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Researching the Effects of Automation and Digitalization on Manufacturing Companies' Productivity in the Early Stage of Industry 4.0

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Abstract

In recent years, great expectations have developed concerning the digitalization of industry and its potential to increase manufacturing performance. The terminology currently used in this context indicates that exponential advances are expected. Concrete case studies, however, suggest that there are in fact many forms of digitalization that need to be considered separately. Moreover, it appears that simply integrating digital technologies into production does not automatically imply increased productivity and rarely occurs as a frictionless process. Finally, anecdotal evidence suggests that digitalization occurs as part of a systemic effort, so that its specific contribution may be overrated. In this paper, we present the findings of our research into the effects of advanced manufacturing technologies (relevant for Industry 4.0) on production performance. Focusing on the early stages of digitalization, when the political term "Industry 4.0" became fashionable, we conducted an analysis based on a dataset from the Fraunhofer Institute for Systems and Innovation Research's 2012 *German Manufacturing Survey*. In addition to confirming the generally positive effects of automation technologies at that time, our results show that, while certain effects are indeed directly attributable to digitalization, these did not emerge without preconditions on their own. Furthermore, the results suggest that the "digitalization" of industry has progressed gradually, in a sequence of steps, as was the pattern for the introduction of all past breakthrough technological innovations into the production system, from the steam engine to electricity. Typically, the invention of breakthrough technologies first spurs the development of other, related technologies before these technologies become prevalent in the production system.

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1. Introduction

Depending on the context, the now fashionable term ‘digitalization’ relates to different aspects of socioeconomic activity. In manufacturing companies, it refers particularly to upgrading production processes, i.e. integrating robotics, advanced automation and other digital technologies [1–3]. In addition to the classical automation of production, which began in the early 1970s, digitalization incorporates smart processes that enable firms to manage and control their internal production system as well as their involvement in value chains [4]. In recent years, the trend towards the digitalization of the manufacturing environment that focuses on establishing intelligent production processes [3,5,6] is generally referred to as “Industry 4.0”.

This term was first coined at Germany’s HANNOVER MESSE in 2011. Due to its potential benefits, not least with regard to productivity, production lead time and quality, it has received increasing attention in both academic and policy debates [5]. On many accounts, it has come close to being regarded as a panacea once the discussion extended to the potentially beneficial influence of comprehensive digitalization efforts beyond automation [4,7,8]. Despite the projected benefits for production efficiency, however, many companies have continued to struggle or hesitate to implement digital technologies [9]. Findings from the existing literature suggest that this is due to cultural and organizational barriers and a lack of knowledge about how to adapt business models [10–12]. Even today, many processes of digitalization are abruptly halted or result in substantial transaction costs [13]. Even in production environments that are substantially automated in the traditional sense, steps taken towards additional digitalization may not result in immediate concrete benefits [14].

Against this background, we were interested in analyzing the effects of smart manufacturing- or Industry 4.0-relevant technologies in the German manufacturing sector during the early 2010s when the concept of Industry 4.0 was heavily promoted both politically and practically. For this period of transformation, we analyze the differences between the effects resulting from advanced, yet still traditional automation technologies, and those resulting from an emerging, more comprehensive digitalization in production processes.

Our findings contribute to the existing literature from two perspectives. First, by testing whether the purported impact of Industry 4.0-relevant technologies on selected aspects of manufacturing performance could already be detected during the early 2010s. Second, by illustrating in which domain the effects of industrial automation and digitalization are traceable with regard to production productivity.

2. Effects of efforts to increase production efficiency

In comparison to product innovation success – which is directly reflected in the market launch of new products – advances in process innovations are more difficult to trace and document [15]. One of the main reasons is that they cannot be measured directly using indicators like the *share of new products in overall sales*. Instead, process innovations target performance dimensions like speed, efficiency, and quality as "competitive imperatives" for firms in a globalized market environment [16]. At company level, two of the most common measures are labor productivity and total factor productivity (TFP) [17,18].

Labor productivity reflects the amount of value added generated per euro of labor cost. There is a clear focus here on the efficiency of using human resources in companies. In this paper, we define labor productivity in price terms as "valued added (turnover minus inputs of purchased parts, materials, operations and services) per employee" measured in thousand euros. This provides a very direct reflection of (technical) production efficiency. **Total factor productivity** takes into account the costs for labor and the depreciation of machinery and equipment. It is therefore influenced by other inputs, e.g. material, or capital. In this paper, TFP is given as the value added (sales minus intermediate inputs) divided by the sum of labor costs and depreciation for machinery and equipment. Thus, it is a more indirect outcome of production efficiency that - in spite of different intervening factors - only changes significantly if substantial and sustainable changes have been made to a specific firm's production process over time.

In light of these indicators and the different functions and potentially different expectations that could be derived from them, this paper tests the following two main hypotheses:

Hypothesis 1*: Even during its early uptake, digitalization was positively associated with labor productivity in manufacturing companies*

Hypothesis 2: *Even during its early uptake, digitalization was positively associated with the total factor productivity of manufacturing companies*

Given that, even in the early 2010s, companies rarely started from a level playing field, and the fact that the literature has found technological uptake to depend on pre-existing production environments [3–5,8,12,19], we add a third hypothesis:

Hypothesis 3*: The presence of pre-existing activities to improve production efficiency (such as traditional automation) should facilitate the introduction of digital technologies in manufacturing firms.*

3. Data and methodology

To analyze which effects automation and digitalization were already having on manufacturing companies' performance at the time when Industry 4.0 was more commonly promoted, we conducted empirical research based on data from the *German Manufacturing Survey* 2012 (GMS), compiled by the Fraunhofer Institute for Systems and Innovation Research (ISI). 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 at 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 manufacturing firms were asked to fill in the questionnaire, of which 1,594 returned useable replies [20]. The dataset represents a cross-section of the manufacturing sectors: machinery and equipment make up 17% of the total, metal products 20%, electronic and electrical products 11%, chemical, rubber and plastic products 10%, and the remainder are 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 the manufacturing industry including information on their use of innovative production technologies, the launch of new products, organizational practices, performance indicators and general company data. Therefore, the data enable us to examine the effects that automation and digital technologies have on manufacturing process performances.

Dependent variables: Efficiency and performance indicators

As justified in the conceptual section, we measure firms' **production efficiency** in terms of "labor productivity" and "total factor productivity". These figures were not collected directly by the GMS questionnaire but calculated by processing 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)". We obtained the two above mentioned productivity indicators at firm level based on this information, calculated firm-level value added figures ("value added per employee (1,000 euros)") and considered information from further questions on "overall labor cost (million euros)" and the "depreciation of machinery and equipment (million euros)".

Independent variables: main explanatory factors

The GMS collects information on whether a manufacturing firm deploys certain technologies or not by asking the respondents to provide answers to a closed list of possible technologies. The survey also captures the "extent of actual utilization compared to the most reasonable potential utilization in the factory". We constructed the following operationalization based on statements that the technology is already in full use (rather than in the early phases of being implemented or piloted). Where two technologies are listed, we defined the resulting indicator based on the "or" principle of either technology being used.

We propose that two key type technologies can be selected to operationalize traditional, non-integrated automation: Industrial robots/handling systems in manufacturing and assembly, and automated warehouse management systems (WHS). We refer to the resulting aggregate variable as "*automation*".

Among an arguably larger range, two main technologies appear to be suitable proxies for more advanced digitalization that extends beyond the limits of the firm or substantially increases the integration of its internal organization of production: Technologies for the digital exchange of operation scheduling with data suppliers/customers (supply chain management systems), and technologies of virtual reality and/or simulation in production reconfiguration. We refer to the resulting aggregate variable as "*digitalization (in production)*".

To address Hypothesis 3, we included the indicator for interaction effects (*digitalization*automation)* in our analysis to differentiate firms investing in both technologies from those that did not.

Independent variables: additional factors

As is common in studies of industrial performance, we control for *sectoral attribution*, *firm size* as well as *export orientation including the share* of *exports, all of* which are known to influence technical production efficiency [15,21]. Additionally, the GMS data enable us to introduce *product complexity* as another factor likely to have a substantial impact on the relevant production processes [21,22] and therefore likely to be an intervening factor in both cases.

The relevant literature has unambiguously established that production efficiency not only depends on the above mentioned, more generic factors, but is influenced specifically, and more so than other performance measures, by the *batch size* that the firms typically produce [internal economies of scale, 21], the position of the firm in the *value chain* (concentration of value creation at certain steps of the production chain, [23] and, as proxy for the knowledge, capital or labor orientation of its business model (which directly influences the relation of value added to hours worked), as well as the *average qualification level of the employees*.

Method

With a view to production efficiency, all the relations could be analyzed using standard OLS regression models, as both of the dependent variables are metric. For labor productivity, we applied a logarithmic transformation as the indicator is not normally distributed and a decreasing marginal utility is meaningful for our hypothesis. The model requirement of homoscedasticity is met using the transformed indicator. In general, we ran all regression analyses with a limited number of basic factors to start with, controlling for firm and production characteristics in order to explore whether the relation in question could be detected at all (the relations are: firm size, sector, product complexity and, in the case of production efficiency, batch size). Subsequently, we extended the models by all the above mentioned control variables in order to investigate how robust the detected impact of digitalization remains, even when controlling for other relevant factors.

4. Results

With a view to hypothesis 1 and 3, model A1.1 (cf. table 1) documents a clear and positive impact of digitalization on productivity, even when controlling for sector, firm size, product complexity and batch size. It is not, however, as significant or strong as the impact of traditional automation, i.e. the introduction of robots to the production process. When introducing the final producer, export orientation and qualification of employees as further controls (model A1.2), the overall picture is even more robust. **Both automation and digitalization display statistically significant, positive effects on labor productivity** – although the regression coefficient for automation is once again notably higher. Moreover, the negative interaction effect is still statistically significant when controlling for substantial influencing factors. This indicates that, in 2012, the parallel use of robots and digital technologies to increase production efficiency resulted in a considerably smaller positive impact on productivity. **The model documents that the parallel use of robots and digital technologies did not enhance production efficiency in 2012,** but seems to have caused interference, resulting in a reduced impact of both technologies on productivity. In contrast, it has to be highlighted that, when looked at separately, both technological applications boosted production efficiency considerably. With 0.078 and 0.153, the adjusted R^2 of models A1.1 and A1.2, respectively, are relatively high. Not surprisingly, several control variables do affect labor productivity in addition to automation and digitalization.

Table 1. Linear regression models of effects on labor productivity.

dV: ln_value added	Model A1.1				Model A1.2			
	□	Coeff.		Std. Err.	□	Coeff.		Std. Err.
Automation	**0.117**	**0.131**	***	**0.041**	**0.131**	**0.146**	***	**0.042**
digitalization (production)	**0.067**	**0.075**	*	**0.042**	**0.087**	**0.098**	**	**0.042**
automation*digitization	**-0.063**	**-0.097**		**0.061**	**-0.088**	**-0.133**	**	**0.061**
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
final producer					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
Constant		4.149		0.119		3.837		0.136
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.

With a view to hypotheses 2 and 3, model A2.1 (cf. table 2) documents that, when controlling for sector, firm size, product complexity and batch size, **a positive effect on total factor productivity can only be documented for automation, not for the use of digital technologies in 2012 to increase production efficiency**. Even the effect associated with the use of robots is only statistically significant at the 10% level. We did not detect any significant interaction of their effects. When introducing final producer, export orientation and the qualification of employees as further controls (model A2.2), even the positive effect associated with the use of automation technologies disappears. In general terms, the regression coefficients are still consistent with other models, but it has to be concluded that the implementation of digital technologies to increase production efficiency did not have any statistically significant effects on total factor productivity in 2012. However, this 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 among the control variables as well. According to the model, total factor productivity is associated with sectoral differences, and correlates positively with export orientation and the share of highly qualified personnel.

Table 2. Linear regression models of effects on total factor productivity.

dV: Total Factor Productivity	Model A2.1				Model A2.2			
	β	Coeff.		Std. Err.	β	Coeff.		Std. Err.
automation	**0.073**	**0.064**	*	**0.036**	**0.066**	**0.057**		**0.037**
digitalization (production)	**0.024**	**0.022**		**0.037**	**0.021**	**0.018**		**0.038**
automation*digitization	**-0.010**	**-0.012**		**0.053**	**-0.016**	**-0.019**		**0.055**
Constant		0.391		0.103		0.258	**	0.121
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
final producer					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
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.

An interaction effect between digitalization and automation is not detectable. Thus, the model documents that the parallel use of robots and digital technologies to increase production efficiency did not provide any positive amplification in 2012.

5. Discussion and conclusions

Based on one of the most robust and comprehensive data sources available for the German manufacturing sector, we analyzed the effects of automation and digitalization on manufacturing companies' performance during the early 2010s, i.e. at a time when the concept of Industry 4.0 was increasingly promoted in Germany. In a sense, this paper thus provides ‘before the fact’ findings, to serve as a reference for subsequent analyses using more recent data.

In this paper, we demonstrated how to operationalize the rather vague notion of “Industry 4.0-relevant technologies” in terms of concrete process innovations in manufacturing. We illustrated that, while there is indeed an overarching trend of digitalization or digital transformation in production, this is made up of multiple composite parts and streams that effect the performance of firms at different leverage points. With regard to our findings, we highlight the following implications for future research, entrepreneurial practice and support policies:

- First, our findings underline that digitalization in manufacturing is **neither a new trend nor one at too early a stage to monitor and analyze**. Its significant impacts on manufacturing companies' performance can be demonstrated as early as 2012, before it was broadly promoted in political terms.
- Second, **earlier and therefore more established technologies to increase production performance** had a more significant impact on productivity than more advanced but less mature digital technologies. In our study, we confirmed the strong, positive effects of traditional automation on manufacturing productivity, which have already been proven in many other studies [5,24].
- Third, our findings show that, at the early stages of industrial digitalization, **automation and digitalization interfered with each other rather than mutually reinforcing each other.** This finding confirms that the integration of digital technologies into existing production set-ups is not always seamless [12] and sheds doubt on the sometimes evoked image of companies progressing smoothly through the different stages of firm-level modernization [3,19,25]. Instead, it raises questions concerning parallel introduction, imperfect replacement and the transaction costs associated with gradual processes of learning.
- Fourth, several of our findings suggest that, in one way or the other, **the uptake and deployment of digital technologies remained incomplete or was at least less than fully effective in the early 2010s**. The effects were notably weaker when considering total factor productivity as the dependent variable. While, at the time, digitalization had a first robust impact on simple, straightforward measurements of productivity, the triggered effects were not yet dominant or in place long enough to remain detectable in measures that are subject to a much broader range of additional factors of influence.
- Fifth, irrespective of whether the effects of digitalization remained statistically significant, all our models highlighted a number of additional factors as valid predictors of production efficiency. In all of them, these variables contributed more to the explanatory power of the models than the effects of digitalization itself. As could be expected, **digitalization is** but one, albeit central, **factor in the production process that is and remains contingent on others.**

In summary, our analysis suggests that the uptake and integration of digital solutions into existing production environments is not necessarily smooth, but can – at least for a certain period – be characterized by transaction costs, mutual interference and organizational friction that impede rather than improve production performances. This was the situation at an early stage of the uptake cycle. Later studies should explore whether this situation persists.

Overall, this paper provides ample evidence that expecting a digital revolution in production is unrealistic. It is more likely that we will see a gradual – though sometimes fast and relentless – uptake of technologies into existing manufacturing processes. From a company perspective, many other factors were more important than digitalization. Even though time has since passed, these differentiated findings on the origins of industrial digitalization remain relevant for current studies, not least of "follower" countries and regions.

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