How Smart Is a 'Smart Factory'?: An Organizational View*

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Abstract

This paper investigates the game-changing paradigm in modern manufacturing, known as the "smart factory", from an organizational perspective. Factories get smarter—or smartized—by becoming more data-intensive and more tightly integrating operations with management. We design a unique survey to measure this intangible organizational capital accumulation process for 939 Korean manufacturing plants. Observing heterogeneous levels of smartization across factories, we explore their relationship with three performance dimensions: productivity, cost efficiency, and product variety. The drivers of smartization are also identified. Our analysis uncovers a strong association between smartization and heightened productivity, with varying interactions with other performance metrics based on specific manufacturing process (e.g., lower defect rate only in assembly line process). Importantly, we find that investments in digital technologies drive smartization only when complemented by structured incentive management and proper CEO leadership.

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"Automation applied to an inefficient operation will magnify the inefficiency."

– Bill Gates (The Road Ahead 1995) –

1 Introduction

"Smart factory" or "smart manufacturing," popularized by the German initiative Industrie 4.0, has become the standard term for describing the ongoing digital transformation in manufacturing (Kagermann *et al.*, 2013). While information technology (IT) has revolutionized the work environment in management offices, the factory floor has largely remained analog for decades. The recent development of digital technologies, particularly operation technology (OT) used on the shop floor, along with improved interoperability, now offer new possibilities for overcoming the limitations of the existing manufacturing system. By integrating OT with IT, factories can collect, distribute, and analyze digital data to optimize production, thereby becoming smarter (Kusiak, 2017, 2018).

The past decade has witnessed a significant increase in the implementation of smart factory-related technologies across major countries.[1] Concurrently, however, many leading firms have encountered challenges when incorporating these new technologies into their existing factory systems (Davenport and Westerman, 2018), with some experiencing complete failures (Sutcliff *et al.*, 2019). Followers of the industry recognize the imperative need for smarter manufacturing in the digital era, as exemplified by the COVID-19 pandemic (McKinsey Digital, 2020), but concerns about preparedness and operational risks persist (Deloitte, 2020). These accounts emphasize the need for a comprehensive understanding of the smart factory concept and its operational mechanisms. Merely adopting technology and relying on policy support may prove to be inefficient and ineffective in achieving desired outcomes.

This paper aims to provide a systematic analysis of this topic by introducing an empirical measure of factory smartness, which allows the assessment of its relationship with factory performance and readiness for effective digital transformation. Specifically, we address three

[1] Figure A1 presents relevant statistics on this digital transformation trend in manufacturing sector.

key questions: (i) What defines a smart factory and how can we quantify its smartness? (ii) Does a smarter factory ensure significant advantages, and if so, in what manner? (iii) What factors contribute to driving a factory towards greater smartness?

To answer the first question, we review the literature to define two key characteristics of a smart factory. One is network integration of the entire factory system (system integration, or SI), and the other is data sharing and data-driven decision making (data share and use, or DSU). Namely, the level of SI and DSU serves as a measure of factory smartness, with an increase in either or both resulting in smartization. We then conduct a survey of about one thousand manufacturing establishments (hereafter, factories or plants) in South Korea, covering eight major (sub-)industries with plants of various sizes. The survey is designed to construct indices representing the degree of SI and DSU, which are averaged to gauge the factory-level smartness in 2015 and 2017. It also gathers data on the adoption status of digital technologies and various organizational characteristics that are potentially associated with smartization.

The survey results reveal significant differences in factory-level smartness and their associations with other factory attributes. The distributions of smartness levels across the 939 sampled factories exhibit considerable diversity, aligning with the non-transferable nature of organizational capital. Notably, smartization between 2015 and 2017 demonstrated uneven patterns, with most factories still far from achieving full smartness. Variation in the adoption rate of digital technologies was also evident across the sampled factories, indicating a substantial proportion of factories lagging in digital technology adoption. Looking at correlations between smartness and other factory attributes, positive associations emerged with the number of adopted digital technologies, automation levels, employment, sales per worker, and the production management score.

The paper then delves into an investigation of how these uneven factory smartizations are interwined with three distinct dimensions of production performance: productivity, cost efficiency, and new product variety. Using panel estimation models that carefully control for variables such as the technologies adopted, we find that factory smartization is strongly associated with higher productivity, lower defect rates, and greater product variety. To be precise, these positive impacts vary in magnitude across different types of manufacturing processes, but for all types, they are ultimately linked to an increase in physical productivity (measured by daily output) and revenue productivity (measured by sales). Intriguingly, the sole adoption of digital technologies fails to account for the observed productivity enhancements, highlighting the role of smartization as a mediator of productivity improvement.

Regarding the last question, we examine factors associated with factory smartization and explore their potential complementarities. The adoption of relevant technologies, good management practices, the presence of an ICT division, and certain CEO characteristics (e.g., interest in upgrading the manufacturing system, risk preference, and family ownership) are found to be important for achieving a smarter factory, with technology adoption considered the primary factor. Furthermore, the impact of technology adoption is shown to be highly dependent to the quality of incentive management practices. While technology adoption has no significant association with smartization in factories with low incentive management quality, its influence becomes stronger as the management quality improves. Thus, technology adoption alone is neither sufficient for productivity improvement nor for factory smartization.

Answering each of the questions relates and contributes to the literature in multiple fields. First, we conceptualize the factory smartness as a form of organizational capital, aligning with prior literature that views IT and complementary investments as intangible assets (Lev, 2001; Brynjolfsson *et al.*, 2002; Saunders and Brynjolfsson, 2016; Tambe *et al.*, 2020). We expands this view to the factory floor and thereby offer a useful framework for understanding the economic implications of digital transformation in manufacturing. Additionally, our paper has the advantage of directly measuring the level of system integration and data-related practices, instead of relying on proxies such as IT expenditures commonly used in the existing literature. A survey-based metric is constructed to that end following the literature on measuring organizational IQ (Mendelson, 2000), managerial practices (Bloom and Van Reenen, 2007; Bloom *et al.*, 2019) and data-driven decision making (DDD) (Brynjolfsson and McElheran, 2016, 2019).

Second, assessing the impact of technology adoption on organizational performance is a main research topic in economics and management. Previous literature investigates the effects of IT on firm or plant performance (Bharadwaj *et al.*, 1999; Melville *et al.*, 2004; Bartel *et al.*, 2007), while recent studies focus on newer technologies like versatile robots and artificial intelligence (AI) (Acemoglu and Restrepo, 2019; Agrawal *et al.*, 2019). The smart factory, as a real-world application of these technologies, tends to be mistakenly perceived as a technology-packed, fully automated factory. However, the purpose of a smart factory lies in reducing inefficiency and waste in technologies, often caused by excessive automation (Zuehlke, 2010; Porter and Heppelmann, 2015).[2] Consistent with the purpose, our findings on the second question demonstrate how smartization, rather than technology or automation, helps to build an efficient manufacturing system that facilitates better performance.

Third, the findings related to the last question contribute to the literature on the organizational "fit" with technology adoption (Milgrom and Roberts, 1992, 1995). In particular, we highlight the role of worker incentive management for successful smartization, in line with prior studies that demonstrate how misaligned worker incentives can undermine the effectiveness of technology adoption (Atkin *et al.*, 2017; Bloom *et al.*, 2012). We find similar results for smart factories. Another consistent finding with the existing literature is the influence of CEO characteristics in shaping organizational capital (Bertrand, 2009; Dessein and Prat, 2022). Relationship with the founder (Villalonga and Amit, 2006; Bennedsen *et al.*, 2007), interest in the factory system (Thong and Yap, 1995), and preference on risk (Galasso and Simcoe, 2011; Hirshleifer *et al.*, 2012) are all significant factors in the process of smartization.

The remaining sections are structured as follows. Section 2 presents a framework for understanding factory smartness. Section 3 introduces our survey, data collection, and measure of smartness. Sections 4 and 5 present empirical tests addressing the second and third questions, respectively. Section 6 concludes with study limitations and policy implications.

2 Conceptual Framework

2.1 Background

Modern manufacturing is challenged by the growing demand for customized and versatile products, while grappling with complex structures and control systems (Zuehlke, 2010). Sev-

[2] Elon Musk confessed on his Twitter that "excessive automation at Tesla was a mistake." (on April 13, 2018) after the production slowed down due to relying on too many robots.

eral schemes for the next generation of manufacturing have been proposed, each with its own merits, but until recently no notable changes have been realized, primarily due to the technological immaturity and the lack of collaborative efforts among countries (Kusiak, 2018).[3]

Over the past decade, the two external obstacles have been significantly removed. On the technology front, improvements in operation technology (OT)—including sensors, advanced robotics, and the Internet of Things (IoT)—have enabled the collection of large amounts of real-time data from manufacturing processes.[4] This big data is then processed not only by traditional specialized IT software (e.g., enterprise resource planning or ERP), but also by cutting-edge technologies such as cloud computing and artificial intelligence (AI). (Zhong *et al.*, 2013, 2017; Mabkhot *et al.*, 2018; Frank *et al.*, 2019). These technologies, recognized as crucial enablers of smarter manufacturing, have witnessed rapid rates of adoption as shown in Figure A1. Moreover, their adoption pattern shows a strong complementarity among IT and OT: Acemoglu *et al.* (2022) report that 90% of firms that have embraced robotics (OT) also utilize specialized software (IT) in the US.

On the policy front, the launch of Germany's Industrie 4.0 initiative in 2011 triggered a competitive environment among countries vying for technological leadership. This initiative also popularized the term smart factory. Subsequently, several national initiatives (e.g., Manufacturing USA, Made in China 2025, Korea's Manufacturing Innovation 3.0) and industry consortia (e.g., Industrial Internet Consortium, Edgecross Consortium) were established. International cooperation between these initiatives and consortia has also been active to establish global standards for interoperability between technologies and systems.

All in all, the smart factory is an evolving blueprint for the future of manufacturing. However, unlike in the past, significant advances in technologies coupled with international policy efforts have propelled us into the next revolution in manufacturing (Porter and Heppelmann, 2015; Schwab, 2015).

[3]Examples of the new manufacturing scheme include computer-integrated manufacturing (CIM) (Harrington, 1974), intelligent manufacturing (Kusiak, 1990), and reconfigurable manufacturing (Mehrabi *et al.*, 2000).

[4]Gartner defines operation(al) technology as "hardware and software that detects or causes a change, through the direct monitoring and/or control of industrial equipment, assets, processes and events." (source: https://www.gartner.com/en/information-technology/glossary/operational-technology-ot).

2.2 Engineering Concept

To better understand the technical concept of smart factory, let us first present a real case (PC Control, 2014, 2018; McKinney, 2016). In 2014, Nobilia operated two factories with the capability to produce 2,600 fully customized kitchens per day. This achievement was made possible by the seamless integration of a PC-based controller with both the lower-level manufacturing equipment and the higher-level ERP system, which were further linked to computer-aided design (CAD) software. The integrated system facilitated business process reengineering, allowing the dispatch department to efficiently synchronize production schedules with delivery schedules. The factories also collect data from each production process and use it to make decisions. For example, each piece of work in process is tracked in real time as IoT machines scan the barcode attached to the piece. The information is used to identify where and how defects occur. Similarly, drilling data (motor power, vibration, hole temperature, etc.) is used as control parameters to improve the assembly process.

Two key features deserve attention in this case. First, Nobilia has achieved the extensive integration of the manufacturing system, which enables universal data sharing. Although ERP and controllers have been used for decades in back offices and on factory floors, respectively, they typically run in silos. Second, the real-time data flows through the entire factory, serving as a "digital thread" that delivers relevant information to all production entities, including machines, computers, and human workers. As a result, the factory requires active human-machine interaction and data-related worker practices.

These two characteristics closely match the core characteristics articulated in the engineering literature and related white papers on the smart factory.[5] Based on this review, we define that a factory becomes smarter in the following ways. First, as depicted in Figure A2, it expands the scope of its network through vertical integration of different hierarchical levels in the manufacturing system (from level 1 to level 4) as well as horizontal integration among the

[5] A widely cited report on Industrie 4.0 by Kagermann *et al.* (2013, p. 5) describes the core characteristics of smart factory as "vertically networked with business processes within factories and enterprises and horizontally connected to dispersed value networks that can be managed in real time". The National Institute of Standards and Technology (NIST) in the US reports that a smart factory maximizes its capabilities "by using advanced technologies that promote rapid flow and widespread use of digital information within and between manufacturing systems" (Lu *et al.*, 2016, p. 1). Most articles reviewing the concept, reference architecture, and enabling technologies of the smart factory follow some of these definitions (Lucke *et al.*, 2008; Hermann *et al.*, 2016; Wang *et al.*, 2016b; Zhong *et al.*, 2017; Moghaddam *et al.*, 2018; Zeid *et al.*, 2019; Osterrieder *et al.*, 2020).

functions in the product value chain (Kagermann *et al.*, 2013; Wang *et al.*, 2016a). We refer to this networking capability as system integration (SI). Next, the factory aims to optimize the gathering, sharing, and utilization of digitized data within its integrated system (Esmaeilian *et al.*, 2016; Kusiak, 2017; Tao *et al.*, 2018). We refer to this data utilization capability as data share and use (DSU). After all, the degree to which a factory is smart is represented by the degree of SI and DSU. When a factory improves one or both of these degrees, it becomes smarter or "smartized".

2.3 Analytical Framework

The conceptual framework presented in Figure 1 encapsulates the discussion so far. It begins with the simultaneous development of digital technologies, broadly classified into OT and IT, that can interoperate with each other. This, together with policy supports, encourages factories to adopt the technologies. Factories reconfigure their manufacturing and related business systems to internalize the new technologies, but only those that successfully go through this adaptation process become smartized.[6]

We interpret smartness as part of organizational capital or, in a dynamic sense, smartization as the process of accumulating a certain type of organizational capital.[7] This organizational view leads to the insight that the degree of smartization can be heterogeneous across factories, influenced by factors such as CEO leadership and incentive management. The importance of the former in determining smartization is inspired by Dessein and Prat (2022), who show that top leadership strongly affects organizational capital accumulation.[8] The role of incentive management practices is emphasized in Bloom *et al.* (2012). In our context, aligning workers' incentives with the purpose of the technology adoption can be crucial for smartization.

Once a factory undergoes smartization, it has the potential to create value by improving performance in many dimensions. Our assessment focuses specifically on the following

[6]A long strand of economics and management literature stresses the need for complementary investments to the technology adoption, which jointly form an implicit, intangible capital. See Brynjolfsson and Hitt (2000) and Brynjolfsson and Milgrom (2013) for comprehensive reviews.

[7]Organizational capital can be defined as an agglomeration of technologies or knowledge that enables an organization to consistently create value from its given tangible and intangible resources (Atkeson and Kehoe, 2005; Lev and Radhakrishnan, 2005). See also Teece *et al.* (1997) for a related concept, dynamic capability.

[8]Dessein and Prat (2022) characterize organizational capital as any organization-specific asset that (i) changes slowly, (ii) is not perfectly observable, (iii) improves performance, and (iv) is influenced by the leadership.

key performance indicators (KPIs): physical productivity (measured by daily production or lead time), cost efficiency (measured by defect rate or operating rate), and new product variety (measured by the number of product varieties or the number of buyers). Note also that each KPI improvement can vary due to the inherent characteristics of the manufacturing process. To understand the variations, we consider three distinct types of manufacturing processes—batch (including job-shop), assembly line, and continuous—following the standard classification by Hayes and Wheelwright (1979a,b) (See Figure A3).

The batch process is commonly used for producing limited quantities of customized products, organizing production steps into batches.[9] Smartization is expected to increase product variety in a batch process by enhancing its ability to adapt quickly to different setups and optimize production sequences. However, such an enhancement may not be as evident in a continuous process, where raw materials are constantly processed to create a homogeneous product with a high volume. In that process, smartization instead can reduce product lead time by utilizing real-time data for monitoring and control, as well as identifying optimal operating parameters. The assembly line process follow a fixed path through workstations, each dedicated to a specific task. This process is efficient for producing complex functional products with many parts. Thus, systematic management and monitoring through smartization may particularly minimize defect rates resulting from mis-assembly. By analyzing these distinct manufacturing processes and their respective KPIs, we can gain an in-depth understanding of how smartization affects factory performance.

Our conceptual framework resembles the conventional literature investigating the complementary effect of IT and management on firm performance (Milgrom and Roberts, 1990, 1995; Bresnahan *et al.*, 2002), but has two notable differences. Firstly, the literature typically hypothesizes a direct relationship between input (technology adoption, often with managerial adjustment) and output (sales or productivity). Our framework instead proposes a sequential relationship: $\Delta Input$ (technology adoption + management) $\rightarrow$ Smartization (SI + DSU) $\rightarrow$ $\Delta Output$ (KPIs). This approach explicitly emphasizes the role of smartization as a bridge between input and output changes. Secondly, whereas the conventional approach treats the el-

[9]The job shop process is a batch process with a lot size of 1.

ements of smartness, SI and DSU, as two distinct types of capital that complement each other, our framework defines the entire melding as organization-specific capital. This is because the boundaries between them are becoming increasingly blurred in practice.[10] For example, the Lean Kanban, a DSU practice that supplements a given technological system (Womack *et al.*, 1990), can be automated in a smart factory using IoT and AI-powered system.

3 Data and Descriptive Statistics

3.1 Survey Design and Measurement

Here, we introduce the main survey questions and explain how the variables of interest are constructed. A full description of the survey questionnaire is provided in the Appendix.

3.1.1 Smartness

Section C of the survey is designed to measure the level of smartness for the years 2015 and 2017. Questions C5 and C6 assess vertical and horizontal system integrations, respectively, recognizing that these two dimensions are interconnected and cannot be measured independently. The five levels in C5 follows the technology standards set by the Korea Smart Factory Foundation (KOSF), the public-private partnership agency promoting smart factories in Korea.[11] C6 assesses the degree of interconnection between production phases through the use of ICT. Higher levels indicate a greater level of interconnectedness among the phases. To quantify the level of system integration (SI), the selected choices in C5 and C6 are converted into a scale ranging from 0 to 1 and then averaged. Factories with the highest SI level demonstrate the capability for autonomous operation, self-optimization in manufacturing, and effective dissemination of information across the production value chain using ICT.

Questions C10 and C11 are designed to measure DSU. C10 inquires for what and how frequently data analytics are used for decision-making (i.e., the degree of data-driven decision-making or DDD) in the manner of Brynjolfsson and McElheran (2016, 2019). Six common

[10] In Brynjolfsson and McElheran (2016, 2019), for instance, IT infrastructure is complementary to but distinct from data-driven decision-making. A few recent studies try to measure the aggregate value of all IT-related assets to deal with the non-separability issue (e.g., Saunders and Brynjolfsson, 2016).

[11] Porter and Heppelmann (2014) also employ a similar level criterion.

tasks, from manufacturing process optimization to demand forecasting, are presented as sub-questions. The DDD level is measured on a scale from 0 to 1, with 1 indicating real-time utilization of data analytics and 0 indicating the infrequent use of data analytics, possibly on an annual basis. The overall DDD level is the average of the six sub-levels. C11 assesses the scope and frequency of data sharing. It employs a similar approach and scoring method as C10. The overall level of DSU for each year is then determined by averaging the DDD and data-sharing scores. Factories with the highest DSU level engage in data sharing with all entities involved in the product value chains and utilize data in real-time for all six production activities.

Finally, the level of smartness is measured as following:

$$Smart = f(SI, DSU) \approx \frac{SI + DSU}{2} = \frac{Vertical + Horizontal + DataShare + DDD}{4}. \quad (1)$$

The level of smartness can be expressed as a function of the two elements, SI and DSU, which can be further decomposed into vertical and horizontal integrations for SI, and data-sharing and DDD for DSU, as shown in Eq. (1). We employ a linear approximation with equal weights assigned to the four sub-elements. This measure is preferred because it closely aligns with the engineering definition, avoiding any assumptions regarding the functional form or the weights assigned to the elements. Moreover, we consider the four sub-elements as substitutable for each other by treating them as the same type of capital that contributes to the overall smartness. This approach is consistent with the method to calculate the structured management score in Bloom *et al.* (2019).

3.1.2 Enabling Technologies, KPIs, and Other Key Variables

C7 and C7-2 provide two measures of the level of technology adoption: the number of adopted technologies and the total expenditure on the procurement of these technologies. C7 pertains to the introduction of twelve digital technologies in the factory and the respective year of implementation. These technologies, classified according to the ISA-95 Standard, fall into five operation technologies (MES, SCADA, PLC, Smart Sensor or IoT, CPS) and seven information technologies (ERP, PLM, SCM, FEMS, Big-data Analytics, Cloud computing, AI).

As shown in Figure A2, they are implemented across different production phases to enhance vertical and horizontal integration, thereby facilitating data sharing and use. The sub-question C7-2 asks about the total cost of purchasing these technologies during 2016 and 2017.

Section F collects information on major KPIs. Specifically, F2 asks the average values of six different KPIs in 2015 and 2017. These KPIs are (i) daily output: the quantity of the main output produced per day, (ii) lead time: the total time spent from the initial order to the shipment of the main product, (iii) defect rate: the percentage of output that fails to meet a quality target, (iv) operating rate: the percentage of capacity utilization, (v) product variety: the number of customized or differentiated products, and (vi) number of customers. The first two indicators represent the (time-based) physical productivity of the factory. The next two reflect the efficiency of resource utilization. The last two indicators pertain to new product variety. By considering these three dimensions of factory performance, we can account for the diverse relationship of smartization with different aspects of factory operations.

Other key variables used in the empirical analysis are listed with the corresponding question number(s) of the survey: type of manufacturing process (A3), the level of automation (B1), whether received government supports for the factory smartization (C12), the structured management practices as used in Bloom *et al.* (2019) (D1 through D8), CEO's interest in innovating the production process (D11), whether had specialists or a department fully dedicated to optimizing the production process (D12), CEO's risk preference (D14), labor union status (F1-5), whether founders or their family members hold the CEO position (F1-6), plant-level sales (F2-1), and employment by occupation (F3). The original survey questions, along with a brief explanation, can be found in the Appendix.

3.2 Sampling and Implementation of the Survey

The sample population is limited to all manufacturing factories that meet the following three conditions. First, the factories employed at least 10 or more employees in both 2015 and 2017. Second, their business operations must have started in or before 2015. Third, the main activity of the factories must fall within one of six 3-digit or two 5-digit (sub-)industries, based on the 10th revision of Korea Standard Industrial Classification (KSIC).[12]

The selection of the eight specific industries reflects their importance in Korean manufacturing, as well as their notable adoption of enabling technologies with the support of government subsidies.[13] The eight industries collectively account for about 35% of the aggregate manufacturing employment and 27% of the total value-added as of 2016. In addition, more than half of the 3,200 factories that received the government subsidies between 2014 and 2017 belong to these eight industries. Such targeted approach focusing on specific industries helps mitigate the presence of heterogeneous unobserved characteristics across factories and enhances the identification (Ichniowski and Shaw, 2013). However, this benefit comes at the expense of external validity.

The FactoryOn database, provided by the Industrial Complex Corporation (KICOX), contains information on approximately 22,000 registered manufacturing factories in Korea that meet the three criteria. From this population, the study aimed to randomly select 1,000 factories using the following sampling method. First, the sample distribution across the eight industries is designed to match the distribution observed in the population. Next, within each industry, factory size (based on 2017 employment) was divided into four groups: (i) 10 to 19, (ii) 20 to 49, (iii) 50 to 99, and (iv) 100 or more employees. Unlike the industry groups, larger factories were oversampled to ensure the inclusion of those more likely to have pursued smartization.[14] In addition, the recipient factories of government subsidies were set to constitute 20% within each industry-size group. Within the groups defined by industry, size, and subsidy status, factories were randomly selected and interviewed (if permitted) until the desired sample size was reached. The resulting sample distribution of 939 factories obtained from this process is presented in Table 1.

The survey was conducted face-to-face over approximately two months, from August to October 2018. We collaborated with the professional survey team at the Korea Development Institute. A total of 51 interviewers and their supervisors underwent comprehensive training

[12] Table 1 shows the list of the eight industries.

[13] The government subsidy typically covers half of the total cost of installing digital technologies for smartization. The overall program started from 2014 and is run by the Korea Smart Factory Foundation (KOSF), a public-private partnership agency. We obtained the list of subsidized factories from the Ministry of SMEs and Startups.

[14] The target proportions were set to be 20% for the first group (10 to 19), 40% for the second, 25% for the third, and 15% for the last group, respectively.

on the survey structure and basic knowledge of smart factories. Additionally, both interviewers and survey respondents were provided with a separate glossary of survey terms. During the interviews, the interviewers were responsible for recording all answers themselves. We ensured that the survey respondents were individuals in charge of manufacturing with a thorough understanding of the overall production process.

After completion of the survey, initial verification was conducted by different supervisors. They cross-checked the survey to confirm that it was indeed conducted in person by directly confirming with the survey respondents. Our own team then undertook a second verification process. In cases where the responses were deemed inadequate or extreme, we reconfirmed them via telephone. Despite these efforts, respondent bias or lack of information may have resulted in response errors.

3.3 Descriptive Statistics

Figure 2 displays the distributions of smartness levels in 939 sample factories for 2015 and 2017. The distributions clearly show that the levels of smartness across factories are dispersed, consistent with the characteristic of organizational capital that is not readily transferable to other factories. The observed heterogeneity is substantial, with a standard deviation of smartness in 2017 of 0.13, similar to the standard deviation of the non-incentive management score highlighted in Bloom *et al.* (2019). See Table A1 for the detailed statistics.

The average levels of smartness are 0.27 in 2015 and 0.34 in 2017. Factories are smartized by 0.07 on average over the two-year period, but most of them are far from the reaching the full level of smartness. Also, not all factories are smartized to the same extent as shown in Figure 3. The circles above the 45-degree line in the figure represent the smartized factories over the two years. 555 factories exhibit varying degrees of smartization. About one-third (343) of the factories remain changed in the level, while 41 have become less smart, indicating that smartness is a slowly evolving and depreciable form of capital. The variation in both level and change of smartness allows for our empirical analyses.

Figure 4 provides the relationships between smartness and other factory characteristics. The levels of smartness are grouped into deciles by year so that each bar represents the average level of the corresponding variable in the decile. Positive correlations are observed between smartness and (a) number of adopted digital technologies, (b) level of automation, (c) employment, and (d) sales per worker. These results are consistent with our intuition. Another positive relationship is seen in (e) with the production management score, which measures the targeting and monitoring of KPIs (See the Appendix for more information). In fact, some of the responses in our study directly correspond to the measure of DDD used by Brynjolfsson and McElheran (2016, 2019). Sub-figure (e) reflects the relationship between our measure of DDD and theirs.[15] However, (f) presents a counter-intuitive finding, as smartness is not associated with the incentive management score (correlation coefficient=-0.01). This lack of correlation has important implications that we will discuss in detail later.

Figure 5 presents the cumulative adoption rate of digital technologies among the sampled factories by year. While the digital transformation in manufacturing has gained momentum in recent years, it is important to note that a significant portion of factories still lag behind in adopting digital technologies.[16] ERP has been the most commonly adopted IT software since 2010, with its adoption rate steadily rising to nearly 50% in 2017. MES, a major OT software, has experienced rapid growth in adoption in recent years. As depicted in Figure A2, MES plays a central role in vertical and horizontal integrations by facilitating real-time information flow between the factory floor and the back office. When we narrow down the sample period to the last two years, we observe that 311 factories have implemented at least one of these technologies. This number is considerably lower than the 555 smartized factories depicted in Figure 3, implying that technology adoption is not the sole driver of smartization.

4 Factory Smartization and Performance Improvement

4.1 Model Specification

To identify the relationship between factory smartization and performance improvement,

[15] The preferred measure of DDD in Brynjolfsson and McElheran (2016, 2019) is the indicator of whether a factory satisfies the following four criteria simultaneously: (i) a great deal of data or all the data is available to support decision-making; (ii) decision making relies heavily or entirely on data; (iii) have 10 or more KPIs; and (iv) use both long-term and short term production targets.

[16] This observation holds true, especially when considering our emphasis on industries and larger factories that have actively embraced digital technologies.

we employ the following econometric model:

$$ln(KPI_{ijt}) = \alpha + \beta Smart_{ijt} + X_{ijt}\gamma + (G_g \times t)\delta + \lambda_{ij} + \mu_t + \epsilon_{ijt} \quad (2)$$

where KPI_{ijt} is one of the six KPIs in factory i in industry j at year t. The right-hand side of Eq. (2) includes the measure of smartness, $Smart_{ijt}$, and other factory-level observables (X_{ijt}) such as employment and material costs.

This model controls for all confounding factors that are either time-invariant or time-varying but common within the specified groups. To account for common time trends within groups, the model incorporates group dummies (G_g) interacting with the linear time trend (Heckman and Hotz, 1989). The group dummies include approximately 80 industry groups based on 5-digit KSIC, exporter group (*Exporters*), startup group with less than seven years old as of 2017 (*Startups*), and the government-subsidized group in purchasing or developing relevant technologies (*Subsidy*). The time-invariant unobserved heterogeneity across all factories and industries is absorbed by λ_{ij} and year-specific effects are captured by μ_t. Unless there are more unobserved factors directly affecting the KPIs that are correlated with $Smart_{ijt}$, the model identifies a causal effect. However, we do not rule out the possibility of potential endogeneity and maintain a correlational interpretation of all estimation results.

Having noted that, we proceed to estimate the first-differenced specification of Eq. (2):

$$\Delta ln(KPI_{ijt}) = \beta\Delta Smart_{ijt} + \Delta X_{ijt}\gamma + G_g\delta + \eta_t + u_{ijt} \quad (3)$$

where $\Delta x = x_t - x_{t-2}$ as we have data for 2015 and 2017. $\eta_t = \Delta\mu_t$ and $u_{ijt} = \Delta\epsilon_{ijt}$. Note that $\Delta Smart_{ijt}$ is a level change, but the difference in the dependent variable implies the percentage change. Thus, the coefficient β in Eq. (3) exhibits the semi-elasticity.

Eq. (3) estimates the average KPI changes shown by smartized factories across the entire sample. However, individual factories operate with unique manufacturing processes, which can be broadly classified into three types as discussed in section 2.3. To account for varying strength of correlation contingent on the manufacturing process type, we add interaction terms as follows:

$$\Delta ln(KPI_{ijt}) = \beta_0 \Delta Smart_{ijt} + \sum_{k=1}^{2} \beta_k \Delta Smart_{ijt} Process_k + \Delta X_{ijt}\gamma + G_g\delta + \eta_t + u_{ijt} \qquad (4)$$

where $process_{k\in\{1,2\}}$ indicates assembly line and continuous processes. β_0 is the average correlation between smartization and KPIs for small batch process, while β_1 and β_2 capture the additional interactions for assembly line and continuous processes, respectively.

4.2 Estimation Results

Table 2 reports the estimated results of Eq. (3) using daily output of the main product as the KPI. We consider daily output as the primary performance indicator, which serves as a measure of physical productivity. All model specifications control for industry-specific linear time trends. Robust standard errors for the coefficients are clustered at the 5-digit industry level in parentheses.

The first column includes smartization as a standalone factory-level covariate. It shows a significant positive correlation between smartization and daily output growth. The estimate suggests that a 0.1 points smartization is associated with a 6.3% growth in the production of the main product per day.[17] The second and third columns use the number of newly adopted digital technologies during 2016 and 2017 ($\Delta\#DT$) and the log of total spending on these technologies ($DT.Spend$), respectively, as the sole explanatory variables. Both variables are alternative measures of the level of digital technology adoption and turn out quantitatively important for daily output.[18] However, columns (4) and (5) demonstrate that when measures of technology adoption are included alongside smartization in the estimations, their statistical significance diminishes. This suggests that the notable growth in daily output is not directly attributed to technology adoption, but rather through smartization.

[17] To illustrate 0.1 points smartization, suppose that a factory did not utilize any ICT in its production phases (marked as choice 1 in survey question C6) in 2015. However, by 2017, the factory was using ICT in some production phases without any interconnectivity between them (marked as choice 2 in C6). The factory began leveraging the data generated from this technology to optimize its manufacturing process on a weekly basis (a change from choice 5 to choice 3 in question C10-(1)). Additionally, workers in the production division occasionally shared data as needed (a change from choice 1 to choice 2 in question C11-(1)). These organizational changes collectively smartize the factory by about 0.1.

[18] According to Brynjolfsson and Hitt (2003), the estimated coefficients in these columns reflect the combined effect of technology adoption and complementary investments, rather than technology adoption alone.

Columns (4) and (5) incorporate several covariates and group dummies to control for potential confounders of the relationship between smartization and output growth. Clearly, employment and material costs are found as significant factors of daily output. In contrast, the positive relationship between automation and daily output implied by Figure 4 is not supported. Groups of startups, exporters, and subsidized factories, known to possess distinct productivity-related characteristics according to the literature, have minimal impact on the estimation results. Column (6) adds one more covariate, capital stock. Despite large missing values for capital stock in our data (see Table A1), the inclusion of the variable does not change the overall result.

In all, Table 2 indicates that factories smartized by 0.1 points would observe a daily output growth ranging from approximately 4.4% to 6.3%. Put another way, given the 90–10 percentile spread in smartness as of 2017 (0.51-0.18=0.33), factories at the 10 percentile could potentially achieve up to 21% ($\approx 0.33 \times 0.632$) higher productivity if they were smartized to the level of the 90 percentile factories.

Table 3 estimates Eq. (4) using the six KPIs that measure physical productivity (panel A), cost efficiency (panel B), and new product variety (panel C). Each panel conducts three estimations. The first column (i.e., columns (1) and (4)) include only industry dummies as controls, whereas the second column (columns (2) and (5)) include all covariates from Table 2 except capital stock. The last column (columns (3) and (6)) estimates the same specification as the second but with a subsample. As our study relies entirely on the survey, there are concerns about the respondents' knowledge of the true KPI values in both 2015 and 2017 if they did not maintain records. Survey question D2 reveals that 6% of the sample factories reported having no KPIs, and nearly one-third monitored only one or two KPIs. The responses from these factories may be less reliable. Hence, the third column focuses on a subsample of factories that monitor three or more KPIs.

In panel A of Table 3, the correlation between smartization and daily output growth are significantly positive across all three columns. The non-significance of the interaction terms suggests no statistical differences in the relationship among different production processes. Columns (4) to (6) present the estimation results for lead time as the KPI. Lead time and daily output tend to be negatively correlated because reducing lead time implies more production within a given time-frame. In columns (4) and (5), the coefficients for smartization and its interaction terms are not individually significant. However, the three coefficients are jointly significant at the 10% and 5% levels, respectively, indicating an association with shorter lead time of the main product.[19] Furthermore, in column (6) we observe a notably significant reduction in lead time for the continuous process, a finding consistent with our expectation.

Panel B presents the differential impact of factory smartization on cost efficiency, measured by the defect rate of the main product and the equipment operating rate. Columns (1) to (3) show that smartization has a statistically significant correlation with a lower defect rate in the assembly line process. This is intuitive given the complexity of products assembled from multiple parts. The negative correlation between smartization and defect rate weakens in the batch process, and disappears in the continuous process. We do not observe any statistically significant correlation with equipment operating rate from columns (4) to (6). Panel C examines the relationship between smartization and new product variety. Two measures, the number of products and the number of customers, consistently show the same result that smartization is strongly correlated with more product variety in the small batch process, while the correlation significantly weakens in the continuous process.

4.3 Robustness Checks

We conduct several robustness checks on the previous findings and present the outcomes in the Appendix. First, we aim to further investigate whether smartization ultimately helps to an increase in revenue productivity (measured by sales). Our main analysis focused on six major KPIs. In this test, we use revenue productivity as the performance measure. The standard estimation method is employed: In column (1) of Table A2, (log of) plant sales is regressed on number of employees, material costs, and capital stock, along with smartness, using the first-differenced model. It shows a significant positive association between smartization and sales growth, controlling for other production inputs. Columns (2) and (3) with more covariates show that newly adopted technologies and higher automation do not have a meaningful

[19] The corresponding F-statistics are 2.31 (P-value=0.084) for column (4) and 2.74 (P-value=0.049) for column (5).

relationship with sales growth, while smartization does. Quantitatively, the columns suggest that a 0.1 points smartized factory experiences about a 4% sales growth, comparable to the results for physical productivity in Table 2.[20]

Secondly, since we are using survey data, we intend to validate these results by leveraging sales data from corporate financial statements. We utilize alternative external sales data sourced from KISLINE, a proprietary database of corporate financial statements, which is less susceptible to biases or measurement errors compared to our survey data. However, sample attrition occurs due to the matching process, reducing the sample size by about one-third. Also, firm-level sales may differ from factory-level sales unless the entire firm's output is produced in a single factory. We circumvent this problem by either assuming that factory sales are proportional to firm sales in terms of their production share, or by focusing only on factories with a 100% production share. Using both approaches, Table A3 consistently presents a positive relationship between smartization and sales growth.

Lastly, we delve deeper into the connection between smartization and the enhancements in the six KPIs in Table A4. Given that our smartness measure results from integrating SI and DSU measures, we explore their distinct association with the KPIs by differentiating these two elements in panel A. Our findings show that each element exhibits a varying level of correlation with the KPIs. However, the joint significances, indicated by F-statistics, align with the results in Table 3, supporting the validity of the single composite index of smartness. In Panel B, we explore the potential for a non-linear, compounded relationship between smartization and KPI improvements. This relationship might feature a threshold or tipping point of smartization beyond which KPIs exhibit significant enhancements. However, our observations do not indicate such non-linearity, as we find the square term of smartization to be statistically insignificant.

[20]Given the keen interest from both academia and the policy circle, we conducted a simple test for the relationship between smartization and employment growth in columns (4) to (6) of Table A2. The regression results suggest no significant relationship between the two.

5 Drivers of Factory Smartization

5.1 Model Specification

The significant association between factory smartization and performance makes it important to understand what drives changes in smartness. While an obvious source of smartization is the adoption of relevant technologies, we also investigate other potential factors as well as their complementarities with the adopted technologies. We use the following first-differenced model similar to Eq. (4):

$$\Delta Smart_{ijt} = \beta_0 \Delta \# DT_{ijt} + \sum_{k=1}^{K} \beta_k \Delta \# DT_{ijt} Complements_i^k + G_g \delta + \eta_t + u_{ijt} \tag{5}$$

where $\Delta Smart_{ijt}$ is now the dependent variable and the number of newly adopted digital technologies ($\Delta \# DT$) is the main enabler. The complementarities between adopted technologies and other factors are tested via the set of interaction terms, where $Complements_i^k$ is the k-th quasi-fixed organizational characteristic of factory i. As explained in the conceptual framework, we expect that incentive management ($Incen.MS$) and CEO characteristics serve as potential candidates for complementarity.

The group variables (G_g) contain a number of organizational characteristics and industry-specific time trends to control for their possible link to smartization. The factory-level characteristics include a dummy variable indicating the presence of a department or personnel fully specialized in process optimization ($Specialist$), quintiles by the employment share of process technicians ($\% of\ Technicians$), a dummy for the provision of a worker training program before adopting new digital technologies ($Tech.Training$), a dummy for the presence of a labor union ($Union$), a dummy for the family firm ($CEO.Family$), and quartiles by the level of CEO's interest in process innovation ($CEO.Interest$). This choice of variables is not only motivated by the previous literature, but also corroborated by our interviews with managers prior to designing the survey.

5.2 Estimation Results

Table 4 provides the estimation results of Eq. (5). Column (1) considers the number of newly adopted technologies as a single covariate with industry-specific fixed effects. The coefficient indicates a significant correlation of 0.029 between adopting one digital technology and smartization. According to the findings in 2, this adoption can be associated with a potential growth of up to a 1.8% ($\approx 0.029 \times 0.632 \times 100$) in daily production. In column (2), total spending on adopted technologies replaces their counts, and the result is similar. Column (3) examines differences in the impacts of technology adoption between IT and OT types, while treating MES separately due to its popularity and importance in information sharing. We find a significant correlation between all technology types and smartization, with the adoption of MES and other OTs exhibiting magnitudes more than twice as large as ITs.

Column (4) adds three group-level variables indicating the technological readiness of the factory. The estimates support our prediction that smartized factories generally have a digital-ready organizational structure and workforce. Factories with dedicated specialists or a department for process optimization show a stronger inclination towards smartization. Digital-ready factories also tend to have a skilled workforce composition that aligns with smartization: The ratio of process technicians to total employees, converted to quintiles and scaled into 0–1, is significantly correlated with smartization. Lastly, providing workers with opportunities to learn about technology adoption increases the likelihood of factory smartization.

We further add three organizational characteristics as group controls in column (5). The estimated coefficients of labor union and family firm indicate a significant negative impact on smartization. The negative correlation with labor union suggests potential worker resistance to technological or organizational change. Similarly, existing literature indicates that founders or family member CEOs are often less inclined to invest in R&D activities compared to non-family CEOs (Pérez-González, 2006; Chrisman and Patel, 2012), aligning with our findings. CEO's interest in process innovation, as emphasized in Thong and Yap (1995), emerges as another critical organizational feature for smartization. Our field interviews repeatedly confirmed that the CEO's willingness was vital in overcoming the obstacles faced when upgrading the production systems of the factory. The estimated coefficient for the CEO's interest may capture such unobservable effects.

In column (6), we examine the interaction between the newly adopted technologies and two quasi-fixed organizational characteristics: incentive management practices and CEO's risk preference. Interestingly, the main term of technology adoption loses its statistical significance, while the two interaction terms become highly significant. The impact of technology adoption on smartization ranges from nearly zero to 0.06, depending on the levels of complementary characteristics. The first interaction term ($\Delta\#DT \times Incen.MS$) implies that technology adoption effectively promotes factory smartization only when combined with sound management practices for workers. Introducing new technology may require workers to adjust to a system that may not align with their incentives, a well-documented challenge in the literature (Bloom *et al.*, 2012; Garicano and Rayo, 2016; Atkin *et al.*, 2017). We demonstrate that this issue is also significant in the context of digital transformation.

The other complementarity arises from the CEO's leadership or management style (Bertrand and Schoar, 2003; Dessein and Prat, 2022). Given the difficulty to measure such characteristics, we ask survey respondents about the CEO's risk tolerance in managing their company, as it reflects their overconfidence and is associated with innovation success (Galasso and Simcoe, 2011; Hirshleifer *et al.*, 2012; Sunder *et al.*, 2017). Risk preference is subjectively measured on a scale of 0 (risk-averse) to 1 (risk-loving). Consistent with the literature, we observe a strong complementarity between risk tolerance and technology adoption in enhancing the factory's smartness. Despite potential measurement errors, the result can at least claim the importance of the CEO's certain leadership in smartization.[21]

Table 5 repeats the estimation of Eq. (5), using SI and DSU as separate dependent variables to determine the primary channel through which the factors influence smartization. The findings indicate that some factors affect smartization through only one channel, while others affect both channels. For instance, the impacts of newly adopted technologies in columns (1) and (4) are statistically significant for both dimensions of smartness. However, the presence of dedicated specialists or a process optimization department is only associated with SI,

[21] We also examined the complementarity between digital technology adoption and CEO's interest ($\Delta\#DT \times CEO.Interest$), but found no meaningful relationship. Therefore, risk preference represents a distinct characteristic of the CEO that is not captured by their interest in process innovation.

while the labor union only affects DSU. This aligns with intuition as system integration is more technology-focused, while data sharing and utilization primarily involve workers. The two interaction terms also affect smartization through different channels. Column (6) demonstrates that when new digital technologies are introduced, well-structured incentive management creates an environment conducive to data-centric management practices. Conversely, CEO's risk preference shows significant synergy with the adopted technologies in building an integrated manufacturing system, as indicated in column (3).

6 Concluding Remarks

The smart factory, a vital aspect of digital transformation in manufacturing, is considered a critical strategy for businesses and government policies. However, empirical research on this subject has been limited. This study is the first to quantitatively define and investigate factory smartness from an organizational standpoint, shedding light on its implications. Our unique survey data of 939 manufacturers in Korea reveals that increasing smartness has significant potential to enhance factory performance. The influences may vary depending on the manufacturing process and KPIs, but smartization is consistently linked with improved physical and revenue productivity. We also identify important drivers of smartization, including the adoption of digital technologies, organizational readiness, and CEO characteristics. Notably, technology adoption is more effective in making factories smarter when it aligns with worker incentives and proper leadership.

We acknowledge that our empirical analysis, based on a sample survey, may raise concerns regarding measurement errors and potential selection biases, despite our diligent efforts to minimize the issues. Also, the absence of an appropriate exogenous variation to instrument for the potentially endogenous smartization only led us to conduct an analysis based on correlational evidence. It is important to interpret these findings within the limitations of our research design, recognizing the need for further research that utilize independent and objective measures to establish causal relationships.

Nevertheless, our discussion thus far provides valuable insights for policymaking. The question at hand is how governments should intervene to promote smartization, particularly for small and medium-sized factories. Based on our findings, we advocate for policies that foster smart factories, emphasizing the coordination among different policy measures. In the context of Korea, where technology adoption subsidies are prevalent, addressing issues of poor incentive management is essential for their effectiveness (Chung, 2023). One potential solution is to combine management consulting with technical subsidies (Giorcelli, 2019). Implementing such coordinated policies may be challenging, but smart factories require smart policies.

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Figure 1: Conceptual Framework

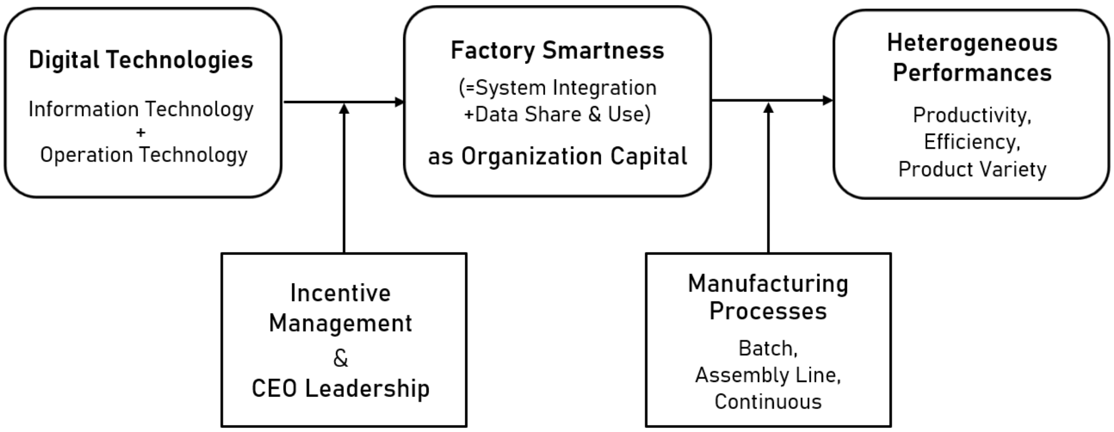
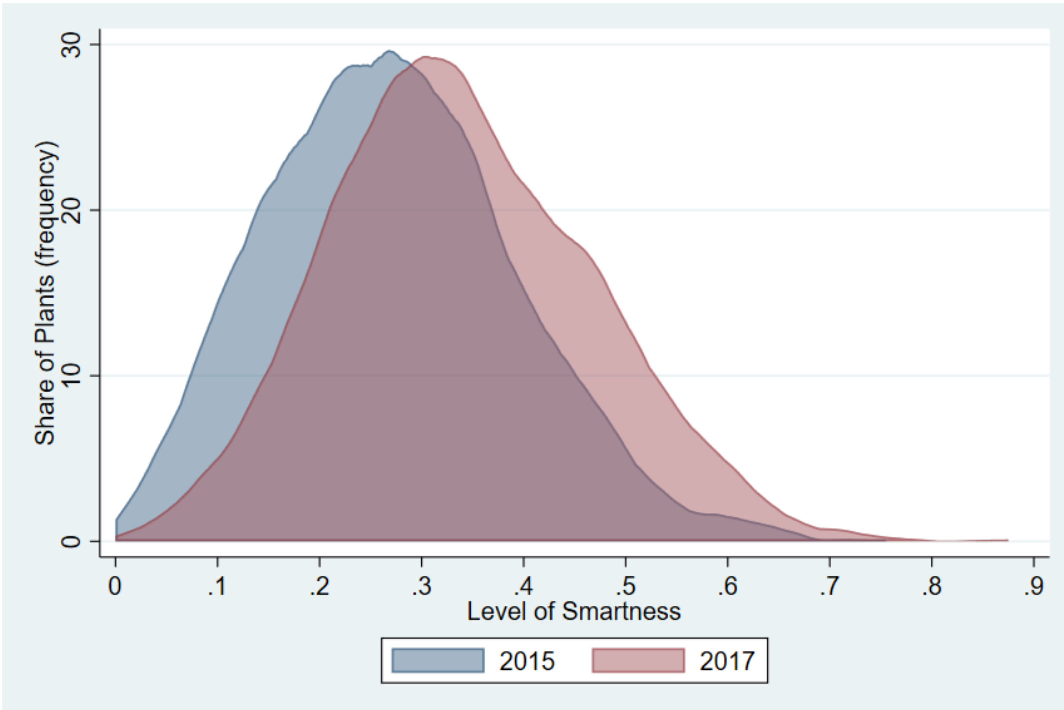


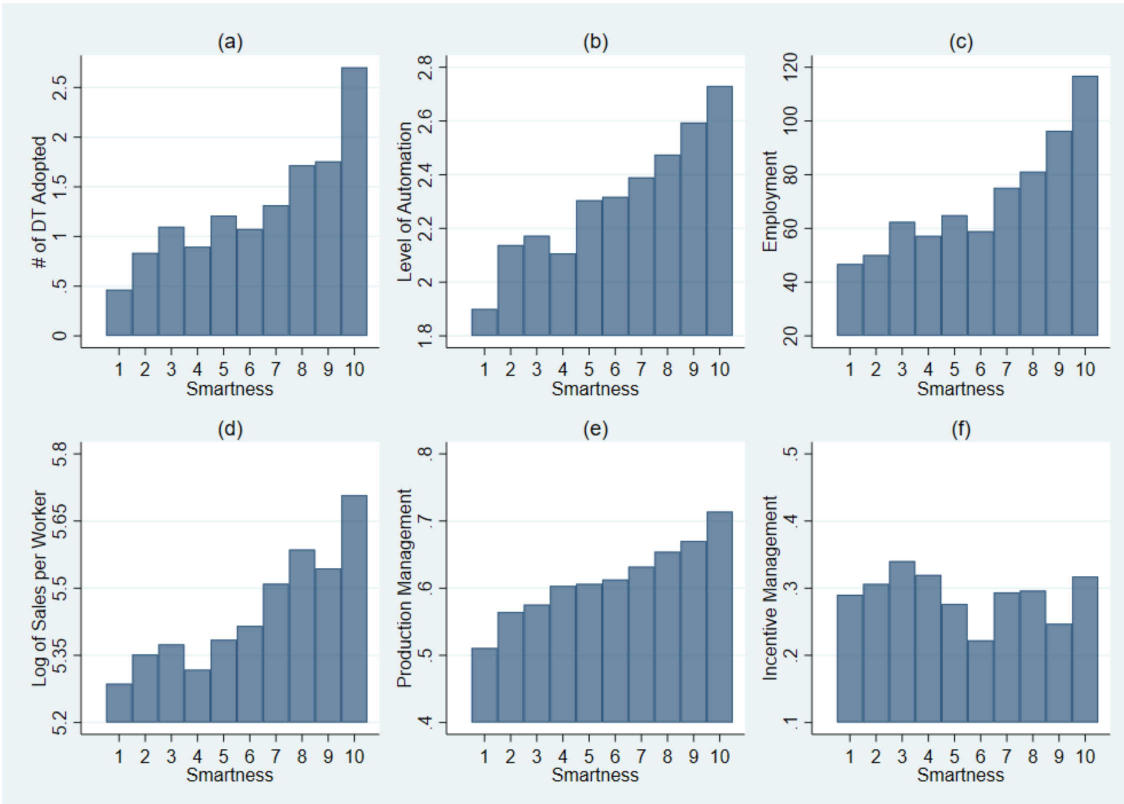
Figure 2: Distribution of Factory Smartness: 2015 vs. 2017



Notes: Y-axis indicates the number of factories (frequency) at a given level of smartness. The average levels of smartness are 0.27 in 2015 and 0.34 in 2017. See also Table A1 for associated statistics.

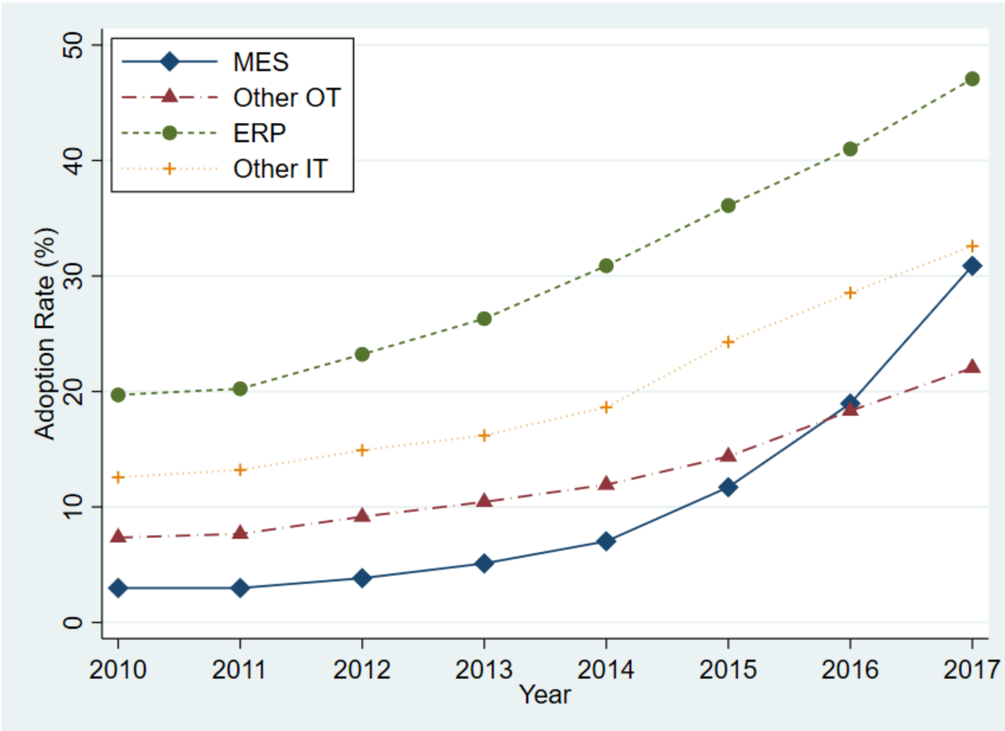
Figure 3: Smartization over the Years 2015–2017

Figure 4: Relationship between Smartness and Six Variables



Notes: In all subfigures, each decile presents the mean value of the variable in Y-axis. Subfigures (a) through (d) are drawn with both 2015 and 2017 values, whereas (e) and (f) only use 2017 value.

Figure 5: Trends in the Adoption of Digital Technologies



Notes: OT includes MES, PLC, SCADA, Smart Sensor (IoT), and CPS; IT includes ERP, PLM, SCM, FEMS, Big Data Analytics, Cloud Computing, and AI. A brief explanation about each technology is provided in C7 in the survey questionnaire in the Appendix.

Table 1: Sample Distribution by Industry and Size

Industry (KSIC 3 or 5-digit)	Size (Employment in 2017)				Total
	10~19	20~49	50~99	100 or more	
C134	12	39	18	9	78
C222	25	48	25	25	123
C259	23	64	30	24	141
C262	23	44	29	27	123
C291	32	53	26	29	140
C303	30	78	49	47	204
C20423	8	10	9	5	32
C29294	20	44	28	6	98
Total	173	380	214	172	939

Notes: C134=dyeing and finishing of textiles and wearing apparel, C222=manufacture of plastics products, C259=manufacture of other fabricated metal products, C262=manufacture of electronic components, C291=manufacture of general purpose machinery, C303=manufacture of parts and accessories for motor vehicles, C20423=manufacture of perfumes and cosmetics, C29294=manufacture of mould and metallic patterns.

Table 2: Smartization and Daily Output Growth

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Smart$	0.632***			0.537**	0.586**	0.443**
	(0.231)			(0.215)	(0.222)	(0.198)
$\Delta \#DT$		0.044**		0.018		0.017
		(0.018)		(0.019)		(0.019)
$log(DT.Spend.)$			0.020**		0.002	
			(0.008)		(0.008)	
$\Delta Automation$				-0.210*	-0.209*	-0.233*
				(0.110)	(0.111)	(0.128)
$\Delta log(Employment)$				0.165*	0.168*	0.204**
				(0.092)	(0.092)	(0.079)
$\Delta log(Material)$				0.188***	0.190***	0.154***
				(0.052)	(0.052)	(0.042)
$Startups$				0.099*	0.099*	0.068*
				(0.054)	(0.055)	(0.039)
$Exporters$				0.020	0.017	0.029
				(0.024)	(0.024)	(0.025)
$Subsidy$				0.038	0.054	0.009
				(0.044)	(0.041)	(0.044)
$\Delta log(Capital)$						-0.015
						(0.014)
Observations	808	808	808	764	764	576
R^2	0.104	0.100	0.095	0.204	0.202	0.224

Notes: The dependent variable is $\Delta log(daily\ Output)$ in all columns. All specifications include KSIC 5-digit industry-specific linear time trend. Robust standard errors for coefficients are clustered at the industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 3: Smartization and Various KPI Improvements

Panel A: Physical Productivity

	$\Delta log(Daily\ Output)$			$\Delta log(Lead\ Time)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Smart$	0.578**	0.450**	0.492**	-0.129	-0.155	-0.171*
	(0.222)	(0.201)	(0.229)	(0.087)	(0.113)	(0.099)
$\Delta Smart \times Line$	0.032	0.025	-0.025	-0.074	-0.057	0.035
	(0.254)	(0.256)	(0.291)	(0.182)	(0.183)	(0.223)
$\Delta Smart \times Cont.$	0.208	0.393	1.001	-0.319	-0.332	-0.432**
	(0.433)	(0.443)	(0.860)	(0.237)	(0.241)	(0.188)
Add Controls	No	Yes	Yes	No	Yes	Yes
Observations	808	764	457	891	832	497
R^2	0.104	0.206	0.257	0.103	0.115	0.210

Panel B: Cost Efficiency

	$\Delta log(Defect\ Rate)$			$\Delta log(Operating\ Rate)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Smart$	-0.107	-0.168	-0.682	0.080	0.046	0.025
	(0.219)	(0.312)	(0.410)	(0.053)	(0.050)	(0.086)
$\Delta Smart \times Line$	-0.821*	-0.801*	-0.883**	0.010	-0.003	-0.012
	(0.450)	(0.434)	(0.440)	(0.078)	(0.074)	(0.102)
$\Delta Smart \times Cont.$	0.062	0.102	0.126	-0.072	-0.048	-0.043
	(0.301)	(0.323)	(0.494)	(0.056)	(0.061)	(0.129)
Add Controls	No	Yes	Yes	No	Yes	Yes
Observations	841	791	478	888	833	499
R^2	0.093	0.104	0.162	0.062	0.151	0.262

Panel C: New Product Variety

	$\Delta log(\#of\ Products)$			$\Delta log(\#of\ Customers)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Smart$	0.222	0.221	0.409**	0.521***	0.601***	0.650***
	(0.149)	(0.138)	(0.167)	(0.132)	(0.164)	(0.179)
$\Delta Smart \times Line$	0.160	0.064	-0.007	-0.262*	-0.382**	-0.485***
	(0.126)	(0.128)	(0.163)	(0.152)	(0.161)	(0.141)
$\Delta Smart \times Cont.$	-0.267**	-0.286**	-0.349**	-0.361**	-0.406**	-0.296
	(0.128)	(0.127)	(0.167)	(0.157)	(0.187)	(0.207)
Add Controls	No	Yes	Yes	No	Yes	Yes
Observations	900	835	501	890	829	500
R^2	0.091	0.119	0.214	0.081	0.128	0.173

Notes: All six columns include the 5-digit industry-specific dummies. Columns (2), (3), (5) and (6) additionally control for the following variables: $\Delta\#DT$, $\Delta Automation$, $\Delta log(Employment)$, $\Delta log(Material)$, $Startups$, $Exporters$, and $Subsidy$. Column (3) and (6) use the sub-samples of factories with at least three KPIs being monitored in both years. Robust standard errors for coefficient estimates are clustered at the industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 4: Drivers of Smartization

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta \# DT$	0.029***			0.023***	0.021***	-0.004
	(0.003)			(0.004)	(0.003)	(0.006)
$log(DT.Spend)$		0.017***				
		(0.001)				
MES			0.040***			
			(0.007)			
$\Delta Other\ OTs$			0.042***			
			(0.010)			
ΔITs			0.015**			
			(0.007)			
$Specialist$				0.031***	0.020***	0.017**
				(0.007)	(0.006)	(0.007)
$\%\,of\ Technicians$				0.041***	0.034***	0.031***
				(0.008)	(0.007)	(0.007)
$Tech.Training$				0.025***	0.021***	0.025***
				(0.008)	(0.007)	(0.008)
$Union$					-0.025***	-0.023***
					(0.009)	(0.008)
$CEO.Family$					-0.032***	-0.023***
					(0.007)	(0.007)
$CEO.Interest$					0.053***	0.046***
					(0.008)	(0.009)
$\Delta \# DT \times Incen.MS$						0.039***
						(0.010)
$\Delta \# DT \times CEO.Risk$						0.024**
						(0.011)
Observations	939	939	939	937	937	906
R^2	0.250	0.277	0.259	0.313	0.354	0.371

Notes: The dependent variable is $\Delta Smart$ in all columns. OT includes MES, PLC, SCADA, Smart Sensor (IoT), and CPS; IT includes ERP, PLM, SCM, FEMS, Big Data Analytics, Cloud Computing, and AI. All specifications include the KSIC 5-digit industry-specific linear time trends. Robust standard errors for coefficients are clustered at the 5-digit industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Drivers of System Integration and Data Share & Use

	System Integration (ΔSI)			Data Share & Use (ΔDSU)		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\#DT$	0.042***	0.033***	0.008	0.015***	0.009**	-0.015
	(0.004)	(0.004)	(0.007)	(0.003)	(0.004)	(0.009)
$Specialist$		0.031***	0.030***		0.009	0.005
		(0.008)	(0.009)		(0.008)	(0.007)
$\%\,of\ Technicians$		0.044***	0.044***		0.024**	0.019**
		(0.014)	(0.014)		(0.011)	(0.008)
$Tech.Training$		0.019**	0.021**		0.024**	0.028***
		(0.008)	(0.009)		(0.009)	(0.010)
$Union$		-0.004	-0.004		-0.046***	-0.041***
		(0.014)	(0.012)		(0.009)	(0.008)
$CEO.Family$		-0.037***	-0.031***		-0.026***	-0.016*
		(0.009)	(0.009)		(0.009)	(0.009)
$CEO.Interest$		0.054***	0.046***		0.052***	0.046***
		(0.010)	(0.011)		(0.011)	(0.012)
$\Delta\#DT \times Incen.MS$			0.017			0.060***
			(0.017)			(0.009)
$\Delta\#DT \times CEO.Risk$			0.037***			0.010
			(0.012)			(0.016)
Observations	939	937	906	939	937	906
R^2	0.258	0.339	0.350	0.137	0.206	0.226

Notes: All specifications include the KSIC 5-digit industry-specific linear time trends. Robust standard errors for coefficients are clustered at the 5-digit industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Appendix. Survey Structure and Questionnaire

This section introduces the overall survey structure and the main questions. The original survey questionnaire is in Korean, but a fully translated version into English is available upon request.

Section A. Production Environment

This section asks about the main products of the plant (A1), their location in the supply chain (A2), and the type of manufacturing process (A3). The types in A3 are categorized into four processes: one-off or job shop process, batch process, assembly line process, and continuous process. The question self-contains a brief explanation about each process.

A3. Which of the following best describes the production at this establishment?

2015	2017

① (One-off, Job shop) Produce individual products (e.g., prototype, machine tool, shipbuilding)

② (Batch) Produce variants of the same type of product using the same machines while assigning different lot number (e.g., shoemaking, pottery)

③ (Assembly line, Flow) Produce along the series of workstations (e.g., cars, refrigerators)

④ (Continuous) Continuous process in which automated facilities run nonstop (e.g., steel, brewing, paper)

Section B. Level of Automation

This section measures factory-level automation as of 2015 and 2017. The question B1 (see below) asks the self-assessment of automation level ranging from 1(mainly manual work) to 5(entire process automation). Scores on the 0–1 scale are in parentheses for each choice (red color), which are not actually shown in the questionnaire. This section also asks about the number of industrial robots and costs for maintenance (B2). The question B3 asks the factory's plan for buying robots in coming two years including the year of survey.

B1. What best describes the level of automation throughout the entire production process at this establishment?

2015	2017

① Mostly manual (0)

② Some parts of operations (1/4)

③ Major parts of operations (2/4)

④ Most parts of operations (3/4)

⑤ Entire operations (1)

Section C. Level of Smartness

This section includes questions on the level of smartness in the factory, the status of relevant technology adoptions, and plans for (additional) adoptions in two years. The level of system integration is composed of two kinds of integration, vertical and horizontal. C5 asks the level of vertical integration in the manufacturing process as of 2015 and 2017 and C6 asks the level of horizontal integration from sales forecasting to production, inventory management and logistics. Both vertical and horizontal integration levels are measured with five stages.

C5. What best describes the **manufacturing phase** at this establishment?

2015	2017

① (Check) Manual check of production logs or checklists, or simple planning using EXCEL program. (0)

② (Monitoring) Operations are systematically managed so that production history can be traceable at any time. (1/4)

③ (Control) Problems in operations are automatically identifiable through real-time data and resolvable by remote controller. (2/4)

④ (Optimization) Big data and technology solutions can control and optimize the entire process, and anticipate problems in advance. (3/4)

⑤ (Autonomous operation) Optimized factory can control and solve problems in case of abnormalities with little human intervention. (1)

C6. From sales forecasting to production, inventory management and logistics phases, what best describes the **utilization of ICT** at this establishment?

2015	2017

① No ICT is used in any production phase. (0)

② ICTs are applied to management system at some production phases. (e.g., design, operation, inventory, accounting) (1/4)

③ ICT-based management systems at some production phases are partially linked with one another in real-time. (e.g., ordering information ⇒ production planning) (2/4)

④ ICT-based management systems at each production phases are linked with one another in real-time. (e.g., sales ⇔ design ⇔ manufacturing ⇔ resource management) (3/4)

⑤ All information generated at all production phases is linked through ICTs. (1)

This section also asks how frequently the results from data analyses are utilized for decision-making (C10) and how much the data is shared among the participants in the value-generating process of the product (C11). They are supposed to be answered in five or six separate steps. Additionally, the section includes the question number 27 of the U.S. Management and Organizational Practice Survey (MOPS) conducted in 2015, which is labeled as C9 in our survey. The question is about how often the four types of data collected from production activities are used in decision making. The original MOPS survey questionnaire is available from Buffington *et al.* (2016).

C10. How frequently did your establishment apply data analysis results into the following activities?

Type of Activity	Year	① Real-time (1)	② Daily (3/4)	③ Weekly (2/4)	④ Monthly (1/4)	⑤ Yearly or not used (0)
(1) Optimization of manufacturing process	2015					
	2017					
(2) Higher product quality and lower defect rate	2015					
	2017					
(3) Anticipation of failures of production facilities	2015					
	2017					
(4) Development of new products or services	2015					
	2017					
(5) Supply chain (supplier or customer) management	2015					
	2017					
(6) Product demand forecast and marketing strategies	2015					
	2017					

C11. At what level and scope were the data that are collected or analyzed from each production activity shared?

Type of Activity	Year	① Not shared at all (0)	② Occasionally shared as needed (1/4)	③ Shared by an agreed scope (2/4)	④ Shared by an agreed scope, plus as needed (3/4)	⑤ Always shared in real-time (1)
(1) Between workers within the divisions	2015					
	2017					
(2) Between divisions within the establishment	2015					
	2017					
(3) Between establishments within the affiliated firms	2015					
	2017					
(4) Between suppliers or buyers in the supply chains	2015					
	2017					

Another important questions surveyed in this section are the factory's current state of a dozen types of technology adoption related to the system integration. C7 asks about the year of the adoption or future plans for adopting seven types of information technology (3, 4, 5, 6, 7, 10, 11) and five types of operation technology (1, 2, 8, 9, 12). The question self-contains a brief explanation of each individual technology. For the factories where any of the twelve technologies have been adopted in 2017 or earlier, the following sub-question C7-1 asks the total yearly maintenance cost of all adopted technologies. Another sub-question C7-2 asks the total costs of purchasing every technology that has been installed during the years 2016 and 2017 (see below).

C7. When have the following technologies been adopted at this establishment? If not, is there a plan for future adoption of any of them by 2019?

Type of Technology	Adoption Status
1) **Digital Control Unit** (PLC, CNC, HMI, etc): Device for monitoring and controlling machines	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
2) **Central Control System** (DCS, SCADA): Control system that visualizes data such as uptime, operation rate, etc.	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
3) **Product Design/Development System** (PLM) (e.g. PDM, CAD, CAM, CAE, etc.): System that manages entire process from design to production to add value and reduce costs	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
4) **Manufacturing Execution System** (MES): System that tracks and analyzes data generated from order to shipment in order to optimize production process	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
5) **Enterprise Resource Planning** (ERP): Integrated and real-time management system of key information of corporate activities	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
6) **Supply Chain Management** (SCM): Optimize supply chain activities such as procurement and logistics through sharing information between supply-chain partners	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
7) **Energy Management System** (FEMS): Optimize energy usage in real time through monitoring, analysis, and remote control.	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
8) Devices or products that use **smart sensor (IoT), RFID, NFC, Bluetooth, etc.** to collect data	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
9) **Factory big data analysis:** Apply big data (real-time information on device or production process) analysis techniques	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
10) **Cloud computing service:** Store and use data on internet server instead of individual PC	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
11) **AI or Machine learning:** Computer recognizes product image or machine data and processes them for decision making	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)
12) **Cyber Physical System (CPS):** Construct virtual system of production process and use it for various simulations	① Yes (Year of adoption: _________) ② No (Plan to adopt: ⓐYes ⓑ No)

C7-2. Approximately how much is the total cost of purchasing the above technologies that have been introduced during the years 2016 and 2017?

Million Won

The technologies include systems that have been used in modern manufacturing as well as relatively new digital technologies. The five operation technologies (OTs) are the technologies directly associated with factory floor information. Digital control unit (Programmable Logic Controller, PLC), smart sensor (Internet of Things, IoT), and central control system (Supervisory Control and Data Acquisition, SCADA) are operational systems that monitor and automatically control machines and devices at the shop floor. Manufacturing Execution System (MES) transmits information from the shop floor to the back office in real time. Cyber Physical System (CPS) optimizes production process in the cyber space—the twin of the physical factory—by simulating the shop floor data. The seven ITs correspond to Enterprise Resource Planning (ERP), Product Lifecycle Management (PLM), Supply Chain Management (SCM), Factory Energy Management System (FEMS), cloud computing, big data analytics, and artificial intelligence (AI or machine learning). These software systems integrate the information needed for data-driven management.

Other questions in section C include the degree of prior knowledge on smart factories (C1), how many of nearby factories have adopted or plan to adopt the digital technologies (C2), whether the factory conducted a preliminary investigation for digital technologies (C3), whether the factory offered worker training before adopting the technologies (C4), factory manager's satisfaction and future expectation from since the technology adoption (C7-3 and C7-4), and major reasons for the adoption and non-adoption of digital technologies (C7-6 and C8).

Section D. Management Status

This section surveys on management practices in the factory. Bloom *et al.* (2019) have successfully proposed a replicable survey method for measuring structured management practices in manufacturing plants. Hence, the section employs the 16 multiple choice questions about production targeting, monitoring, and incentive management developed in their study. Questions D1 through D8 below correspond to them. We sorted the questions into two categories: Production Management (D1~D6-1) and Incentive Management (D6-2~D8).

Question	Question Text
D1	What best describes what happens at your establishment when a problem in the production process arises?
D2	How many key performance indicators (KPI) are monitored in your establishment?
D3	Where are display boards showing key performance indicators (KPI) located in your establishment?
D4	How frequently are key performance indicators typically reviewed by managers and non-managers at your establishment? Answer separately for managers and non-managers.
D5	Who was aware of the operational targets at your establishment?
D6	What best describes the time frame of operational targets at your establishment?
D6-1	How easy or difficult is it in your establishment for people to typically achieve their operational targets?
D6-2	What are managers and non-managers' performance bonuses usually based on in your establishment? Answer separately for managers and non-managers.
D6-3	When targets are met, what percent of managers and non-managers received performance bonuses? Answer separately for managers and non-managers.
D7	What is the primary way managers and non-managers are promoted in your firm? Answer separately for managers and non-managers.
D8	When is an under-performing manager and non-manager usually reassigned or dismissed? Answer separately for managers and non-managers.

Note: These questions and responses are from the MOPS and they were carefully translated into Korean to be close to the original MOPS questions. Refer to Buffington *et al.* (2016) for responses of each question.

This section also includes questions such as the degree of participation of production workers in decision-making and problem-solving in production process (D9 and D10), the degree of the CEO's interest in process innovation (D11), the presence of personnel or a department fully specialized in integrating and optimizing production process (D12), and the CEO's risk preference (D14). D14 asks respondents to assess the risk preference of their firm CEO from a 0–10 scale where 0 is the most risk-averse and 10 is the most risk-loving.

Question	Question Text	Response
D9	Did production workers participate in decision-making in production process or in workplace reorganization?	Yes, they participated. (1)
		No, they did not participate. (0)
D10	When a problem in the production process arises, to what extent have production workers participated in problem-solving?	Never participated. (0)
		Assisted a problem-solving team. (1/3)
		Participated in significant portion. (2/3)
		Fully in charge of the process. (1)
D11	What best describes the interest of the headquarter CEO in process innovation such as buying robots for automation or adopting technology for smartization?	Had no interest. (0)
		Had a little interest. (1/3)
		Had some interest. (2/3)
		Had lots of interest. (1)
D12	Does your establishment have fully specialized personnel or a department for optimizing production process using digital technology?	No. (0)
		Has specialized personnel or a department. (1)
D14	What best describes the attitudes of the headquarter top management towards risks? (Scale: 0~10)	Avoids risks as much as possible and seeks the most stable direction (0)
		Fully take risks and challenge (1)

Section E. Employment and Work Characteristics

This section aims to understand the impact of smartization on employment and demand for workers' job competency (E2). Worker types are categorized into 3 types which are office workers, process control engineers and production workers. The question E3 asks expected change in demand for each type of workers.

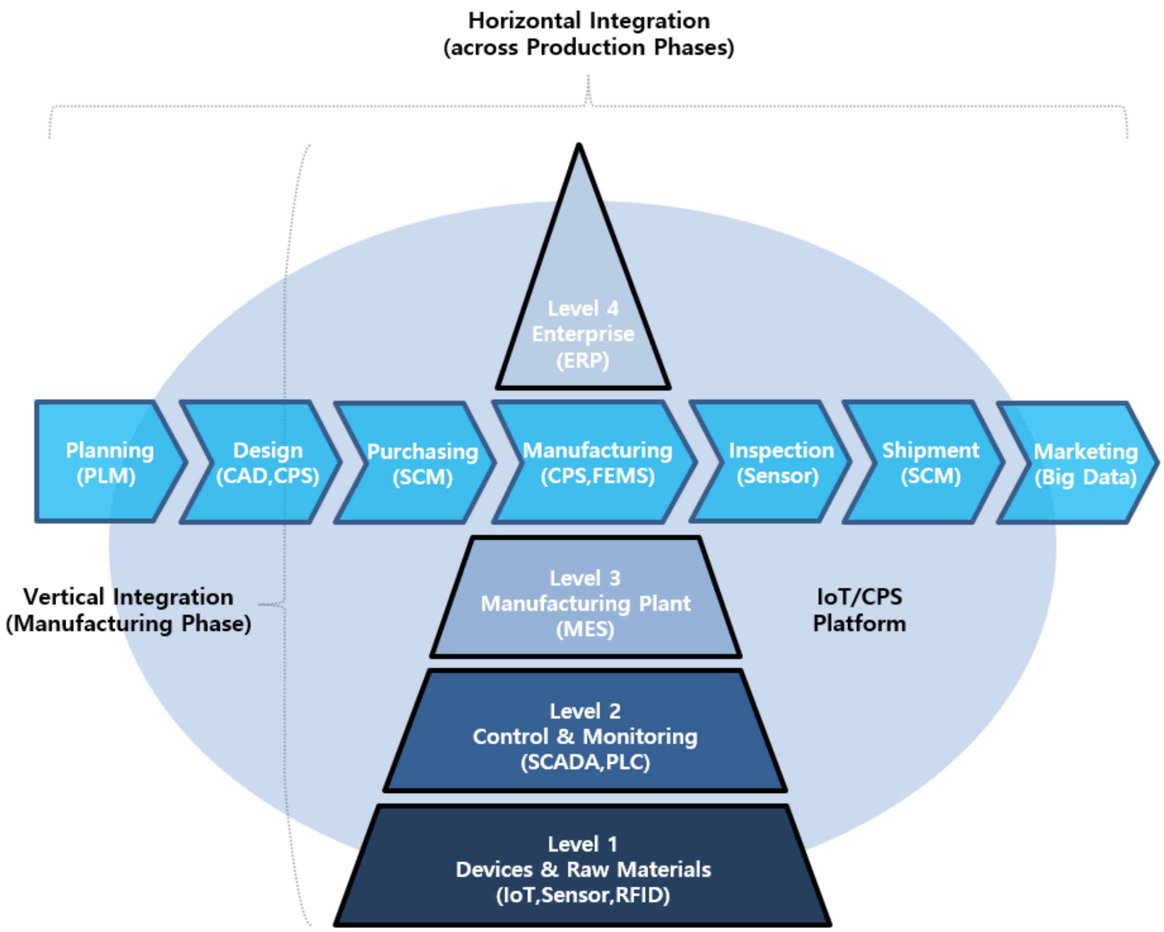
Section F. Establishment Characteristics

This section asks about basic characteristics of the plant (total number of establishments, number of overseas subsidiaries, labor union status, family ownership, foreign investment, etc. in F1) and the various performance indicators of the factory (F2). Key performance indicators include (i) the daily output of the main product; (ii) the lead time of the main product (from order to factory delivery); (ii) the defect rate of the main product; (iv) the number of products produced; and (vi) the number of customers. The question F2 also includes accounting information such as sales and costs of raw materials.

Figure A1: Manufacturing Firms Using Smart Factory-related Technology

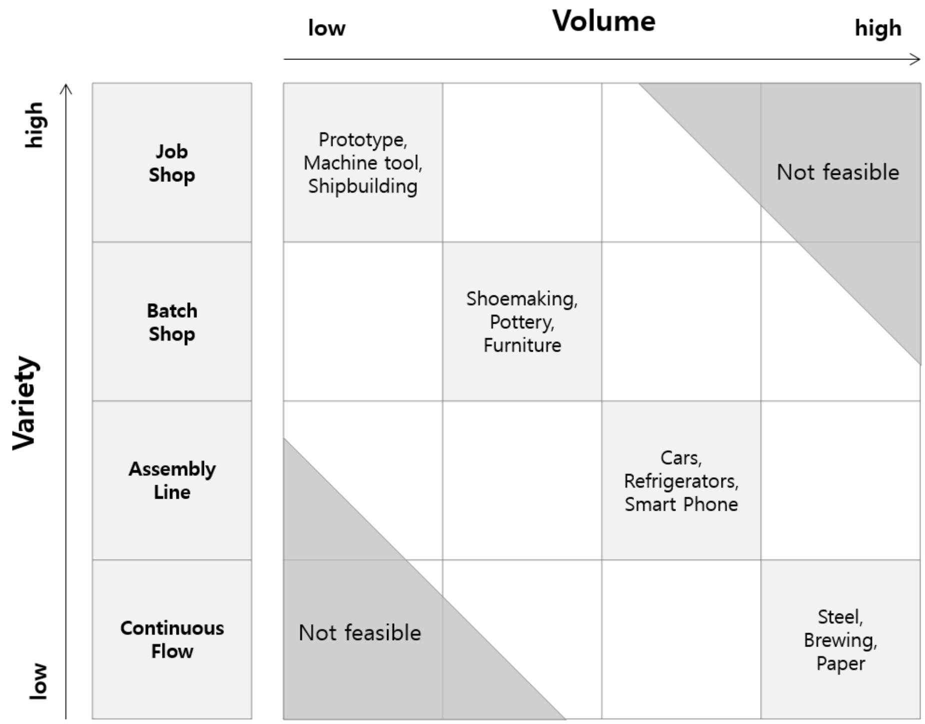
Notes: All subfigures present the average percentage of businesses utilizing specific technologies in the manufacturing industry. These percentages are calculated based on data collected from OECD and accession countries, where the data are available, for each year.
Source: OECD.Stat, ICT Access and Usage by Businesses Database (http://oe.cd/bus)

Figure A2: Horizontal & Vertical Integration of Factory System



Notes: Operation technology (OT) includes MES, PLC, SCADA, Smart Sensor (IoT), and CPS. Information technology (IT) includes ERP, PLM, SCM, FEMS, Big Data Analytics, Cloud Computing, and AI. See question C7 of the survey questionnaire in the Appendix for a brief explanation about individual technologies.

Figure A3: Product-Process Matrix



Source: Modified from Hayes and Wheelwright (1979a,b).

Table A1: Summary Statistics

	# of obs.	Mean	S.D.	p10	p25	p50	p75	p90
A. Smartness (in 2017)								
Smartness (0~1)	939	0.34	0.13	0.18	0.25	0.33	0.43	0.51
SI (0~1)	939	0.21	0.17	0.00	0.13	0.25	0.25	0.50
Vertical (0~1)	939	0.18	0.18	0.00	0.00	0.25	0.25	0.50
Horizontal (0~1)	939	0.25	0.21	0.00	0.00	0.25	0.25	0.50
DSU (0~1)	939	0.46	0.18	0.23	0.32	0.46	0.63	0.71
DataShare (0~1)	939	0.54	0.24	0.25	0.31	0.50	0.75	0.88
DDD (0~1)	939	0.39	0.21	0.08	0.21	0.38	0.54	0.67
B. Investment on Digital Technology (for 2016 and 2017)								
#DT.Adopt (0~12)	939	0.59	1.11	0	0	0	1	2
MES (0 or 1)	939	0.19	0.39	0	0	0	0	1
#Other OT (0~4)	939	0.13	0.44	0	0	0	0	0
#IT (0~7)	939	0.27	0.63	0	0	0	0	1
DT.Spend (log)	939	1.31	2.09	0	0	0	3.71	4.80
C. Key Performance Indicators (in 2017)								
Daily Output (log)	817	6.78	4.05	1.10	3.69	7.31	9.90	11.51
Leadtime (day)	896	13.60	35.96	1.50	3.00	5.00	10.00	30.00
Defect Rate (%)	887	2.58	4.29	0.05	0.30	1.00	3.00	5.00
Operating Rate (%)	896	82.41	15.91	65	75	80	95	100
#Products	906	210.40	1387.3	1	4	15	96	300
#Customers	900	80.72	506.59	3	7	20	43	100
D. Plant Characteristics (in 2017)								
Age (Years)	939	19.36	11.05	6	11	18	26	33
Sales (log)	934	9.25	1.36	7.59	8.31	9.19	10.18	10.95
Material Cost (log)	869	8.04	1.76	5.90	7.00	8.15	9.17	10.09
Capital Stock (log)	731	8.24	1.50	6.41	7.56	8.36	9.18	9.86
Employment	939	71.09	119.52	15	22	41	80	143
%Technician (0~1)	937	0.14	0.13	0.05	0.07	0.11	0.18	0.30
Automation (0~1)	939	0.37	0.21	0	0.25	0.25	0.50	0.50
TFP (log)	654	5.14	0.97	4.10	4.61	5.07	5.67	6.27
Production MS (0~1)	908	0.61	0.13	0.44	0.53	0.63	0.71	0.78
Incentive MS (0~1)	908	0.29	0.19	0.06	0.17	0.29	0.42	0.54
Exporter (0 or 1)	939	0.38	0.48	0	0	0	1	1
Specialist (0~1)	939	0.36	0.28	0	0	0.50	0.50	0.50
Union (0 or 1)	939	0.11	0.31	0	0	0	0	1
Subsidy (0 or 1)	939	0.19	0.39	0	0	0	0	1
Tech.Training (0~1)	939	0.12	0.18	0.00	0.00	0.00	0.33	0.33
E. CEO Characteristics (in 2017)								
Interest (0~1)	939	0.78	0.41	0	1	1	1	1
Family (0 or 1)	939	0.64	0.30	0.33	0.33	0.67	1	1
RiskTaking (0~1)	939	0.54	0.24	0.20	0.30	0.50	0.70	0.90

Notes: All monetary values are in million Korean Won.

Table A2: Smartization, Revenue Productivity and Employment Growth

	$\Delta log(Sales)$			$\Delta log(Employment)$		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Smart$	0.339***	0.395***	0.395**	0.219*	0.139	0.167
	(0.117)	(0.147)	(0.168)	(0.128)	(0.164)	(0.166)
$\Delta log(Employment)$	0.316***	0.280***	0.292***			
	(0.086)	(0.078)	(0.098)			
$\Delta log(Material)$	0.469***	0.446***	0.457***	0.072***	0.082***	0.072***
	(0.066)	(0.071)	(0.078)	(0.018)	(0.021)	(0.020)
$\Delta log(Capital)$	0.064**		0.068**	0.016		0.012
	(0.027)		(0.030)	(0.012)		(0.013)
$\Delta \#DT$		-0.010	-0.000		0.009	0.001
		(0.017)	(0.012)		(0.009)	(0.009)
$\Delta Automation$		-0.185	-0.171		0.050	0.010
		(0.142)	(0.179)		(0.078)	(0.072)
Add Controls	No	Yes	Yes	No	Yes	Yes
Observations	651	855	651	652	856	652
R^2	0.374	0.400	0.434	0.051	0.130	0.165

Notes: Controls include all group dummies: *Startups*, *Exporters*, *Subsidy*, and the 5-digit industry dummies. Robust standard errors for coefficients are clustered at the industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A3: Smartization and Revenue Productivity Growth (with External Data)

	Sales proportional to production share			Sample with 100% production share		
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta Smart$	0.368***	0.453**	0.441**	0.460**	0.523*	0.503*
	(0.138)	(0.208)	(0.215)	(0.189)	(0.280)	(0.295)
$\Delta log(Employment)$	0.338***	0.337***	0.325***	0.308***	0.294**	0.278**
	(0.086)	(0.101)	(0.099)	(0.100)	(0.115)	(0.114)
$\Delta log(Material)$	0.438***	0.441***	0.424***	0.455***	0.475***	0.458***
	(0.068)	(0.079)	(0.076)	(0.077)	(0.095)	(0.093)
$\Delta log(Capital)$	0.074**		0.080**	0.068*		0.068
	(0.034)		(0.038)	(0.038)		(0.044)
$\Delta \# DT$		0.004	0.001		0.005	0.002
		(0.014)	(0.012)		(0.016)	(0.016)
$\Delta Automation$		-0.068	-0.090		-0.077	-0.101
		(0.207)	(0.208)		(0.255)	(0.256)
Add Controls	No	Yes	Yes	No	Yes	Yes
Observations	629	631	629	458	460	458
R^2	0.376	0.432	0.449	0.375	0.465	0.475

Notes: The dependent variable is $\Delta log(Sales)$ in all columns. Controls include all group dummies: *Startups*, *Exporters*, *Subsidy*, and the 5-digit industry dummies. Robust standard errors for coefficients are clustered at the industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table A4: Smartization and KPI Improvements: Additional Results

Panel A: System Integration, Data Share & Use, and KPIs

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Variable (Δ)	Daily Production	Lead Time	Defect Rate	Operating Rate	Product Variety	Number of Customers
ΔSI	0.309*	0.026	-0.011	0.064	0.081	0.242***
	(0.172)	(0.057)	(0.192)	(0.045)	(0.073)	(0.076)
ΔDSU	0.222	-0.295**	-0.554***	-0.035	0.121*	0.084
	(0.143)	(0.146)	(0.158)	(0.035)	(0.065)	(0.117)
Add Controls	Yes	Yes	Yes	Yes	Yes	Yes
F-Statistics	3.212**	2.889*	6.238***	1.370	2.682*	6.418***
Observations	764	832	791	833	835	829
R^2	0.204	0.120	0.100	0.153	0.114	0.124

Panel B: Nonlinearity between Smartization and KPI Improvements

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome Variable (Δ)	Daily Production	Lead Time	Defect Rate	Operating Rate	Product Variety	Number of Customers
$\Delta Smart$	0.671**	0.163	-0.814*	0.075	0.344**	0.386
	(0.330)	(0.293)	(0.463)	(0.136)	(0.161)	(0.265)
$\Delta Smart^2$	-0.446	-1.382	0.950	-0.133	-0.489	-0.159
	(0.874)	(1.186)	(1.165)	(0.380)	(0.461)	(1.013)
Add Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	764	832	791	833	835	829
R^2	0.204	0.116	0.096	0.151	0.115	0.123

Notes: F-statistics in Panel A test for the joint significance of ΔSI and ΔDSU. All specifications include the following control variables: $\Delta Tech$, $\Delta Automation$, $\Delta log(Employment)$, $\Delta log(Material)$, $Startups$, $Exporters$, $Subsidy$, and the KSIC 5-digit industry dummies. Robust standard errors for the coefficient estimates are clustered at the industry level in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.