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Effects of Automatisation and Digitalisation on Manufacturing Companies' Production Efficiency and Innovation Performance

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1 Introduction

In recent years, the debate on the digitalisation of industry has gained momentum not only in the political, but also in the academic sphere. As part of a broader debate on the digitisation of life, it has touched upon many relevant dynamics of industrial transformation that will, without doubt, substantially affect the way in which production as such takes place as well as the role it plays in and for diverse value chains and innovation networks.

However, as much as the digitalisation debate addresses pertinent questions for future industrial innovation and production, much of it continues to suffer from a lack of clarity regarding both the very substance of the discussion and the factual consequences that it already develops in the industrial sphere. The first and arguably most pressing issue is that while the term "digitisation" succinctly captures a generic societal trend, it conveys comparatively little about the actual (catalogue of) technologies that we mean by it.

A debate that moves from a general observation of "digitisation" to a more focused analysis of "industrial digitalisation" can only then yield relevant results if it is specific about the concrete technologies involved and the concrete effects in industrial innovation and production that can be expected. In the majority of cases, specific papers like this one, will only be able to address spread and effect of a certain number of digital technologies.

So far, many parts of the discussion fail to deliver on these needs for differentiation not only with regard to the concrete technologies additionally deployed but also with regard to the changes in firm performance that they are supposed to trigger. While mutually related, industrial innovation and industrial production remain distinct areas on and in which the impact of "industrial digitalisation" needs to be studied separately as the set of concrete digital technologies which matter for them differs substantially.

Consequently, this paper suggests that it appears reasonable to distinguish between the diverse cause-effect relationships that occur in the course of the spread of digitalisation. These need to be clearly formulated with respect to their technological foundation as well as the area of industrial activity in which change is triggered. Hence, it proposes that a structured understanding of the broad dynamic of digitalisation that we are witnessing needs to be gradually built by hypothesising, confirming and disconfirming specific relationships.

Furthermore, it appears likely that "digitalisation" of industry will take effect gradually, in a step-by-step manner, as did all past breakthrough innovations from the introduction of the steam engine and, later, electricity into the production system to the various changes in the prevalent means of transportation that the past two centuries have witnessed. Typically, the invention of breakthrough technologies first spurred a development of more, related technologies before those technologies became fully implemented as prevalent means in the production system.

2 Conceptual framework

Since the end of the 18th century, technological development has been driving industrial performance and thus its dynamics. Nowadays, as never before, manufacturing companies need to be able to continuously offer flexibility combined with a high quality/price ratio. One of the crucial prerequisites for achieving and maintaining competitiveness on turbulent markets is the adoption and effective usage of a broad range of advanced manufacturing technologies (AMTs) (Bourke and Roper 2016; Swink and Nair 2007). Across the board, much of the existing literature recognises these technologies as drivers of competitive advantage, improving productivity, production speed, operating precision as well as energy and material consumption. Moreover, they are seen as innovation multipliers applied to facilitate development of new products (Task Force for Advanced Manufacturing on Clean Production 2014; High Level Group on Key Enabling Technologies 2010).

As a result of strong price competition, in particular due to substantially lower production costs in emerging economies, manufacturing companies have invested heavily into an upgrading of their production processes, including robotics, advanced automation and further digital technologies (Kromann et al. 2011; Bourke and Roper 2016). In advanced economies, this has led to a transition from labour intensive production to capital intensive flexible specialization even in the last remaining niches of the manufacturing sector (Kromann et al. 2011). In recent years, this trend towards automation and digitalisation of the manufacturing environment has been focusing on establishment of intelligent products and production processes (Oesterreich and Teuteberg 2016; Brettel et al. 2014) and, in a generic manner, become referred to as "Industry 4.0". Due to the potential benefits not least with regard to productivity, production lead time, and quality "industrial digitalisation" has received increasing attention in both academic and policy debates (Oesterreich and Teuteberg 2016) and on many accounts, come close to be regarded as a panacea.

In more concrete terms, "Industry 4.0" describes the digital upgrading of industrial **products** and **production processes** by using technologies of **automation** and **digi-**

talisation, as well as the increasing bridging between virtual and real worlds. In addition to increasing automation in production, which already began in the early 1970s, it incorporates smart processes that enable managing and controlling the production system within individual companies, as well as in complete value chains (Kagermann et al. 2013). Simultaneously managing products and the production system, Industry 4.0 applications enable a transformation of production, allowing faster, more flexible, and more efficient processes and higher-quality goods at reduced costs. This in turn increases both **manufacturing productivity** and **innovation capability** – ultimately changing the competitiveness on the market (Rüßmann et al. 2015; Oesterreich and Teuteberg 2016).

In order to increase competitiveness and business performance companies follow a great variety of innovation-based strategies (Tidd et al. 2013; Kirner et al. 2009). Depending on their concrete strategic ambitions, different types of innovations can be instrumental to achieve specific objectives (Horvat and Gust 2018; Dreher et al. 2006; OECD 2005). A fundamental and from different perspectives relevant distinction in this regard is that between product and technical process innovations (Subrahmanya 2005; Raymond et al. 2009). By developing new products, companies aim to improve and maintain their position in an existing market or establish it in an emerging one. By improving their processes, companies aim to increase productivity and efficiency, by lowering production cost but equally – and nowadays more commonly – by increasing flexibility, adaptability, and agility (Raymond et al. 2009; OECD 2005).

Against this background, this paper will distinguish between efforts to improve production efficiency through process innovation and efforts to improve innovation performance through product innovation. With regard to the former, the authors will further differentiate between effects resulting from advanced, yet still traditional automatisation and those resulting from a more comprehensive, systemically transformation by digitalisation of the production process. With regard to the latter, we will introduce a distinction between directly output oriented changes and those that seek to transform the internal set-up of the innovation process in the long run.

The findings of the paper contribute to the recent research from a threefold perspective. Firstly, by defining hypotheses regarding cause-effect relationships between concrete technologies and focused areas of expected impact. Secondly, by empirically testing whether the suspected impacts could be detected at a comparatively early point in time. Thirdly, by illustrating in which domain the effects of industrial digitalisation became traceable, with a view to production efficiency or with a view to innovation performance.

Research Question: Drivers of production efficiency

The last two decades substantial advances in electronics and information technology have contributed significantly to an increased automation of the manufacturing sector (Kagermann et al. 2013). Today, there are hardly any production processes without elements of programming predetermined sequences of operations and handling steps that are performed independently with little or no human intervention (Gupta and Arora 2007; Mittal and Nagrath 2003). In recent years, new digital technologies have additionally improved the effectiveness of automation making whole sequences of operations more flexible, smart and efficient. Hence, automation is recognized as a widespread and central component of modern factories, and as such considered as the most important driver of the technology-driven changes of society (Miller and Atkinson 2013).

The central element of any automated production is the industrial robot. According to the classical view, it represents a mechatronic device which is designed to automatically manipulate or transport parts or tools (Stauffer 1979). However, in the recent era of advanced digital technologies, industrial robots represent smart techniques that are "[a]n automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which can be either fixed in place or mobile for use in industrial automation applications" (IFR 2013).

In an "Industry 4.0" context, industrial robots become more autonomous, flexible, and cooperative parts of the production system (Kagermann et al. 2013). Moreover, they interact with one another and work safely side by side with humans (Rüßmann et al. 2015). From the comprehensive, company-wide perspective, the traditional robotisation of production is more and more often combined with e.g. automated warehouse management systems so that automatisation is less and less commonly limited to the technical process of production proper, but instead cover different areas of the internal organisation of production. From a management perspective, automatisation approaches become increasingly desirable for different applications due to sinking prices for complex solutions combined with disproportional increases in production efficiency.

The benefits of using robots are various, ranging from e.g. delivering superior quality to being able to work in hazardous environments (Beckert et al. 2016). Moreover, with new smart features based on digital technologies, the advanced robots transform the work place in a man-machine cooperative working environment, the so-called cyber-physical-systems (Robotics 2013; Kagermann et al. 2013). They simplify complex activities for production employees improving the process speed and product quality while simultaneously decreasing scrap rate (Kromann et al. 2011; Jäger et al. 2015) and therefore improving the manufacturing companies' productivity.

Furthermore, the discussion on production efficiency has been increasingly extended to the possibly beneficial influence of not directly automation related, more comprehensive digitalisation efforts (Kagermann et al. 2013; Chryssolouris et al. 2009; Matzler et al. 2016; Lerch et al. 2017).

First, in addition to the traditionally used sensors, actuators and robots have been complemented by techniques of augmented reality as well as virtual modelling and simulation of products and processes represent critical elements of the high flexibility in production (Posada et al. 2015; Macpherson et al. 2005; Brettel et al. 2014). Visual computing has become intensively used for acquiring, processing and visualising data for manufacturing system planning, design and reconfiguration along the entire product life-cycle (Posada et al. 2015). More than before, managers and engineers are in a position "to investigate the complexity of their systems and the way that changes in the system's configuration or in the operational policies may affect the performance of the system or organization" (Chryssolouris et al. 2009). Moreover, advanced systems for simulation or reconfiguration of production processes are increasingly used. Different from the abovementioned deployment of automisation in different areas of production organisation, these systems are capable of optimising diverse aspects pertaining to e.g. logistics, technological viability and customer specifications at the same time, moving internal automisation from a patchwork of individual solutions to an integrated company-wide approach to steering processes and coordinating material flows from supply to outbound delivery. Such a cross functional collaboration using digital technologies results in a smart manufacturing environment (Oesterreich and Teuteberg 2016), enabling flexible and reconfigurable systems in factories (Posada et al. 2015).

Second, it refers to technologies integrating and coordinating processes external to the firms, i.e. its interaction with customers and suppliers up and down the value chain (Raymond et al. 2009). The significance of such digital supply chain management systems that extend coordination beyond the internal organisation of production has heavily increased with a growing need for production according to customers' individual requirements. Relevant technologies facilitate data exchange and processing in vertical and horizontal networks, digital technologies and are considered to be key enabler of flexible and reconfigurable manufacturing systems (Kagermann et al. 2013) with increased performance achieved through optimized production processes. Facilitating integration across different actors of the value chain, digital technologies enable better cooperation with suppliers, customers, and distributers (Posada et al. 2015; Li et al. 2015). Such a closer collaboration with partners may contribute significantly to effectiveness of their resource, supply chain and logistics management system. Consequently, collaborative networks are supposed to encourage manufacturing companies' agility and adaptability to the requirements of volatile markets (Brettel et al. 2014).

Despite their projected benefits on production efficiency, however, many companies still struggle or hesitate to comprehensively implement digital technologies (Hirsch-Kreinsen et al. 2015). Many current studies observe that due to cultural and organisational barriers and a lack of knowledge about how to readjust business and management models (Liere-Netheler 2017). Hence, many processes of digitalisation come to a halt rather quickly or results in a substantial level of transaction costs to implement "fundamental changes" that "take time" (Carcary et al. 2017). Even where traditional automatisation is achieved, steps taken towards additional digitalisation may not results in immediate concrete benefits (Rüßmann et al. 2015).

Drivers of product innovation performance

As the market is characterised by an increasing variation and elaboration of customer needs, manufacturing companies are facing increasing demands with respect to product differentiation, adaptation and refinement that require internal development efforts (Brettel et al. 2014; OECD 2005). In this context, digital technologies can play a crucial role to increase effectiveness in product innovation with the objective of conceiving novel or elaborating varieties of existing solutions (Gausemeier et al. 2015; Brettel et al. 2014; Kagermann et al. 2013; Raymond et al. 2009; Ariss et al. 2000).

In the framework of a firm's research and development effort, digital solutions like idea management systems or advanced simulation tools can facilitate the acquisition and processing of product-specific technical knowledge, help feed in customer requirements and specification and thus expedite product conceptualisation and design. In this complex, but at the same time even shorter process, digital technologies – as tools of digital engineering – allow closing the gap between customer needs and requirements, product design and production, as well as marketing (Posada et al. 2015). In this case, the expected and partially already observed relation between the deployment of new technologies in the development process and the resulting improvements in efficacy is a rather direct one. Hence, the effects of the deployment of such technologies can be expected to positively affect the resulting extent of new products launched on the market (Rüßmann et al. 2015), even within a comparatively short time perspective.

Moreover, digital technologies can complement product lifecycle management (PLM) techniques that seek to enable an effective integration of product-related knowledge starting from the generation of ideas, the description of concepts, the analyses of business cases, product design and solution, technical implementation and testing, to the successful entrance to the market, service, maintenance and product improvement. In other words, the digitalisation of PLM enables the integration of the digital and real world from product design to manufacturing and customer relationship management (Kagermann et al. 2013). In the long term, this improved cooperation with customers during the whole product life cycle may additionally increase innovation performance (Li et al. 2015; Manyika et al. 2011; Kaufmann 2015). However, its impact logic is an indirect one, based on feedback loops between different stages of the innovation process. Hence, there is a structurally longer time horizon between the technology deployment and the analysis of its impacts.

3 Hypotheses

While the conceptual section has focused on introducing technologies commonly considered to prompt advances in production or innovation performance, the following section will specify how exactly production or innovation performance can be measured and, on that basis, expressly define hypotheses for further analysis.

Effects of efforts to increase production efficiency

In comparison to product innovation – which can be easily measured by referring to the presence of new products – assessing the effects of process innovations is a much more complex issue (Kirner et al. 2009). One of the main reasons is that process innovations cannot be directly linked to indicators like the *share of new products in overall sales*. Instead, they target process-related performance dimensions like speed, efficiency, and quality as "competitive imperatives" for firms in a globalised competitive market environment (Wheelwright and Clark 1992). Thus, process innovations affect the relation of overall outputs to inputs so that their effect can be gauged by measures of productivity (van Ark 2014). At the company level, two of the most common measures in that respect are labour productivity and total factor productivity (TFP) (Lay et al. 2009).

Labour productivity reflects the amount of value added generated per euro of labour cost. Hence, it takes a clear focus on the efficiency of human resources' use in companies.

In this paper, labour productivity is expressed in price terms as "valued added (turnover minus inputs of purchased parts, materials, operations and services) per employee" measured in thousand euros.

Total factor productivity takes into account the costs for labour and depreciation of machinery and equipment. Hence, it is influenced by other inputs like e.g. material, or capital. In this paper, TFP is stated as the value added (sales minus intermediate inputs) divided by the sum of labour costs and depreciation for machinery and equipment.

Hence, this paper will test the following three hypotheses with a view to digitalisation-based efforts to increase production efficiency

Hypothesis 1a: Automation and digitalisation are positively associated with manufacturing companies' labour productivity

Hypothesis 1b: Automation and digitalisation are positively associated with manufacturing companies' total factor productivity

Hypothesis 1c: Digitalisation will not (yet) reinforce effects of automatisation in either case as introducing advanced digital technologies is now to meet with organisational friction.

Effects of efforts to increase innovation performance

In general, the impact of firm-internal change on product innovation performance can be measured easier, product innovations can clearly be attributed to certain sections of a firm's outputs. In various innovation surveys and hence much of the related literature success in terms of product innovation is measured by the fact of whether any such product could be launched at all (within the past 3 years), the number of new products which could be launched on the market (within the past 3 years) and/or the share of business income that could be realised with the sale of newly launched products ((Kirner et al. 2009). In this paper, the first and the third will be taken up for the following reasons.

The fact of whether any new product could be launched on the market reflects whether any innovation process has successfully been performed and concluded in the respective manufacturing company. At a quite fundamental level, this indicator demonstrates whether a company is capable of innovating so that innovation becomes a strategic option.

The share of sales realised with newly launched products takes the assessment one step further towards an assessment of whether innovative products matter commercially for the respective firms. Other than the first indicator, it clearly distinguishes between firms for which innovation is a niche activity and those for which it is constitutive.

Hence, this paper will test the following two hypotheses with a view to digitalisation-based efforts to increase innovation performance

Hypothesis 2a: Digitalisation positively influences manufacturing companies' general ability to launch product innovations. This fundamental relation between digitalisation and a firm's innovation capability will not be influenced notably by intervening factors.

Hypothesis 2b: Digitalisation is positively associated with manufacturing companies' share of turnover with new products. However, the set-up of the company and the specific layout of its production process may constitute intervening factors.

4 Data and method

Data

We conducted our empirical research based on the *German Manufacturing Survey* 2012 (GMS) of the Fraunhofer Institute for Systems and Innovation Research (ISI), which is part of the *European Manufacturing Survey* (EMS). The objective of this regular, questionnaire-based postal survey is to systematically monitor manufacturing industries in Germany and their modernization trends. The survey addresses firms with 20 or more employees from all manufacturing sectors (NACE Rev. 2, 10-33). Questionnaires are completed by high-level representatives of the manufacturing sites, i.e. production or general managers (CEOs).

The *German Manufacturing Survey* was first launched in 1993 and is currently conducted every three years. In 2012, 15,383 firms in manufacturing industries were asked to fill in the questionnaire, of which 1,594 returned useable replies (Jäger and Maloca 2013). The dataset represents a cross-section of the manufacturing sectors. E.g. manufacturers of machinery and equipment represent 17% of the total, manufacturers of metal products 20%, firms of electronic and electrical products 11%, producers of chemical and rubber and plastic products 10%, and the remainder come from firms in other sectors such as paper and publishing, wood and woodworking, food processing, textiles and transport equipment.

The survey provides a large set of data on firms in manufacturing industry including information on their use of innovative production technologies, launch of new products, organizational practices, performance indicators and commonplace company data. Therefore, the survey enables the examination of the effects automation and digital technologies have on process performances and product innovation.

Dependent variables: Efficiency and performance indicators

As mentioned, this paper will measure company-level **production efficiency** in terms of "labour productivity" and "total factor productivity". As scientific measures, these figures are not directly collected through the GMS questionnaire. To produce them, the authors processed information from questions on the "annual turnover 2011 (million euros)", the "number of employees of your firm in 2011" and the extent of "procured services and materials 2011 (million euros)". Based on this information, firm-level value added figures ("value added per employee (1,000 euros)") could be calculated and used in the analyses. Taking into account information from further questions on "overall labour cost (million euros)" and the "depreciation of machinery and equipment (million euros)" the two abovementioned productivity indicators could be swiftly and reliably calculated.

As mentioned, this paper will measure (product) **innovation performance** from two perspectives. First, the "fact whether any new product could be launched" was operationalised through the GMS question "*Has your factory introduced products since 2009 that were new to your factory or incorporated major technical changes? (e.g. application of new materials, modifications in product function, modifications in principles of operation, etc.)*". Second, the relevance of the "share of sales realised with newly launched products" was taken into account by distinguishing between firms which did not introduce any new products, firms which realize a very low share with their new products and firms which realize at least five percent of their turn-over with new products. The threshold between the two latter categories represents the lower 25 percentile of all firms which successfully offer new products on the market based on their answer to "*What share of turnover did these products have in 2014?*". Table 1 below gives a descriptive overview of the dependent variables.

Table 1: Descriptives of Dependent Variables

General Construct	**Indicator**	**Mean (Std. Dev.) / of firms**	**Percentile**			**Valid N**
			5%	**50%**	**95%**	
production efficiency	Labour productivity [1,000 € VA per employee]	92,9 (61,1)	33,3	80,7	187,5	1,109
	Total factor productivity	1,850 (0,953)	0,923	1,630	3,438	0,973
innovation performance	Share of product innovators [%]	59%				1,522
	Share of significant product innovators [%]	37%				1,480

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI.

Independent variables: main explanatory factors

As mentioned above, responses to the GMS collect direct information on whether a manufacturing firm deploys certain technologies or not by asking the respondents to provide information on a closed list of possible technologies. Additionally, the "extent of actual utilization compared to the most reasonable potential utilization in the factory" is captured. The following operationalisation is build on statements that the technology is already in full use (rather than e.g. being in the early phases of being implemented or piloted). Where two technologies are listed, the resulting indicator was construed based on the "or" principle of either technology being used.

As implicitly mentioned in the conceptual section, the authors propose that two key type technologies can be selected to operationalise classic, non-integrated automatisation:

- Industrial robots/handling systems in manufacturing and assembly, and
- Automated warehouse management systems (WHS).

The resulting aggregate variable is "*automatisation*".

With respect to more advanced digitalisation that either reaches beyond the limits of the firm or substantially increases the integration of its internal organisation of production, two main technologies appear as suitable proxies among an arguably larger range:

- Technologies for digital exchange of operation scheduling with data suppliers/customers (supply chain management systems), and
- Technologies of virtual reality and/or simulation in production reconfiguration.

The resulting aggregate variable is "*digitalisation (in production)*".

To take into account that both technologies may have an interplay while affecting the production efficiency, and indicator for interaction effects (*digitalisation*automation)* has been included to differentiate those firms which invested in both technologies from those who did not.

Concerning digital technologies aimed at increasing innovative capacity, two groups of digital technologies, were selected which facilitate the development of products from idea generation to product design and simulation of functionalities:

- IT systems for storage and management of ideas (idea management systems),
- Virtual reality and/or simulation in product design and development.

The resulting aggregate variable is "*digitalisation (in product innovation)*".

Furthermore, firms' efforts to restructure their innovation processes with a long term perspective was reflected by considering responses to the question whether it implements "product lifecycle management processes".

The resulting variable is "*product lifecycle management*".

Table 2 provides a descriptive overview of the use of these technologies in German manufacturing.

Table 2: Descriptives of Independent Variables

General Construct	Indicator	Mean (Std. Dev.) / % of firms	Percentile			Valid N
			5%	50%	95%	
improving production efficiency	Automatisation	39%				1,504
	Digitalisation (production)	38%				1,488
	Automatisation * Digitalisation	15%				1,480
improving innovation performance	Digitalisation (innovation)	8%				1,480
	Product life cycle management	8%				1,459

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI.

Independent variables: control variables (generic)

As is common in industrial studies, the authors control for *sectoral attribution*, *firm size* and *export orientation* which are commonly known to influence both production efficiency and innovation performance (Kirner et al. 2009; Jäger et al. 2015). Additionally, the GMS data enables us to introduce *product complexity* as a further factor likely to have a substantial impact on the nature of relevant production and development processes (Kinkel and Maloca 2010; Jäger et al. 2015) and would hence in both cases be an intervening factor distracting from the focus of the analysis.

Independent variables: control variables (production efficiency)

In the relevant literature, it has been unambiguously established that production efficiency does not only depend on the abovementioned, more generic factors but is specifically, and more than other performance measures susceptible to the *batch sizes* that the firms typically produces (internal economies of scale, Jäger et al. 2015), the position of the firm in the *value chain* (concentration of value creation at certain steps of the production chain, (Kirner et al. 2015a) and, as proxy for the knowledge, capital or labour orientation of its business model (which directly influences the relation of value added to hours works), as well as the *average qualification level of the employees*.

Table 3: Descriptives of Control Variables

Indicator	Mean (Std. Dev.) / % of firms	Percentile 5%	Percentile 50%	Percentile 95%	Valid N
ln firm_size Log of number of employees	4.4 (1.1)	4.2	3.1	6.5	1,535
sec 1 Food etc. sector (10 - 12)	9%				136
sec 2 Chemical industry (20, 21)	5%				70
sec 3 Rubber and plastics (22, 23)	16%				248
sec 4 Metal industry (24, 25)	22%				341
sec 6 Electronic/Electric industry (26, 27)	11%				169
sec 7 Automotive industry (29, 30)	3%				51
sec9 Other manufacturing sectors	17%				258
Reference category: Machinery (28)	17%				262
batch_single Simple products	20%				1,489
batch_smallmid Products with medium complexity	50%				1,489
Reference category: Complex products	30%				1,489
No export	13%				1,379
ln export_quota Log. of share of export [%]	2.8 (1.4)	3,2	,0	4,4	1,379
Single unit production	27%				1,492
Small or medium batch/lot	55%				1,492
Reference category: Large batch/lot	18%				1,492
value_chain Final producer for industrial business	42%				1,527
z-val_share_highqual Share of qualified personel (z transformed)	0 (1.0)	-0.23	-1.07	2.31	1,430
z-val_share_noqual Share of semiskilled and unskilled workers (z transformed)	0 (1.0)	-0.41	-1.01	2.08	1,430
comp_by_innovation Innovative products as one of the most important competitive factors	37%				1,435
dev_by_cust_spec Product development according to customers' specification	54%				1,372
no_randd Share of non R&D performing firm	54%				1,515
ln randd Log of share of R&D expenditure	0.6 (1.0)	0.0	0.0	2.3	1,452

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI.

Independent variables: control variables (innovation performance)

In turn, the relevant literature on business innovation unambiguously demonstrates that in manufacturing firms' inclination to innovate depends on the *innovation orientation of their business model (Kirner et al. 2015b)*, the *openness of their product development process* (Som et al. 2014) and the *presence and extent of research and development (R&D) investment* in the firm which could prompt and sustain activities in the field of product development (Kinkel et al. 2005). While in the model analysing the presence of innovation activities, only the presence of R&D investment will be controlled for, the model analysing the extent of innovation activities will consequently also consider the extent of R&D investments.

Table 3 provides a descriptive overview of these indicators used in our multiple regression models.

Method

With a view to production efficiency, all relations could be analysed in standard OLS regression models, as both of the dependent variables are metric. For added value, a logarithmic transformation has been applied as the indicator is too far away from being normally distributed. Using the transformed indicator the model requirements of homoscedasticity is met.

With a view to the mere presence of innovation activity, relations had to be analysed by means of a logistic model, as the dependent variable is dichotomous.

With a view to the extent of innovation activity, we chose to classify firms in three groups of non-innovators, moderate innovators (below 5% of sales, lower 25% percentile) and strong innovators (above 5% of sales). Hence, the analysis had to be conducted by means of an ordinal regression. The assumption of Proportional Odds has been tested by additional multinomial logistic regressions.

In general, all regression analyses were first run with a limited number of basic control variables, to explore if the relation in question could at all be detected (those being: firm size, sector, product complexity and, in the case of production efficiency, batch size). Subsequently, the models were extended by all further abovementioned control variables, to investigate how robust the detected impact of digitalisation remains, even when controlling for relevant other known factors.

5 Results

Concerning hypothesis 1a

With a view to hypothesis 1a, model A1.1 (cf. table 4) documents a clear and positive impact of relevant digitalisation on productivity, even when controlling for sectors, firm size, product complexity and batch size. It is not, however, equally significant or strong as the impact of traditional automatisation, i.e. the introduction of robots to the production process. When final producer, export orientation and the qualification of employees are introduced as further controls (model A1.2), the overall picture becomes even more robust. Both automatisation and digitalization display statistically significant, positive effects – with the regression coefficient for automatisation once more notably higher. Moreover, the negative interaction effect becomes statistically significant, underscoring that the parallel use of robots and digital technologies to increase production efficiency did in 2012 indeed result in a considerably smaller positive impact on productivity. With 0.078 or 0.153 the adjusted R^2 of models A1.1 and A1.2 are relatively high. Not surprisingly, several control variables do affect labour productivity additionally to automatisation and digitalisation.

Concerning hypothesis 1b

With a view to hypothesis 1b, model A2.1 (cf. table 5) documents that when controlling for sectors, firm size, product complexity and batch size, a positive effect on total factor productivity can only be documented for automatisation, not for the use of digital technologies to increase production efficiency. Even the effect associated with the use of robots is only statistically significant at the 10% level. As a tendency the use of digital technologies to increase production efficiency is again positive while the interaction effect is negative, but neither of them is statistically significant. When final producer, export orientation and the qualification of employees are introduced as further controls (model A2.2), even the effect associated with the use of automatisation technologies loses its significance. In general terms, the regression coefficients still point into directions consistent with the other models, but it has to be concluded that the implementation of digital technologies to increase production efficiency did not exert any statistically significant effects on total factor productivity in 2012. This, however, has to be seen in the context of the fact that total factor productivity is by definition subject to a number of other factors (wages, prices, etc.) that are not directly controlled for in the model, resulting in low levels of adjusted R^2 and a limited prevalence of statistically significant effects also among the control variables. According to the model, total factor productivity is associated with sectoral differences, positively related to export orientation as well as to the share of highly qualified personnel.

Concerning hypothesis 1c

The interaction effect between digitalisation and automatisation is negative. Even more clearly than expected, the model documents that the parallel use of robots and digital technologies to increase production efficiency does not provide any positive amplification, but seems to have caused interferences, resulting in a reduced impact of both technologies on productivity.

Concerning hypothesis 2a

With a view to hypothesis 2a, model B1.1 (cf. table 6) documents that when merely controlling for sectors, firm size, and product complexity, the use of digital technologies to improve innovation capacity does significantly increase the odds that a specific firm introduces (any) new products. The use of product lifecycle management processes, in contrast, is not associated with a similar positive effect. Clearly, the use of digital technologies to improve innovation capacity does thus cause an effect that other approaches do not to the same extent. Remarkably, the effect remains stable even when further controls with respect to other characteristics that are relevant for the uptake of innovation activities are introduced (model B1.2). In concrete terms, even after controlling for competitive strategy, export orientation, value chain position and R&D activity, the effect of the use of digital technologies to improve innovation capacity remains statistically significant. Again, no comparable effect can be found resulting from the use of product lifecycle management technologies. With a Nagelkerke R^2 of 0.290 and several statistically significant predictors for the uptake of innovative activity, model B1.2 can be considered as relatively comprehensive and the continued significance of the effect attributed to the introduction of digital technologies to improve innovation capacity can be interpreted as an indication that it did have a robust and notable effect in 2012.

Concerning hypothesis 2b

With a view to hypothesis 2b, model B2.1 (cf. table 7) documents that under control for sectors, firm size, and product complexity, the use of digital technologies to improve innovation capacity not only does impact whether a firm uptakes on product innovation, but also seems to have a statistically significant impact on the extent of turnover realized with innovative products and solutions while the introduction of product lifecycle management approaches, as above, did not matter. When introducing further controls for competitive strategy, export orientation, value chain position and R&D activities (model B2.2), however, the effect of digitalisation in product innovation still points in a consistent direction but the estimation decreases and becomes statistically insignificant. Most of the additional variables known to be relevant for the uptake of innovation activities were of significant effect as in the models for the introduction of (any) new products. Additionally, the R&D expenditures turned out to be an important factor. In contrast, a separate effect for the deployment of digital technologies to improve innovation was not detected in 2012.

Overall, the ordinal model reaches a Nagelkerke R^2 of 0.249, similar to the above logistic model's 0.290. In principle, models B2.1 and B2.2 indicate that there could have indeed been an emerging effect of digital technologies to improve innovation capacity, but it could at that time not be detected independently from the more directly relevant effects of competitive strategy, and R&D activities.

To validate the findings of the ordinal regressions for model B2.2, multinominal logistic regressions were conducted on the same sets of variables as well as separate logistic regression models for each threshold. Special attention was put on testing the appropriateness of the assumption of proportional odds. This test is known that it nearly always results in rejection of the proportional odds assumption particularly when there is a continuous explanatory variable in the model (O'Connell Ann A. 2006). Overall, the test results did not deviate markedly from those illustrated in Table 7. Interestingly, they point to the fact that digitalisation to improve innovation capacity is mainly affecting the threshold between non-innovators and firm which uptake on product innovation, but does not yet impact on the amount of innovation output.

Table 4: Linear regression models of effects on labour productivity

dV: ln_value added	**Model A1.1**				**Model A1.2**			
	β	Coef.		Std. Err.	β	Coef.		Std. Err.
sec1 (NACE 10, 11, 12)	-0.042	-0.086		0.078	0.055	0.116		0.085
sec2 (NACE 20 21)	0.123	0.322	***	0.090	0.139	0.359	***	0.090
sec3 (NACE 22 23)	-0.030	-0.043		0.062	0.065	0.093		0.064
sec4 (NACE 24 25)	-0.059	-0.077		0.056	0.081	0.105	*	0.060
sec6 (NACE 26 27)	-0.051	-0.090		0.066	-0.046	-0.079		0.068
sec7 (NACE 29 30)	-0.064	-0.201	*	0.104	-0.008	-0.023		0.103
sec9 other NACE	-0.101	-0.145	**	0.061	-0.008	-0.011		0.063
ln firm_size	0.130	0.073	***	0.019	0.077	0.043	**	0.020
prod_comp_simple	0.011	0.014		0.052	0.109	0.144	***	0.054
prod_comp_medium	-0.022	-0.024		0.041	0.079	0.085	*	0.042
batch_single	-0.082	-0.102	*	0.055	-0.093	-0.116	*	0.058
batch_smallmid	-0.099	-0.109	**	0.046	-0.088	-0.096	*	0.047
value_chain					0.072	0.079	**	0.035
no_export					0.014	0.024		0.078
ln export_quota					0.195	0.076	***	0.020
z-val_share_highqual					0.162	0.099	***	0.022
z-val_share_noqual					-0.105	-0.059	***	0.020
automatisation	**0.117**	**0.131**	*****	**0.041**	**0.131**	**0.146**	*****	**0.042**
digitalisation (production)	**0.067**	**0.075**	***	**0.042**	**0.087**	**0.098**	****	**0.042**
automisation*digitization	**-0.063**	**-0.097**		**0.061**	**-0.088**	**-0.133**	****	**0.061**
Constant		4.149		0.119		3.837		0.136
Sector Dummies	YES				YES			
Observations	1,035				919			
R^2 adjusted	0.078				0.153			
Sig.	.000				.000			

Significance Level: ***p<0.01, **p<0.05, p<0.1

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI. Own analysis.

Table 5: Linear regression models of effects on total factor productivity

dV: Total Factor Productivity	Model A2.1				Model A2.2			
	β	Coef.		Std. Err.	β	Coef.		Std. Err.
sec1 (NACE 10, 11, 12)	0.072	0.113	*	0.068	0.148	0.233	***	0.074
sec2 (NACE 20 21)	0.059	0.120		0.077	0.069	0.135	*	0.079
sec3 (NACE 22 23)	0.035	0.040		0.055	0.079	0.090		0.058
sec4 (NACE 24 25)	-0.036	-0.037		0.050	0.045	0.045		0.054
sec6 (NACE 26 27)	-0.080	-0.112	*	0.059	-0.077	-0.103	*	0.061
sec7 (NACE 29 30)	-0.050	-0.123		0.090	-0.005	-0.011		0.092
sec9 other NACE	0.034	0.038		0.053	0.063	0.069		0.057
ln firm_size	0.038	0.017		0.017	0.010	0.005		0.018
prod_comp_simple	0.027	0.028		0.045	0.076	0.078		0.048
prod_comp_medium	-0.018	-0.016		0.036	0.044	0.037		0.038
batch_single	0.029	0.029		0.048	0.031	0.030		0.051
batch_smallmid	0.016	0.014		0.040	0.004	0.004		0.041
value_chain					0.055	0.048		0.031
no_export					0.015	0.020		0.069
ln export_quota					0.118	0.036	**	0.018
z-val_share_highqual					0.082	0.039	**	0.019
z-val_share_noqual					-0.021	-0.009		0.017
automatisation	**0.073**	**0.064**	*****	**0.036**	**0.066**	**0.057**		**0.037**
digitalisation (production)	**0.024**	**0.022**		**0.037**	**0.021**	**0.018**		**0.038**
automisation*digitisation	**-0.010**	**-0.012**		**0.053**	**-0.016**	**-0.019**		**0.055**
Constant		0.391		0.103		0.258	**	0.121
Sector Dummies		YES				YES		
Observations		908				814		
R^2 adjusted		0.016				0.031		
Sig.		0.013				0.001		

Significance Level: ***p<0.01, **p<0.05, *p<0.1

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI. Own analysis.

Table 6: Logistic regression models of effects on odds being product innovator

dV: new products y/n	**Model B1.1**				**Model B1.2**			
	Coef.	Exp (B)		Std. Err.	Coef.	Exp (B)		Std. Err.
sec1 (NACE 10, 11, 12)	-0.419	0.658	*	0.254	0.115	1.121		0.341
sec2 (NACE 20 21)	0.123	1.131		0.324	0.190	1.209		0.416
sec3 (NACE 22 23)	-0.370	0.691	*	0.213	-0.132	0.876		0.264
sec4 (NACE 24 25)	-0.964	0.381	***	0.197	-0.406	0.666		0.252
sec6 (NACE 26 27)	0.045	1.046		0.239	0.115	1.122		0.298
sec7 (NACE 29 30)	-0.867	0.420	**	0.359	-0.476	0.621		0.429
sec9 other NACE	-0.448	0.639	**	0.211	-0.002	0.998		0.266
ln firm_size	0.344	1.411	***	0.063	0.157	1.170	*	0.082
prod_comp_simple	-0.536	0.585	***	0.176	0.148	1.160		0.232
prod_comp_medium	-0.263	0.769	*	0.140	-0.002	0.998		0.173
comp_by_innovation					0.827	2.286	***	0.161
no_export					-0.371	0.690		0.339
ln export_quota					0.086	1.090		0.085
value_chain					0.370	1.447	**	0.151
dev_by_cust_spec					-0.409	0.664	***	0.153
no_randd					-1.317	0.268	***	0.153
digitalisation (innovation)	**0.833**	**2.300**	*******	**0.300**	**0.819**	**2.269**	******	**0.379**
product lifecycle managmt	**0.237**	**1.267**		**0.272**	**0.412**	**1.510**		**0.377**
Constant	-0.535	0.586		0.330	0.206	1.229		0.526
Sector Dummies		YES				YES		
Observations		1,402				1,102		
R^2 (Cox & Snell)		0.980				0.211		
R^2 (Nagelkerke)		0.132				0.290		
Hosmer-Lemeshow		0.727				0.547		

Significance Level: ***p<0.01, **p<0.05, *p<0.1

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI. Own analysis.

Table 7: Ordinal regression models of effects on odds being significant product innovator

dV: Significant product innovator (3 cateogries)	**Model B2.1**			**Model B2.2**		
	Estimator		Std. Err.	Estimator		Std. Err.
sec1 (NACE 10, 11, 12)	-0.430	*	0.223	0.183		0,293
sec2 (NACE 20 21)	-0.004		0.262	0.009		0,332
sec3 (NACE 22 23)	-0.357	*	0.181	-0.149		0,226
sec4 (NACE 24 25)	-0.900	***	0.169	-0.399	*	0,216
sec6 (NACE 26 27)	0.015		0.192	0.020		0,248
sec7 (NACE 29 30)	-0.705	**	0.298	-0.410		0,366
sec9 other NACE	-0.386	**	0.179	0.038		0,227
ln firm_size	0.233	***	0.052	0.060		0,070
prod_comp_simple	-0.609	***	0.159	-0.087		0,204
prod_comp_medium	-0.209	**	0.120	0.057		0,151
comp_by_innovation				0.736	***	0,136
no_export				-0.355		0,312
ln export_quota				0.110		0,075
value_chain				0.255	*	0,131
dev_by_cust_spec				-0.332	**	0,133
no_randd				-0.855	***	0,177
ln randd				0.285	***	0,094
digitalisation (innovation)	**0.452**	**	**0.230**	**0.211**		**0,268**
product lifecycle managmt	**-0.071**		**0.222**	**-0.017**		**0,275**
Sector Dummies	YES			YES		
Test of parallel lines	0.002			0.000		
Observations	1,365			1,038		
R^2 (Cox & Snell)/(Nagelkerke)	0.083/0.094			0.222/0.252		
Chi2 (df)/Sig.	117,938 (12)/0.000			260,442 (19)/0.000		
Thresholds						
[prodinno25 = -1]	0.101		0.289	-0.203		0.472
[prodinno25 = 0]	1.002***		0.289	0.874*		0.472

Significance Level: ***p<0.01, **p<0.05, *p<0.1

Source: *German Manufacturing Survey* 2012, Fraunhofer ISI. Own analysis.

6 Discussion

With a view to the conceptual introduction, the above findings have interesting implications at several levels of analyses.

First, they underline that digitalisation is neither a new trend nor one that is too early a stage to monitor and analyse. Even in 2012, and under substantial controls, relevant impacts on both production efficiency and innovative performance could be detected.

Second, they corroborate the premise that "digitalisation" is not a homogeneous trend but that different sets of digital technologies matter for different purposes. While both digital technologies to increase production efficiency and digital technologies to increase innovative performance were found to create impact in 2012, they did so only in their respective domain. Further validation, not documented here, unsurprisingly demonstrated that e.g. digital technologies to increase production efficiency did not have any notable effect on the innovative performance of firms.

Thirdly, however, the findings highlight that there is a general danger to attribute more effects to digitalisation than actually pertain to the introduction of these technologies. Irrespective of whether the effects of digitalisation eventually remained statistically significant, all models highlighted a number of additional factors as valid predictors of production efficiency or innovative performance. In all of them, these variables contributed more to the explanatory power of the models than the effects of digitalisation. As could be expected, digitalisation is but one, even if central, factor in the production process that is and remains contingent on others.

Fourth, digital technologies become embedded in a pre-existing framework of earlier approaches to increase production efficiency or innovative performance. In the case of production efficiency, classic automatisation was still found to be very effective. Likewise, the in theory more directly effective approaches to improve innovative performance were indeed found to display first effects, while the more complex and long term oriented like product lifecycle management did not yet reflect any notable change triggered by the introduction of new technologies.

Fifth, various perspectives on our findings illustrate that the uptake and deployment of digital technologies remained incomplete or at least less than fully effective in 2012. When considering more comprehensive indicators as dependent variables, the effects were typically much weaker. Although digitalisation has a first robust impact of simple, straightforward measurements of productivity or innovative performance, the prompted effects were not yet dominant or in place long enough, to remain detectable in measures like total factor productivity or turnover with innovative product that are subject to a much broader range of additional factors of influence.

Sixth, the finding that the positive effects of automatisation and digitalization did in 2012 not yet mutually reinforce but instead interfere with each other confirms the notion of a not always seamless integration of digitalization into existing production set-ups and questions the sometimes evoked image of companies moving smoothly through subsequent stages of firm level modernization. Instead, it raises notions of parallel introduction, imperfect replacement and transaction costs associated with gradual processes of learning. Having shown elsewhere that this paper's analysis reflects an early stage of the digitalisation process, however, the assumption remains that this mutual relation will eventually have changed meanwhile.

7 Conclusions

In summary, the findings emphasise that an empirically sound analysis of the effects of digitalisation is possible only when the concrete nature and purpose of technologies subsumed under the heading of "digitalisation" are defined clearly.

Based on one of the most robust and comprehensive data sources available for the German manufacturing sector, this paper demonstrates that and how it is possible to disaggregate and thus operationalise "digitalisation" in terms of concrete technologies deployed for specific purposes. It illustrates that, while there is indeed an overarching trend of digitalisation, it is made up of multiple composite parts and streams that effect the internal organisation and performance of firms as we know it at different leverage points.

Consequently, the analysis emphasises that the uptake of different digital technologies is embedded in and interrelates with other technologies that are deployed for similar functional purposes. Different to prevalent claims, this paper demonstrates that the process of uptake and integration in existing production need not necessarily be smooth, but can – at least for an initial period – be characterised by transaction cost, mutual interference and organisational friction that impedes, rather than improves production efficiency. With a view to digital technologies aimed at improving innovation performance the analysis found indications that as such known management methods like PLM, who are often implicitly assumed to be digitised and effective in "new value networks" may, in reality, need more time to develop this effectiveness than commonly assumed.

Overall, this paper provides ample evidence to not unrealistically expect a revolution in production and innovation when what we will see is a gradual – if fast and relentless – uptake of technologies into existing production and innovation chains. At the time of observation, their main contribution lay in the fact that they prompted activities and spurred change where incumbent approaches had not. From a commercial perspective, however, many other factors remained more directly important. Even though time has passed since, these differentiated findings on the origins of industrial digitalisation remains relevant for current studies, not least of "follower" countries and regions. Certainly, however, the swift development of the digital sector suggests that, for Germany, this or a similar study be repeated with more current data as soon as possible.

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