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Software Development and Innovation – Exploring the Software Shift in Innovation in Swedish Firms

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Software development and innovation

- exploring the software shift in innovation in Swedish firms

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ABSTRACT

Several scholars as well as industry professionals have claimed that there is a "software-biased shift" in the nature and direction of innovation in that software development is a core part of innovation activities in firms across a wide array of industries. Empirical firm-level evidence of such a shift is still scant. We employ new and unique firm-level survey data on the frequency and nature of software development among firms in Sweden, matched with the Community Innovation Survey (CIS). We find robust evidence supporting a software-bias in innovation in that software development is associated with a higher likelihood of introducing innovations as well as higher innovation sales among firms in both manufacturing and services industries. Furthermore, this positive relationship is stronger for firms employing in-house software developers than for those that only use external developers, suggesting that there is a hierarchy but possibly also a complementarity between internal and external software development. We also find support for complementarity between software-based technology and human capital; the estimated marginal effect of software development on innovation is particularly strong for firms that combine in-house software development with a highly educated workforce in STEM as well as in other disciplines.

Keywords: innovation, software, software development, digitalization, human capital, software bias, digital technology, absorptive capacity

JEL: O15, O32, O33, O43, L25

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"Software is and will be at the core of most innovation during the next several decades"
(Quinn et al. 1996)

1. INTRODUCTION

Digitalization has evolved from being primarily associated with the ICT-industry in the early 1990s to become a General Purpose Technology (GPT) that permeates the entire economy (Bresnahan and Trajtenberg 1995, McAffee and Brynjolfsson 2017). This puts digital technologies on par with steam power and electricity, but unlike these previous GPTs digitalization affects the flow and use of information rather than energy. This has implications for how the new technology affects innovation in the economy

Software's role in digitalization

Distinguishing features of GPTs are that they are "pervasive, improving over time and able to spawn new innovations" (Brynjolfsson and McAfee 2014, p. 76). This is because there is a common technological core, from which a wide variety of different applications can be developed, diffused and recombined across sectors or markets. There are at least three common denominators to digitalization as a GPT: (i) processing capacity, (ii) large decentralized networks and (iii) software.

Computational processing capacity sets the conditions for what type of operations computers can perform within a given frame of time and energy. Decentralized digital networks connect people, firms and machines and at the same time generate large amounts of data from network interactions. Software is what makes digital technologies programmable. It is the intangible infrastructure used to leverage and direct the resources associated with processing capacity, networks and data, making it possible to tailor programs and applications to address specific needs. Put differently, software programing is essentially what makes digital technologies GPTs. Because of this, software also plays a central role in how existing businesses use and adapt to using digital technologies to gain productivity benefits.

Software development can, in this sense, be thought of as utilizing an "ever-expanding set of lego bricks" (Branstetter et al 2019, p. 543). It enables changes of the conceptual structure of products, services and business models across different industrial sectors and contexts (Porter and Heppelmann 2015, Svahn et al 2017). It also facilitates the development of new forms of emergent entrepreneurship and innovation (Caiazza et al 2020 and 2015, Belitski et al 2019). Because applications of digital technologies developed in one sector can spread to other parts of the economy and be recombined with other applications of the same technology, digitalization holds a considerable potential for new applications and innovation.

Research literature on software and innovation

There is a growing body of empirical evidence suggesting a "software-biased shift" in the nature and direction of innovation in recent decades (Branstetter et al 2019), i.e. that new innovations are becoming increasingly software-centered or software-dependent. While this shift towards software-intensive innovation started in industries such as electronics, semiconductors and IT hardware in the 1980s (Arora et al 2013), it appears to have grown outside of the traditional ICT industry during the 2000s. Many firms in manufacturing industries as well as in the services develop software to differentiate their products and services, as well as to increase user value.[4] Software development has thus become increasingly integrated into firms' innovation activities.

While this shift towards software-intensive innovation may seem intuitive, there is still little empirical evidence as to its extent and variation across the economy. There are three main lines of research addressing the link between software development and innovation: 1) one studying the growth in software patents and its relationship to firm performance, 2) one investigating software intensity or software dependence in innovation by looking at citations of software patents, and 3) one focusing on the direct use of software in the innovation process.

Two of the research strands build predominantly on patenting data. The first approach attempts to link software patents to the performance of firms. Software patenting captures software development activity as it refers to intellectual property protection of new and unique intangible assets in the form of e.g. a computer program, user interface or algorithm. A general finding in this literature is that software patenting tends to be associated with higher market value (Hall and McGarvie 2010, Chung et al 2019). Firms with a larger share of software patents in their patenting activities are also shown to be in a better position to differentiate their products and in this way 'escape' competitive pressure in their respective product markets (Kim et al 2019).

In the second approach patenting data is used to study the software-intensity of patent citations, also including non-software patents that cite software patents. Branstetter et al (2019) find that increased software intensity is positively associated with R&D productivity (patent output per dollar invested in R&D) across a range of manufacturing firms in different countries and Software-intensive firms also appear to receive considerably higher valuation in equity markets.[5] Although these studies do not

[4]The argument of a software-bias in innovation is also broadly in line with Haskel's and Westlake's (2018) argument of the rising role of intangible assets in innovation and productivity growth. They emphasize that software is a key intangible asset that is imperative for explaining innovation and performance of firms in many different types of industries.

[5]In addition, the authors find that the share of software patents among the observed firms increased fourfold, that citations pertaining to software patents increased threefold during the period, and that software-patents are 24 percent more likely to be cited than non-software patents even after controlling for the growing number of software patents.

measure innovation outcome directly, they do show that firms that are more deeply engaged in software development and related technologies in their inventive activities perform better than other firms.

Another line of research studies innovation outcome explicitly and analyzes the relationship between innovation and the adoption and use of various types of software.[6] Engelstätter (2012) estimates the respective influence of enterprise resource planning (ERP), supply chain management (SCM) and customer relationship management (CRM) systems on product and process innovation among a sample firms in Germany. The study finds that the use of such types of software systems is associated with higher likelihood of introducing product and process innovations. Another study in the same vein is Niebel et al (2019), who employ firm-level data for Germany to assess how the use of "big data analytics" influence the probability to introduce product innovations as well as the sales attributed to product innovations. They find a positive influence of the use of big data analytics on innovation and argue that this is consistent with the idea that big data provides firms with new information and decision-support, which puts them in a better position to innovate. Several authors also argue that software-based tools, such as simulation and prototyping programs, are in different ways contributing to reshaping the innovation process within firms in different parts of the economy (Quinn et al. 1996, Nambisan et al 2017, Kim et al 2019, Yoo et al 2010).

While these types of analyses establish a link between use of enterprise software systems and innovation outcomes, they are more loosely connected to the idea of a software-biased shift in innovation as the adoption or use of such systems do not necessarily imply that firms develop software to refine or develop new products or services. In fact, they may capture adoption of generic "off-the-shelf" enterprise software systems. Engelstätter and Sarbu (2013) also find that among knowledge-intensive services firms in Germany, the adoption of more generic (sector-specific) software has no relationship to innovation, whereas adoption of firm-specific software, i.e. software that is customized for a specific firm, does appear to influence firm-level innovation.

Contribution and summary of main findings

This paper contributes to the existing literature with a firm-level analysis of the relationship between software development and innovation outcomes across the Swedish economy. We employ new and unique firm-level survey data on the frequency and nature of software development in Swedish firms which allow us to assess the relationship between innovation outcomes and software development while controlling for several confounding factors. The main hypothesis underlying the empirical analysis is

[6]There is also a literature that focuses on the link between innovation and various types of ICT more generally (see e.g. Spieza 2011, Brynjolfsson and Saunders 2009, Kleis et al 2012, Mohnen et al 2017) as well as the link between ICT and productivity growth of industries (Edquist and Henrekson 2017ab).We focus here on the subset of papers that has a specific focus on software and software development.

that if there is a software-biased shift in firms' innovation activities, then firms engaged in software development should indeed be more likely than other firms to develop new innovations.

In contrast to previous studies, our survey-based data capture software development in firms active in both manufacturing and services and is not contingent on a specific type of secondary indicator like the adoption of enterprise software system. Capturing software development in this way is warranted for several reasons. For instance, software development activity is not part of the regular firm-level statistics of firms. Available measures of intangible assets, or investments in such assets, typically do not separate software from other types of intangibles, such as brands, goodwill and other intellectual assets (Haskel and Westlake 2018). Data on ICT investments include software development, but this is oftentimes bundled with acquisition of equipment and expenditures on 'off the shelf' software. When presented in this manner, it is hard to distinguish software development from lower-order indicators of digital technology like buying computers.[7]

The firm-level survey of software development also allows us to track software development in firms that are not involved in software patenting.[8] The data include a large-scale sample of 4,598 firms that took part in a survey of software development during 2019. The survey questions cover, among other things, whether the firm develops software, as well as whether the software they develop is developed 'in-house' by own personnel or through the use of external service providers, such as software development services firms. In the empirical analysis, we consistently separate between internal and external software development as they represent different degrees by which software development is integrated in firms' business operations.

The firm-level survey data on software development have been matched with the latest Community Innovation Survey (CIS 2018), which allows us to develop established measures of innovation outcomes in the form of introduction of new products as well as sales attributed to innovation. They have also been matched with regular firm-level statistics including information on number of employees, industry of operations, ownership structure and international operations. Like Niebel et al (2019), we estimate two types of models. First, we analyze Probit models to assess whether the propensity to introduce

[7] OECD defines ICT investments as follows: "the acquisition of equipment and computer software that is used in production for more than one year. ICT has three components: information technology equipment (computers and related hardware); communications equipment; and software. Software includes acquisition of pre-packaged software, customised software and software developed in-house." See: https://data.oecd.org/ict/ict-investment.htm

[8] Studies of software patents show that there is significant heterogeneity among firms and industries in terms of software patenting. Empirical studies point to that it is primarily large firms in manufacturing industries with a tradition of accumulating large patent portfolios and of pursuing patents for strategic reasons that develop software patents (Bessen and Hunt 2007). Using software patenting to measure software development thus runs the risk of introducing a bias towards large manufacturing firms in specific industries. Furthermore, although software patenting is common in countries like the US and China, software patents are not as common in many European countries.

product innovations (new goods or services) is larger for firms that develop software. Second, we estimate a fractional response model (Papke and Wooldridge 1996) to assess the link between innovation sales (defined as the proportion of sales attributed to product innovations) and software development.

We find evidence in favor of the hypothesis of a software-bias in innovation across firms in both manufacturing and services industries in the sense that software development is strongly linked to the propensity to introduce innovations as well as innovation sales. Even after controlling for R&D investments, human capital, international sales, size, industry and several other typical determinants of firms' propensity to introduce product innovation, we find that the subset of firms that develop software are more likely to introduce product innovations. These findings also hold when analyzing innovation sales, as well as when we run separate models for manufacturing and services firms as well as for firms of different size. Furthermore, the link between software development and innovation is strongest for the firms that develop software in-house. In fact, the conditional marginal effect between innovation sales and software development is primarily statistically significant for firms that develop software in-house. Additional estimations for subsets of firms with different human capital intensities point to the role of absorptive capacity and complementarity between technology and human capital. The link between software development and innovation is particularly strong for firms that combine software development with strong in-house human capital in both STEM (science, technology, engineering and mathematics) as well as other 'softer' disciplines, such as the social sciences. Our analyses provide new empirical evidence on the software-bias in innovation in firms by showing that software development, in particular in-house software development, is associated with a higher likelihood of introducing innovations as well as higher innovation sales.

2. THREE HYPOTHESES ABOUT SOFTWARE DEVELOPMENT AND INNOVATION

2.1 Software development and innovation

How can software development improve or promote innovation? Firms in different industries have used software for many years to improve their operations, including innovation activities. More than 20 years ago, Quinn et al (1996) claimed that software is a key element in the whole innovation process from basic research to innovation. Their argument was that firms can cut and change several steps in the innovation process and thus make it faster and more efficient by using software. For example, the use of digital CAD/CAM software allows manufacturing firms to simulate the performance of different designs and thereby eliminate many so-called "build and bust" tests. A similar situation applies to firms in chemicals and biotechnology, as firms in these areas can design and assess new molecules by using various types of software before actually constructing or building new chemical structures. Another example is that the use of software in products and services can allow customers to modify products and

services to their specific needs, thereby enhancing consumer value while at the same time providing the firms developing such products with better feedback on user needs.

While most of the arguments of Quinn et al (1996) center on the *use* of software in various parts of the innovation processes, the research on a software-biased shift in innovation suggests that new innovations are also becoming increasingly software-intensive or software-dependent in firms ranging from finance, to manufacturing and services. That is, firms not only use software as a tool in the innovation activities, but increasingly develop software as part of their innovation activities or develop new innovations that incorporate or rely on existing software patents.

What this essentially entails is that even firms that do not explicitly sell software products are using software to improve their products and services, to make their internal processes and logistics more efficient or even to reshape their business model. This shift includes emerging cloud service providers, but also restaurant chains. For example, the pizza company Domino's uses digital technologies and analytics to improve consumer experience and thus gain a competitive advantage.

The same logic applies to manufacturing firms. Most manufactured products today contain embedded software systems which improve the performance of the hardware product. Ebert and Jones (2009) cite data suggesting that more than 10 years ago (in 2008) there were in the order of 30 embedded microprocessors in products in developed countries and at least 2.5 million function points of embedded software. One example is the automotive industry, in which embedded software combined with electronics hardware is crucial. Embedded software opens up significant opportunities to improve and differentiate vehicles, e.g. in terms of safety enhancements, infotainment, navigation as well as other types of comfort improvements of the passengers (Sedgwick 2015, Grimm 2003, Voget 2003).

The role of software in manufacturing innovation is further illustrated by the large share of R&D employees in large manufacturing-based multinational firms working with software development. In a survey among the 39 largest R&D-firms in Sweden (including multinational firms like Ericsson, Volvo cars, SAAB, Scania, ABB, Sandvik, GKN aero and Electrolux) conducted in 2016, firms reported that four out of 10 R&D employees, i.e. 40 %, are involved in software development.[9]

Terms like 'Industry 4.0', 'Industrial Internet of Things (IIoT)' or 'Smart Manufacturing' are sometimes used to describe the transformation of manufacturing in the wake of digitalization.[10] A key component

[9] https://www.nyteknik.se/innovation/4-av-10-fou-anstallda-utvecklar-programvara-6578226

[10] This development is driven by the adoption, maturity and price reduction of several different technologies like computer aided design (CAD) and engineering (CAE) software, cloud computing, Internet of Things, advanced

in this development is the embeddedness of sensors in devices, machines and products that measure and track performance and generate data in real-time (Ezell et al 2018). This creates a new layer or infrastructure which firms can exploit in their innovation efforts by developing software to generate and to analyze data, design new and improved services, products and processes. Here, software programming is a tool that can be leveraged to design data-driven products and services, adapt product attributes, improve user services as well as develop new business models. It can also be used for process innovations like improved management and control systems, logistics and improved overall real-time intelligence about production and logistics processes. Both product, process and system innovations in manufacturing industries therefore often involve significant efforts in software development.

Moreover, in the last 10-15 years several new types of firms have entered that exploit digital platforms to develop new business models that 'disrupt' established markets, while also developing new types of markets. Examples of such firms include the 'giant' digital firms like Alibaba, Facebook, Google, Amazon, AirBnb and Uber. In 2011, Marc Andreessen, a software developer who built one of the first widely adopted web browsers and co-founded Netscape, coined the phrase "Software is eating the world" to describe how software-based business models are outcompeting traditional businesses.[11] The argument he makes, using the rise of Amazon as an example, is that software-based online business models are able to leverage global networks of customers and at the same time provide an unprecedented variation in supply that is easily searchable, as compared to a physical bookshop with limited supply and geographical constraints on customer reach. These multisided platform economies have been described as 'matchmaking' businesses (Evans and Schmalese 2016). Software-based innovations and business models are a core part of the innovations that these types of firms bring to the market. Following a similar logic, emerging digital healthcare providers and edtech companies strive to provide software-based platforms and matching services for healthcare and education.

Taken together, the overview above suggests that software development and software infrastructure provide opportunities that are becoming increasingly important to the competitiveness of firms across economy (Iansiti and Lakhani 2014). Software and digitalization are frequently claimed to open up opportunities for new services, products, business models as well as new ways to improve operational efficiency, and to bring considerable potential for combinatorial innovation (Schwab 2017, Raman and Wagner 2011). Against this backdrop, we formulate the following hypothesis:

H1: *There is a positive relationship between software development and innovation in firms across different sectors in the economy.*

sensor technologies, 3D printing, industrial robotics as well as data analytics, machine learning and wireless connectivity.

[11] https://www.wsj.com/articles/SB10001424053111903480904576512250915629460

While previous studies have narrowed in on specific sectors to find a positive relationship between software development and innovation, it is not evident that such a relationship holds across different sectors of the economy and this makes it worth investigating. Previous studies indicate considerable heterogeneity both in terms of software use within businesses and in the practice of software development (Andersson et al. 2020). For example, some firms may develop software aimed at support activities while others may develop software that affects the core of their business model. Because digitalization, including software, is a GPT, it has many different uses in different parts of the economy.

2.2 Differences between internal and external software development

Firms that develop their own software may do so either by hiring their own developers or by contracting external developers. Some firms may only require software development skills temporarily or for small amounts of recurring work, while others may contract consultants to do development work that could easily have justified hiring an in-house developer. Thus, while all firms that develop software arguably have reached some common basic level of digitalization, it may prove hard to make more precise deductions about how far they have come in leveraging digital technologies.

However, firms that hire their own developers are on average more invested in leveraging digital technologies than those that do not.[12] First of all, the amount a firm spends to internalize software development skills translates into a lot of consulting hours. This is especially true in the Swedish labor market where taxes on income are considerably higher than the corresponding value added on services. Furthermore, in-house developers contribute continuously to the absorptive capacity (Cohen and Levinthal 1990) of the firm through their own skills and their interactions with co-workers. External developers, especially those that are contracted for longer periods of time, may also become part of the working environment, but never more so and oftentimes less than employees.

Against this backdrop, we argue that firms using in-house software developers will, on average, be more advanced in their use of digital technologies and thus software development in these firms will also be more deeply integrated into their business operations. If this is the case, and if there is a positive relationship between software development and innovation, then we should expect a difference between firms employing in-house developers and those using external developers only. This leads us to the second hypothesis:

[12]In our empirical analysis, we will separate between firms that have in-house developers (whether or not they also use external developers) and those that only use external developers.

H2: The effect of *in-house software development activity on innovation is greater that than the effect of external software development on innovation.*

2.3 Complementary human capital and absorptive capacity

Successful innovation that involves software-development is likely to need complementary human capital in order to design products and services in ways that appeal to customers, and to also adapt organizational practices and routines to leverage the full potential of digital technology. This brings us to the role of complementary human capital and absorptive capacity.

Established literature in innovation studies suggests that absorptive capacity plays a key role in leveraging the potentials of new technology (Cohen and Levinthal 1990, Cockburn and Henderson 1998, Arora and Gambardella 1994). For example, exploiting the benefits of software require software capabilities, and characteristics of organizations and routines may not be adapted in ways that make it possible to reap the gains from software. Brynjolfsson and Hitt (2000) make the case that as computers became cheaper and more powerful, the limit to their business value is not technical but organizational. A historical example is the adoption of the electrical motor, where established firms with sunk costs in physical capital incompatible with the new technology could not leverage it and were outcompeted by others (McAfee and Brynjolfsson 2017).

A variety of analyzes supports the role of human capital and absorptive capacity in the context software and digital technology in general. For example, there is significant evidence that the nature of recent technological change, in particular digitalization and the computerization of many workplaces, has been 'skill-biased' in the sense that it has increased the relative demand for skilled employees (Autor et al. 2003). In other words, adoption of digital technologies and an increasing use of computers in firms and organizations tend to imply greater demand, as well as higher willingness to pay, for human capital. There is also empirical evidence in favor of that investments in ICT, reorganization of workplaces and investments in new products and services are complementary in the sense that doing all three simultaneously rather than in isolation have strong effects on productivity as well as on demand for skills (Bresnahan et al 2002). Similar findings are reported by Hempell (2003) who assess complementarities between investments in ICT and firm-sponsored training of employees among firms in Germany. Brynjolfsson et al (2002) also provide several examples of how leveraging the potential gains from digital technologies requires changes in routines and organizational capital. Their analysis also shows that firms with high levels of *both* computer investments and relevant organizational capital have significantly higher market evaluation and also stronger measured productivity. Moreover, the recent analysis of Niebel et al (2019) on the relationship between the use of big data analytics and innovation outcome among firms in Germany also finds that this relationship is stronger for firms with higher levels of human capital. They infer from this that it reflects the role of absorptive capacity. Their

analysis further illustrates that human capital, as measured by the overall education-level of employees, is indeed a relevant way to capture absorptive capacity in firms.

We can thus expect heterogeneity across firms in terms of the link between software-development and innovation that is related to the extent to which firms have relevant absorptive capacity, as evidenced by human capital. If firms pre-maturely invest in software-development without having necessary absorptive capacity and complementary skills, then the overall link between software and innovation could in fact be weak. In view of this, we formulate the following hypothesis:

H3: *The relationship between software development and innovation is stronger in firms with stronger absorptive capacity, as reflected by the level of human capital of their workforce.*

3. DATA, EMPIRICAL STRATEGY AND DESCRIPTIVES

3.1 Data

The analysis is based on a combination of a new and unique firm-level survey data on software development (SWD) which has been combined with Community Innovation Survey (CIS) data as well as firm-level register data. The SWD-survey took place during 2019 and is centered on questions concerning whether or not firms develop software, if software is developed by in-house employees or external consultants and what function software development has in the firms business.[13] It also includes questions related to the firm's own perception of the market situation, specifically the degree of competition and whether it is a new or established market segment. The design of survey questions as well as the population frame was developed in collaboration with SWEDSOFT and Statistics Sweden (SCB), who also conducted the survey and validated the results.[14]

Survey questions were sent out to 9,425 firms in Sweden and 4,598 firms submitted their response, which implies a response rate of 49 %. The person who responded the SWD survey had to be part of the firm's management board, with a role corresponding to chief technology officer or CEO. The survey was merged with the firm-level Community Innovation Survey (CIS 2018). The number of firms that are part of both surveys are 4,321, which means that we lose 1,752 firms (27.6%) from CIS and 277 firms (4.4%) from the SWD-survey.

The SWD survey was undertaken in 2019 and the CIS 2018 refers to years 2016-2018. This discrepancy in timing is less of an issue in our empirical context since we are interested in the overall relationship between software development and innovation outcome in firms, rather than a strict causal analysis. The

[13]The complete set of survey questions are available from the authors upon request.
[14]Information about SWEDSOFT is available here: https://www.swedsoft.se/en/

SWD survey is also designed to identify firms that have software development as a part of their business operations, rather than a survey designed to assess if a firm developed software the particular year in which the survey was sent out. Moreover, software development is typically not a one-off event, but rather involves continuous development, refinements and testing (Ruparelia 2010, van der Weerd 2006, Ebert 2007).

We also draw information on firms in the matched sample (SWD-CIS) from full population register data. These register data include the Firm and Establishment Dynamics database (FEK), Foreign Trade data and the individual-level data from the Longitudinal Individual Level database (LISA). From these register data sources we obtain information on value-added, international trade, ownership structure and composition of employees. All data are accessed through the Microdata Online Access (MONA) service provided by SCB and refers to year 2017.[15] After merging the SWD-CIS data with the balance sheet data, we arrive at 4,082 firms. After removing observations with less than 10 employees, we have 3,947 firms (135 firms were dropped).

The combination of the different sets of data allow us to develop a dataset with unique and detailed information on software development, innovation activities as well as several background characteristics of firms, such as firm size, education of employees, industry affiliation, export activity, multinationality and R&D investments.

3.2 Empirical models, variables and descriptives

Our measures of innovation outcome are based on CIS 2018 that follows the Oslo Manual recommendations on measuring the degree of innovation in firms (OECD, 2005). First, we rely on information whether the firm has introduced a new or substantially improved product or service over a three-year time span (2016-2018). Following standard practice in the empirical analysis of innovation, the *product innovation* dummy is a binary variable, which takes the value one if the firm has introduced a product innovation and 0 otherwise (Colombelli et al 2013, Mairesse and Robin 2012). The product or service can be new to the market or new to a particular firm.

To estimate the relationship between innovation and software development, we first set up a Probit model with which we estimate the respective influence that in-house and external software development has on the probability that a firm introduces a new product innovation. Formally, this model is given by:

[15] https://www.scb.se/en/services/guidance-for-researchers-and-universities/mona--a-system-for-delivering-microdata/

$$\Pr(I_i = 1|\mathbf{X}_{\boldsymbol{i}}) = \Phi(\mathbf{X}'_{\boldsymbol{i}}\boldsymbol{\Gamma})$$

(1)

$$\mathbf{X}'_{\boldsymbol{i}}\boldsymbol{\Gamma} = \alpha + \beta_1 SW_i^{internal} + \beta_2 SW_i^{external} + \mathbf{Z}'_{\boldsymbol{i}}\boldsymbol{\gamma} + \varepsilon_i$$

where $I_i = 1$ if firm *i* has introduced a product innovation according to CIS 2018 and 0 otherwise. Our key independent variables is $SW_i^{in-house}$ and $SW_i^{external}$. The former is a dummy variable which is 1 if firm *i* develops software in-house, such that the firm has employees that develop software, and 0 otherwise. The latter variable is a dummy which is 1 if the firm develop software only through the use of external service providers and 0 otherwise.[16] $\mathbf{Z}_{\boldsymbol{i}}$ is a vector of control variables. The model in (1) is based on the assumption that software development is an input in the innovation process, which follows empirical papers that treat ICT investments in a similar way (cf. Hall et al. 2013).

Second, we also investigate the link between software development and *innovation sales,* which is the share of total sales attributed to a new or improved product. The sales ratio of innovative products or services can be interpreted as a measure of the commercial success of a firm's innovation (Mohnen and Mairesse 2010).

In empirical models with such type of dependent variables, a typical strategy is to employ a log-odds transformation of the fractional dependent variable *P*, such that $P^* = \ln[P/(1-P)]$. In this case, P^* is assumed to be linearly related to the explanatory variables, and the model is estimated with ordinary least squares (OLS). This transformation yields predictions that lie within the [0,1] interval but, as discussed by Papke and Wooldridge (1996) and Wooldridge (2002, page 662), it has two basic problems. First, it does not allow *P* to take the extreme values 0 or 1. Second, the estimated probability $\mathrm{E}(P|X)$ cannot be recovered without additional distributional assumptions. A large fraction of the firms in our sample has innovation sales 0 as many firms do not introduce any innovations, and there are also firms whose entire sales are attributed to innovations. Against this backdrop, we estimate the relationship between innovation sales and software development with a Fractional Probit Model (Papke and Wooldridge 1996). This model can account for observations for which the fraction is 0 or 1 and is more flexible than an OLS model on log-odds transformed variables (Papke and Wooldridge, 1996). It applies a quasi-maximum-likelihood procedure and is estimated with the log-likelihood function:

(2) $$L = IS_i \ln[\mathrm{E}(IS_i|\mathbf{X}_{\boldsymbol{i}})] + (1-IS_i)\ln[1 - \mathrm{E}(IS_i|\mathbf{X}_{\boldsymbol{i}})]$$

[16] There are no overlaps between these variables. If a firm has both own software development employees and use external service providers, it is registered as a firm that has software development in-house.

in which the expected (E) innovation sales for a firm i, IS_i, is assumed to be related to the explanatory factors through a Probit function $\Phi(.)$. The explanatory variables in this model is the same as in the previous model (1), and the variables of main interest are $SW_i^{in-house}$ and $SW_i^{external}$.

Control variables

In both models, the vector $\mathbf{Z_i}$ includes various firm characteristics that are typical in empirical analyses of innovation outcome in firms. To control for the fact that spending on research and development (R&D) is a typical driver of innovation, we control for *R&D expenses*. Firms that engage in R&D are better apt to introduce new products and services as well as in a better position to absorb technology and knowledge developed elsewhere (Cohen and Levinthal 1990), which adds to their innovativeness (Parisi 2006). We capture R&D expenses by including total R&D spending (in-house plus external) divided by total sales. We also account for whether firms are engaged in *persistent R&D* or *temporary R&D*. These data are drawn from the CIS-survey, and the separation matters as firms engaged in persistent R&D are more likely to develop routines and skills with regards to R&D activities. Empirical research shows that firms undertaking persistent R&D are more associated with innovative activities (Lööf et al. 2012).

Other control variables include firm size, average employee age, and education-level of firms' employees. An extensive literature emphasized a relationship between firm size, innovation and technology adoption (Schumpeter 1942, Cohen 2010), and whether small or large firms are more technologically innovative has engaged the academics for decades. One argument is that small firms are more likely to innovate and account for a large share of innovations (Acs and Audretsch 1988). Smaller firms might for instance be more flexible and adapt to technological change quicker. At the same time, large firms have greater internal resources and capabilities, and might therefore be more likely to involve in and adopt a wider range of new products and services (Pan and Jang 2008). Still, they are could be subject to issues related to bureaucracy and coordination. To control for the influence of firm size on innovation, we measure firms' size by the *logarithm of the number of employees*.

The average age of a firm's employees is one typical determinants of innovation (Schubert and Andersson 2015, Pfeifer and Wagner 2014). A key argument is that older employees may be less motivated to use and adapt to new technologies while younger employees are more inclined to adopt and adapt to recent technological skills or join firms with greater innovation potential (Ouimet and Zarutskie 2014). This suggests that firms with large share of older employees may have lower innovation propensities and innovation sales. We compute the *average age of employees* from information on individual employees in the LISA database.

The education-level of employees is an established proxy for human capital in firms. We develop two measures of human capital. First, we use data on education to identify employees with a long university

education (at least 3 years). The education of each worker in LISA is coded in accordance to the SUN2000 nomenclature (Swedish education nomenclature), which contains information about the level of education.[17] Second, we consider the type of education that is also available in the SUN2000 nomenclature. We use this information to construct two variables: a) *the fraction of employees in the firm with a long university education in STEM (Science, Technology, Engineering and Mathematics)* and b) *the fraction of employees with a long university education in fields other than STEM*.[18] The rational for these two variables is that firms with highly educated and technically qualified employees are typically claimed to be in better position to develop innovations (Freel 2003). By having two variables reflecting education in different fields, we are able to assess the importance of STEM relative to other educational profiles.

In addition, we control for whether the firm is part of a multinational enterprise (*MNE*). Affiliation to an MNE could raise innovativeness because it implies access to knowledge, technology and other internal resources within MNEs, for example through transfers through internal networks from country to country (Cantwell and Iammarino 2005, Frenz and Ietto-Gillies 2007). This implies that firms that belong to a multinational enterprise are more likely to engage in innovation activities than are independent firms. We further include a dummy variable for whether the firm is engaged in exports to foreign markets (*Exporter*). Firms may use the interaction with foreign customers as a source of ideas and inspirations for a new product (Fassio 2018, Cassiman and Golovko 2011, Andersson and Lööf 2009). Moreover, firms exposed to the international market face stronger competition which suggests that they need to be involved in some product modification and process improvements.

We also control for the degree of competition in the market (both domestic and international) and whether a firm is operating in a new or established market segment. The potential relationship between market competition and innovation has been discussed since at least Schumpeter's distinction between Mark I and Mark II (Schumpeter 1934; 1942). Mark I considers low technological entry barriers and a high market competition as drivers of innovation and small firms. Mark II suggests instead that large firms in established markets with high entry barriers should drive innovation (Malerba and Orsenigo 1996). Novel innovative products may open prospects for firms to create a new niche market. Moreover, firms operating in a high competition market may be more driven towards innovative activity since they prone to operate closer to their production frontiers or stimulate the adoption of new technologies. To capture the degree of competition, we use information in the SWD-survey in which firms were asked to

[17]Long university education is defined as employees with any of the following codes: 53 – three years; 54 – four years; 55 – five or longer. Doctorate education: 64 – PhD; 62 – licentiate.
[18]Code 4 – Biology and environmental science; physics, chemistry and geoscience; mathematics and natural science; computer science. Code 5 – Engineering.

classify the nature of competition in their main markets.[19] Lastly, we account for a structural difference between sectoral environment by including industry dummies constructed from NACE industry codes and looking closer at manufacturing and service firms.

Descriptives

Table A1 in Appendix presents descriptive statistics for all variables used in the empirical analyses and Table A2 presents differences in means between firms with and without software development as well as between firms with in-house and external software development. Table A3 also presents correlations between the variables in the analysis.

With respect to our innovation variables, we see that 41% of the firms are innovators and the average share of sales due to new or improved products and services, i.e. innovations, is 9%. Looking at software development, we see that 21% of the firms in the sample have in-house software development while 11% of the firms develop software externally. Accordingly, 32% of the firms in the sample report that they engage in software development in-house or through external service providers.

The sample of firms mainly consists of small and medium-sized companies (60% of small and 31% of medium firms). The average age of employees is about 41 years with a minimum of 21 years and a maximum of 69 years. The average fraction of employees with a long university education in STEM is 19% while the fraction of employees with a long university education in fields other than STEM amounts to 9%. With a share of 77%, considerably more firms perceive of the market conditions as being best described as an established market with high competition. Additionally, the majority of firms are the part of service sector, while 30% of firms are manufacturers.

Table A2 present differences in means between a) firms with external SWD and no SWD, b) firms with in-house SWD and no SWD and c) between firms with in-house SWD and external SWD. What is clear from this table is that the unconditional differences between firms follow a type of hierarchy whereby the fraction of firms that report innovation is on average highest among firms with in-house SWD, followed by firms with external SWD and finally firms with no SWD. This pattern holds for the innovation dummy as well as innovations sales. It also holds for the indicator of persistent R&D, but there are no significant differences between the groups of firms when it comes to R&D intensity. This implies that firms that develop software on average are more likely to engage in persistent R&D activity, although R&D expenses in relation to sales is not higher than in other firms. SWD-firms are also more likely to be larger, be affiliated to MNEs and having exports. There are no significant differences

[19]Four options were provided: (i) new market with high competition, (ii) new market with low competition, (iii) established market with high competition and (iv) established market with low competition.

regarding the broad sectoral distribution between manufacturing and services. Only firms with in-house SWD have on average larger fraction of employees with long university education in STEM or any other field.

4. RESULTS

4.1 Baseline models

Table 1 presents the results from an estimation of the relationship between software development that probability that firms introduce innovations (equation 1). The table reports marginal effect from a Probit estimation. Six alternative models are presented; (i) full sample, (ii) only firms in manufacturing industries, (iii) only firms in services industries, (iv) small firms (10-49 employees), (v) medium-sized firms (50-249 employees) and (vi) large firms (250- employees).

It is clear from the table that there is a significant positive relationship between software development and innovation outcome. Even after controlling for several set of control variables that are common in the empirical analyses of firm-level innovation, the estimated influence of software development on the likelihood of introducing innovations is significant. It is also evident that the relationship between software development and innovation is particularly strong for in-house software development. The marginal effect of in-house software development on innovation is stronger than the effect of external software development across all specifications. This provides support for H2 and is consistent with the argument that firms that develop software in-house are more deeply invested in leveraging digital technology in ways that also links to their propensity to innovate.

The main results hold across the three size classes of firms. As can been seen from models 2 and 3, there are some differences between manufacturing and services. For manufacturing firms, only in-house software development has a significant, yet weak, conditional relationship with the probability that a firm introduces innovations. Among services firms, however, both in-house and external software development is positively associated with innovation. The difference between manufacturing and services may be explained by that software development may be used in different ways in different industries. Manufacturing firms are more likely to use software in the form of embedded software in products as well as to improve processes, whereas form some services firms the software in may constitute the actual innovation. Many firms with business models built around digital technology also operate in services industries.

Turing to the control variables, we see that the dummy for persistent R&D activity is positive and significant across all specifications which is in line with prior studies (see e.g. Lööf et al 2012). Temporary R&D is only significant for services firms and for small firms. R&D intensity in the form of

R&D expense in relation to sales is insignificant across the board with the only exception for firms in manufacturing industries. One possible reason for the particular role of R&D intensity in manufacturing could be that formal R&D is more common in manufacturing firms and that innovation in manufacturing is more dependent on a combination of e.g. embedded software as well as changes in physical attributes or functions of products which may require formal R&D to a greater extent.

Table 1. Probit regression, dependent variable: dummy for product or service innovation.

	(1) Full sample	(2) Manufacturing	(3) Services	(4) Small	(5) Medium	(6) Large
In-house software development	0.166***	0.070*	0.192***	0.191***	0.136***	0.117**
	(0.020)	(0.040)	(0.023)	(0.029)	(0.034)	(0.052)
External software development	0.096***	0.054	0.114***	0.095***	0.102***	0.102*
	(0.023)	(0.040)	(0.028)	(0.032)	(0.039)	(0.059)
Persistent R&D	0.306***	0.320***	0.242***	0.284***	0.287***	0.293***
	(0.029)	(0.049)	(0.039)	(0.043)	(0.047)	(0.073)
Temporary R&D	0.209***	0.124	0.304***	0.186**	0.261**	0.250
	(0.064)	(0.089)	(0.092)	(0.083)	(0.103)	(0.220)
R&D Expenses (%)	-0.000	2.107**	-0.000	-0.000	0.010	4.471
	(0.001)	(0.931)	(0.000)	(0.000)	(0.010)	(3.407)
Number of employees (in logs)	-0.003	0.015	-0.008	-0.011	-0.023	0.074**
	(0.007)	(0.015)	(0.008)	(0.021)	(0.029)	(0.029)
Average age of employees	-0.005***	-0.008***	-0.004***	-0.006***	-0.004	0.000
	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.004)
Employees with long university education in STEM (%)	0.147***	0.215	0.113*	0.122*	0.046	0.775***
	(0.054)	(0.173)	(0.058)	(0.066)	(0.108)	(0.234)
Employees with long university education, except STEM (%)	-0.023	0.026	-0.016	-0.011	0.074	-0.630**
	(0.070)	(0.320)	(0.071)	(0.083)	(0.140)	(0.294)
Exporter	0.065***	0.047	0.074***	0.090***	0.034	-0.012
	(0.018)	(0.036)	(0.021)	(0.023)	(0.034)	(0.056)
MNE	0.036**	0.034	0.032	0.035	0.051*	0.023
	(0.018)	(0.033)	(0.021)	(0.024)	(0.030)	(0.053)
New market with high competition	0.075	0.031	0.080	0.025	0.277**	0.169
(ref: established market with low competition)	(0.051)	(0.130)	(0.055)	(0.059)	(0.122)	(0.219)
New market with low competition	0.060	0.072	0.055	0.108*	-0.132	0
(ref: established market with low competition)	(0.053)	(0.122)	(0.059)	(0.058)	(0.146)	(0.0)
Established market with high competition	0.001	-0.006	0.007	-0.003	0.036	-0.120
(ref: established market with low competition)	(0.020)	(0.035)	(0.024)	(0.023)	(0.040)	(0.077)
Industry dummies	YES	YES	YES	YES	YES	YES
Pseudo R-squared	0.120	0.143	0.111	0.111	0.116	0.263
# observations	3930	1187	2743	2346	1221	361

Note: Average marginal effects presented. Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

We also find that average employee age is negatively related to innovation in the majority of specifications which is consistent with prior studies. The fraction of employees with a long university education in STEM appears to matter most in large firms. Furthermore, we also find that export is positively associated with innovation in services and in small firms. In larger firms and in

manufacturing, it is other factors that dominate. Firms' perception of the nature and competition of the markets they operate in has no relationship with innovation.

Table 2 presents the results for innovation sales, which is complementary to the analysis of the probability of innovation as it captures commercial success of a firm's innovation (Mohnen and Mairesse 2010). The table reports marginal effects from estimating a fractional probit model (equation 2) for the same set of specifications as in Table 1. Overall, these results confirm the results in Table 1 in that it also shows a statistically significant conditional relationship between software development innovation sales.

Table 2. Fractional Probit Regression, dependent variable: innovation sales (%).

	(1) Full sample	(2) Manufacturing	(3) Services	(4) Small	(5) Medium	(6) Large
In-house software development	0.041***	0.030**	0.043***	0.061***	0.023**	-0.017
	(0.007)	(0.012)	(0.008)	(0.010)	(0.010)	(0.019)
External software development	0.019**	0.009	0.022**	0.026**	0.021*	-0.035
	(0.008)	(0.014)	(0.010)	(0.012)	(0.012)	(0.024)
Persistent R&D	0.057***	0.067***	0.048***	0.055***	0.051***	0.067***
	(0.008)	(0.012)	(0.011)	(0.013)	(0.010)	(0.024)
Temporary RD	0.033*	0.025	0.048**	0.042*	0.024	0.052*
	(0.018)	(0.027)	(0.024)	(0.024)	(0.031)	(0.030)
R&D Expenses (%)	0.000	0.101**	0.000	0.000	0.012***	-0.046
	(0.000)	(0.042)	(0.000)	(0.000)	(0.003)	(0.088)
Number of employees (in logs)	-0.012***	-0.006	-0.014***	-0.026***	-0.005	0.008
	(0.003)	(0.005)	(0.003)	(0.008)	(0.008)	(0.009)
Average age of employees	-0.002***	-0.002**	-0.002***	-0.003***	-0.002**	0.002
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Employees with long university education in STEM (%)	0.068***	0.139***	0.049***	0.072***	0.006	0.196***
	(0.017)	(0.047)	(0.018)	(0.021)	(0.027)	(0.067)
Employees with long university education, except STEM (%)	-0.060***	-0.129	-0.052**	-0.057**	0.006	-0.306***
	(0.022)	(0.095)	(0.022)	(0.028)	(0.033)	(0.106)
Exporter	0.023***	0.006	0.027***	0.021**	0.027**	0.021
	(0.007)	(0.014)	(0.008)	(0.009)	(0.011)	(0.027)
MNE	0.003	-0.014	0.011	-0.002	0.012	0.017
	(0.006)	(0.011)	(0.008)	(0.009)	(0.010)	(0.024)
New market with high competition	0.028**	-0.011	0.032**	0.024	0.048**	0.015
	(0.014)	(0.027)	(0.016)	(0.017)	(0.022)	(0.066)
New market with low competition	0.047***	0.016	0.051**	0.050**	-0.012	-0.665***
	(0.017)	(0.032)	(0.020)	(0.020)	(0.030)	(0.073)
Established market with high competition	0.005	-0.001	0.010	0.003	0.021*	-0.041
	(0.007)	(0.012)	(0.009)	(0.009)	(0.012)	(0.032)
Industry dummies	YES	YES	YES	YES	YES	YES
Observations	3930	1187	2743	2346	1221	363

Note: Average marginal effects presented. Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

In-house software development is significant and positive in all specifications with the exception of large firms. That is, firms that develop software in-house tend to have a greater proportion of their sales attributed to innovation. External software development is only significant for services and small firms,

and these groups appear to drive the results for this variable in the full sample. When looking at innovation sales we also find a pattern of a 'hierarchy' where in-house has stronger influence than external software when looking at both statistic and economic significance.

The control variables in general exhibit similar results to the previous model. Persistent R&D and average age of employees have the expected sign. For innovation sales, employees with long university education in STEM is significant in all specification but for medium-sized firms, which is in line with that STEM employees are important for successful innovation. A difference from table 1 is that firms' perception of the markets they operate in has stronger relationship with innovation sales. In general, operating in markets that firms perceive of as being new is a stronger predictor of the proportion of their sales attributed to innovation. This is consistent with that new markets brought about by technology provides opportunities for innovation and emergent entrepreneurship (Belitski et al 2019, Caiazza et al 2020).

Taken together, the results reported in Tables 1 and 2 confirm our H1 and H2 and are consistent with a software-biased shift in innovation. Firms that develop software, and who thus are more engrained in digitalization, appear to be in a better position to innovate as indicated by both the probability to introduce innovations and in innovation sales. In-house software development is also more strongly linked innovation propensity as well as innovation sales. It should be noted that these results are non-trivial, because software development can be used to 'more of the same' and increase efficiency rather than to adapt to the potential of software and develop innovations.

To further probe the results and show the qualitative difference between firms that undertake in-house and external software development, respectively, Table 3 presents the distribution of firms divided into internal and external SWD and separated by different functions of software development in their business operations (firms that reported in-house or external software development were asked about the main use of the software that they develop).

As can be expected, firms that develop software to support their main business model (i.e. to improve internal processes or distributions and sales) rely to a higher degree on external developers, while firms that develop software that is part of their main business model (i.e. software products and services, embedded software and software development as a service) to a higher degree have internalized their development work. This does not necessarily mean that firms working with embedded software are more digitalized than firms that do not. Rather, firms that work with embedded software are more likely to have internalized their software development, signaling a more advanced use of digital technologies, than firms that develop software to improve their existing business processes.

Table 3. In-house and external software development by use of software (%).

	SW as a service or product	Embedded SW	SW for distribution or sale	SW for own operations	SW development service (consultant)
In-house	92.71	76.37	54.92	50.97	94.52
External	7.29	23.63	45.08	49.03	5.48
Total	***100.00***	***100.00***	***100.00***	***100.00***	***100.00***

Note: Each column repots the fraction of firms that develop software in-house or by external software developers.

Table 4 shows how reported innovation activities among firms are divided between firms based on their use of software development. In line with our argument and findings, the share of software-developing firms that report innovations is larger than among the non-developing firms. Furthermore, the categories of firms with a higher degree of in-house developers exhibit a higher degree of reported innovation than those with higher degree of external developers.

Table 4. In-house and external software development by use of software (%).

	SW as a service or product	Embedded SW	SW for distribution or sale	SW for own operations	SW development service (consultant)	No SW developm ent
Innovation	76.56	73.42	55.25	47.95	46.58	31.88
No innovation	23.44	26.58	44.75	52.05	53.42	68.12
Total	***100.00***	***100.00***	***100.00***	***100.00***	***100.00***	***100.00***

Note: Each column repots the fraction of firms that report having introduced an innovation according to CIS (2018).

These findings suggest two things, both of which deserve further investigation. First, there is a difference between internal and external software development that seems to coincide with different uses of software development. Firms that develop software to support existing business practices are more prone to use external developers and exhibit a weaker link between software development and innovation. Firms that develop software as part of their core business are more prone to hire in-house developers and also exhibit a stronger link between software development and innovation. This could be interpreted as difference in the potential for innovation between different types of business activities but is also consistent with the argument that internalized software development promotes software-intensive innovation in ways that external development does not. Second, the difference between internal and external software development may indicate a form of complementarity, rather than substitution, between the two akin to that found in internal and external R&D (Veugelers 1997, Lokshin et al. 2008, Hagedoorn and Wang 2012, Audrestch and Belitski 2020).

4.2 Testing the role of human capital

Based on arguments related to absorptive capacity and complementarity between human capital and digital technology, our second hypothesis is that the relationship between software development and innovation is stronger in firms with stronger absorptive capacity, as reflected by the level of human capital of their workforce. To test this in our empirical context, we divide the sample of firms in two groups: (i) firms with above-average fraction of employees with long university education in STEM and (ii) firms with below-average fraction of the same type of employees. We then run separate estimations for both groups. If the estimated marginal effect of software development is larger in the former compared to the latter group, it is consistent with that firms' ability to leverage the innovation potential of software development is related to its human capital. We do a similar grouping of firms based on the fraction of employees with a long university education in other fields and also run separate estimations on these groups as well. In this way, we can test whether possible complementarity pertains to both types of human capital.

Table 5 presents the results for the probability to introduce innovations. The first two columns distinguish between firms with high (column 1) and low (column 2) fraction of employees with university education in STEM. The second set of columns distinguishes between firms with high (column 3) and low (column 4) fraction of employees with a long university education in fields other than STEM.

Comparing the estimated marginal effect between columns 1 and 2 as well as between columns 3 and 4, it is clear that our third hypothesis is confirmed in the case of in-house software development. The estimated marginal effect of software development in the probability to introduce innovations is significantly larger among the group of firms with above-average fraction of employees with long university education in STEM as well as in other fields, respectively. This is consistent with the hypothesis that there is complementarity between human capital and digital technology in the sense that human capital is needed in order to leverage the full innovation potential of new technology. The results here suggest that this complementarity not only applies for human capital in STEM that is normally associated with new technology and digitalization, but also with human capital in the form of education in other fields.

Looking instead at external software development, the pattern is reversed. The marginal effect of external software development is somewhat higher for firms with low fraction of employees with long university education in STEM as well as in other fields, although the differences are rather small in quantitative terms. One explanation for this is that issues of human capital complementarity and

absorptive capacity primarily pertains to firms more deeply engrained in digitalization, as reflected by in-house software development.

Table 5. Probit regression by Education Background, dependent variable: dummy for product or service innovation.

	Share of employees with long university education in STEM		Share of employees with long university education, except STEM	
	(1) High	(2) Low	(3) High	(4) Low
In-house software development	0.203***	0.102***	0.210***	0.121***
	(0.028)	(0.028)	(0.032)	(0.026)
External software development	0.074*	0.097***	0.084*	0.099***
	(0.045)	(0.027)	(0.044)	(0.027)
Persistent R&D	0.254***	0.323***	0.239***	0.357***
	(0.036)	(0.050)	(0.047)	(0.036)
Temporary R&D	0.130	0.209**	0.329***	0.186***
	(0.093)	(0.089)	(0.126)	(0.072)
R&D Expenses (%)	-0.000	2.977***	-0.002	0.056
	(0.000)	(0.980)	(0.002)	(0.092)
Number of employees (in logs)	0.001	-0.001	-0.015	-0.003
	(0.013)	(0.009)	(0.013)	(0.008)
Average age of employees	-0.007***	-0.004***	-0.005**	-0.004***
	(0.002)	(0.002)	(0.002)	(0.002)
Employees with long university education in STEM (%)	0.062	0.532*	0.349***	-0.000
	(0.074)	(0.281)	(0.097)	(0.067)
Employees with long university education, except STEM (%)	-0.085	0.031	-0.377***	1.041***
	(0.072)	(0.354)	(0.106)	(0.299)
Exporter	0.041	0.059***	0.062*	0.060***
	(0.032)	(0.022)	(0.033)	(0.022)
MNE	0.031	0.025	0.038	0.025
	(0.029)	(0.023)	(0.031)	(0.022)
New market with high competition	0.035	0.094	0.137**	-0.011
(ref: established market with low competition)	(0.061)	(0.096)	(0.069)	(0.077)
New market with low competition	0.076	0.031	0.143	0.020
(ref: established market with low competition)	(0.080)	(0.073)	(0.100)	(0.065)
Established market with high competition	-0.023	0.015	0.002	0.004
(ref: established market with low competition)	(0.034)	(0.024)	(0.036)	(0.023)
Industry dummies	YES	YES	YES	YES
Pseudo R-squared	0.151	0.095	0.150	0.115
Observations	1247	2683	1130	2800

Note: Average marginal effects presented. Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level

Table 6 presents estimations based on the same breakdown of firms for the case of innovation sales. All results are from an estimation of a fractional probit model. The results confirm the results in Table 5. The estimated marginal effect of in-house software development on innovation sales is significantly higher among firms with above-average fraction of employees with long university education in STEM (columns 1 and 2) as well as in other fields (columns 3 and 4). For external software-development, the differences in the estimated marginal effects between the groups of firms is negligible. This reinforces the previous interpretation: issues of human capital complementarity and absorptive capacity appears to primarily pertain to firms more deeply engrained in digitalization, as reflected by in-house software development. Taken together, the results in both tables support the second hypothesis.

Table 6. Fractional Probit Regression by education background, dependent variable: innovation sales (%).

	Share of employees with long university education in STEM		Share of employees with long university education, except STEM	
	(1) High	(2) Low	(3) High	(4) Low
In-house software development	0.069***	0.019**	0.051***	0.035***
	(0.013)	(0.008)	(0.013)	(0.008)
External software development	0.021	0.016*	0.013	0.018*
	(0.021)	(0.008)	(0.018)	(0.009)
Persistent R&D	0.065***	0.054***	0.055***	0.057***
	(0.015)	(0.010)	(0.017)	(0.009)
Temporary R&D	0.001	0.050**	0.023	0.035*
	(0.032)	(0.021)	(0.033)	(0.020)
R&D Expenses (%)	0.000	0.223***	-0.000*	0.042**
	(0.000)	(0.076)	(0.000)	(0.018)
Number of employees (in logs)	-0.015***	-0.010***	-0.015***	-0.010***
	(0.006)	(0.003)	(0.006)	(0.003)
Average age of employees	-0.004***	-0.002***	-0.003***	-0.002***
	(0.001)	(0.000)	(0.001)	(0.001)
Employees with long university education in STEM (%)	0.057*	0.038	0.081**	0.039*
	(0.032)	(0.082)	(0.033)	(0.020)
Employees with long university education, except STEM (%)	-0.102***	0.062	-0.139***	0.027
	(0.031)	(0.105)	(0.038)	(0.099)
Exporter	0.029**	0.018**	0.024*	0.020**
	(0.015)	(0.007)	(0.014)	(0.008)
MNE	0.005	0.000	0.007	-0.001
	(0.013)	(0.007)	(0.012)	(0.007)
New market with high competition	0.034	0.012	0.038	0.016
(ref: established market with low competition)	(0.023)	(0.019)	(0.023)	(0.019)
New market with low competition	0.094***	0.005	0.135***	-0.000
(ref: established market with low competition)	(0.033)	(0.020)	(0.035)	(0.019)
Established market with high competition	-0.004	0.009	0.018	0.001
(ref: established market with low competition)	(0.014)	(0.008)	(0.014)	(0.008)
Industry dummies	YES	YES	YES	YES
Observations	1247	2683	1130	2800

Note: Average marginal effects presented. Robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level

5. SUMMARY AND CONCLUSIONS

The evidence presented in this paper add to a small but growing body of empirical evidence that speak to the conclusion that there is a software-bias in innovation across the entire economy. More to the point, we show that firms who engage in software development, especially those with in-house software developers, report higher levels of innovation output and have larger shares of their sales attributed to innovation. These results hold for both manufacturing and service firms and firms of different sizes, clearly indicating that software development and its relationship with innovation is not confined to a subset of the economy but is pervasive. This is consistent with the expectation that digitalization introduces a new GPT into the economy.

Furthermore, firms with higher shares of university-educated employees exhibit a stronger relationship between software development, especially firms with in-house software developers, and innovation propensity, in line with the notion of absorptive capacity. Interestingly, these results hold not only for

employees with STEM educations but also for other types of university degrees, including “softer” disciplines that are not normally associated with technologies and digitalization. A general remark based on these findings is that while technological skills might be necessary to leverage digital technologies in business activities, it may not be sufficient. On the contrary, there appears to be great value in complementary skill sets. Since the future need for so called digital skills is becoming an increasingly prioritized policy issue, this warrants further investigation.

The results not only indicate that software development is important to innovation activities, but also suggest that reported innovation activities exhibit a corresponding bias towards integrating and leveraging digital technologies in business activities, in line with Brynjolfsson’s and Hitt’s (2000) notion of complementary innovations. Put differently, while the number of firms engaging in software development are a minority in the Swedish economy, they may play a key role in both facilitating digitalization and contributing to innovation.

An increasing use of software and software development in economic activities and innovation can be described in one of two ways. First, it indicates a growing software intensity, whereby firms use software and digital technologies to gain productivity benefits or competitive advantage. Second, it implicates that businesses are becoming increasingly dependent on different types of software infrastructure, some of which cross organizational boundaries or are supplied by third parties (e.g. cloud services). Both of these developments contribute to a structural transformation of the economy which entails both innovation potential and new types of risks related to interconnectedness and interdependencies. Furthermore, a shift towards software in innovation may significantly alter the conditions of the trade-off between software development and buying standardized software off the shelf across different sectors and business functions. All of this calls for further investigation in future research.

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APPENDIX

Table A1. Summary statistics.

	N	Mean	SD	Min	Max
Product innovation	3947	0.41	0.49	0	1
Innovation sales (%)	3947	0.09	0.18	0	1
In-house software development	3947	0.21	0.41	0	1
External software development	3947	0.11	0.32	0	1
No software development	3947	0.68	0.47	0	1
Persistent R&D	3947	0.09	0.30	0	1
Temporary R&D	3947	0.01	0.12	0	1
R&D Expenses (%)	3930	0.48	14.9	0	674.00
Small (10-49)	3947	0.60	0.49	0	1
Medium (50-249)	3947	0.31	0.46	0	1
Large (250+)	3947	0.09	0.29	0	1
Number of employees (in logs)	3947	3.75	1.21	2.30	10.00
Average age of employees	3947	41.2	5.95	21.4	69.9
Employees with long university education in STEM (%)	3947	0.19	0.23	0	1
Employees with long university education, except STEM (%)	3947	0.09	0.15	0	0.97
Exporter	3947	0.45	0.50	0	1
MNE	3947	0.36	0.48	0	1
New market with high competition	3947	0.03	0.17	0	1
New market with low competition	3947	0.02	0.15	0	1
Established market with high competition	3947	0.77	0.42	0	1
Established market with low competition	3947	0.16	0.37	0	1
Manufacturing	3947	0.30	0.46	0	1
Services	3947	0.70	0.46	0	1

Table A2. Difference in means between firms according to software development activity.

	External Software Development			In-House Software development			In-House and External Software development		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Mean external	Mean no SWD	diff of mean (1) – (2)	Mean in-house	Mean no SWD	diff of mean (5)–(4)	Mean In-house	Mean external	diff of mean (7)-(8)
Innovation	0.46	0.32	0.146***	0.65	0.32	0.332***	0.65	0.46	0.186***
			(6.03)			(17.81)			(6.50)
Innovation sales	0.085	0.063	0.022**	0.16	0.063	0.100***	0.16	0.085	0.079***
			(2.85)			(14.75)			(6.19)
Persistent R&D	0.10	0.046	0.058***	0.26	0.046	0.215***	0.26	0.10	0.157***
			(4.97)			(19.17)			(6.69)
Temporary R&D	0.011	0.008	0.002	0.031	0.009	0.022***	0.031	0.011	0.020*
			(0.39)			(4.62)			(2.20)
R&D Expenses (%)	0.43	0.34	0.084	0.96	0.34	0.62	0.96	0.43	0.53
			(0.13)			(1.00)			(0.52)
Small (10-49)	0.48	0.67	-0.191***	0.44	0.67	-0.229***	0.44	0.48	-0.038
			(-7.84)			(-12.08)			(-1.28)
Medium (50-249)	0.37	0.28	0.085***	0.37	0.28	0.082***	0.37	0.37	-0.001
			(3.61)			(4.58)			(-0.04)
Large (250+)	0.16	0.049	0.107***	0.20	0.049	0.146***	0.20	0.16	0.039
			(8.56)			(13.56)			(1.70)
Number of employees (in logs)	4.11	3.54	0.572***	4.22	3.54	0.684***	4.22	4.11	0.112
			(10.11)			(15.01)			(1.39)
Average age of employees	41.14	41.55	0.397	41.14	41.12	-0.033	41.12	41.55	-0.429
			(0.310)			(-0.14)			(-1.31)
Employees with long university education in STEM (%)	0.15	0.15	0.002	0.34	0.15	0.184***	0.34	0.15	0.181***
			(0.33)			(21.07)			(13.07)
Employees with long university education, except STEM (%)	0.097	0.090	0.007	0.13	0.090	0.036***	0.13	0.097	0.031***
			(0.89)			(6.38)			(3.66)
Export dummy	0.54	0.38	0.160***	0.61	0.38	0.230***	0.61	0.54	0.070*
			(6.39)			(11.91)			(2.41)
MNE	0.43	0.28	0.148***	0.58	0.28	0.298***	0.58	0.43	0.150***
			(6.30)			(16.25)			(5.14)
New market with high competition	0.025	0.018	0.007	0.076	0.018	0.058***	0.076	0.025	0.051***
			(0.99)			(8.40)			(3.71)
New market with low competition	0.029	0.017	0.011	0.043	0.017	0.025***	0.043	0.029	0.014
			(1.75)			(4.36)			(1.22)
Established market with high competition	0.77	0.79	-0.016	0.72	0.79	-0.065***	0.72	0.77	-0.050
			(-0.75)			(-3.98)			(-1.95)
Established market with low competition	0.17	0.17	0.003	0.15	0.17	-0.014	0.15	0.17	-0.018
			(0.15)			(-1.04)			(-0.85)
Manufacturing	0.34	0.29	0.046	0.30	0.29	0.006	0.30	0.34	-0.039
			(1.95)			(0.39)			(-1.42)
Services	0.66	0.71	-0.046	0.70	0.71	-0.006	0.70	0.66	0.039
			(-1.95)			(-0.39)			(1.42)

Note: *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table A3. Matrix of correlations.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Product innovation	1.0000															
(2) Innovation sales (%)	0.5980*	1.0000														
(3) In-house SWD	0.2575*	0.2242*	1.0000													
(4) External SWD	0.0428*	-0.0043	-0.1830*	1.0000												
(5) Persistent R&D	0.2773*	0.2387*	0.2820*	0.0068	1.0000											
(6) Temporary R&D	0.0754*	0.0503*	0.0748*	-0.0085	-0.0397*	1.0000										
(7) R&D Expenses (%)	0.0083	0.0724*	0.0166	-0.0013	0.0615*	-0.0037	1.0000									
(8) Number of employees (in logs)	0.0978*	-0.0276	0.2032*	0.1067*	0.1632*	0.0047	-0.0216	1.0000								
(9) Average age of employees	-0.0170	-0.0551*	-0.0060	0.0215	0.1045*	0.0006	0.0118	-0.0470*	1.0000							
(10) Employees with long university education in STEM (%)	0.1792*	0.2095*	0.3280*	-0.0554*	0.2818*	0.0386*	0.0611*	-0.0093	-0.0042	1.0000						
(11) Employees with long university education, except STEM (%)	0.0628*	0.0485*	0.1009*	-0.0043	0.0576*	-0.0093	0.0421*	-0.0313*	-0.0224	0.6748*	1.0000					
(12) Exporter	0.1855*	0.1034*	0.1697*	0.0667*	0.2333*	0.0647*	-0.0087	0.2578*	0.2078*	0.0073	-0.0639*	1.0000				
(13) MNE	0.1775*	0.0858*	0.2348*	0.0508*	0.2231*	0.0389*	0.0241	0.4053*	0.0880*	0.1856*	0.0972*	0.4045*	1.0000			
(14) New market with high competition	0.0999*	0.1280*	0.1342*	-0.0122	0.1669*	0.0157	0.0147	-0.0250	-0.0702*	0.2009*	0.0977*	0.0105	0.0695*	1.0000		
(15) New market with low competition	0.0521*	0.1122*	0.0650*	0.0125	0.0756*	0.0371*	0.1435*	-0.0811*	-0.0351*	0.0832*	0.0390*	0.0087	-0.0358*	-0.0280	1.0000	
(16) Established market with high competition	-0.0324*	-0.0643*	-0.0607*	0.0009	-0.0900*	-0.0115	-0.0458*	0.1313*	-0.0567*	-0.1116*	-0.0335*	0.0171	0.0635*	-0.3288*	-0.2892*	1.0000

Note: * significant at 5% level.