills generated over a considerable period of time specifically through learning by doing and trial and error (Mata et al., 1995; Zhu et al., 2006), which can only be obtained and developed when entrepreneurs have experience in those areas (IT and marketing or sales).

Furthermore, the usefulness of the different types of experiential skills (IT experience and business experience) varies for the adoption of EC at the latent and advanced level. Although IT experience allows the adoption of EC at its latent form (i.e., for purchasing), it is less important for the adoption for selling (advanced). Instead, it is business experience that differentiates between latent and emergent entrepreneurs for the case of EC adoption. It appears therefore that IT experience (principles experiential knowledge) might not provide entrepreneurs with the skills needed to recognize the opportunities that can arise from adopting EC for a more advanced, commercially oriented application (i.e., for selling) (West and Noel, 2009). However, EFTs that possess business related experiential skills appear to be better equipped to realize the potential gains of adopting EC for selling.

The findings on the importance of business experience follow Teo and Ranganathan (2004) and suggest that such experience enhances a firm's organizational learning regarding EC adoption and allows entrepreneurs to view EC as an essential commercial tool and adopt it for selling (Jones et al., 2003; Simmons et al., 2008). Our results also extend those of Cunningham and Link (2020) where business experience was found to be vital for the transition from unrealized/latent to emergent entrepreneurship in the form of selling latent technology to another firm. Along similar lines our study also highlights the importance of business experience ("how to" experiential knowledge) but, in this case, for being the main differentiating factor between emergent and latent entrepreneurs for ICT adoption at an advanced than latent level. Therefore, business experience appears to reduce the negative perception entrepreneurs might have regarding the complexities involved in EC adoption and to allow for a better understanding of the benefits involved (Roberts, 2003; Zhu et al., 2006).

Of course, this does not mean that IT skills do not influence the adoption of EC for selling. On the contrary, our results show that IT experience can enhance the adoption of EC for selling when business experience is also present within an EFT. The combination of IT experience and business experience allows entrepreneurs to consider the choices of EC from both IT and business perspectives and therefore develop a better understanding of the risks and benefits associated with the adoption of a particular version of EC and evaluate more effectively the choices between EC for purchasing and selling. Moreover, the interaction between the two types of experience should allow for more effective management of the organizational changes that must occur to accommodate the integration of EC within a firm's functions, business model, and strategy (Ashurst et al., 2012; Giotopoulos et al., 2017; Zhu et al., 2006).

Our findings also showed that different skills allow entrepreneurs to notice and assimilate different types of industry-wide information spillovers, leading to ICT adoption at different levels of sophistication. Specifically, EFTs characterized with higher levels of business ("how to") experiential skills are more likely to notice the increased presence of firms within an industry that have adopted EC at the advanced level. This in turn increases the likelihood that they will adopt EC at an advanced than a latent level. Similarly, the high percentage of latent adopters within the industry in which a firm operates encourages EFTs with IT ("principles") experiential skills to adopt EC at the latent rather than the advanced level. The finding that once IT skilled entrepreneurs are exposed to industry-wide information regarding the latent usage of EC, the chances of adopting EC at the latent than the advanced level increase, echoes arguments regarding the "dark side" of human capital (Ucbasaran et al., 2008). That is, high levels of human capital can lead to entrepreneurs making decisions based only on their existing set of expertise, thereby preventing them from using external information for alternative decisions. The finding also mirrors suggestions from the opportunity identification literature that although certain types of human capital (IT skills in this case) help entrepreneurs to identify and absorb certain information (EC for latent usage), they can also create stereotypical thinking and cognitive entrenchment that can constrain an individual's ability to identify opportunities (EC for sales) based on a different set of external information (Gielnik et al., 2014). In such cases, possession of those types of human capital may lead entrepreneurs to ignore or misinterpret that technology because of a mismatch between their skills or thinking and certain aspects of the technology (Ashurst et al., 2012; Morgan-Thomas, 2016).

Finally, we show that the percentage of firms in an industry that adopts EC at the advanced level induces a firm in the same industry to adopt EC at the same level. However, this is not the case for EC adoption at its latent level. These findings suggest that the spread of information regarding the use of a specific technology is more influential for more sophisticated technology versions. This result may be because although the accumulation of external information assists in bridging the gaps on how complex technologies can be integrated and used effectively, it has little added value regarding more simple technologies for which entrepreneurs might gain a better understanding of those issues with a smaller amount of external information (Peng and Mu, 2011; Frattini et al., 2013).

6. Conclusions

This study answers previous calls (Susan and Acs, 2017) for an in-depth analysis of the skills necessary for entrepreneurs to prepare for different types of technologies and it makes several contributions to the latent and emergent entrepreneurship literature (Caiazza et al., 2016, 2015; Cunningham and Link, 2020; Gohmann, 2012). First, we apply and extend the knowledge spillover construction cycle (Caiazza et al., 2020) for the case of EC adoption by arguing and empirically showing that the effect of different types of industry-wide knowledge spillovers on the adoption of EC at its latent or advanced form varies depending on the type of skills entrepreneurs possess and therefore on whether they are latent on emergent. Second, we contribute by showing that latent and emergent entrepreneurs, regardless of their exposure to external knowledge spillovers, make different decisions regarding whether they should adopt a latent or an emergent version of an EC technology. Third, we show what type of skills and, more importantly, which *combinations of skills* (Colombo and Grilli, 2005; Ganotakis, 2012) differentiate between latent and emergent entrepreneurs regarding EC adoption and are therefore needed in order for latent entrepreneurs to have the mind set of an emergent entrepreneur and be able to adopt advanced EC versions. In this paper we therefore make a final contribution by indicating which configurations of skills work better in order for a firm to adopt more complex versions of an EC technology. Indeed, only a qualitative study (Fillis and Wagner, 2005) suggested that the successful adoption of EC might depend on an EFT possessing a portfolio of diversified skills that consists of technical internet related and marketing-related skills. We add to this knowledge by providing more fine-grained theoretical conceptualizations and quantitative evidence that explain why the interaction between specific *experiential skills* rather than those derived from education is more important for adopting more advanced EC applications.

Overall, we find that "how to" experiential knowledge is the differentiating factor between emergent and latent entrepreneurs with "principles" knowledge being important for adopting EC only at the latent level and that it becomes important for adoption at the advanced level only if "how to" knowledge is also present within an EFT. Ultimately, it is the experiential knowledge regarding the ICT application that appears to allow entrepreneurs to understand how the technology can benefit the firm, enable entrepreneurs to adapt existing strategy and operations to fit the EC adoption (Zhu et al., 2006), and allow a firm to take greater advantage of knowledge spillovers (Caiazza et al., 2016; 2015). Hence, future studies can further investigate the role of this type of knowledge (rather than only principles; e.g., IT) regarding taking advantage of external spillovers and adopting advanced rather than latent versions of technologies, such as ERP (operations and supply chain skills), CRM (marketing skills), and social media or google analytics (online marketing skills), as well as other types of innovation (process, organizational, and marketing), thereby further extending the scope and application of the latent and emergent entrepreneurship literature and frameworks.

Regarding managerial implications, as knowledge is constantly advancing, entrepreneurs should ensure that they carefully explore the range of information available in the external environment (spillovers) on the possible applications of new technologies (Caiazza et al., 2020). Hence, in cases where entrepreneurs believe they lack the skills required to fully comprehend the benefits of such technologies, they should seek the advice of consultants who specialize in brokering technology among firms (Hsieh et al., 2018; Cragg et al., 2013). Finally, policy efforts can be directed toward providing support for resource-constrained firms to access appropriate consultancy advice, especially on adopting technologies that can enhance a firm’s competitive advantage.

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Table 1. Distribution of population and sampled firms by industry (percent)

High Technology Sectors	Sample respondents	Population
Pharmaceutical	3.16	1.19
Computers	4.87	2.82
Electrical	15.57	9.96
TV and Radio	11.44	7.88
Medical, instrumentation, optical	22.39	12.14
Aerospace	1.7	1.22
Telecommunications	5.84	13.71
Software	21.9	39.85
R&D in natural sciences and engineering	6.33	6.12
Technical testing	6.81	5.1
Total	100 % (412 firms)	100% (4000 firms)

Table 2. Distribution of population and sampled firms by size categories

Size categories	Sampled firms	Population
Small	94.0	93.0
Medium	5.5	5.6
Large	0.5	1.4

Table 3. Descriptive statistics of independent variables

	Definition	Mean	S.D.
Dependent variable			
Type of EC users	Categorical variable, assign 0, 1, 2 for non-users, basic and advanced users, respectively.	1.19	0.76
Independent variables			
IT education	Scale variable (0-5)	.27	.92
Business education	Scale variable (0-5)	.64	.92
IT experience	The percentage of the entrepreneurs in an EFT with IT experience	13	31
Business experience	The percentage of the entrepreneurs in an EFT with business experience	29	39
Industry latent users	Percentage of firms adopting EC at the latent level in the industry	77.10	8.74
Industry advanced users	Percentage of firms adopting EC at the advanced level in the industry	39.90	9.80
Control variables			
EFT general education	Average years of education within an EFT	13.94	2.27
EFT general experience	Average years of experience with an EFT	19.74	8.77
EFT size	Number of individuals that founded a firm	1.88	.84
EDI for procurement	Whether a firm used EDI for procurement prior to EC adoption (0/1)	.07	.26
EDI for sales	Whether a firm used EDI for sales prior to EC adoption (0/1)	.04	.20
Firm size	The natural logarithm of the number of employees	1.97	1.26
Firm age	The number of years up to EC adoption	8.44	6.85
Group membership	Other company owns less than 50 % equity or firm is head of group (0/1) prior to EC adoption	.07	.26
Exporter	Whether a firm had a consistent presence in foreign markets (0/1) over a 3 year period	.57	.50
Niche markets	Whether a firm targets specific segments (niches) of the domestic or international market (0/1)	.83	.38
Governmental support	Whether a firm had received governmental support for R&D activities prior to EC adoption (0/1)	.31	.46
Computer Network	Whether a firm installed a computer network prior to EC adoption (0/1)	.67	.47
Science Park	Whether a firm was located in a science park prior to EC adoption	.08	.27
CRM/ERP	Whether a firm installed CRM or ERP prior to EC adoption (0/1)	.16	.37

Table 4. Correlations

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. IT ed.	1.00																
2. Bus. ed.	.05	1.00															
3. IT exp.	.29**	-.001	1.00														
4. Bus. exp.	-.10*	.09	-.23**	1.00													
5. Ind. latent users	.14**	.07	.29**	-.07	1.00												
6. Ind. advanced users	.10	.01	.14**	.14**	-.61**	1.00											
7. Gen. ed.	.12*	.21**	.01	-.10**	.16**	-.10*	1.00										
8. Gen. exp.	-.16**	-.03	-.12*	-.04	-.13*	-.10	-.24**	1.00									
9. EFT size	.13**	.08	.07	.07	.001	.09	-.05	.08	1.00								
10. EDI for pro.	-.003	-.01	.08	.02	.02	.08	-.07	-.12*	-.01	1.00							
11. EDI for sales	.02	-.04	.05	.08	-.07	.09	-.13*	.02	-.03	.35**	1.00						
12. Firm size	-.04	.08	-.03	.17**	-.05	.03	-.01	-.11*	.08	.04	.15**	1.00					
13. Firm age	-.13*	-.11*	-.06	-.04	-.06	-.03	-.07	-.25**	-.04	-.02	-.04	.25**	1.00				
14. Group	.02	.04	.03	.05	-.002	.05	.07	-.10*	.08	.05	.06	.29**	.07	1.00			
15. Exporter	-.07	-.07	-.17**	-.02	-.03	-.15**	.14**	-.02	.01	.05	.07	.13*	.24**	.07	1.00		
16. Niche markets	.05	.07	-.06	-.16**	.11*	-.23**	.17**	.06	.09	-.09	-.01	.001	.01	.03	.08	1.00	
17. Gov. support	-.04	.04	-.17**	-.02	-.07	-.10	.19**	-.08	.06	-.10	-.03	.06	.02	-.01	.22**	.03	1.00
18. Computer network	.093	-.007	.16**	.12*	.010	.21**	.02	-.13	.06	.09	.03	.21	.06	.10	.065	-.08	-.03
19. Science park	.04	.07	.10	.008	0.10	-.09	.17**	-.04	.06	.03	.05	.03	-.08	.09	.05	.-6	.13**
20. CRM/ERP	.001	.05	.03	.22**	-.12*	.29**	-.02	-.18**	-.004	.18**	.05	.36**	.12**	.1	-.02	-.11	-.04

	18	19	20
18. Computer network	1.00		
19. Science park	.06	1.00	
20. CRM/ERP	.26**	-.05	1.00

Table 5a. Multinomial logit: Experience

	Model 1		Model 2	
VARIABLES	Non Users	Advanced Users	Non Users	Advanced Users
Constant	0.00124*** (0.00293)	0.254 (0.457)	0.000964*** (0.00229)	0.190 (0.344)
IT exp. (H1)	0.975** (0.0120)	0.991 (0.00627)	0.978* (0.0131)	0.993 (0.00678)
Bus. exp. (H1)	1.006 (0.00607)	1.009** (0.00460)	1.005 (0.00617)	1.008* (0.00462)
IT exp. * Ind. latent users (H4a)			0.999 (0.000573)	0.999** (0.000295)
IT exp. * Ind. advanced users			1.000 (0.00147)	1.001 (0.000711)
Ind. latent users (H3)	1.006 (0.0144)	0.988 (0.00865)	1.006 (0.0149)	0.991 (0.00906)
Ind. advanced users (H3)	1.003 (0.0287)	1.039** (0.0192)	0.999 (0.0312)	1.040** (0.0196)
EFT Gen. ed.	1.111 (0.121)	1.008 (0.0874)	1.128 (0.124)	1.030 (0.0903)
EFT Gen. exp.	1.072** (0.0299)	1.022 (0.0218)	1.071** (0.0302)	1.019 (0.0223)
EFT size	0.966 (0.283)	1.011 (0.225)	0.998 (0.296)	1.046 (0.239)
EDI for pro.	2.84e-07 (0.000179)	0.304 (0.276)	2.92e-07 (0.000184)	0.310 (0.280)
EDI for sales	33.22** (59.07)	26.72** (37.12)	67.02** (131.5)	57.08** (92.11)
Computer network	1.614 (0.794)	1.027 (0.397)	1.592 (0.791)	0.958 (0.376)
Science park	5.941** (5.227)	4.631** (3.404)	5.520* (4.922)	4.468** (3.359)
Firm size	0.803 (0.182)	0.784 (0.142)	0.804 (0.183)	0.777 (0.145)
Firm age	1.261*** (0.0529)	1.085** (0.0354)	1.265*** (0.0537)	1.089** (0.0362)
Niche markets	1.030 (0.681)	0.378** (0.163)	0.983 (0.656)	0.349** (0.155)
Exporter	1.321 (0.642)	2.766*** (1.017)	1.264 (0.622)	2.673*** (0.992)
Gov. support	1.553 (0.737)	0.897 (0.348)	1.551 (0.740)	0.915 (0.359)
Group	0.0484** (0.0683)	0.559 (0.397)	0.0511** (0.0726)	0.596 (0.426)
CRM/ERP adoption	1.189 (1.016)	0.798 (0.461)	1.172 (1.016)	0.803 (0.476)
Pharmaceutical	5.949 (9.104)	1.350 (2.065)	7.552 (11.71)	1.792 (2.785)
Electrical equipment	3.845 (3.988)	2.256 (1.957)	4.428 (4.627)	2.700 (2.372)
Medical equipment	1.853 (1.691)	1.703 (1.318)	2.061 (1.902)	1.941 (1.524)
Computers	1.130 (1.843)	4.112 (4.642)	1.440 (2.356)	4.791 (5.543)
Aerospace	1.57e-06 (0.00593)	1.24e-06 (0.00331)	1.61e-06 (0.00605)	1.24e-06 (0.00332)
TV & Radio equipment	1.501 (1.553)	2.608 (2.213)	1.702 (1.777)	3.154 (2.717)
ICT (software & telecommunications)	1.881 (2.057)	4.615* (3.837)	1.748 (1.955)	4.820* (4.056)
Technical Services	2.982 (2.980)	2.418 (2.066)	3.085 (3.096)	2.592 (2.226)
Log-Likelihood	-207.478		-204.77	
Pseudo R-squared	22.93%		23.94%	
Observations	254		254	

Note: Coefficients are odds ratios (standard errors in brackets) *** p<0.01, ** p<0.05, * p<0.1

Table 5b. Multinomial logit: Experience

	Model 3		Model 4	
VARIABLES	Non Users	Advanced Users	Non Users	Advanced Users
Constant	0.00110*** (0.00266)	0.219 (0.408)	0.00161*** (0.00383)	0.550 (1.011)
IT exp. (H1)	0.972** (0.0125)	0.988* (0.00661)	0.979 (0.0156)	0.998 (0.00916)
Bus. exp. (H1)	1.007 (0.00623)	1.010** (0.00490)	1.006 (0.00788)	1.012** (0.00545)
Bus. exp.*Ind. latent users	1.000 (0.000377)	1.000 (0.000252)		
Bus. exp.* Ind. advanced users (H4b)	1.001 (0.000806)	1.001** (0.000598)		
IT exp * Bus. exp (H2)			1.000 (0.000479)	1.001* (0.000286)
Ind. latent users (H3)	1.005 (0.0145)	0.988 (0.00881)	1.007 (0.0145)	0.990 (0.00888)
Ind. advanced users (H3)	1.007 (0.0297)	1.040* (0.0215)	1.004 (0.0293)	1.039** (0.0197)
EFT Gen. ed.	1.109 (0.124)	1.006 (0.0912)	1.098 (0.121)	0.976 (0.0862)
EFT Gen. exp.	1.074** (0.0305)	1.024 (0.0224)	1.069** (0.0303)	1.011 (0.0225)
EFT size	0.947 (0.280)	0.981 (0.221)	0.960 (0.280)	0.983 (0.225)
EDI for pro.	1.33e-07 (0.000129)	0.337 (0.326)	1.82e-07 (0.000156)	0.340 (0.309)
EDI for sales	32.33* (57.71)	25.71** (35.67)	27.43* (49.06)	27.30** (38.40)
Computer network	1.529 (0.765)	1.014 (0.403)	1.630 (0.803)	1.013 (0.392)
Science park	6.437** (5.731)	4.985** (3.737)	6.216** (5.513)	5.154** (3.883)
Firm size	0.798 (0.182)	0.771 (0.142)	0.806 (0.183)	0.800 (0.148)
Firm age	1.267*** (0.0538)	1.092*** (0.0362)	1.262*** (0.0532)	1.086** (0.0362)
Niche markets	1.062 (0.707)	0.380** (0.167)	1.028 (0.680)	0.371** (0.163)
Exporter	1.492 (0.740)	3.123*** (1.197)	1.308 (0.641)	2.890*** (1.083)
Gov. support	1.441 (0.686)	0.834 (0.326)	1.644 (0.786)	0.938 (0.369)
Group	0.0414** (0.0595)	0.476 (0.351)	0.0478** (0.0674)	0.550 (0.395)
CRM/ERP adoption	1.203 (1.032)	0.759 (0.450)	1.029 (0.877)	0.593 (0.358)
Pharmaceutical	6.003 (9.255)	1.307 (2.069)	5.877 (9.019)	1.315 (2.009)
Electrical equipment	3.727 (3.921)	2.247 (1.999)	3.641 (3.803)	1.854 (1.621)
Medical equipment	1.818 (1.688)	1.729 (1.368)	1.833 (1.672)	1.539 (1.195)
Computers	1.510 (2.491)	5.625 (6.601)	1.120 (1.835)	4.437 (5.053)
Aerospace	5.01e-07 (0.00292)	3.68e-07 (0.00153)	8.22e-07 (0.00422)	5.76e-07 (0.00210)
TV & Radio equipment	1.691 (1.774)	3.073 (2.660)	1.476 (1.528)	2.463 (2.095)
ICT (software & telecommunications)	2.400 (2.687)	6.197** (5.294)	1.897 (2.102)	5.488** (4.622)
Technical Services	3.367 (3.440)	2.780 (2.419)	2.958 (2.958)	2.474 (2.110)
Log-Likelihood	-204.507		-204.514	
Pseudo R-squared	24.04%		24.03%	
Observations	254		254	

Note: Coefficients are odds ratios (standard errors in brackets) *** p<0.01, ** p<0.05, * p<0.1

Table 6a. Multinomial logit: Education

	Model 5		Model 6	
VARIABLES	Non Users	Advanced Users	Non Users	Advanced Users
Constant	0.00343*** (0.00747)	0.385 (0.673)	0.00134** (0.00430)	0.476 (0.841)
IT ed. (H1)	0.655 (0.215)	0.845 (0.141)	0.00714 (0.0625)	0.817 (0.150)
Bus. ed. (H1)	0.879 (0.151)	0.989 (0.117)	0.874 (0.151)	1.002 (0.122)
IT ed.*Ind. latent users (H4a)			0.993 (0.0213)	1.011 (0.00803)
IT ed.*Ind. advanced users			0.578 (0.573)	1.026 (0.0245)
Ind. latent users (H3)	1.008 (0.0135)	0.990 (0.00832)	1.003 (0.0140)	0.989 (0.00849)
Ind. advanced users (H3)	1.007 (0.0275)	1.044** (0.0185)	0.869 (0.235)	1.050*** (0.0191)
EFT Gen. ed.	1.041 (0.105)	0.973 (0.0818)	1.029 (0.105)	0.973 (0.0824)
EFT Gen. exp.	1.068** (0.0277)	1.023 (0.0211)	1.065** (0.0276)	1.017 (0.0213)
EFT size	1.108 (0.279)	1.009 (0.204)	1.108 (0.281)	0.974 (0.201)
EDI for pro.	2.50e-07 (0.000178)	0.373 (0.332)	1.16e-07 (0.000110)	0.340 (0.306)
EDI for sales	18.64* (32.00)	18.14** (24.59)	28.94* (51.73)	17.68** (23.96)
Computer network	1.481 (0.685)	0.944 (0.346)	1.550 (0.722)	0.901 (0.334)
Science park	2.759 (2.126)	1.886 (1.198)	2.881 (2.262)	2.107 (1.388)
Firm size	0.765 (0.167)	0.827 (0.145)	0.766 (0.170)	0.826 (0.147)
Firm age	1.239*** (0.0488)	1.067** (0.0332)	1.231*** (0.0485)	1.070** (0.0339)
Niche markets	1.406 (0.885)	0.475* (0.195)	1.377 (0.872)	0.448* (0.185)
Exporter	1.578 (0.720)	2.966*** (1.052)	1.561 (0.713)	3.039*** (1.101)
Gov. support	1.627 (0.724)	0.906 (0.338)	1.805 (0.816)	0.951 (0.362)
Group	0.0441** (0.0574)	0.684 (0.428)	0.0355** (0.0481)	0.637 (0.411)
CRM/ERP adoption	1.816 (1.456)	1.196 (0.632)	2.089 (1.765)	1.294 (0.697)
Pharmaceutical	6.803 (10.09)	1.739 (2.590)	5.541 (8.265)	1.607 (2.391)
Electrical equipment	2.288 (2.229)	1.596 (1.332)	2.233 (2.194)	1.544 (1.308)
Medical equipment	1.548 (1.341)	1.788 (1.337)	1.450 (1.261)	1.720 (1.297)
Computers	0.225 (0.373)	1.823 (1.868)	0.181 (0.304)	1.379 (1.461)
Aerospace	6.20e-07 (0.00260)	5.66e-07 (0.00173)	3.26e-07 (0.00187)	3.40e-07 (0.00142)
TV & Radio equipment	1.322 (1.297)	2.279 (1.856)	1.241 (1.227)	2.178 (1.790)
ICT (software, telecommunications)	1.090 (1.073)	3.367 (2.579)	0.832 (0.863)	3.404 (2.640)
Technical Services	3.190 (3.001)	2.249 (1.872)	2.991 (2.832)	2.348 (1.970)
Log-Likelihood	-225.196		-221.204	
Pseudo R-squared	20.16%		21.57%	
Observations	265		265	

Note: Coefficients are odds ratios (standard errors in brackets) *** p<0.01, ** p<0.05, * p<0.1

Table 6b. Multinomial logit: Education

	Model 7		Model 8	
VARIABLES	Non Users	Advanced Users	Non Users	Advanced Users
Constant	0.00440** (0.00962)	0.490 (0.863)	0.00287 (0.0469)	0.400 (0.700)
IT ed. (H1)	0.649 (0.213)	0.849 (0.143)	0.319 (19.02)	0.839 (0.142)
Bus. ed. (H1)	0.881 (0.157)	0.982 (0.122)	0.646 (16.28)	0.979 (0.118)
Bus. ed.*Ind. latent users	0.988 (0.00824)	0.993 (0.00619)		
Bus. ed.*Ind. advanced users (H4b)	1.011 (0.0216)	1.006 (0.0125)		
IT ed. * Bus. ed. (H2)			0.322 (29.86)	1.043 (0.100)
Ind. latent users (H3)	1.008 (0.0136)	0.989 (0.00846)	1.008 (0.0135)	0.990 (0.00833)
Ind. advanced users (H3)	1.008 (0.0285)	1.045** (0.0186)	1.007 (0.0275)	1.044** (0.0185)
EFT Gen. ed.	1.028 (0.104)	0.961 (0.0813)	1.041 (0.105)	0.972 (0.0818)
EFT Gen. exp.	1.065** (0.0276)	1.021 (0.0212)	1.068** (0.0277)	1.023 (0.0212)
EFT size	1.121 (0.284)	1.016 (0.208)	1.111 (0.280)	1.012 (0.205)
EDI for pro.	2.29e-07 (0.000164)	0.363 (0.320)	2.54e-07 (0.000180)	0.373 (0.332)
EDI for sales	17.24* (29.48)	16.84** (22.72)	18.83* (32.46)	18.62** (25.40)
Computer network	1.422 (0.664)	0.922 (0.341)	1.484 (0.686)	0.941 (0.345)
Science park	2.949 (2.295)	2.004 (1.284)	2.712 (2.095)	1.919 (1.221)
Firm size	0.734 (0.163)	0.806 (0.144)	0.764 (0.167)	0.820 (0.145)
Firm age	1.249*** (0.0502)	1.072** (0.0338)	1.238*** (0.0487)	1.067** (0.0332)
Niche markets	1.459 (0.925)	0.489* (0.200)	1.402 (0.881)	0.475* (0.194)
Exporter	1.688 (0.777)	3.171*** (1.148)	1.573 (0.717)	2.957*** (1.048)
Gov. support	1.714 (0.776)	0.922 (0.349)	1.628 (0.725)	0.918 (0.344)
Group	0.0437** (0.0567)	0.651 (0.409)	0.0447** (0.0581)	0.682 (0.428)
CRM/ERP adoption	1.962 (1.583)	1.259 (0.667)	1.799 (1.449)	1.226 (0.656)
Pharmaceutical	6.263 (9.361)	1.587 (2.375)	6.811 (10.11)	1.730 (2.578)
Electrical equipment	2.062 (2.052)	1.442 (1.221)	2.286 (2.226)	1.601 (1.338)
Medical equipment	1.344 (1.190)	1.581 (1.201)	1.554 (1.346)	1.778 (1.331)
Computers	0.192 (0.330)	1.756 (1.818)	0.230 (0.381)	1.820 (1.871)
Aerospace	4.86e-07 (0.00204)	4.68e-07 (0.00143)	6.20e-07 (0.00259)	5.56e-07 (0.00170)
TV & Radio equipment	1.159 (1.151)	2.011 (1.656)	1.326 (1.301)	2.291 (1.868)
ICT (software, telecommunications)	0.966 (0.966)	3.071 (2.388)	1.103 (1.086)	3.309 (2.546)
Technical Services	3.160 (3.043)	2.175 (1.830)	3.168 (2.977)	2.226 (1.857)
Log-Likelihood	-223.841		-225.013	
Pseudo R-squared	20.64%		20.22%	
Observations	265		265	

Note: Coefficients are odds ratios (standard errors in brackets) *** p<0.01, ** p<0.05, * p<0.1