Working Paper Series

#2023-004

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Published 14 Februari 2023

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: **info@merit.unu.edu** | website: **http://www.merit.unu.edu**

Boschstraat 24, 6211 AX Maastricht, The Netherlands
Tel: (31) (43) 388 44 00

UNU-MERIT Working Papers
ISSN 1871-9872

Maastricht Economic and social Research Institute on Innovation and Technology
UNU-MERIT | Maastricht University

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The role of product digitization for productivity – evidence from web-scraping European high-tech company websites

Torben Schubert[1,2,*], Sajad Ashouri[3,4], Matthias Deschryvere[3,5], Angela Jäger[1], Fabiana Visentin[6], Scott Cunningham[7], Arash Hajikhani[3], Lukas Pukelis[8], Arho Suominen[3,4]

[1]Fraunhofer Institute for Systems and Innovation Research ISI, Karlsruhe, Germany

[2]CIRCLE – Centre for Innovation Research, Lund, Sweden

[3]VTT Technical Research Centre of Finland, Helsinki, Finland

[4]Tampere University, Tampere, Finland

[5]Jyväskylä University School of Business and Economics (JSBE), Finland

[6]UNU-Merit, Maastricht University, The Netherlands

[7]University of Strathclyde, School of Government and Public Policy, Glasgow, United Kingdom

[8]PPMI, Vilnius, Lithuania

*Corresponding author: torben.schubert@isi.fraunhofer.de

Abstract: Digitalization is considered an important driver of the unravelling societal and economic transformations. However, holding both promises and challenges, its effects on the performance of individual firms are still underexplored. In this paper, we recognize that digitalization may take many shapes and try isolating the effects specifically of product digitization on firm level labour productivity. Our analyses are based on a large Europe-wide unique dataset combining structured information from ORBIS and PATSTAT with novel web-scraped information on digitalization in firms involved in high-tech manufacturing. We show that digitalization benefits productivity. However, the effect appears to result exclusively from product digitization, while a general digital intensity measure turned out to be insignificant. Moreover, we show that the effects are stronger for firms with higher initial productivity and firms located in countries considered digitally leading. Our results from the European high-tech sector suggest that the digital transformation in Europe is slow paced and scaled-up in only a fraction of the firms.

Keywords: digitalization, processes, products, productivity, innovation

1 Motivation

The advent of digital technologies has spurred hopes about the emergence of substantial productivity gains at the level of the firm (Mokyr 2014). Despite the promises held by digitalisation, a number of studies have demonstrated that the benefits may be much less self-evident. Notably since the provision of digital products has very low or zero marginal costs, it may create downward pressures on prices at the firm level implying that the returns of digital technical progress may not be fully appropriated by the firms (van Ark 2016). Some recent analyses also show that the productivity effects of digital technologies, may only emerge after years of investment (Bäck et al. 2022). Others have highlighted the impeding role of organisational resistances (Horvath et al. 2019, Brynjolfsson et al. 2019, Agrawal et al. 2021). Indeed, Brynjolfsson et al. (2019) have provocatively asked whether digital technologies may not be subject to the return of the Solow paradox, describing the ubiquity of digital technologies except in productivity statistics. Information on this topic is still relatively scarce because of the relatively newness of the topic of digitalization in many industrial settings and because of difficulties defining and measuring the phenomenon. In this paper, we argue that the productivity effects of digitalization may depend on a number of contingency dimensions, which can lead to substantial heterogeneity in the effects. Based on the literature, we propose three sources of heterogeneity.

First, we analyse the question of the type of digitalization. In contrast to the view suggesting that digital reorganization of processes is the main driver of productivity gains (Battistella et al. 2017, Eller et al. 2020, Parida et al. 2019, Annarelli et al. 2021), we isolate the effects of product digitalization (van Ark 2016, Hatzius et al. 2016). Our results show that indeed product digitalization is an important driver of productivity, even when controling for non-product related forms of digitalization. Interestingly, this latter generic non-product form of digitalization was not significantly associated with productivity, which underlines the importance of product digitalization.

Second, we analyse whether the productivity effects of digitalization depend on the type of firm. Specifically, following the idea that firms need unique capabilities to work with digitalization effectively (Agrawal et al. 2021), we test whether firms higher up in the productivity distribution enjoy larger benefits from product digitalization than firms located at the lower part of the productivity distribution. Moreover, we analyse if firm size plays a role and thus test whether effects differ between small and large firms.

Third, we investigate the role of country-heterogeneity in the emergence of productivity effects. More specifically, we argue that the successful implementation and use of digital technologies depends on a more developed infrastructure and market for digital products, and we suggest that firms originating from countries considered digitally leading, enjoy higher benefits.

To explore these three dimensions of heterogeneity referring to the type of digitalization, firm and country, we rely on a unique Europe-wide cross-sectional dataset, which combines structured financial data from Bureau Van Dijk's proprietary ORBIS database with patenting data from the proprietary PATSTAT database and web-scraped data capturing firms' efforts towards digitalization. The final analytical sample contains information on more than 15,000 firms in the high-tech and medium-high-tech manufacturing sectors.

Our findings show that digitalization can be an important driver of firm-level productivity. We do however find strong indications of heterogeneity. Notably, positive productivity effects are found mainly for product digitalization, i.e., genuine provision of digital products, whereas the generic digital intensity in the company does not imply additional significant productivity effects. Moreover, complementary quantile regressions show that effects of product digitalization are strongest for firms in the upper part of the productivity distribution, while for firms in the lower parts of the productivity distribution no productivity gains are visible. We also provide evidence that the positive effects are found exclusively in larger firms with more than 100 employees. With respect to country heterogeneity, we show that firms located in more digitalized economies gain more.

Our contribution relates to conceptualization, empirical results and methodology. *Conceptually*, we emphasize the need to clarify the precise meaning of digitalization. Specifically, to capture heterogeneity adequately, one needs at the very least to distinguish whether digitalization refers specifically to products (Hatzius et al. 2016, van Ark 2016, Fredrich and Bouncken 2021) or if it refers to a set of processes and organisational practices and methods (Parida et al. 2019, Annarrelli et al. 2021).

Empirically, we demonstrate that the productivity effects are highly heterogenous across firms. Despite measurement concerns (Ahmad and Schreyer 2016, Grömling 2016) and competitive challenges associated with digital technologies (van Ark 2016), our results show that there are robust positive productivity effects from product digitalization but that the effects of non-product related digitalization are smaller and less significant. Moreover, we show that the effects depend on the size of the firm, the position in the overall productivity distribution, and home country characteristics. In some respects, our results suggest that the positive productivity effects of digital products are a phenomenon primarily found in larger firms with ex-ante high productivity located in countries with already more digitalized economies.

Methodologically, we rely on a unique database coming from an extensive scraping exercise. This approach allowed us to compile new types of indicators on a large scale. In that respect, our approach enables a whole new technique to data generation and indicator construction related to digitalization research in innovation studies and the management literature. By relying on web-scraped data to answer our research question, we follow a methodological approach, which has increasingly gained traction in innovation research. As Rammer and Es-Sadki (2022) recently noted, traditional quantitative approaches to innovation at the firm-level relied heavily on structured data from patent and R&D statistics, which however capture only a very limited set of innovation-activities. Digitalization in particular is hard to capture and analyse comprehensively with conventional data because they often relate at best to patentable inventions. Digital aspects of products are however often intangible, relating notably to software, which also calls such approaches into question.

Indeed, survey-information coming for example from the *Community Innovation Surveys* (CIS) or *European Manufacturing Survey* (EMS) can partly cure these problems. They have however the problem of being unable to capture emergent patterns, which the survey designer may not have foreseen. Additionally, approaches to measure directly the degree of digitalization of the product offering are rarely implemented in large scale surveys. Moreover, surveys often scatter across industries very broadly because of the costs of surveying many firms making the samples very heterogenous with comparably few firms in each sector (Kinne and Lenz 2021). Typical CIS survey for example cover a few thousand firms in the micro-samples but cover almost the full breadth of the sectors in the economy. Even the EMS survey with its focus on manufacturing reaches its limits for analysing selected manufacturing sectors (Dachs et. al 2022). While technically it is possible to focus estimations on specific sectors, in practice this is hardly ever done because then the observation numbers drop considerably defying statistical identification.

Although web-scraping such information comes with its own limitations, many of them related to data quality as we will discuss, big data approaches have a high potential to capture digitalization in firms more comprehensively. More specifically, it does not hinge on patentability as patent-based digitalization indicators would. It does not require ex ante definition of the content of digitalization, thus allowing a more emergent approach than surveys. Third, because the costs of web-scraping are largely fixed, the data gathering can be scaled up easily. In our sample, we ultimately work with 15,000 observations from the high-tech sector in 15 countries.

2 Theory & empirical literature

Since the late 20th century, the digital revolution changed the way information is used and exchanged, and thus transformed our societies and economies. The digital domain emerged in the 1940s and it has been impacting firms and industries in different waves. The enabling technologies of product digitization, such as the first internet and the micro-processor were already available in the 1970 and are still developing. Today, we are in the middle of the fourth industrial revolution with a shift towards an era of embedded connectivity with the easy accessibility and commonness of mobile digital devices, the omnipresence of cloud applications, and the first application of artificial intelligence. Digitalization is changing the ways people experience the world around them and is altering the way firms develop and market their goods and services. Moreover, incorporating digital technologies changes the mechanisms employed to deliver, capture and create value by companies. Thus, digitalization is also constantly transforming the economies in the world. (Porter/Heppelmann 2014, van Ark 2016, Lee et al. 2018, Vial 2019, Ritter/Pedersen 2020).

2.1 Digitalisation as a multidimensional construct

Digitalization is a process that started already years ago and shows increasing dynamics. It refers to the application of digital technologies and digitized data which are valuable when transformed into intelligence and actionable knowledge that is enabling, improving and/or transforming business activities (Ritter/Pedersen 2020). In general, digitalization is seen as the road of moving towards digital business and digital transformation, as well as the creation of new – digital – revenue streams and offerings while doing so.

Accordingly, digitalization might affect the production technology itself as well as the internal organization, the product offering as well as the way the innovation process is organized, the business options as well as the opportunities to offer services, and finally might change the entire market environment. The use of digital technologies changes the way firms produce goods and services, innovate, and interact with other firms, workers, consumers, and governments. Moreover, it provides the potential to experiment with new channels of distribution that are more efficient in capturing value (Gal et al. 2019).

Thus, overall, digitalization is a complex phenomenon covering many different strategies and thereby taking on variegated forms, some of which address the organizational process side such as how the goods and services are produced, while some refer to the actual digital content of the goods or services. or how they are delivered to the customer. Because both dimensions differ fundamentally in terms of mechanisms by which their economic consequences unfold, it is necessary to keep them conceptually separated from each other.

In this paper, we will primarily focus on the role of digitalization of the actual products, because arguably in many cases the biggest disruptions of existing markets and profits streams occur when the product portfolio undergoes fundamental shifts. On the product side, digitalization has led to fundamental changes in the markets and profit streams because it implied transformations of analogue products into digital products. These changes can create challenges but also substantial competitive advantages for manufacturing firms. Moreover, product digitalisation can increase the product complexity (Novales et al., 2016) and hinder competitors in offering similar technologies (Hacklin et al., 2013). In the next subsections, we will first review potential benefits and threats of product digitalization (section 2.2) and subsequently review heterogeneity concerning the degree to which productivity benefits are likely to emerge from product digitalization (section 2.3). Based on the literature, we will pay specific attention to differences between ex-ante high and low productivity firms, differences between small and large firms, and regional differences between the firms' country of origin.

2.2 The productivity effects of product digitalization

Regarding the impact of digitalization on firm performance, a huge part of literature is elaborating the assumption that the use of digital technologies and digitalization ultimately lead to productivity improvements and competitive advantages (Syverson, 2011; Kaiser 2002). There are good reasons to believe that investment in digital technologies should have strong positive effects on productivity (e.g. Syverson, 2011; Brynjolfsson/McAfee, 2014). While on the process side, in particular automation (Mishra et al. 2007), smoother digitalized transformation processes (e.g. Bartel et al. 2007; Rahmati 2021; Schweikl/Obermaier 2020), and greater organizational flexibility through customized production (Drnevich & Croson 2013; Nylén & Holmström 2015; Wamba et al., 2017), may benefit firm-level productivity, the introduction of new digital products can support the promotion of a chain of combinational innovations, such as data platforms and analytics software (Yoo et al. 2012; Björkdahl 2020; Kollmann et al. 2021; Lanzolla et al. 2021; Ciarli et al. 2021; Urbinati et al. 2022).

Productivity effects of digitalization then can result from reorienting the business strategy towards a more customer-oriented perspective as well as the business opportunities. Organizations may change their business models, as to broaden their offerings through servitization, or the bundling of customer-oriented goods and services. Moreover, by affecting the output quality, a firm can receive price premiums due to superior or innovative products. It has been argued that absorbing new digital business resources to promote novel innovations, products, or services demands strengthening firms' capabilities in technical and market contexts. Thereby, digitalization not only allows to invent new products for new, or already existing markets but also creates completely new markets which is in itself the digitalisation of the economic context the firm is embedded in (Wang 2021, Selander et al. 2013).

Finally, advanced services might be key to capture the benefits of digitalization (Kohtamäki et al. 2020). The improved use of digitised data enhances customer engagement and enables the development of product-service systems, e.g. through improvements in remote diagnostics, development of operational services or outcome-based services. Servitization allows manufacturers to differentiate from competitors. Moreover, the interlinkage with customers offers many new opportunities for generating additional revenues, retaining customers, and expanding and stabilizing order volumes. Through the use of digital solutions, interaction with the customer as part of service production can largely be decoupled in terms of time and space. Additionally, services are an essential factor for innovations in manufacturing through deeper knowledge of the customer's needs which enables offering new business models by integrating solutions of products and services (Baines et al. 2009, Bruhn and Hadwich 2016, Kindström and Kowalkowski 2009, Lerch/Gotsch 2015, Kohtamäki et al. 2020).

Although the list of arguments is long regarding the assumption of a positive relationship between digitalization and performance, this relationship is complex and other important factors are also key to productivity; some factors even moderate this link of digitalization and performance. Studies showed that manufacturers seem to struggle with capturing value from digitalization. On an aggregated level, results depict that despite ongoing digitalisation, productivity among digitalizing firms and industries is only growing slowly. In the literature, this phenomenon is discussed as the digitalization paradox and rephrases the productivity paradox famously elaborated by Robert Solow in 1987 (Bäck et al. 2022; Brynjolfsson, 1993; Brynjolfsson & McAfee, 2014, Rahmati et al. 2021).

At the firm level, two main arguments occur in this context. On the one hand, the need for large investments for successful digitalisation is hardly compensated by increased value creation or value appropriation, as previous investments are easily outdated in this rapidly evolving field. Moreover, the deployment of digital technologies requires reorganization of the firm around the new technology and demands for further resources and investments. These new requirements for companies will at least partially override operational productivity benefits (Black and Lynch, 2001; Bresnahan, Brynjolfsson, and Hitt, 2002; Zimmer and Ziehmer 2018).

2.3 Heterogeneity in the productivity effects across firms

The simultaneous existence of productivity benefits and threats associated with product digitalization is likely to lead to considerable heterogeneity in the actual productivity effects across firms. This heterogeneity is likely to be governed by both firm-internal and external actors. At the level of the firm, several scholars claim that the value into digital technologies may be questionable if not supported by these complementary capabilities. Thus, investments in digital technologies need to be complemented at various organizational levels to realize their full potential (as through R&D, skilled labor, aligned management priorities, reconfiguration of resources, and organizational change) and lead to a higher return on investment for firms (e.g. Hall et al., 2013; Pieri et al., 2018; Kohtamäki et al. 2020; Annarelli et al. 2021; Ciarli et al. 2021). The specific advantage of digitalisation through scale-free resources (such as data, software, or AI) always needs complementary non-scale resources such as human and managerial resources (Teece, 1986). The importance of scaling, which is inherent in digitalization is likely to bring considerable consequences on the productivity benefits, which may easily imply that productivity effects differ by firm size. Indeed, the digital divide between large and small firms is a fairly well-known phenomenon (e.g. Gobierno de España 2021, Thrassou et al. 2020). Depending on available resources, skilled personnel, management, education and training capacities, larger businesses on average tend to be more digitally mature than their smaller competitors. Moreover, ICT tends to be more complementary with the division of labour in larger firms. Thus, it can be assumed that the valuable business potential and productivity gains will differ between SMEs and larger firms.

From literature it is known that the productivity benefits of digital technology are greater in companies with a higher intensity of routine tasks that already have high levels of productivity. By replacing and optimising routine tasks, digitalisation can have a greater impact on productivity (Akerman et al. 2013, Gal et al. 2019). Moreover, some literature suggests that productivity benefits from e.g. software investment are strong for low productivity firms (Borowiecki et al. 2021), other empirical results suggest that productivity gains are higher for high productivity firms (Dabla-Norris et al. 2023). Thus there may also be differences across the productivity distribution, with ex-ante more productive firms being more likely to reap the productivity benefits of product digitalization.

As concerns the firm-external factors, the prerequisites for effective digitalisation and possible productivity effects outside the company must also be taken into account (Arthur 2009, Zimmer and Ziehmer 2018): As technologies change companies, so does the industrial and economic context in which the company operates; digitalisation is not limited to the realm of production or business. The emergence of novel technologies always sets off a train of further technological adaptations, leading to new problems, creating new opportunities for fulfilment, which in turn require further innovation and introduce further technologies and problems. Thereby, the industrial structure mirrors the changes in its technologies in terms of newly introduced processes and its agility. The pattern of goods and services produced and consumed readjusts, and costs and prices (incentives for novel technologies) change accordingly which in turn requires complementary developments, for example in education or organisation (e.g. Brynjolfsson and McAfee 2014). Therefore, it does not only depend on the individual company whether digitalisation leads to productivity advantages, but it is important to always consider the company context as well. Consequently, it is helpful for empirical analyses to set clear specification of the context in order to be able to clearly grasp effects. With a regional perspective, a country requires a productively functioning network of supporting institutions and norms, logistics and technological infrastructure, and coordinating processes to enable smooth market operations (Rahmati et al., 2021). Moreover, firms which offer digitalized products will benefit from operating in a highly digitalised industry or region (Syverson, 2017). Cross-country data on the adoption of digital technologies at the firm level show significant differences (Gal et al. 2019, Andrews et al. 2018).

3 Data and identification

Focusing specifically on the question of how product digitalization affects firm-level productivity in this section, we will present the modeling strategy and the data. We start by presenting the structural econometric model in the next subsection 3.1. Then, in subsection 3.2, we discuss the data sources, the construction of the key explained and explanatory constructs as well as the additional control variables. Finally, we conclude with an empirical description of the key features of the dataset in chapter 3.3.

3.1 Model and identification strategy

To identify the effects of firms' product digitalization on productivity, we use a standard labour productivity regression

$$\log(prod_i) = x_i\delta + \varphi \cdot digiprod_i + v_i \qquad \text{(Equation 1).}$$

where x_i is a vector of control variables, v_i is an unobserved normally distributed error term, $prod_i$ our measure of labour productivity and $digiprod_i$ is our measure of product digitization, respectively.

Concerning the estimation of Equation (1), for our baseline models we rely on ordinary least squares estimation because logged labour productivity is continuously distributed over the real axis. However, a number of potentially unaddressed estimation issues arise. One aspect concerns a priori existing *differences in the sample of digitalized and non-digitalized firms,* which begs the question of whether observable effects would hold across these samples. To control for this potential source of estimation bias, one possibility is to rely on pre-regression matching to reduce estimation issues resulting from heterogeneous subpopulations. A particularly convenient method of obtaining robust heterogeneous samples relies on introducing regression weights, which are based on entropy balancing. Entropy balancing determines regression weights such that the treatment and control groups are *a priori* similar in their characteristics. We define treatment in this context as a dummy that is equal to one if the dichotomous product digitization measures is unity. We then use the determined regression weights again in our OLS models.

Another aspect concerns robustness with the *set of control variables*. Specifically, using too many controls can greatly increase mean squared error, while using too few can induce omitted variable bias. To test whether baseline results remain stable with respect to changes in the set of control variables, we use weighted average least squares (WALS) estimator, which presents model-averaging results resulting from using alternate sets of controls.

Beyond the more technical robustness checks, we also tested for *differences*_across the productivity distribution, firm's size and country groups. To test whether the effects differ across productivity, we estimate Equation (1) not only by estimators that identify effects on the expected values but also by using quantile regression techniques where we observe effects at the distribution deciles. As concerns firm size and country differences, we include splits to check whether the results differ by subgroups. In specific, we use splits between small (less than 100 employees) and larger firms (more than 100 employees) and between country groups. For the latter, we rely on the European Digital Economy and Society Index (DESI), where the sample countries are split into three groups defined by DESI 2019 as digital pioneers (including: SE, GB, DE, FR, AT), digital mainstreamers (including BE, ES, SI, CZ, HU) and digitalization followers (including PT, BG, RO, IT, PL).

3.2 Data construction and variables

3.2.1 Data sources

Estimating Equation (1) requires access to data sources comprising information on productivity, and product digitalization, and other relevant control variables. For this end, we construct a unique European firm-level dataset that combines *administrative data* with *web-scraped data*.

The administrative data obtained via the *ORBIS database* of Bureau Van Dijk contain information on productivity as well as key firm characteristics such as their size, age, sector, and capital intensity. Besides, the productivity equation considers firms' patenting activity for a more accurate estimation of the genuine impact of digitalization on productivity. The patent data acquired using *PATSTAT* reflects the information on the annual number of patent applications in the main patent jurisdictions, i.e., the United States Patent and Trademark Office (USPTO), the European Patent Office (EPO), the Japan Patent Office (JPO) and the World Intellectual Property Organization (WIPO).

We utilized *web-scraping* to gather information on our main independent variable, product digitalization, as well as two further independent control variables, servitization and digital intensity. In the literature, measuring different aspects of digitalization in firms has typically been conducted based on survey data or use of third-party datasets (Björkdahl 2020, Blichfeldt and Faullant 2021, Horvat et al. 2019, Kohtamäki et al. 2020, Lerch and Maloca 2020), Still, such approaches suffer from limited data coverage (Arora et al. 2020). Specialized manufacturing surveys as the *European Manufacturing Survey* (EMS), which cover product innovation by questions on digital extension of products or introduction of new digital products lack geographic coverage.For instance, the EMS is conducted only in a dozen European countries (Horvat et al. 2019, Dachs et al. 2022). Also, studying of firms' digital activities in reference surveys such as the *Community Innovation Survey* (CIS) is not yet well-established. For example, the Finland CIS survey does not tackle digitalization activities consistently in each update and it provides relatively low coverage for digitalization-related questions. In the Finnish CIS of 2018, less than 10% of studied entities have reacted to such questions. Finally, third-party datasets also do not provide this output view on digitalisation. Such databases usually contain information on monetary ICT investments providing an input view on digitalisation, or they capture sales to different industries that do not clearly reflect the companies' digital product offering but rather describe their role in the market (e.g. Rahmati et al. 2021).

Instead, our analysis measures digitalization using a novel methodology based on the *companies' web pages*. Websites provide valuable information on company behaviour (Gök, Waterworth and Shapira 2015; Kinne and Axenbeck 2020; Axenbeck and Breithaupt 2021), which is not exclusively limited to technical expertise, prices, or innovative outputs but also expresses the firms' products, processes, alliance network, human resources, etc. (Gök, Waterworth and Shapira 2015). Utilizing web pages as a data source facilitates more frequent and updated data compared with conventional data sources (Arora et al. 2020). Moreover, examination of firms' products can lead to a broader understanding of the firms' activities. Websites are an important source to identify companies' products in a cost-effective way. Such dissemination channel is a valuable means for companies to present their technologies and signal their competitive advantage to their competitors. Therefore, exploring websites enables the investigation of firms' efforts toward developing digital products, which is referred to as product digitization.

3.2.2 Sample construction and selection

The sample for analysis is constructed based on a set of data-cleaning steps. In our study, the firm population of interest is medium high-tech and high-tech firms[1] in the European Union (EU) as in the borders before Brexit. The relevant sectors were identified based on the Eurostat aggregation of manufacturing industries based on their technological intensity and using NACE revision 2 coding. The selection then identified whether the companies belong to any of the selected NACE 3-digit codes using ORBIS and covers companies from pharma industry, air and

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[1] For source for classification see EC: https://archiwum.ncbr.gov.pl/fileadmin/gfx/ncbir/userfiles/_public/programy_krajowe/go_global_en/eurostat_indicators_on_high-tech_industry_and_services.pdf

spacecraft producers, machinery to producers of medical and dental instruments and supplies.[2] The ORBIS population of all European medium high-tech and high-tech firms contains 183 161 firms. To construct our population of interest and be able to carry out our analysis multiple data cleaning steps are applied. As the focus is on active firms with at least 10 employees we retain the firms that have ORBIS information available on 2019 turnover and employment, which leaves us with 40,897 firms. As not all firms have webpages, not all firms could be scraped. Moreover, not all firms feature product pages on their domain. Thus for some firms, information of web-based indicators cannot be calculated. Moreover, information on the value-added needed to construct our productivity measure is not available for all the firms in sample. Finally, the observations from countries and industries with limited coverage were removed. The necessary data cleaning steps leave us with a cross-section of 15,529 high-tech firm observations from 15 European countries.

In terms of the data's time structure, the coverage depends on the data sources and specific variables. The dependent variable captures productivity levels at the end of the year 2020. The cross-sectional data that were obtained via web-scraping during the period December 2020 to August 2021 have been used to construct our explanatory variables that capture digitalization and the control variables that capture servitization and R&D cooperation. Patent intensity refers to the period 2015 to 2019 while all other control variables refer to 2019, the year before the webscraping took place.

3.2.3 Construction of variables

3.2.3.1 Productivity

The *productivity* measure was constructed as the value-added in 2020 divided by the number of employees in 2020, available through ORBIS. Due to the skewed distribution and the continuous nature of the indicator, we use the logged version of the labour productivity measure. This measure constitutes the dependent variable of the model.

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[2] Companies are identified as high technology when classified as manufacturer of basic pharmaceutical products and pharmaceutical preparations (21), manufacturer of computer, electronic and optical products (26), manufacture of air and spacecraft and related machinery (30.3). Medium high-tech group is defined as companies of the following sectors: manufacturer of chemicals and chemical products (20), manufacturer of weapons and ammunition (25.4), manufacturer of electrical equipment (27), manufacturer of machinery and equipment n.e.c. (28), manufacturer of motor vehicles, trailers and semi-trailers (29), manufacturer of other transport equipment (30) excluding Building of ships and oats (30.1) and excluding manufacturer of air and spacecraft and related machinery (30.3), manufacturer of medical and dental instruments and supplies (32.5).

3.2.3.2 Product digitalization

To construct a novel measure of *product digitalization* we focus on product-related data and actual product descriptions that appear on companies' webpages. This product digitalization information is retrieved through web-scraping process within the company's website domain (Ashouri et al. 2022). The product description is transformed by Microsoft Academic Graph (MAG) to certain knowledge categories, and subsequently presence terms relating to digitalization are identified.

As digital technologies cover a wide range of technology domains, investigation of digital technologies within the products requires a comprehensive tool which is capable to identify various digital technologies. Existing approaches capture the digitalization of products mainly through surveys but also patent data have been used to identify digital products. Some attempts were made to produce a technical classification of firms by analysing the text of technology and product descriptions using "digital" search terms (Fredrich & Bouncken, 2021). However, this approach overlooks the large number of non-patented products. Moreover, it suffers from inadequate coverage where digital technologies such as artificial intelligence, computer design, cloud computing do not contain the term "digital".

MAG comprises over 120 million publications and associated bibliometric metadata, making it a large and heterogeneous database. The transformation process involved interlinking the web-scraped textual data from the company websites to Microsoft Academic FOS codes. Consequently, a quantitative representation of the text data and publications was created. Using the information of publications associated with FOS codes, the input text data infer an association with the vector containing the associated FOS codes and their similarity score (Hajikhani et al. 2022). Therefore, using this approach enables the transformation of high-dimensional textual data into structured fields of study (FOS IDs) reflecting organised information on the input information.[3]

To construct a variable measuring product digitalization, after the identification of companies' products are identified through their web pages, consequently, the relevant products' text is aggregated and then, mapped onto FOS codes. The generated vectors as a result of classification represent the product's embedded FOS (Ashouri et al. 2022). To identify the related digital

[3] We share both the compiled model and the code in the Jupyter notebook format with detailed descriptions of the steps. The code can be accessed from Github at https://github.com/arash-hajikhani/Bigprod_FOS/blob/main/Text-to-FOS-Similarity.ipynb. In addition, the code for FOS similarity assessment can be accessed from Github at https://github.com/arash-hajikhani/Bigprod_FOS/blob/main/FOS_Similarity.ipynb

knowledge embedded in the product, the presence of computer science associated FOS IDs for each firms' product is examined. Products containing the related FOS IDs, as digital products, are scored as one, otherwise zero. The aggregation and average of such product-based binary scores at the firm level reveal how the firm offers digital products in its product portfolio. Equation (2) defines the product digitalization score, where $n_{digital}$ is the number of digital products of the firm and $n_{non-digital}$ is associated with the number of non-digital products.

$$prod\_digi\_cont = \frac{n_{digital}}{n_{non-digital} + n_{digital}} \qquad \text{Equation (2)}$$

To mitigate the risk of confounding sector biases, we normalise Equation (2) concerning each sector by calculating a dummy equalling one if the firm-level measure is larger than the sector average. Thus, the product digitalization indicator reflects whether a firm's product portfolio is digitalized above average in comparison to the portfolio of firms in the same sector.

3.2.3.3 Controls

When estimating the relationship between product digitalization and productivity, we included in our analysis three main controls additional to the usual key firm characteristics. First of all, we control for the digitalization intensity of the firm because digitalization may appear in other companies' activities such as supply chain, production process, human resources and so forth, which can yield consequences on the productivity . Second, the innovativeness of the company is controlled for. Third, we consider the role of servitization.

Digitalization intensity: The indicator for digital intensity measures the level of digitalization of the entire organization. This indicator is built on the companies' website information which reflects the firms' activities and capabilities in product development, alliances, social responsibilities, ethics and compliances, supply chain partnerships and so forth. Therefore, this measure controls for the use of digital technologies at any organizational level other than firms' products. The construction of this indicator uses a methodology similar to the one used for product digitalization, but separate sources of information. The measure utilises the companies' website FOS IDs by linking and classifying companies' website content with FOS codes (Ashouri et al. 2022). Once the activities of a company are represented at a higher level of granularity and harmonised, this allows for additional indicators with a more thematic orientation. The digitalization intensity measure is constructed based on the relative importance (or weight) of digital FOS IDs in comparison to all the FOS codes identified on the website. This relative weight mirrors the extent to which a company signals its digital activities throughout the webpage.

Technically, for the digitalization intensity measure, the weights of all digitalization-related FOS IDs obtained by MAG are summed. Equation (3) reports the formula for the process digitalization score, where$x^{i}_{digital}$ is the similarity score for a digital FOS ID i concerning the other *n* digital FOS IDs found on that web page, and $x^{j}_{non-digital}$ is the similarity score of a non-digital FOS ID *j* found on the web page concerning the other m non-digital FOS IDs on the web page. The final value ranges from 0 to 1, where 0 represents non-digital firms and 1 is associated with fully digital companies:

$$digi\_int\_cont = \frac{\sum_{i=0}^{n} x^{i}_{digital}}{\sum_{i=0}^{n} x^{i}_{digital} + \sum_{j=0}^{m} x^{j}_{non-digital}} \qquad \text{(Equation 3)}$$

Again, we compute a dichotomous sector-cleaned version of this measure by creating a dummy equalling one if the firm-level measure is larger than the sector average. Thus, the digitalization intensity indicator reflects whether firms published more extensively about their digital activities and organizational process or not than the average firm of the same sector does.

Patenting intensity: There is an established literature on the relationship between patenting intensity and productivity, and information on patenting activities is a long-established measure of innovation performance. Although the indicators based on it are limited in their coverage and applicability, they clearly reflect the innovative capacity of manufacturing firms, especially those in the high-tech sectors (e.g. Hagedoorn/Cloodt 2003; Cockburn et al. 2010). Therefore, patenting intensity is used to control for the innovativeness of the companies. The patenting measure was constructed by considering all patent applications in the period 2015–2019. Patents were retrieved from PATSTAT and linked to each company. The patent intensity variable was constructed by dividing the total patent applications in 2015–2019 by the number of employees in 2019. To exclude the effect of duplication for patents in the same patent family, we selected those with the earliest filing date.

Servitization: Similar to digitalization measures, although surveys are the traditional methodology for examining servitization, the servitization measure in our analyses is constructed using web-mined data. The measure of servitization employs a novel methodology to explore service offerings based on scraped text from company websites. The keywords identified throughout the company web pages are sources of information that companies use to communicate with their audience (Ashouri et al. 2022), which have been in the focus of previous studies for firms' innovation activities (Héroux-Vaillancourt et al. 2020, Li et al. 2018). To evaluate servitization, the corresponding measure proposes a dummy variable which equals one when the company website covers the keywords "service" or "service + <other terms>", and equals zero otherwise.

Key firm characteristics: Furthermore, to incorporate the effect of non-digital products on productivity, the productivity equation includes the number of products per employee. The econometric analysis also examines the key firm characteristics impacting productivity, including capital intensity obtained by total assets in 2019 per employee, firm age, firm size (described by number employees and existence of multiple establishments as control variables), and firm's sector and country dummies. All these indicators were extracted from ORBIS.

3.3 Descriptive Statistics

We present the main descriptive results in Table 1. The mean values of the analytical sample of 15,529 firms are displayed. In comparison, the values of the sample of 38,042 firms is depicted in comparison. The comparative sample is referred to active firms, with at least 10 employees in 2019, with the selected countries and NACE code, regardless of the availability of a productivity information.

Table 1: Descriptive statistics (analytical and comparative sample)

	Comparative sample			Analytical sample		
Variable	Obs	Mean	Std. Dev.	Obs	Mean	Std. Dev.
Productivity 2020	27,078	74.588	324.803	15529	76.107	363.463
Product digitalization	18,762	0.338	0.474	15529	0.332	0.471
Digitalization intensity	26,024	0.368	0.488	15529	0.362	0.480
Patent intensity 2015-2019	38,042	1.004	0.448	15529	1.006	0.336
Servitization	26,854	0.253	0.489	15529	0.247	0.431
Employees	38,042	333	5472.561	15529	416	7481.590
Capital intensity	36,823	365.355	4004.120	15529	366.336	4038.940
Firm age	37,971	31	21.015	15529	29	19.715
Number of products per employee	18,762	0.458	1.602	15529	0.455	1.500
Multiple establishments	37,420	0.750	0.433	15529	0.750	0.433
NACE 20	38,042	0.149	0.357	15529	0.151	0.358
NACE 21	38,042	0.037	0.188	15529	0.037	0.190
NACE 26	38,042	0.135	0.341	15529	0.143	0.350
NACE 27	38,042	0.150	0.357	15529	0.138	0.345
NACE 28	38,042	0.427	0.495	15529	0.445	0.497
NACE 29	38,042	0.091	0.288	15529	0.076	0.264
NACE 30	38,042	0.010	0.102	15529	0.009	0.095

country==AT	38,042	0.015	0.121	15529	0.011	0.105
country==BE	38,042	0.014	0.121	15529	0.014	0.119
country==BG	38,042	0.019	0.136	15529	0.019	0.135
country==CZ	38,042	0.028	0.165	15529	0.008	0.091
country==DE	38,042	0.183	0.387	15529	0.036	0.187
country==ES	38,042	0.111	0.314	15529	0.144	0.351
country==FR	38,042	0.061	0.240	15529	0.061	0.238
country==GB	38,042	0.063	0.242	15529	0.054	0.225
country==HU	38,042	0.033	0.178	15529	0.011	0.106
country==IT	38,042	0.315	0.465	15529	0.483	0.500
country==PL	38,042	0.058	0.234	15529	0.072	0.260
country==PT	38,042	0.024	0.152	15529	0.018	0.132
country==RO	38,042	0.028	0.166	15529	0.0160	0.126
country==SE	38,042	0.036	0.186	15529	0.040	0.194
country==SI	38,042	0.011	0.106	15529	0.013	0.112

When inspecting the overall characteristics of the analytical sample, we see that the average firm in the sample has approximately 416 employees. However, there was great heterogeneity, with many small firms, while the largest had more than 600,000 employees and the smallest one having 5 employees . Across the considered high-tech and med-high tech manufacturing sectors (NACE 20, 21, 26, 27, 28, 29, 30), the distribution has a heavy side on NACE 28 (mechanical engineering). Only a minority of firms belonged to NACE 30 (other automobiles). The other sectors are relatively equally represented. The average firm has a labour productivity of 76,000€ per employee. For the larger comparative sample, we find similar average values except for the firm size in terms of number of employees. The average company of the comparative sample is with around 333 employees significantly smaller than the companies of our analytical sample; however, the distribution remains very similar.

Focusing on the key explanatory variable, we see several very interesting patterns. For the product digitalization measure, we see that roughly one-third of all firms are identified as more active than the industry average. Looking at our controls, about 36% of our firms are involved in digitalization at general organizational levels, and approximately 24% of our firms offer services. The average firm was relatively young, being 29 years old; 75% of the firms in our sample had multiple establishments.

A final noteworthy point is that the country-wise distribution was substantially more skewed, with 48% of the firms based in Italy. While this does not allow for any claims to country-wise representativeness, we do however include country dummies to control for country-level heterogeneity. Moreover, since the overall sample is relatively large, we are at least principally able to identify country heterogeneity. We explore this dimension by including country splits in the robustness section.

4 Results

In this section, we present the main regression results of the effects of product digitalization on the firms' innovation activities and their realized productivity levels. In the second part of this section, we conclude with a series of robustness checks to show that the key results are not overly dependent on the specific modelling choices.

4.1 Main results

The results of the productivity regression, Equation (1), are reported in Table 2, column 1. First and most importantly, we find that product digitalization leads on average to an increase in productivity (elasticity of 0.027%). Secondly, several further effects on the control variables are interesting to note. Digitalization in overall (digitalization intensity) does not affect productivity. As expected, patent intensity affects productivity. The coefficient indicates that a 1% increase in patenting is associated with a 0.33% increase in productivity. Additionally, the coefficient of servitization is positive and statistically significant. Firms offering services have 7% higher productivity. Finally, we note that, in general, larger and older firms, firms with more products per employee as well as firms with multiple establishments, also enjoy higher productivity.

Table 2: Digitalization and labour productivity

	(1 - standard linear regression) Log productivity 2020	(2 - with entropy balancing) Log productivity 2020	(3 - WALS model averaging) Log productivity 2020
Product digitalization	0.02690*	0.02681*	0.02748*
	(2.35)	(2.35)	(2.40)
Ln patent intensity	0.33607***	0.32045**	0.33202***
	(3.35)	(2.93)	(3.31)
Digitalization intensity	0.00651	0.00424	0.00726
	(0.59)	(0.38)	(0.66)
Servitization	0.06746***	0.06317***	0.07746***
	(5.31)	(5.14)	(6.11)
Ln employees	0.04626***	0.04463***	0.04317***
	(11.02)	(11.11)	(10.28)
Capital intensity	0.00002***	0.00002***	0.00002***
	(16.78)	(18.18)	(16.47)
Ln firm age	0.04276***	0.04768***	0.04146***
	(5.30)	(6.06)	(5.14)

Number of products per employee	0.02215***	0.02374***	0.02412***
	(5.85)	(7.18)	(6.41)
Multiple establishments	0.09630***	0.09915***	0.09652***
	(7.49)	(7.67)	(7.55)
Constant	4.08354***	4.02830***	4.05228***
	(68.45)	(70.19)	(67.93)
Sector dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
N	15529.00000	15529.00000	15529.00000
r2	0.32829	0.32089	
P	0.00000	0.00000	

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.2 Robustness checks of the baseline model

To probe the robustness of our baseline results, we performed several more technically-oriented robustness checks. One particularly important concern is that digitalised and non-digitalised companies may differ substantially a priori. This may lead to estimation biases if the effects of digitalization do not extend across the equations. The results of the entropy balancing OLS model are presented in , column 2. We see that the coefficients differ only mildly, with statistical significances being largely unchanged.

Beyond the entropy balancing approach, we conducted several further robustness checks. The first consists of an approach to test for dependence on the choice of covariates. For this, we implement a Bayesian model averaging WALS estimator in which we treat all variables—except for the digitalization measures —as potentially dispensable. As we can see in column 3, the results do not vary in any relevant respect, which implies that, overall, the coefficients do not appear to depend much on the choice of the set of control variables.

4.3 Analyzing sources of heterogeneity of the digitalization effects

Although we find overall positive effects of product digitalization, our sample is quite heterogeneous in terms of both country composition and firm characteristics such as firm size or productivity levels. We therefore analyze whether the results that hold on average are in fact heterogeneous across these dimensions. We will specifically focus on the question of whether results differ over the productivity distribution, by firm size and country location.

Starting with the productivity distribution, we implement a quantile regression approach, where the main regression results are reported in Table 3. A visual representation of the effects of the two digitalization dimensions is presented in Figure 1.

Table 3: Digitalization and productivity at different locations of the productivity distribution

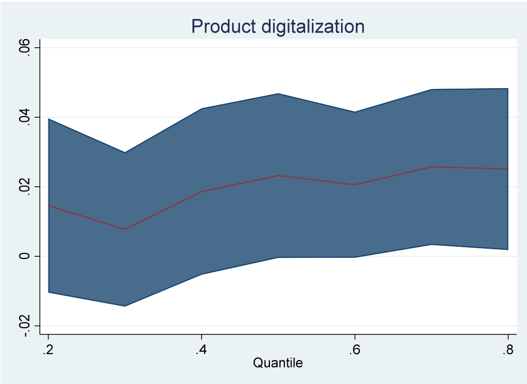
	(1) Log productivity 2020	(2) Log productivity 2020	(3) Log productivity 2020	(4) Log productivity 2020	(5) Log productivity 2020
Product digitalization	0.01461	0.01864	0.02323	0.02060	0.02511*
	(1.14)	(1.53)	(1.92)	(1.92)	(2.11)
Digitalization intensity	0.03274**	0.01105	0.01668	0.01832	0.00741
	(2.65)	(0.94)	(1.43)	(1.77)	(0.65)
Ln patent intensity 2015-2019	0.16389	0.39457***	0.35359***	0.27222**	0.14719
	(1.46)	(3.69)	(3.34)	(2.90)	(1.41)
Servitization	0.04505**	0.04803***	0.03931**	0.03262**	0.04603***
	(3.17)	(3.54)	(2.93)	(2.74)	(3.49)
Ln employees	0.08736***	0.06678***	0.05708***	0.04698***	0.02246***
	(18.60)	(14.91)	(12.88)	(11.93)	(5.15)
Capital intensity	0.00002***	0.00007***	0.00026***	0.00043***	0.00077***
	(15.23)	(49.17)	(183.15)	(344.61)	(555.82)
Ln firmage	0.06564***	0.03622***	0.02848***	0.02033**	0.01095
	(7.27)	(4.21)	(3.34)	(2.69)	(1.31)
Number of products per employee	0.00649	0.02963***	0.03122***	0.03926***	0.03933***
	(1.53)	(7.33)	(7.81)	(11.06)	(10.00)
Multiple establishments	0.06094***	0.07686***	0.08347***	0.08421***	0.07208***
	(4.24)	(5.61)	(6.16)	(6.99)	(5.40)
Constant	3.40829***	3.96980***	4.07463***	4.19008***	4.43041***
	(51.10)	(62.38)	(64.73)	(74.94)	(71.55)
Sector dummies	Yes	Yes	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes	Yes	Yes
N	15529.00000	15529.00000	15529.00000	15529.00000	15529.00000
pseudo-r2	0.26240	0.22693	0.21717	0.21692	0.23630

t statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

We observe that the effects of product digitalization increase across the productivity distribution, where the effects at the 20% are with 0.014 small but steadily increase to 0.025 at the 80%-quantile. Moreover, at the lower end of the productivity distribution, up to the 80% quantile, the effects are non-significant. Only above the 60% quantile of the productivity distribution did the effects turn statistically significant, taking their highest value with a coefficient of 0.025. At the same time, product digitalization appears to largely benefit high-productivity firms, whereas low-productivity firms do not gain from introducing digital products.

Figure 1: Representation of the effects product digitalization across the productivity distribution (point estimators and 95% confidence intervals)



A number of reasons could explain why the productivity effects differ across the productivity distribution. One argument may be that the effects differ substantially across firm size. Bäck et al. (2021) for example have shown that in particular large firms benefit from AI. Since productivity and firm size are usually positively related, a reason for the finding that in particular product digitalization affects productivity positively may be that firm size is an important driver. A second explanation would be that primarily firms within a digitalization leading economic context benefit from digital activities, while firms in other regions may not to the same degree. Thirdly, the higher benefit from digital products in high productive firms can supported by higher resources in distribution and promotion of the products. According to the findings in Table 3, high productive firms experience higher productivity growth from the expansion of their products. Therefore, the high productive firms either can have stronger resource and capacity in development of more unique products, offering novel competitive advantages, or their effective sales and distribution channels can improve their revenues.

To analyze the role of firm size and country of origin, we first split the firms by country of origin, taking into account the differential impact of countries that are leading, lagging, or lagging behind in digitization based on the Digital Economy and Society Index (DESI 2019) indicator provided by the European Union. In Table 4, in Column 1, we show the results for digitalization pioneers. In Column 2, we report the results for intermediate digitalization mainstreamers and in Column 3 we show the results for the digitalization followers. It is interesting to see that the product digitalization measures are very large and statistically significant only for the digitalization pioneers (b=0.065, p<0.01), while the effects are insignificant both for the mainstreamers and the followers, despite the fact that the latter two groups constitute the majority of the sample. This indeed suggests that the overall positive effects of product digitalization may in fact be quite heterogeneously distributed across countries, where only firms in the most digitalized countries actually benefit from digitalization efforts.

Table 4: Digitalization and labour productivity (by country digitalization level)

	(1) Log productivity 2020 Dig. pioneers	(2) Log productivity 2020 Dig. mainstreamers	(3) Log productivity 2020 Dig. followers
Product digitalization	0.06535**	-0.01779	0.02008
	(2.80)	(-0.80)	(1.39)
Digitalization intensity	-0.02208	0.02898	0.01661
	(-0.93)	(1.36)	(1.21)
Ln patent intensity 2015-2019	0.22103	-0.20149	0.38019***
	(0.95)	(-0.66)	(3.40)
Servitization	0.00154	0.05295*	0.06904***
	(0.06)	(2.31)	(4.12)
Ln employees	0.00272	0.05976***	0.06992***
	(0.34)	(6.88)	(12.97)
Capital intensity	0.00002***	0.00046***	0.00071***
	(13.48)	(24.54)	(38.17)
Ln firm age	0.04602**	0.04851**	0.03305***
	(2.79)	(2.85)	(3.32)
Number of products per employee	0.00167	0.01361	0.01770***
	(0.24)	(1.65)	(3.67)
Multiple establishments	0.09081*	0.07965***	0.03512*
	(2.08)	(3.43)	(2.34)
Constant	4.39479***	3.10037***	3.23138***
	(51.48)	(39.40)	(59.56)
Sector dummies	Yes	Yes	Yes
Country dummies	Yes	Yes	Yes
N	3123.00000	2965.00000	9441.00000
r2	0.15195	0.38534	0.41343
p	0.00000	0.00000	0.00000

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Finally, to analyse whether firm size plays a role we split the sample into firms with less and more than 100 employees. Table summarizes the results and shows that only larger firms with more than 100 employees appear to benefit from product digitalization. For them, the coefficient is with 0.05 substantially larger than also the average (b=0.027, compare Table 2) and statistically significant at the 1%-level. For firms with below 100 employees, product digitalization does not appear to lead to productivity effects. Interestingly, for firm with less than 100 employees, where the product digitalization does not influence productivity, servitization significantly affects the firms' productivity.

Table 5: Digitalization and labour productivity (by firm size)

	(1) Log productivity 2020 *<100 employees*	(2) Log productivity 2020 *>=100 employees*
Product digitalization	0.00641	0.05141**
	(0.46)	(2.75)
Digitalization intensity	0.00847	0.00152
	(0.65)	(0.08)
Ln patent intensity 2015-2019	0.30926**	0.44089*
	(2.78)	(1.99)
Servitization	0.06983***	0.03063
	(4.37)	(1.61)
Ln employees	0.06858***	0.03611***
	(9.92)	(4.06)
Capital intensity	0.00002***	0.00054***
	(15.11)	(23.58)
Ln firm age	0.05078***	0.02379
	(5.20)	(1.80)
Number of products per employee	0.02585***	0.35095***
	(6.48)	(4.36)
Multiple establishments	0.08776***	0.08191*
	(6.35)	(2.10)
Constant	4.09821***	4.01012***
	(36.58)	(44.36)
Sector dummies	Yes	Yes
Country dummies	Yes	Yes
N	11671.00000	3858.00000
r2	0.26543	0.57158
p	0.00000	0.00000

Overall, results confirmed that digitalization has robust and positive effects on firm-level productivity. Specifically, the results on productivity mirror and corroborate the statistically stable relationship between firm-level innovation and productivity, which has been documented in a well-established and extensive literature in innovation economics. On a conceptual level, our results suggest that the nascent literature on the productivity effects of digitalization may benefit from integrating key insights from the innovation literature. This should however clearly not hide away the fact that digital and non-digital innovations may also have important differences, which limits the ability to transfer directly all insights.

In addition, our results showed that the positive effects of product digitalization are not universal. They seem to be limited to firms at the higher end of the productivity distribution. Moreover, only larger firms benefit, which corroborates findings by Bäck et al. (2022). In addition, we find that also country of origin matters. Positive effects are observable for firms in digital pioneer countries but not for firms from the mainstreamers and follower group. When the positive effects of digitalization are more observable for firms in digital-leader countries, firms established in digitally follower countries do not experience productivity gains from digitalization.

5 Conclusions

Our paper contributes to the literature both methodologically and in terms of the results. As concerns methodology, we present one of the first systematic attempts to derive digitalization indicators for firms based on a large web-scraping exercise across European countries and match them to structured firm-level data sources. The scope of this approach allowed us to derive a comparably large sample of firms for relatively homogenous set of high-tech sectors, where existing survey-based studies usually must lump together firms from very heterogeneous sectors to achieve a sufficient sample size. Moreover, the web-scraping approach proved to be useful because even once data is scraped new indicators can be created in a relatively flexible way as the need occurs. The analysis however also revealed some of the limitations of this approach by showing that sample selection stemming either from non-existence of webpages or the gaps in the structured firm databases, ORBIS in this case, may be a non-trivial issue. Another concern clearly is the (heterogeneity in the) quality of indicators derived from websites. We provided some initial insights showing that the information may be better than initial expectations. However, more in-depth analysis, potentially also relying on case-studies are warranted. While the relevance of potentially resulting biases remain unknown, our exercise transparently documents some of the weaknesses as well as the strengths of approaches based on web-scraping of firm-level indicators.

Going beyond the methodological contributions, our analysis provided a number of important results as concerns the role of digitalization for firm productivity. Recognizing that digitalization comprises quite different phenomena within the firm, we managed to isolate the role of product digitalization, i.e., the effects resulting from offering and selling products featuring digital components. Our results highlighted the specific importance of this form of digitalization vis-à-vis other forms including for example the digitalization of firm internal processes or routines. Notably, we found that our product digitalization measure was highly significant in many circumstances, while our generic control for non-product-related digitalization was not.

Despite the overall importance of product digitalization, we uncovered a high degree of heterogeneity across several dimensions. First, we showed that the positive effects largely pertain to overperformers in terms of productivity. In particular, by using complementary quantile regressions our results showed that only for firms above the 80%-quantile in the productivity distribution the results turned significant. This is in line with the evidence that digitalization efforts are usually far from frictionless and requires specific capabilities that only a-priori high-performers may possess. Second, we showed that the effects differ also by country of origin. Specifically, only firms located in countries identified as innovation pioneers by the Digital

Economy and Society Index (DESI) appeared to benefit from product digitalization. While the reasons for these patterns are not fully clear, one explanation may be that firms offering digital products rely also on digital infrastructure as well as developed markets for digital products, making the country-level institutional set-up an important driver of benefits derived from firm-level product digitalization activities.

Overall, our results emphasize the role of heterogeneity as concerns the effects of digitalization. This finding is indeed more surprising than it seems on first sight because our sample, by focusing on a relatively narrow set of high-tech sectors, actually removes larger parts of the sector-level heterogeneity that is usually implied by survey-based approaches. Thus, our results underline that heterogeneity is likely to an inherent issue in digitalization across a diverse set of dimensions even when trivial sources such as heterogeneity across sectors is controlled for, which underscores also that digitalization in firms is likely to be contingent of the specific firm-level context.

Our approach has a number of conceptual but also methodology-related limitations, which pave the way for future research.

First, we neatly isolated the effects of product digitalization while controlling for a generic measure of non-product-related digitalization processes. This latter measure however presumably does not have a straightforward interpretation, e.g. as measure of process digitalization. Indeed, it likely consists out of different dimensions related to processes, organisational practices and skills. This would require a much more in-depth, probably key-word-based approach to telling apart the specific sub-dimensions. The implied lack of conceptual clarity presumable does not affect negatively our ability to isolate the effects of product digitalization. However, it does not allow us to analyse for example how product or process digitalization relate to each other. Questions about complementarity or substitutability of different dimensions of digitalization therefore remain unanswered within the scope of this paper. However, they provide worthwhile avenues for future research, which appears, based on the proposed methodologies, to be principally feasible.

Second, the short duration of the project under which the analysis was performed, did not allow us to perform multiple web-scraping rounds. A more regular web-scraping approach instead would allow for the construction of panel data, which would deliver at least two important benefits. On the one hand, by resorting to panel data, it would be easier to control for unobserved heterogeneity, which may alleviate concerns about endogeneity. On the other hand, a panel data would allow for a cleaner analysis the implied lag-structure. While we do not expect substantial changes in the short-run, because web pages may, depending on the firm, reflect actual changes inside the firm only sluggishly, over the course of several years, they may convey valuable information on the speed of digitalization processes and on how fast performance effects emanate.

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