n

Tasks and Skills in Additive versus Traditional Manufacturing: A First Look at Evidence from Job Vacancies

Avner Ben-Ner*, Ainhoa Urtasun and Bledi Taska*****

May 24, 2019

Draft

Abstract

Additive manufacturing is poised to transform production of many parts and finished goods. Little is known about its effects on work. The paper provides the first analysis of differences in tasks and skills of core production employees – engineers, technicians and operators – in additive manufacturing (AM) and traditional manufacturing (TM). In order to control for unobservable heterogeneity that may affect tasks and skill requirements, we focus on hybrid AM-TM manufacturing establishments (plants). We study 1,304 US plants that posted jobs for both AM and TM core workers during between January 2014 and February 2019. We find that, for the three occupations, AM vacancy postings reflect considerably more complex tasks, slightly more interdependent tasks and require more cognitive, social and technical skills than TM postings.

*Carlson School of Management, University of Minnesota–Twin Cities

**Department of Management, Public University of Navarra

***Burning Glass Technologies

Tasks and Skill in Additive versus Traditional Manufacturing: A First Look at Evidence from Job Vacancies

Avner Ben-Ner, Ainhoa Urtasun and Bledi Taska

An industrial revolution is unfolding at an increasing speed. It is additive manufacturing, the production of just about anything, from spare parts to complex geometric forms to airplane parts to entire houses through the layer-by-layer addition of many varied materials until the product is completed. The additive manufacturing technology emerged in the 1980s and has been used primarily for prototyping. During the past decade, the use of AM in production of parts and finished goods has grown rapidly. Early adopters were primarily small new firms, but in recent years large firms, such as Adidas, Boeing, GE and HP, as well as many auto, aircraft and medical device manufacturers have added additive manufacturing production lines (see Figure 1). Observers in academe and industry expect AM to grow rapidly out of a niche technology to an important if not dominant manufacturing technology.[1] During the 2000s, educational institutions have incorporated additive manufacturing in the curriculum in many engineering, design and other degree programs, and leading universities have established research centers and graduate degrees focused on additive manufacturing.[2] Many K-12 schools and public libraries have 3D printers, from basic thermoplastic filament-only printers to machines capable of printing functional multiple materials. Increasing number of people in the education system and in industry are exposed to and come in contact with additive manufacturing. Figure 2 illustrates the growth in the number of job postings for three core manufacturing occupations, engineers, technicians and operators/machinists, in additive and traditional manufacturing (henceforth, AM and TM, respectively).

---

[1] A March 2018 job posting by HP illustrates the company's expectations for the future of AM: "*HP is pioneering a revolutionary new technology in Metals 3D printing that can scale into mass production of metal parts in a variety of industries such as Automotive, Medical, Aerospace, Consumer, etc. We are looking for visionaries who will be responsible for unlocking the potential of this transformational technology and turning it into commercially successful products. You will act as a catalyst for disrupting the $12 trillion global manufacturing industry that goes to the very heart of how the world conceives, designs, creates, distributes and experiences, well... everything, everywhere.*"

[2] See, for example, an article from 2017 surveying additive manufacturing research in universities, and a listing of universities with additive manufacturing specialization.

Car Parts and Manufacturing Tools	• Integration of many parts in a unified composite part • Production of jigs, fixtures and other tools for traditional manufacturing • Production of spare parts and accessories • Fast standardization
Aerospace/Aeronautics	• Production of parts with complex geometry • Control of density, mechanical properties • Production of parts that are lighter than those produced by traditional methods
Medical Devices/Pharmaceuticals	• Planning of surgical operation with the use of accurate anatomic models • Production of customized prosthetics, implants, hearing aids and dentures • Use of printed simulated corpse for medical training in anatomy • Printing of biodegradable living tissues for tests during the development phase of the medicinal product • Printing of medicinal drugs for extended release
Sports Equipment	• Production of accessories of complex geometry • Production of customized running shoes • Creation of adjusted protective equipment for better application and use • Creation of prototypes of multiple colors and composite materials for products testing
Construction	Manufacturing of concretes for conventional building • Novel design of functional concretes such as self-cleaning concrete • Building construction using diverse materials other than cement • Rapid construction

Figure 1. Principal Industries and Applications of AM Technology
Adapted from Tofail, Koumoulos, Bandyopadhyay, Bose, O'Donoghue, and Charitidis (2018).

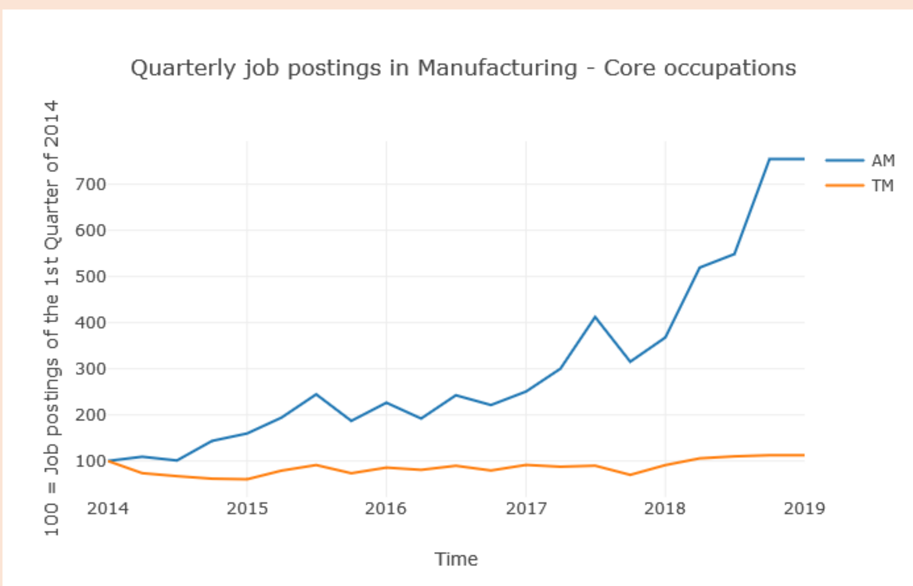


Figure 2. Evolution of Additive Manufactural and Traditional Manufacturing Job Vacancies in Core Occupations: Engineers, Technicians and Operators. Source: Burning Glass Technologies

This versatile general-purpose technology is poised to have important effects on the economy in the future. Compared to most TM techniques, AM entails more challenging design of parts and finished products, assembly processes are drastically reduced, economies of scale are considerably smaller, production may be located closer to customers and easiely customized, and supply chains are simpler and shorter, to name just a few differences (Lipson and Kurman, 2013, Jiang, Kleer & Piller, 2017, Ben-Ner and Siemsen, 2017, Niacko and Nonino, 2018, Hedenstierna et al., 2019). The production process also differs between AM and TM, such that workers, machines and software do different tasks and combine their respective contributions in different ways. Even at the visual level, a shop that produces by AM looks different from one that produces similar products by TM techniques: the former is smaller, less cluttered, with little debris strewn around, and there are fewer people in sight. But how is production work in AM different from work in TM? Are the tasks of core manufacturing employees more or less complex or interdependent under AM than TM in comparable contexts? Do workers need more or fewer analytical and problem-solving skills or various technical skills under AM and TM? No evidence exists at this point regarding these issues that are central to understanding of what the manufacturing workplace of the future may entail and for employees in various occupations, for technical education and training, and for the organization of companies, including where in the organizational hierarchy various decisions are made and what is the level and type of pay of employees in different roles. The present paper investigates whether engineers, technicians and operators/machinists carry out their work in AM differently than in TM, and whether the skills they need to possess differ. We analyze job postings by more than a thousand "hybrid" manufacturing plants, plants that have posted jobs for these core manufacturing employees in both technologies during the past five years.

The introduction of computer-based technologies a few decades ago has generated enormous interest about its effects on work organization and skill requirement (see, for example, Zuboff 1988, Autor, Levy and Murnane, 2003 and Ben-Ner and Urtasun, 2013). More recently, machine learning/artificial intelligence has prompted questions tinged with anxiety about the future of work (see, for example, National Academies of Sciences, 2017, Frank et al., 2019). It is time to start a conversation about what may AM bring to the world of work relative to traditional manufacturing. We explore two central questions: (1) How does task complexity and interdependence compare under AM vs. TM? (2) How do cognitive, social and technical skill requirements compare under the two technologies?

The manufacturing sector is extremely heterogeneous. The size distribution of firms and establishments suggests substantial diversity.[3] The diversity extends to technology, sophistication of techniques, types of employees, management styles and productivity (Bloom and Van Reenen, 2010, Syverson, 2011). Some firms employ techniques that were developed long time ago, whereas other firms rely on advanced manufacturing techniques, including extensive computerization and automation. In order to compare meaningfully AM and TM technologies we need to handle issues that arise from heterogeneity. With this consideration in mind, we focus on plants (establishments) that use both AM and TM technologies in the sense that they posted job openings for both AM and TM engineers, or AM and TM technicians, or AM and TM operators, from January 2014 through February 2019. Plants generally specialize in the production of a narrow range of products, employing workers with similar backgrounds and often drawn from the same geographic area. Plants usually have a small human resources staff who use similar language for similar job postings. Differences in AM and TM postings for the same occupation in the same plant therefore result from differences in the tasks the workers need to perform and the skills they are expected to possess. We focus on the three core manufacturing occupations, engineers, technicians and operators, who carry out the main production tasks. Certain activities associate with production tasks may be carried out by different occupations in AM and TM. In this paper we do not analyze specific activities but want to assess the difference in the high-level attributes of the tasks. We do not distinguish among specializations within occupations, such as mechanical and materials engineers, allowing for the possibility that some activities are bundled differently under AM and TM due to differences in the production process. In a similar vein, we study differences in high-level skills required of workers in the three occupations in AM versus TM.

[3] For example, the Aerospace Product and Part Manufacturing industry (NAICS 3364) contained in 2016, 1,389 firms with 1,828 plants (establishments), of which 785 firms employed fewer than 20 employees (all these firms had a single plant), whereas 113 firms had more than 500 employees in 504 plants. At a more detailed level, Aircraft Engine and Engine Parts Manufacturing (NAICS 336412), there were 352 firms with 458 plants, with 166 firms with fewer than 20 employees (same number of plants), and 41 firms with 137 plants employing more than 500 employees each (US Bureau of Census, https://www.census.gov/data/tables/2016/econ/susb/2016-susb-annual.html).

Purging heterogeneity is not without drawbacks. Whereas we learn what happens to tasks and skills in the plants we study, we can only speculate about what may happen in the event of wider adoption of AM technology.

Technology, the Production Process, Tasks and Skills

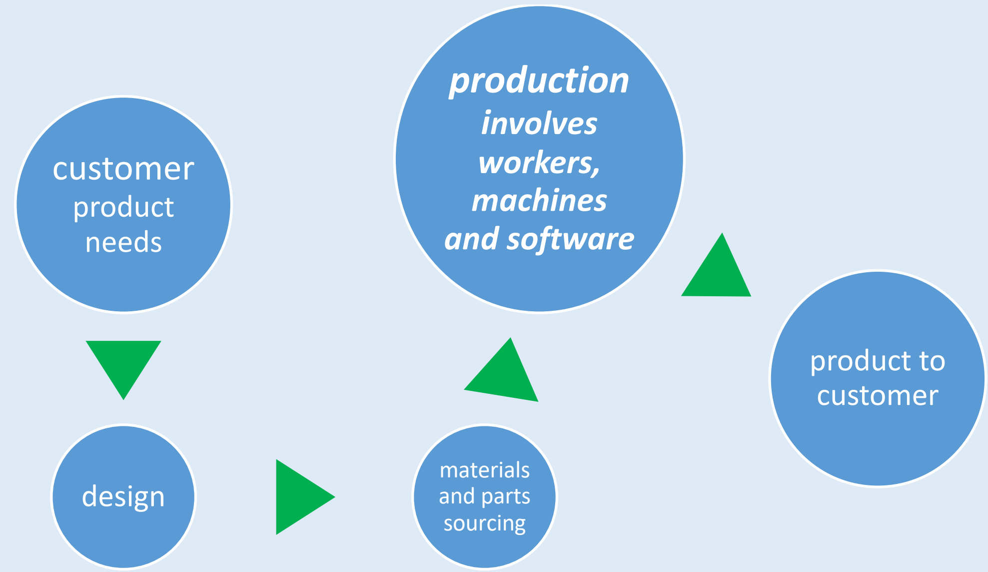
To lay the ground for the empirical analysis of the implications of differences between AM and TM for work, we first look at the production process (Figure 3) and examine high-level attributes of manufacturing tasks[4] and worker skill requirements (Figure 4). Next we explore how key differences between AM and TM production processes affect task attributes and skill requirements in different occupations in the production of simple and complex products.

Flow of the production process

The production process in Figure 3 is part of the value chain, and entails the transformation of inputs into output. It starts with specification of a customer's needs. The customer may be another department in the company requiring a part, such as a fuel nozzle for airplane engines, audiologists ordering hearing aids for their patients, a manufacturing unit needing specific jigs and fixtures to be used in manufacturing. The next node is product design, which considers customer needs, including cost, durability, quality, appearance and other product specifications characteristics, in view of materials availability and production considerations, which represents the next two nodes. Materials and parts are part of supply chain and logistics considerations, which must be balanced with production operational concerns. The production node is the making of the product and quality control. The activities in different nodes may be carried out independently, or they may be tightly interdependent such that there is a lot of back and forth discussion across nodes. The customer may engage not only with designers but also with materials experts and production engineers to articulate needs and understand alternative options for design, quality, cost and so on (Baumers, Dickens, Tuck, and Hague, 2016). There may be repeated interactions between design and materials nodes, and between design and production. The activities carried out in different nodes and their interdependence vary with the nature of the product and technology of production.

[4] We are not comparing the task attributes of specific activities such as welding, design and material extrusion, but the ways in which the tasks of the workers who carry out such tasks are described in job vacancies.

Figure 3. The flow of the production process. The production flow moves in one direction, culminating in a product. However, in some instances, such as complex or customized products, there may be considerable feedback and back-and-forth communication.



Tasks and skills

Consider now the central production node in Figure 3. Workers, machines and software transform materials and parts into a product. This is generated by a series of ***tasks***. Tasks are combinations of ***activities***, which may be carried out by workers with diverse ***skills.*** Workers, machines and software complement and substitute for each other in various ways, determined by technology and their relative prices. The relationship between output, tasks and skills described here reflects the conceptual "task framework" employed by Autor, Levy, and Murnane (2003), Gathmann and Schönberg (2010), Autor and Handel (2013), Ben-Ner and Urtasun (2013), and others).

Tasks and skills may be characterized in various ways. For the purpose of a high-level examination of skill requirements we characterize tasks in terms of high-level task ***attributes***. The central attribute identified in the literature is ***complexity*** (March and Simon 1958, Perrow 1986, *Dictionary of Occupation Titles* 1972, Prendergast 2002, Campbell 1988, Ham, Park and Jung 2012 and Liu and Li 2012). Complexity refers to the degree of difficulty of execution of a task and the predictability of its outcomes. A task is highly complex if successful execution of the activities associated with it requires contingent adherence to rules and procedures, with deviations based on analysis and judgment of the worker in changing circumstances. In contrast, a simple task is carried out by consistent adhering to routines, rules and procedures. The execution of complex tasks involves activities that may be taken in variable sequences, depending on the results of preceding actions; this introduces uncertainty regarding the outcomes of the task, and makes it difficult to analyze *ex post*.[5] The difficulty of analyzing the task and the uncertainty regarding outcomes are experienced by supervisors and managers, and it is a source of asymmetric information that gives rise to the classic principal-agent situation. The worker who carries a complex task also may be unable to fully analyze the task and predict its outcome, albeit both to a lesser degree than a manager. Task complexity plays an important role in the choice of organization structure, such that greater complexity induces delegation of decision-making, higher level of pay and reliance on incentives and less direct monitoring of workers (Prendergast 2002, Foss and Laursen 2005, Ben-Ner, Kong and Lluis 2012).

The execution of complex tasks requires that workers be able to analyze alternative ways to accomplish a task with details depending on the concrete situation and think analytically, creatively and critically. These and other relevant set of skills is often referred to as ***cognitive and problem-solving skills.*** Other skills include knowledge of specific techniques (such as metal sintering or computer numerical control, managing logistics, knowledge of software (such as CAD/CAM) and statistical analysis, and more, collectively termed ***technical skills.***

A second important task attribute is ***interdependence***. This refers to the extent to which the completion of the tasks of different workers depend on each other, in contrast with task independence, whereby each task can be completed in isolation from other tasks (Thompson, 1957, Perrow, 1988, Saavedra, Earley and Van Dyne 1994, Gully, Devine and Whitney, 1995). Task interdependence requires collaboration and coordination among workers, and the successful execution of a worker's tasks depends on the successful execution of tasks by other workers.[6] Highly interdependent tasks are often carried out in teams of workers who make some decisions

[5] Brynjolfsson, Mitchell, and Rock (2018) rate the complexity of numerous tasks. For example, the task *"Implement and administer enterprise-wide document management systems and related procedures that allow organizations to capture, store, retrieve, share, and destroy electronic records and documents"* is rated as complex whereas "*Directly supervise and coordinate the activities of helpers, laborers, or material movers*" is rated as less complex; "*Communicate with others to coordinate material handling or movement*" is rated between the previous two tasks in terms of complexity.
[6] Four forms of task interdependence may be distinguished: pooled, sequential, reciprocal and team (Saavedra et al. 1993). For the purposes of this paper, the distinction are a matter of degree of interdependence, which we capture both in the conceptual discussion and in the empirical analysis.

together, and are partly compensated for group results, in addition to individual accomplishments. Workers whose tasks are interdependent must possess a set of relevant ***communication and social skills.*** Figure 4 illustrates the task attributes and skills requirements. We will focus our analysis on what we consider the two principal task attributes, complexity and interdependence, and the skills that are required to support them, cognitive and problem-solving, technical, communication and social skills.[7]

The degrees of task complexity and interdependence are derived from the nature of the product and the technology of production. As we will comment later, there is a positive relationship between task complexity in various nodes of the production process and product complexity, and a milder correlation with task interdependence, for a given technology. Variation in the degrees of task complexity and interdependence are also induced by variations in the technology of production, given a product; this is, of course, the central concern of this paper. We turn next to an evaluation of how AM and TM may affect task attributes and skill requirements.

[7] There are other task attributes noted in the literature. Brynjolfsson, Mitchell, and Rock (2018) consider several additional attributes. Routine received prominence in the analysis of Autor, Murnane and Levy (2003), who regard routine tasks as principal candidates for execution by computer algorithms. That stage technological development has been almost exhausted by now in the United States and elsewhere.

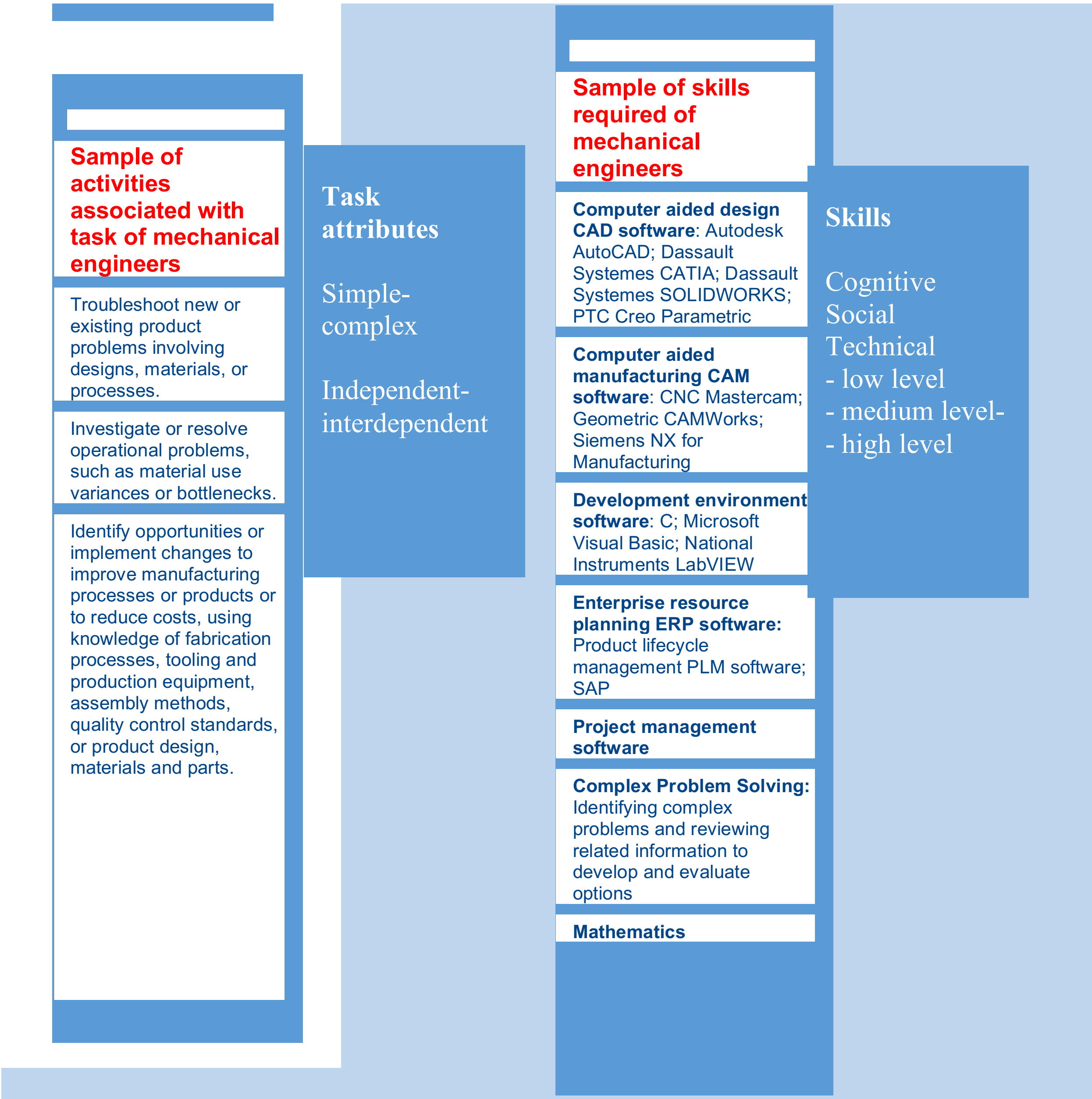


Figure 4. Task attributes and skill requirements of workers involved in the production process. We characterize tasks in terms of the degree of their complexity and interdependence. The more complex a task, the more task-specific technical knowledge it requires, and greater cognitive skills to evaluate alternatives and to cope with uncertainties. The more interdependent a worker's task is on other workers' tasks, the greater the need for communication, negotiation and coordinate with others' actions. The activities below are a subset of activities that are associated with the task of mechanical engineers; the task of specific engineers may contain only some of these activities. The task of a specific engineer may be characterized in terms of its complexity and interdependence with the tasks of others workers. The skills listed below are a sample of skills that engineers need to possess; the skills requirements of specific engineer positions vary. Source: O*NET

Tasks and skills under AM vs. TM

Production technology affects the complementarity and substitution relationships between workers, software and machines. This means that technology may affect what workers in different occupations need to do and what skills they need to accomplish their tasks. To understand how AM and TM affect tasks and skills, we examine first how these technologies work.

Most TM techniques entail (a) subtraction of materials from a solid block, using a wide range of output-specific tools and dies, (b) forming or forging, using diverse presses, or (c) injecting materials into a product-specific limited-use mold. Usually, this is followed by post-processing to enhance the thermal/chemical stability and surface quality of the product, typically a part. A final product is made of multiple parts that are assembled together through fitting (tongue-in-groove), using bolts and nuts, soldering and similar techniques. For example, a golf cart consists of a few thousand parts, produced in different plants, shipped to various locations for partial assembly, and then to final assembly. For another example, consider a fuel nozzle that passes the burning mix of air and fuel to the back of a jet engine. A common nozzle (see Figure 5, right) is made of 20 parts produced in different plants and soldered together before being placed into an engine. Workers are involved in all activities in the production node, handling, tending and repairing the various tools and machines, moving materials, finishing the produce, maintaining the work space, performing quality control, and so on. Sometimes, operators interact with computers that control some aspects of the production process (e.g., CAD/CAM).

Figure 5: Jet engine fuel nozzle tips made by GE through AM (left) as a single piece, and through TM (right), 20 parts soldered together

In AM, materials are extruded through nozzles or placed in a vat to build up, layer by layer, a part or a finished product. The layers may be of different materials, and are combined together through heating, cooling or optical energy.[8] The process is directed seamlessly by computer programs. Human involvement in the central production node is limited to operating the computer that controls production, feeding materials, removing output from the build (printing) space and removing residuals, as well as finishing the product (possibly including some machining), and inspecting it for quality. The software that runs AM machines is similar to that used in TM (CAD/CAM). There is little assembly required. For example, a small car launched for mass production in early 2019 has a few dozen parts (a few still manufactured by traditional methods). Another example is the fuels nozzle for jet engines, printed all in one piece without assembly or soldering and is 25% lighter and more durable than the TM version (Figure 5, left).[9]

Engineers and technicians, select specific production parameters (technique, materials, temperature, scaffolding requirements, etc.) suitable for a specific product. In the case of relatively complex products, the range of choices is larger in AM than in TM. The activities of higher-skill AM workers include product design, choice of materials, test and optimize printing parameters and their sequencing in the production process to achieve desired properties, and solving problems associated with multiple operational constraints (different temperatures at which various materials harden and adhere to each other, and so on). These represent complex

---

[8] There are various AM techniques, known as Material Extrusion (including the common Fused Deposition Modeling, FDM), Material Jetting, Binder Jetting, Directed Energy Deposition, Sheet Lamination, Vat Polymerization, Stereolithography (SLA), Powder Bed Fusion (including the common Selective Laser Sintering, SLS). See https://www.lboro.ac.uk/research/amrg/about/the7categoriesofadditivemanufacturing/.

[9] Some plants have mixed production methods, with jigs and fixtures produced by AM and used in TM for production of other output. This is the case, for example, in auto manufacturing, such as Volkswagen. For another example, consider the production of a part of a pump. "MW Smith's request was for the production of two heads for an obsolete gas compressor which is no longer in production. Made from Class 40 Cast Iron, the traditional manufacturing method for these parts would be wood pattern based casting with machining. For the traditional process, ExOne estimates that manufacturers would typically run up a tooling bill of around $70,000. The cost is largely due to the custom tooling required. In additive manufacturing, no tooling is required to reproduce the shape. PumpWorks used their ExOne S-Max, to make molds for the heads in silica sand using a furan binder. Approximately one week of 3D printing and complete casted part turnaround were required to complete each mold, as opposed to the expected 8/9 weeks for a wood pattern. When assembled, the mold measured 46 x 38 x 46 inches. Liquid cast iron was then poured into the mold and cooled, then the mold was removed, leaving the part to be finished and delivered to the customer." (https://3dprintingindustry.com/news/exone-saves-pumpworks-castings-9-weeks-of-lead-time-with-industrial-3d-printing-154969/)

tasks that require broad technical knowledge, extensive complex problem solving, creativity and ability to understand customers' needs and cost-benefit tradeoffs.[10] Lower-skill workers, operators, have to identify materials, treat vulnerable products with appropriate care, select and construct appropriate work spaces in the build machine, immerse them in chemicals for cooling, hardening and cleaning, and in case of metal products, do some post-production machining, and maintain the build machines. This range of tasks is broader than in most TM operations, including CNC, and the tasks are more complex due to the higher intensity of the supplier-user interaction process (Zairi, 1998). Products that have complex geometric shapes require under TM multiple parts to be assembled to achieve the desired product. Under AM, such products can be made of just a few parts, or even just one, reducing drastically assembly work, as in the case of the fuel nozzle. The importance of activities such as selecting and installing product-specific jigs, dies and other tools, as well as assembly of parts is greatly diminished under AM. Fewer AM operators are needed, and their role change as compared to TM operators in similar products.

In industrial AM, the areas of current competitive advantage relative to TM are associated with flexibility in product design, materials and volume. The demands of flexibility cut across the entire organization and demand greater skill on the part of engineers, technicians and machine operators, as well as managers (Eyers, Potter, Gosling and Naim, 2018).[11] [12]

---

[10] Friesike, Flath, Wirth, and Thiesse (2018) discuss differences in the design of AM and TM products, and the creativity demands entailed by the flexibility associated with AM.

[11] Some of the key differences between AM and TM are captured in the following quote. *"While production runs in conventional manufacturing processes could fail mainly due to the tools breaking (among other common causes of failure), the halts in AM processes can be largely attributed to the insufficient skill levels of designers and manufacturers [22], and the struggle to figure out the best configuration of machine's parameters and the part's CAD. This aspect becomes even more critical if one considers long cycle times of AM machines and the very realistic probability that the operations may fail in the very last hours (11th hour) of the cycle. Time and cost considerations are the most prominent factors, which need to be considered while dealing with this issue. The problem in dealing with the level of skills and know-how contributes to a larger measure of uncertainty, since each machine has a range of parameters and settings that can be altered for a production run, and the fact that dimensions of the part as well as the type of raw materials can also be changed accordingly would only increase this uncertainty and further complicate the decision-making process. At present, the industry's default solution to this issue is trial and error, i.e., trying different materials and going through various settings to experimentally figure out the best configuration(s) which is far from an ideal situation, since this can lead to inconsistencies both in mechanical properties and the production process itself"* (Zanoni et al., 2019).

[12] In the production of simple outputs that are made of a single material, and the geometry of the product is not fragile, the role of workers is reduced to selecting the suitable file for the product, handling materials and products, cleaning and maintenance of the machines. This entails low task complexity and little interdependence, and requires limited cognitive and problem-solving skills, or communication and social skills, and limited technical skills; this is due to the highly automated manufacturing process. Production of similar products in TM generally entails greater operator involvement and complexity of tasks, and therefore greater skills. Note, however, that, as Figure 1 shows, this kind of simple products is rarely produced commercially. The reason is that, at this time, TM has a cost advantage; AM production of simple products is confined to "prosumers" (producers-consumers).

Data and Measures

Our data consist of content culled from the near-universe of online job vacancy postings in the manufacturing sector for January 1, 2014 - February 28, 2019. The data were collected by *Burning Glass Technologies (BGT),* a labor market analysis consulting firm. BGT scrapes vacancy postings from more than 40,000 online job boards and company websites. It removes duplicate postings and codes keywords and phrases into a very large number of unique terms. BGT classifies systematically the information contained in job postings, including occupation, tasks, and requisite skills, education, certification and experience, as well as employer name, industry and location. BGT data have been used recently to analyze jobs and skills by Hershbein and Kahn (2018), Deming and Kahn (2018), Börner et al. (2018) and others.[13]

Job postings are a very useful source of information about what tasks employees need to perform and what skills they to possess for their jobs. The new hires in each occupation and technology are likely to reflect current and anticipated needs of AM and TM production lines in terms of tasks and skills.[14] However, there are several limitations and sources of unobserved heterogeneity in job posting practices that may influence analyses based on the content of postings. (1) There are differences in how rich the information contained in postings, often associated with different norms across the human resources departments of different companies. (2) There might be differences associated with the skill level of an occupation, such that postings for higher-skilled occupations contain more detailed information. (3) Some firms may seek to fill some positions by hiring directly from schools and universities while others tend to advertise their positions; this difference may be associated with company size (such that larger firms go directly to schools and universities) or industry. (4) It is possible that a new AM production line in an existing plant will be staffed not only with new hires but also by moving workers from exiting TM lines after training; it is possible that within-firm moves will be more common for lower-skill operators than for engineers.

[13] Employer name, industry and location are missing in a minority of postings. For discussion of this issue, see Appendix to Deming and Kahn (2018). There is no reason to expect that there is a systematic bias in missing information that would affect our analysis of differences between AM and TM postings.
[14] Tambe and Hitt (2013) and Tambe (2014) show that hiring decisions can be used as a proxy for technology adoption.

To deal with these sources of unobserved heterogeneity, we focus on within-plant comparisons, and distinguish among three occupations that differ in educational and skill levels: engineer, technician and operator job postings.[15] These correspond to the 2010 Standard Occupational Classification numbers 17-1000 and 17-2000 for engineers, 17-3020 and 17-3030 for technicians and 49-0000 and 51-0000 for operators. The jobs were posted between January 1, 2014 and February 28, 2019. Our sample consists of postings in hybrid AM-TM plants, which we define as plants that have posted positions for either of the three occupations in both AM and TM during our sample period. Our sample excludes postings made by pure AM and pure TM plants – plants that posted positions in just one of the two technologies. Job postings are identified as AM if they contain keywords such as "additive manufacturing" and "3D printing." All other postings are classified as TM.

The distribution of postings for the three occupations in the three types of plants is shown in Table 1. There were 430 plants that posted only AM core occupation positions, most of them for engineers. The pure AM plants are single-plant firms, and are small – posted about 1.5 jobs per plant. Pure TM firms posted vastly larger numbers of openings, most for operators, with about 6 openings per plant. The last column of Table 1, our sample, shows that there were 1,308 such plants that belonged to 634 firms. These plants had a total of 3,055 AM engineer, 476 AM technician and 574 AM operator openings. In contrast, the same plants had about 45 times more openings in TM. AM postings in hybrid firms are much more oriented towards higher-skilled occupations (74.4% of AM postings are for engineers, 11.6% for technicians and 14.0% for operators) as compared to TM postings (63.% of TM postings are for engineers, 9.7% for technicians and 27.1% for operators). It is quite possible that the different proportions of job postings reflect different occupational composition in AM and TM. This is in line with the fact that AM is a labor-saving process that relies less on lower-skill labor than TM. However, it is possible that more operator jobs than engineer and technician jobs are filled by training and moving workers from existing lines, so online job postings may not provide an accurate picture of the occupational composition of the workforce in existing plants.

[15] The restriction to the manufacturing sector implies that we do not include postings by schools, universities and libraries, design firms, construction companies and other entities that hire AM employees.

Table 1. Distribution of postings for core manufacturing positions across pure AM, pure TM and hybrid AM/TM plants			
	Type of plants		
	Pure AM plants	**Pure TM plants**	**Hybrid *AM*/TM plants**
Number of plants	430 in 334 firms	235,669 in 64,235 firms	1,308 in 634 firms
Number of engineers	429	413,780	*3,055*/110,424
Number of technicians	75	152,931	*476*/16,955
Number of operators	134	821,829	*574*/47,374
Total number of postings	638	1,388,540	*4,105*/174,753

Notes: (1) Job postings were removed if there was no employer name, or no geolocation, or no skill terms (1,240 AM postings and 833,993 TM postings). (2) A pure AM plant does not have TM job postings; a pure TM plant does not have AM job postings.

The industry distribution of the hybrid plants is illustrated in Table 2. The industries represented in this table overlap significantly with those in Figure 1.

Table 2. Industry distribution of AM and TM job postings by occupation, 1/1/14-2/28/19
Same plant, 1,308 plants in 634 companies

	Car	**Aerospace**	**Health**	**Metal**	**Machinery**	**Computer**	**Electrical**	**Other**
2017 NAICS	**3361, 3362, 3363**	**3364**	**3254, 3391**	**331, 332**	**333**	**334**	**335**	
AM								
Engineers[plants]	34[17]	666[137]	175[53]	125[26]	153[66]	433[118]	166[39]	166[39]
	(0.02)	(0.35)	(0.09)	(0.07)	(0.08)	(0.23)	(0.09)	(0.09)
Technicians	4	84	32	13	29	40	4	4
	(0.01)	(0.31)	(0.12)	(0.05)	(0.11)	(0.15)	(0.01)	(0.01)
Operators	6	68	40	6	112	52	8	8
	(0.02)	(0.21)	(0.12)	(0.02)	(0.35)	(0.16)	(0.02)	(0.02)
TM								
Engineers	6,072	38,125	8,985	1,677	7,493	20,959	1,338	1,338
	(0.06)	(0.40)	(0.10)	(0.02)	(0.08)	(0.22)	(0.01)	(0.01)
Technicians	798	4,366	1,203	531	1,770	2,828	284	284
	(0.06)	(0.32)	(0.09)	(0.04)	(0.13)	(0.21)	(0.02)	(0.02)
Operators	1,865	13,571	4,256	1,095	3,959	4,824	1,546	1,546
	(0.05)	(0.37)	(0.12)	(0.03)	(0.12)	(0.13)	(0.04)	(0.04)
Output complexity	2.28	2.14	1.66	1.10	1.30	2.76	1.35	0.82

Notes:
1. Missing NAICS code for 1,606 AM and 30,086 TM job postings, not included in the table but included in pairwise comparisons.
2. Output complexity=number of postings for engineers in both AM and TM divided by total number of postings in the three occupations

Empirical measures of technology, tasks and skills

Each job posting is converted by BGT into a string of terms. A BGT term is a simple word, or a compound word such as "problem solving" and "purchase requisitions processing." These BGT terms include a mix of activities and skills, collectively describing tasks and their skill requirements.[16] To identify in BT terms the task attributes and skills that we identified in section 2, above, we follow the literature and preselect a set of keywords that represent the various task attributes and skills.[17] We augment these keywords with synonyms for the lemmas of part-of-speech keywords, using an automated natural language processing approach.[18] We discuss below how handle terms that signify both activities and skills (e.g., creativity) in order not to create artificial correlations between task attributes and skills.

We follow the literature and assign each job posting a score on each task attribute and skill that represents ***the count of keywords*** identified in a posting. We normalize each score by dividing it by the mean count for ***all*** postings for engineers, technicians and operators in both AM and TM (1,568,036 postings, the sum of the bottom row in Table 1). This division by a constant is inconsequential, but permits to compare a particular category (e.g., task complexity of AM engineer postings) with that of all manufacturing job postings.

Count of all words

The more terms it takes to describe a job, the more numerous and varied the activities and skills it entails. The ***count of all words (terms)*** in a job posting is a measure of a job's breadth and

---

[16] We exclude postings with without any BGT terms, less than 2.5% of job postings. We do include single-term postings because they convey relevant information, such as "aerodynamics," "mechanical engineering" and "creativity".

[17] Autor, Levy and Murnane (2003), drawing keywords from the Dictionary of Occupational titles (DOT), use "set limits, tolerances, or standards" and "finger dexterity" to identify routine tasks; "direction, control, and planning" to identify managerial and interactive tasks; and "mathematics" to capture analytical reasoning tasks. Deming and Kahn (2018) use "problem solving", "research", "analytical", "critical thinking", "math", and "statistics" to identify cognitive skills and "communication," "teamwork", "collaboration", "negotiation", and "presentation" to identify social skills. Alabdulkareem et al. (2018) identify a socio-cognitive skill cluster and a sensory-physical skill cluster out of the 161 O*NET workplace skills, knowledge and abilities. Brynjolfsson, Mitchell, and Rock (2018) use keywords and phrases such as "intuition or highly involved reasoning" to identify task complexity; "explaining something deeply to another person" for task interdependence; "repetitive" for task routine; and "intense physical work" for manual tasks.

[18] The following advanced natural language processing tools are used: The Penn Treebank tagset for part-of-speech (POS) tagging and the Wordnet corpus for lemmatizing and synonyms, from spaCy python library, and the Snowball stemmer for stemming from nltk python library

variety of activities and skills it entails, and may be a measure of task complexity (Prendergast, 2002) and variability.

Keywords for task attributes and skills

For each task attribute and skill, we identify below the respective keywords, and the number of times each appears in our sample, and point out to the principal literature from which the keywords were drawn. The measures that include stemming, lemmatization and synonyms are presented in Appendix A.

Task Complexity

To implement empirically complexity as defined conceptually, we add up difficult, creative and cognitively demanding activities and subtract simple activities, which are not under the control of the worker.

Keywords: Advanced, Analyses, Analysis, Change, Complex, Design, Development, Experiments, Hazard, Improvement, Innovative, Investigation, Learning, Mathematics, Modeling, Modification, Multi-Tasking, Multiple, New, Prediction, Project, Research, Risk, Scientific, Scientific, Statistics. **Keywords that reflect simple activities** contribute -1 to the score: Order, Procedure, Protocol, Repetitive, Standard
Count in sample: 3079, 78, 64980, 4509, 22, 101703, 52648, 5628, 1195, 16316, 34, 119, 1425, 3111, 4623, 486, 9242, 678, 7720, 1, 33197, 25928, 3168, 97, 14772, 3868; For simple activities: 1121, 1348, 1830, 8, 162
References: Autor, Levy and Murnane (2003), Brynjolfsson, Mitchell, and Rock (2018), Matthes et al. (2014), Liu and Li (2012)
Comments: Keywords for which there were no matches in postings: Ambiguity, Contingent, Forecast, Math, Routine, Rule-based; Occupation-specific words, such as Engineering, Technical or Operation, or AM-specific words such as Prototypes are not selected as keywords

Task Interdependence

Our measure of task interdependence is a very broad one, including terms that reflect interdependence within and across nodes in the production process, as well as within and across occupations and organizational hierarchies. As such, this measure degrees of interaction, collaboration, coordination and joint activities of the three occupations.

Keywords: Agreement, Assistance, Coaching, Communication, Consulting, Coordination, Cross-Functional, Educational, Feedback, Group, Guidance, Instructional, Integration, Interaction, , Leadership, Leading, Meetings, Mentoring, Negotiation, Negotiations, Networking, Organizational, Persuasion, Presentation, Presentations, Relationship, Social, Supervision, Support, Teaching, Training, Conflict Management, Staff Development, Team Management
Count in sample: 417, 3054, 85, 36232, 191, 545, 44, 48, 668, 67, 139, 49, 6950, 212, 19769, 19769, 3, 44, 5855, 185, 2, 494, 16363, 922, 117, 1621, 193, 1240, 286, 19710, 975, 10733, 2243, 73, 498

References: Brynjolfsson, Mitchell, and Rock (2018), Matthes et al. (2014)
Comments: Keywords for which there were no matches in postings: Answer, Ask, Conjoin, Conversation, Cooperate, Counsel, Delegation, Discuss, Explanation, Influence, Interdependent, Interpersonal, Join, Motivate, Motivational, Participate, Relation, Speak, Supervise

Appendix A Measures that include lemmatization, synonyms and stemming

List of word stems (and counts) used for task complexity and cognitive skills broad definitions
Advanc,3079; Alter,0; Analys,78; Analysi,67187; Analyz,1968; Chang,4621; Cognit,32; Complex,22; Creativ,14304; Design,103883; Develop,53080; Examin,28; Experi,16815; Expertis,8576; Hazard,3825; Improv,16422; Initi,1169; Innov,34; Intellig,1139; Investig,229; Knowledg,24355; Labor,190; Learn,1425; Mathemat,3498; Model,5688; Modif,486; Modifi,0; Multipl,678; New,7720; Oper,14324; Order,3096; Pattern,172; Predict,7263; Procedur,1812; Project,36071; Protocol,1965; Repetit,8; Research,25928; Risk,3169; Scienc,7262; Scientif,97; Simul,14822; Standard,5859; Statist,13496; Studi,2869.
List of word stems (and counts) used for task interdependence broad definition
Agreement,489; Assist,3121; Coach,96; Communic,38912; Consult,340; Coordin,2571; Educ,67; Feedback,668; Group,142; Guidanc,139; Instruct,458; Integr,8928; Interact,220; Leadership,19769; Lead,194; Meet,3600; Mentor,5855; Motiv,0; Negoti,187; Network,5697; Organiz,16363; Persuas,936; Present,1817; Relationship,7977; Social,1240; Supervis,307; Support,19711; Teach,975; Train,10789.

Cognitive skills

We use two measures, one that we construct and the other constructed by Deming and Kahn (2018). Our measure incorporates the Deming and Kahn terms, but excludes terms that were included in activities that are used to define task complexity (Research and Analytical – but we include the term Analytical Skills) and include additional terms (Cognitive, Creativity, Experience, Expertise, Independent Thinking, Initiative, Intelligence, Knowledge, Science, Strategic Thinking).

Keywords: Analytical Skills, Cognitive, Creativity, Critical Thinking, Experience, Expertise, Independent Thinking, Initiative, Intelligence, Knowledge, Science, Strategic Thinking.
Count in sample: 7048, 32, 12259, 2036, 7846, 8576, 332, 1167, 1139, 23941, 42195, 7058, 352.
References: O*NET**,** Deming and Kahn (2018)
Comments: Keywords for which there were no matches in postings: Math

Alternative measure using only Deming and Kahn (2018) keywords: Problem Solving, Research, Analytical, Critical Thinking, Math, Statistics

Social skills

We use again two measures, one that we construct and the other constructed by Deming and Kahn (2018). Our measure incorporates the Deming and Kahn terms, but excludes terms that were included in activities that are used to define task interdependence, as well as narrowing their terms by specifying "skills" to distinguish from activities.

Keywords: Communication Skills, Negotiation Skills, Presentation Skills, Supervisory Skills, Teamwork/Collaboration.
Count in sample: 72300, 1122, 9763, 2183, 33932.
References: O*NET, Deming and Khan (2018)
Comments: Overlap between task interdependence and social skills was avoided by subtracting the count for communication skills, negotiation skills and presentation skills from communication, negotiation and presentation task attributes, respectively.

Alternative measure using only Deming and Kahn (2018) keywords: Communication, Teamwork/Collaboration, Negotiation, Presentation

Technical skills

We classify technical skills into three levels, based on skill families coded by BGT, which are based on O*NET. This is a sample of skills families that we have judged to belong in different categories based on the occupations with which they more centrally associate. There are many terms included within each skill family, so the definitions for technical skills list only skill families, omitting the hundreds of underlying keywords.

***Low* Skill Families:** Basic Computer Knowledge, Equipment Operation, Equipment Repair and Maintenance, Hand Tools, Inventory Maintenance, Machine Tools, Machinery, Material Handling, Procurement
Count in sample: 8157, 2732, 36965, 14714, 313, 35995, 9823, 8036, 14916.
***Medium* Skill Families:** Application Programming Interface (API), Cache (computing), Computer-Aided Manufacturing, Computer Hardware, IT Automation, Mathematical Software, Other Programming Languages, Product Inspection, Programming Principles, Project Management Software, Statistical Software, Technical Support
Count in sample: 54, 146, 1825, 14466, 1450, 11554, 145, 7012, 4331, 3688, 3335, 21500.
***High* Skill Families:** Business Intelligence Software, IT Management, Laboratory Research, Logistics, Manufacturing Design, Materials Process, Materials Science, Mathematical Modeling, Mathematics, Physics, Product Development, Research Methodology, Statistics.
Count in sample: 554, 1078, 7388, 2482, 5819, 3338, 12392, 2047, 4653, 16863, 31541, 7420, 10079.
References: O*NET
Comments: Skill families instead of terms were selected in this case. Counts refer to the list of words or terms included in each skill family.

Figure 6 provides illustrations of our method, listing the terms for AM and TM postings from three GE establishments. The scores for the task attributes and skills calculated using the keywords identified above are also provided. For the first example, information is provided for all three occupations, whereas for the remaining two, for space reasons, only for engineers. There are several takeaways from Figure 6. First, although the postings come from the same human resources offices of the three establishments, respectively, they display variation across AM and

TM, and across occupations. Second, although the establishments, the first a research center and the other two manufacturing establishments (the third produces the fuel nozzle tips in Figure 5) belong to the same company, there are substantial differences in the terms used in the postings, reflecting product and plant circumstances. Third, there are many terms that are not used to characterize tasks or skills; however, many of terms included in the postings may have been matched with technical terms that belong to technical skill families, which include hundreds of terms not listed in our keywords. In comparisons with other keyword-based approaches (such as Deming and Kahn, 208) the number of out matches between keywords and terms in job postings is higher simply because we use more keywords. (We are working on a project that seeks to incorporate all terms in our tasks and skills measures).

Figure 6. Examples of terms used in AM and TM job postings in two plants and the associated measures for task attributes and skills [normalized scores in brackets]

Example 1. GE research center in New York State

	Engineers		Technicians		Operators	
Terms in AM posting	Structural Design, Experiments, Product Design, Research, Pro/ENGINEER, Creativity, Unigraphics, Materials Processing, Industrial Engineering Industry Expertise, Finite Element Analysis, Project Management, Electrical Systems, Written Communication, LS-DYNA, Ansys ,Machinery, Prototyping, Mechanical Engineering, Analytical Skills, Product Knowledge, Teamwork/Collaboration, Repair, Meeting Deadlines, 3D Printing/Additive Manufacturing (AM)		Verbal/Oral Communication, Communication Skills, Budgeting, Supply Chain Knowledge, Staff Management, Research, Analytical Skills, Mechanical Engineering, Manufacturing Processes, Materials Science, Physics, Writing 3D Printing/Additive Manufacturing (AM), Meeting Deadlines		Artificial Intelligence, Budgeting, Research, Product Development, Robotics, 3D Printing/Additive Manufacturing (AM)	
Terms in TM posting	Power Generation, Writing, Digital Signal Processing (DSP), Hybrid Vehicle, Budgeting, Electronic Engineering, Prepare Presentations, Communication Skills, Verbal/Oral Communication, Hardware Experience, Field-Programmable Gate Arrays (FPGA), MATLAB, Firmware, Mathworks Simulink, Planning, Electronic Circuits, Simulation, Research		Detail-Oriented, Quality Management, Writing, Physics, Quality Assurance and Control, Chemistry, Research, Verbal/Oral Communication, Manual Dexterity, Communication Skills		Lathes, Blueprints, Self-Starter, Written Communication, Physical Abilities, Lifting Ability, Research	
	AM	**TM**	**AM**	**TM**	**AM**	**TM**
Task complexity	6 [5.888]: Analysis (1), Design (2), Experiments (1), Project (1), Research (1)	2 [1.963]: Research (1), Simulation (1)	1 [0.981]: Research (1)	0 [0]	2 [1.963]: Development (1), Research (1)	1 [0.981]: Research (1)
Task interdependence	1 [1.196]: Communication (1)	2 [3.831]: Presentations (1), Verbal/Oral Communication (1)	1 [1.196]: Verbal/Oral Communication (1)	1 [1.196]: Verbal/Oral Communication	0 [0]	1 [1.196]: Communication (1)
Cognitive skills	4 [8.080]: Analytical Skills (1), Creativity (1), Expertise(1), Knowledge (1)	1 [2.020]: Experience (1)	2 [4.040]: Analytical Skills (1), Knowledge (1)	0 [0]	1 [2.020]: Intelligence (1)	0 [0]
Social skills	1 [2.232]:Teamwork/Collaboration (1)	1 [2.232]: Communication Skills (1)	1 [2.232]: Communication Skills (1)	1 [2.232]: Communication Skills(1)	0 [0]	0 [0]
Technical skills – low	1 [1.108]: Machinery (1)	1 [1.108]: Hardware Experience (1)	0 [0]	0 [0]	0 [0]	1 [1.108]: Lathes
Technical skills – medium	0 [0]	1 [3.472]: MATLAB (1)	0 [0]	0 [0]	0 [0]	0 [0]
Technical skills - high	2 [7.018]: Experiments (1), Prototyping (1)	0 [0]	2 [7.018]: Materials Science (1), Physics (1)	1 [3.509]: Physics (1)	1 [3.509]: Product Development (1)	0 [0]

Example 2. GE engine manufacturing plant in Wisconsin

	Engineers	
Terms in AM posting	Six Sigma, Process Engineering, Project Management, Packaging, Manufacturing Engineering, Communication Skills, New Product Development, Troubleshooting, Process Design, Technical Training, Purchasing, 3D Printing/Additive Manufacturing (AM), Planning, Training Materials, Technical Support, Manufacturing Processes, Good Manufacturing Practices (GMP), DMAIC, Teamwork/Collaboration"	
Terms in TM posting	Product Improvement, Technical Support, Planning, Industrial Engineering, Compliance Training, Legal Compliance, Quality Management, Quality Assurance and Control, Product Design, Manufacturing Engineering, Industrial Engineering Industry Expertise, Lean Manufacturing, Packaging, Troubleshooting"	
	AM	**TM**
Task complexity	4 [3.925]: Design (1), Development (1), New (1), Project (1)	2 [1.963]: Design (1), Improvement (1)
Task interdependence	3 [5.747]: Support (1), Training (2)	2 [3.831]: Support (1), Training (1)
Cognitive skills	0 [0]	1 [2.020]: Expertise (1)
Social skills	2 [4.464]: Communication Skills (1), Teamwork/Collaboration (1)	0 [0]
Technical skills – low	1 [1.108]: Purchasing (1)	0 [0]
Technical skills – medium	1 [3.472]: Technical Support (1)	1 [3.472]: Technical Support (1)
Technical skills - high	1 [3.509]: New Product Development (1)	0 [0]

Example 3. GE jet engine components plant in Alabama

	Engineers		Operators	
Terms in AM posting	New Product Development, Process Engineering, Communication Skills, Written Communication, Six Sigma, Scheduling, Engineering Drawings, Manufacturing Processes, Detail-Oriented, Problem Solving, Leadership, Organizational Skills, Engineering Activities, 3D Printing/Additive Manufacturing (AM), Planning, Lean Six Sigma, Purchasing.		Project Management, Communication Skills, Written Communication, Quality Assurance and Control, Process Improvement, Six Sigma, Leadership, Manufacturing Processes, Systems Analysis, Quality Management, Lean Six Sigma, 3D Printing/Additive Manufacturing (AM).	
Terms in TM posting	Manufacturing Processes, Product Delivery, Leadership, Problem Identification, Research, Manufacturing Engineering, Communication Skills, Written Communication.		Machinery, Detail-Oriented, Heavy Lifting, Energy Management, Written Communication.	
	AM	**TM**	**AM**	**TM**
Task complexity	2 [1.963]: Development (1), New (1)	1 [0.981]: Research	3 [2.944]: Analysis (1), Project (1), Improvement (1)	0 [0]
Task interdependence	3 [5.747]: Leadership (1), Organizational (1), Communication (1)	2 [3.831]: Leadership (1), Communication (1)	2 [3.831]: Communication (1), Leadership (1)	1 [1.196]: Communication
Cognitive skills	1 [2.020]: Problem Solving (1)	0 [0]	0 [0]	0 [0]
Social skills	1 [2.232]: Communication Skills (1)	1 [2.232]: Communication Skills (1)	1 []: Communication Skills (1)	0 [0]
Technical skills – low	1 [1.108]: Purchasing (1)	0 [0]	0 [0]	1 [1.108]: Machinery (1)
Technical skills – medium	0 [0]	0 [0]	0 [0]	0 [0]
Technical skills - high	1 [3.509]: New Product Development (1)	0 [0]	0 [0]	0 [0]

Descriptive statistics and correlations are presented in Appendix B Table 1 for the entire sample, for AM and for TM engineers. Correlations for technicians and operators are in Appendix B Table 2. The means of measures of task attributes and skills will be discussed in detail later; here we focus on some correlations. As expected, task complexity is substantially correlated with cognitive skills and high technical skills, less so with medium technical skills, and hardly at all with low technical skills. Task complexity is also correlated with social skills. Task interdependence is substantially correlated with social skills, as expected (and substantially less correlated with other skills). This provides support for the validity of our measures.

Appendix B Table 1. Descriptive statistics and correlations, hybrid AM/TM plants

Table 1a. All occupations, 178,858 postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.260	0.750	0.050	9.660							
2	Task Complexity	1.940	2.210	-6.870	20.610	0.57***						
3	Task Interdependence	1.390	1.820	0.000	15.330	0.36***	0.15***					
4	Cognitive Skills	1.290	1.690	0.000	14.140	0.42***	0.24***	0.17***				
5	Social Skills	0.670	0.750	0.000	4.000	0.38***	0.23***	0.29***	0.24***			
6	High Technical Skills	2.070	3.430	0.000	35.080	0.34***	0.47***	0.04***	0.22***	0.13***		
7	Medium Technical Skills	1.350	2.410	0.000	31.230	0.34***	0.2***	0.16***	0.07***	0.06***	0.12***	
8	Low Technical Skills	0.750	1.270	0.000	16.290	0.18***	-0.13***	-0.07***	-0.01***	-0.08***	-0.05***	0.13***

Table 1b. AM engineers, N = 3,055 postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.950	0.880	0.250	7.820							
2	Task Complexity	3.730	2.860	0.000	19.620	0.68***						
3	Task Interdependence	1.570	1.930	0.000	11.500	0.29***	0.08***					
4	Cognitive Skills	2.130	2.050	0.000	12.120	0.29***	0.14***	0.14***				
5	Social Skills	0.810	0.750	0.000	3.000	0.27***	0.13***	0.25***	0.19***			
6	High Technical Skills	6.190	5.850	0.000	28.060	0.28***	0.41***	-0.1***	0.18***	0.05*		
7	Medium Technical Skills	1.830	2.780	0.000	13.880	0.34***	0.18***	0.18***	0.04+	0.02	0.08***	
8	Low Technical Skills	0.730	1.010	0.000	7.130	0.26***	0.06*	0.04+	0.03+	0	-0.09***	0.23***

Table 1c. TM engineers, 110,424 job postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.340	0.770	0.050	9.660							
2	Task Complexity	2.580	2.320	-6.870	20.610	0.6***						
3	Task Interdependence	1.470	1.810	0.000	15.330	0.35***	0.11***					
4	Cognitive Skills	1.480	1.760	0.000	12.120	0.39***	0.18***	0.13***				
5	Social Skills	0.740	0.760	0.000	4.000	0.36***	0.19***	0.26***	0.21***			
6	High Technical Skills	2.580	3.680	0.000	35.080	0.33***	0.44***	0.01***	0.21***	0.11***		
7	Medium Technical Skills	1.460	2.420	0.000	20.820	0.34***	0.22***	0.18***	0.05***	0.07***	0.11***	
8	Low Technical Skills	0.450	0.800	0.000	13.240	0.28***	0.06***	0.05***	0.12***	0.03***	0.01*	0.13***

Table 2a. AM technicians, 476 job postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.610	0.630	0.250	3.760							
2	Task Complexity	1.710	1.740	-0.980	8.830	0.31***						
3	Task Interdependence	1.830	1.810	0.000	7.670	0.39***	0.09+					
4	Cognitive Skills	1.430	1.800	0.000	8.080	0.32***	0.14*	0.31***				
5	Social Skills	0.720	0.750	0.000	3.000	0.2***	0.18***	0.29***	0.38***			
6	High Technical Skills	3.520	4.270	0.000	17.540	0.3***	0.4***	0.12*	0.04	-0.02		
7	Medium Technical Skills	1.990	3.000	0.000	20.820	0.37***	0.08+	0.04	-0.03	-0.07	0.14*	
8	Low Technical Skills	1.440	1.570	0.000	8.150	0.41***	-0.06	-0.01	0.03	-0.1+	0.02	0.19***

Table 2b. TM technicians, 16,955 job postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.150	0.690	0.050	7.230							
2	Task Complexity	1.060	1.540	-3.920	16.680	0.43***						
3	Task Interdependence	1.310	1.760	0.000	13.420	0.35***	0.17***					
4	Cognitive Skills	1.140	1.550	0.000	10.100	0.41***	0.2***	0.17***				
5	Social Skills	0.540	0.700	0.000	3.000	0.33***	0.23***	0.31***	0.2***			
6	High Technical Skills	1.480	2.760	0.000	24.550	0.24***	0.35***	0.07***	0.13***	0.1***		
7	Medium Technical Skills	1.170	2.300	0.000	24.290	0.35***	0.18***	0.22***	0.12***	0.1***	0.06***	
8	Low Technical Skills	1.130	1.530	0.000	15.270	0.33***	-0.11***	-0.11***	0.08***	-0.06***	-0.03***	0.06***

Table 2c. AM operators, 564 job postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.410	0.670	0.250	3.860							
2	Task Complexity	1.120	1.400	0.000	10.790	0.45***						
3	Task Interdependence	1.480	2.020	0.000	9.580	0.5***	0.28***					
4	Cognitive Skills	1.410	1.480	0.000	6.060	0.36***	0.18***	0.14**				
5	Social Skills	0.900	0.850	0.000	3.000	0.11*	0.04	0.07+	0.31***			
6	High Technical Skills	1.970	3.370	0.000	14.030	0.32***	0.35***	0.03	0.14**	-0.07+		
7	Medium Technical Skills	2.540	3.760	0.000	17.350	0.56***	0.19***	0.25***	-0.01	-0.17***	0.12*	
8	Low Technical Skills	1.260	1.900	0.000	9.160	0.37***	-0.04	-0.07+	-0.07+	-0.27***	0.1+	0.38***

Table 2d. TM operators, 564 job postings

ID	Variables	Mean	SD	Min	Max	1	2	3	4	5	6	7
1	Words-Count	1.070	0.660	0.050	9.660							
2	Task Complexity	0.670	1.190	-3.920	16.680	0.44***						
3	Task Interdependence	1.220	1.830	0.000	15.330	0.41***	0.24***					
4	Cognitive Skills	0.830	1.410	0.000	14.140	0.42***	0.25***	0.25***				
5	Social Skills	0.530	0.700	0.000	4.000	0.41***	0.28***	0.36***	0.28***			
6	High Technical Skills	0.830	2.050	0.000	24.550	0.26***	0.27***	0.05***	0.09***	0.07***		
7	Medium Technical Skills	1.100	2.370	0.000	31.230	0.27***	0.12***	0.1***	0.05***	0.01*	0.11***	
8	Low Technical Skills	1.310	1.740	0.000	16.290	0.25***	-0.12***	-0.16***	-0.06***	-0.12***	0.09***	0.23***

We proceed with a within-plant comparison of AM and TM of measures of task attributes and skills, by occupation. As emphasized earlier, it is important to conduct comparisons at the plant level in order to control for unobserved heterogeneity in product complexity at the plant level, which may drive task complexity. We find that the average number of terms used in plant-level AM engineer postings is significantly correlated with that of TM engineers (.41, p=.000); their respective task complexity scores are also substantially correlated (.32, p=.000). This is indicative of similar product complexity of AM and TM processes.

As Table 3 indicates, most hybrid plants (938) posted both AM and TM engineers jobs (2,952 and 98,584, respectively), and fewer hybrid plants posted both of the other two occupations.

Table 3. Number of AM and TM workers in plants that posted for workers in both AM and TM, by occupation

	Engineers *938 plants*	**Technicians** *180 plants*	**Operators** *285 plants*
AM	2,952	411	529
TM	98,584	5,056	14,081

For each plant, we compute the mean of each measure for each occupation, separately for AM and TM. We thus have two values for each measure (e.g., task complexity) for each occupation (e.g., engineers) – one for AM and one for TM. We test whether the two values differ, using a two-sided Wilcoxon signed-rank test (rather than paired Student t-test because our data are not normally distributed). We first present bar graphs for means of measures of task attributes and skills at the plant for AM and TM workers by occupation, replicating the means and adding p-values of Wilcoxon test in the left panels of Tables 4 and 5; the right panel in the tables replicates the measures using the stemmed and lemmatized keywords with synonyms.[19] The two panels in both tables are fully consistent; the discussion follows the bar graphs, with reference to significance in the tables.

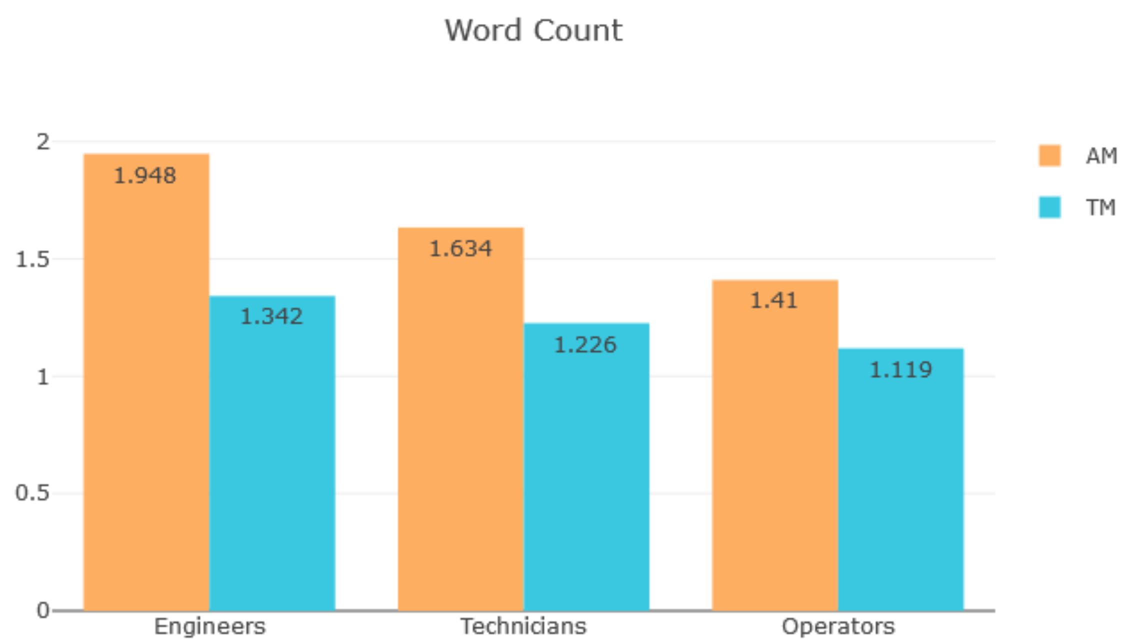
[19] This procedure is applied to words and not to terms.

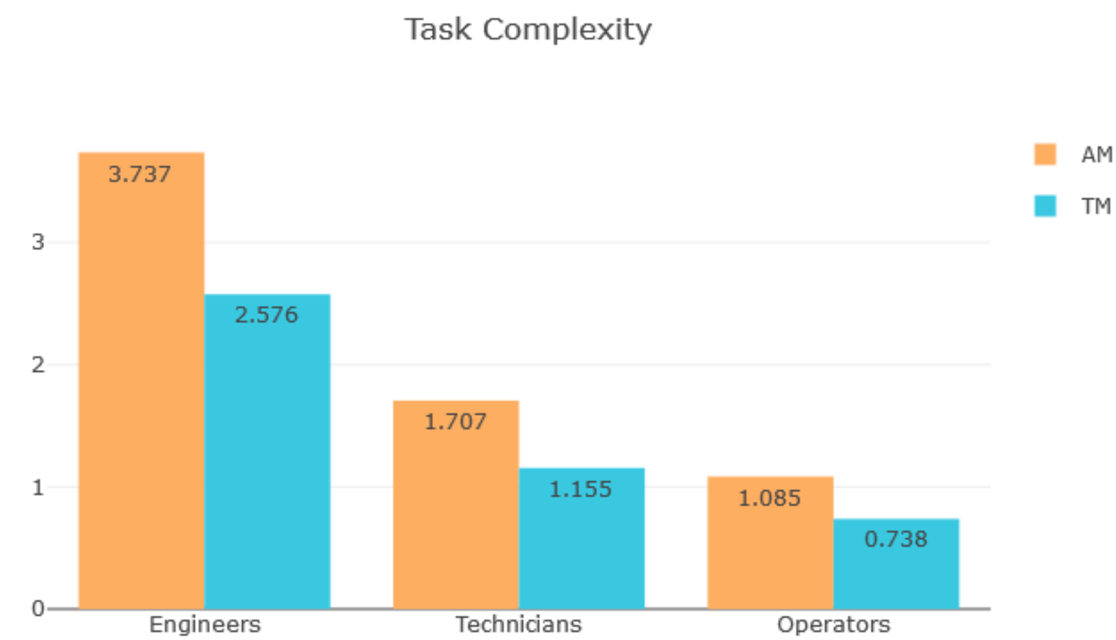
All three occupations in AM postings have, on average, a larger number of words than TM postings. Furthermore, engineer postings use more words than technician postings, and technician postings rely on more words than operator postings. Our sample plants use, on average, more words for posting than the average manufacturing postings for the same positions, which we construe to reflect production of more complex products.

Task complexity in our sample is greater than the average manufacturing job posting. The task complexity differences across occupations accord with the hierarchy of occupations. Task complexity in AM is greater than in TM across the three occupations. The differences are large.

Task interdependence is slightly greater in AM than in TM across occupations.

Figure 7. Mean keyword count, task complexity and task interdependence in AM and TM




Task Complexity
AM
TM
3.737
2.576
1.707
1.155
1.085
0.738
0
1
2
3
Engineers
Technicians
Operators

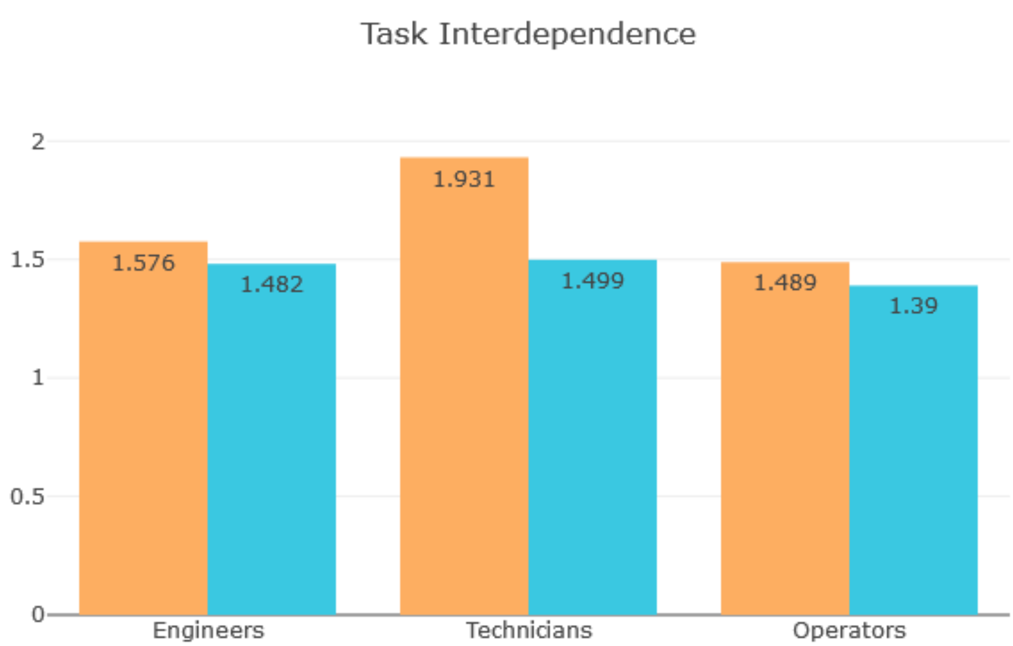

Task Interdependence
1.576
1.482
1.931
1.499
1.489
1.39
0
0.5
1
1.5
2
Engineers
Technicians
Operators

Table 4. Within-plant comparison of means of task attributes of AM and TM postings

	Core keywords			Keywords and synonyms		
	Engineers	**Technicians**	**Operators**	**Engineers**	**Technicians**	**Operators**
			Word Count			
AM	**1.948**	**1.634**	**1.410**	NA	NA	NA
TM	**1.342**	**1.226**	**1.119**	NA	NA	NA
p	*0.00*	*0.00*	*0.00*			
			Task complexity			
AM	**3.737**	**1.707**	**1.085**	**4.263**	**1.666**	**1.053**
TM	**2.576**	**1.155**	**0.738**	**2.976**	**1.284**	**0.718**
p	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*	*0.16*
			Task interdependence			
AM	**1.576**	**1.931**	**1.489**	**1.473**	**1.914**	**1.478**
TM	**1.482**	**1.499**	**1.390**	**1.457**	**1.553**	**1.554**
p	*0.14*	*0.01*	*0.00*	*0.03*	*0.02*	*0.00*

Note. p-values for Wilcoxon signed-rank tests for pairwise comparison

Consider next skill requirements. AM postings require greater cognitive and social skills in the three occupations; the difference is not statistically significant for technician cognitive skills (Table 5). Social skills requirements in TM follow the hierarchy of occupations, but not so in AM. Deming and Kahn (2018) keywords (DK in Figure 8) generates similar results.

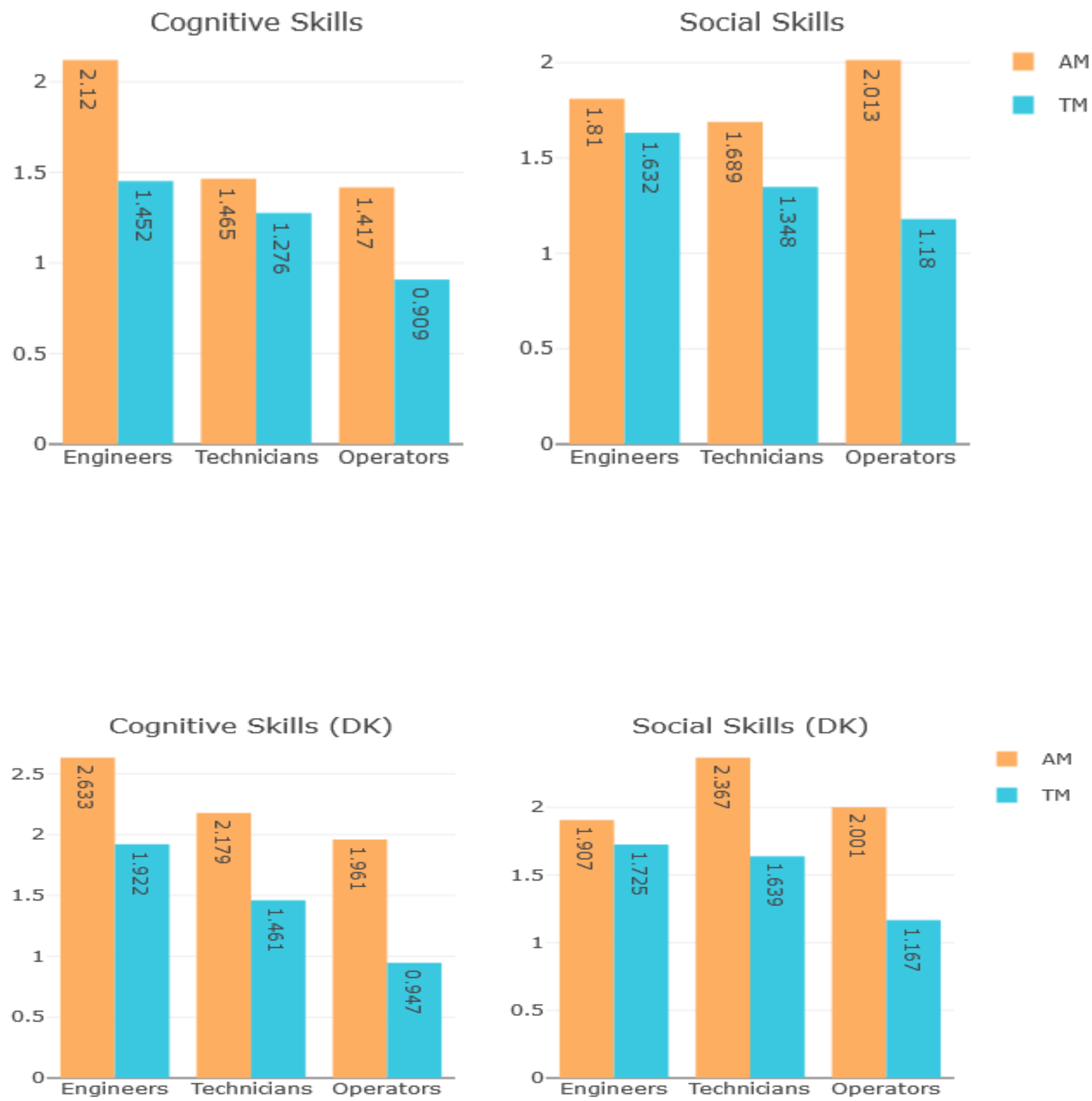
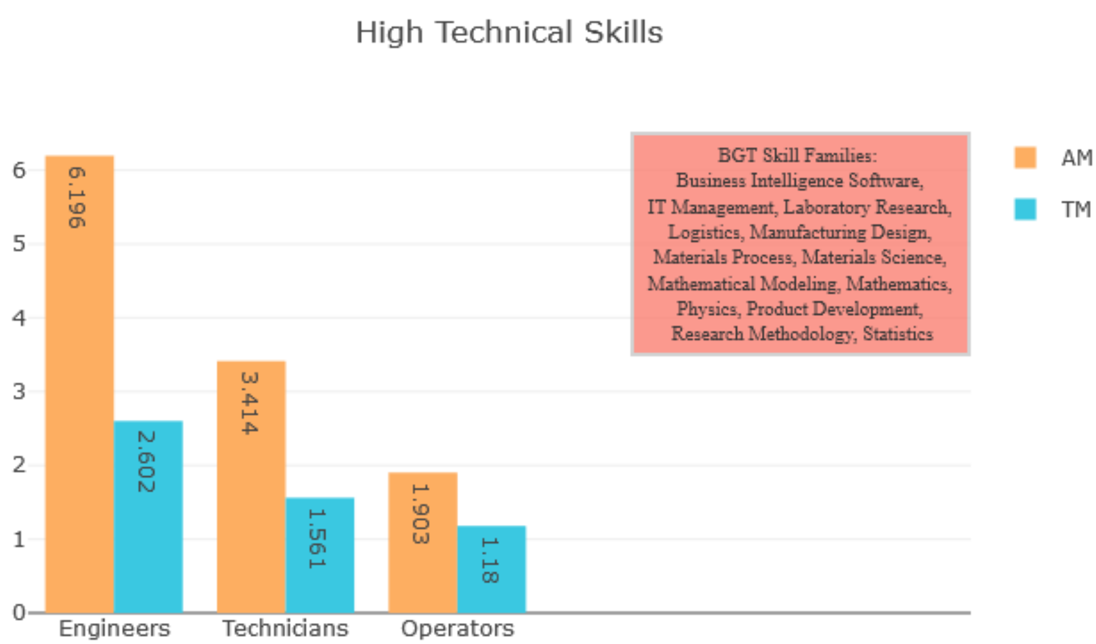


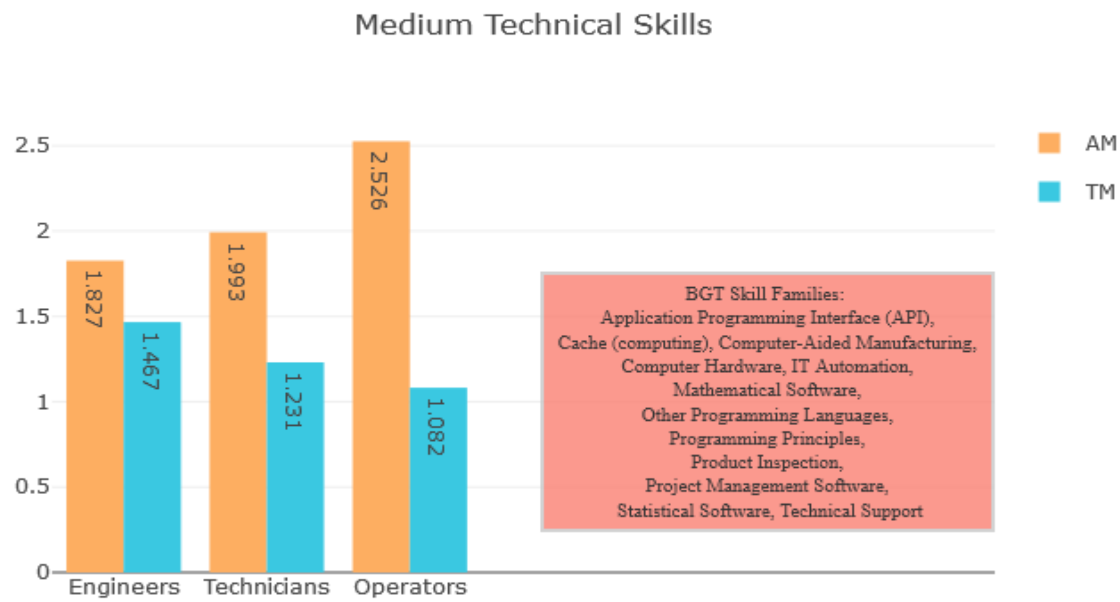
Figure 8. Mean keyword count, cognitive and social skills in AM and TM

Consider now differences in technical skills. Both AM and TM engineers have higher high-skill requirements than technicians, who have higher requirements than operators. This indicates that the skill families that comprise high skills reflect the occupational skill hierarchy. As for medium technical skills, there is less clarity in differences across occupations, whereas low technical skills are possessed more by operators and technicians than by engineers. This also appears to support the classification of technical skills.

AM has higher skill requirements in all three categories of technical skills, and for the three occupations (although the differences are not statistically significant for low skills for technicians and operators). For medium technical skills, which comprise knowledge of various programming, automation and statistical software, the AM operator requirements are higher than those of the other occupations in both AM and TM, whereas their TM counterparts need the least of these skills. Operators in AM also need much more than their TM counterparts in high skills, those related to management and business abilities as well as research skills. Likewise technicians are required to possess the high skills more than TM technicians by a substantial margin. The greatest difference is for engineers, especially with respect to high level technical skills.

Figure 9. Mean technical skills in hybrid AM/TM plants




Medium Technical Skills
2.5
2
1.5
1
0.5
0
1.827
1.467
1.993
1.231
2.526
1.082
Engineers
Technicians
Operators
AM
TM
BGT Skill Families:
Application Programming Interface (API),
Cache (computing), Computer-Aided Manufacturing,
Computer Hardware, IT Automation,
Mathematical Software,
Other Programming Languages,
Programming Principles,
Product Inspection,
Project Management Software,
Statistical Software, Technical Support

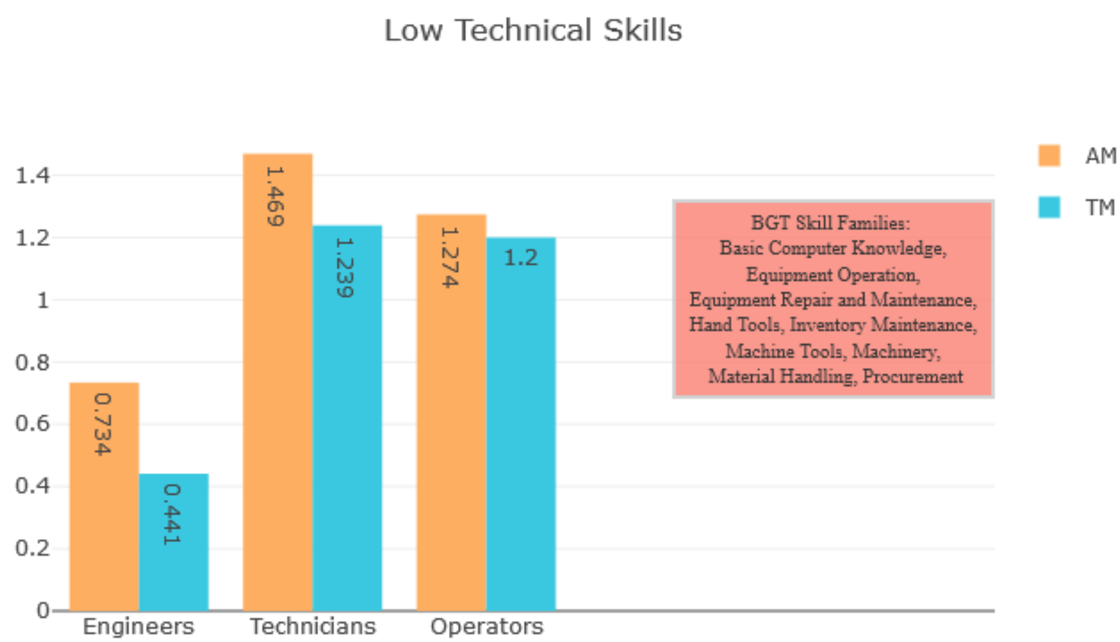

Low Technical Skills
1.4
1.2
1
0.8
0.6
0.4
0.2
0
0.734
0.441
1.469
1.239
1.274
1.2
Engineers
Technicians
Operators
AM
TM
BGT Skill Families:
Basic Computer Knowledge,
Equipment Operation,
Equipment Repair and Maintenance,
Hand Tools, Inventory Maintenance,
Machine Tools, Machinery,
Material Handling, Procurement

Table 5. Within-plant comparison of means of skills of AM and TM postings

	Core definition			Broad definition (including lemmatization and synonyms)		
	Engineers	**Technicians**	**Operators**	**Engineers**	**Technicians**	**Operators**
			Cognitive skills			
AM	**2.120**	**1.465**	**1.417**	**2.336**	**1.682**	**1.396**
TM	**1.452**	**1.276**	**0.909**	**1.513**	**1.323**	**0.884**
p	*0.00*	*0.49*	*0.00*	*0.00*	*0.25*	*0.00*
			Social skills			
AM	**1.810**	**1.689**	**2.013**	NA	NA	NA
TM	**1.632**	**1.348**	**1.180**	NA	NA	NA
p	*0.32*	*0.00*	*0.00*			
			High Technical Skills			
AM	**6.196**	**3.414**	**1.903**	NA	NA	NA
TM	**2.602**	**1.561**	**0.816**	NA	NA	NA
p	*0.00*	*0.00*	*0.00*			
			Medium Technical Skills			
AM	**1.827**	**1.993**	**2.526**	NA	NA	NA
TM	**1.467**	**1.231**	**1.082**	NA	NA	NA
p	*0.00*	*0.01*	*0.00*			
			Low Technical Skills			
AM	**0.734**	**1.469**	**1.274**	NA	NA	NA
TM	**0.441**	**1.239**	**1.200**	NA	NA	NA
p	*0.00*	*0.69*	*0.19*			

Note: p-values for Wilcoxon signed-rank tests for pairwise comparison

The findings obtained from the comparison of means concerning differences between AM and TM are confirmed by regression analysis in Table 6, controlling for the time when postings were made, output complexity (measured as the proportion of engineers among core manufacturing workers), state in which a plant operates, and plant employment (proxied by number of postings). When we replicate these regressions by occupation we confirm the results obtained above.

Table 6. Determinants of task attributes and skills in AM and TM: OLS

	Dependent variable:							
	Word Count	**Task Complexity**	**Task Interdependence**	**Cognitive Skills**	**Social Skills**	**High Technical Skills**	**Medium Technical Skills**	**Low Technical Skills**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TM vs. AM	-0.481***	-0.862***	-0.127***	-0.509***	-0.100***	-2.905***	-0.499***	-0.183***
	(0.011)	(0.032)	(0.028)	(0.026)	(0.012)	(0.052)	(0.038)	(0.019)
Operators vs. Engineers	-0.315***	-1.814***	-0.325***	-0.630***	-0.189***	-1.635***	-0.267***	0.776***
	(0.004)	(0.012)	(0.011)	(0.010)	(0.004)	(0.020)	(0.014)	(0.007)
Technicians vs. Engineers	-0.229***	-1.489***	-0.207***	-0.345***	-0.185***	-1.078***	-0.231***	0.624***
	(0.006)	(0.017)	(0.015)	(0.014)	(0.006)	(0.027)	(0.020)	(0.010)
Time Trend (Quarters)	0.001***	0.002***	-0.007***	0.001	0.0004	0.0002	0.006***	0.005***
	(0.0003)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)	(0.0005)
Output Complexity	-0.147***	0.754***	-0.304***	0.194***	0.068***	0.828***	0.356***	-0.359***
	(0.010)	(0.027)	(0.024)	(0.022)	(0.010)	(0.044)	(0.032)	(0.016)
Size	-0.0001***	-0.0003***	-0.0001***	-0.0002***	- 0.00003***	-0.0002***	-0.0001***	-0.00003***
	(0.00000)	(0.00001)	(0.00001)	(0.00001)	(0.00000)	(0.00001)	(0.00001)	(0.00000)
Constant	1.741***	3.020***	1.454***	1.582***	0.647***	4.873***	1.453***	0.711***
	(0.018)	(0.049)	(0.044)	(0.041)	(0.018)	(0.081)	(0.059)	(0.030)
Observations	178,858	178,858	178,858	178,858	178,858	178,858	178,858	178,858
R^2	0.089	0.197	0.034	0.059	0.051	0.103	0.019	0.113
Adjusted R^2	0.088	0.197	0.033	0.059	0.051	0.103	0.019	0.113
Residual Std. Error	0.720	1.983	1.788	1.640	0.727	3.250	2.392	1.193
F Statistic (df = 55; 178802)	316.061***	797.044***	112.821***	205.122***	174.051***	374.012***	62.828***	414.397***

Notes:
1) *p<0.1; **p<0.05; ***p<0.01
2) All models include US state dummies for location of plants
3) Output complexity=number of postings for engineers in both AM and TM divided by total number of postings in the three occupations
4) Size=number of AM and TM postings in the three occupations (during sample period)
5) Error terms clustered by plant

Conclusions

We have compared job postings for AM and TM workers in the same plants during the recent five years. The emerging additive manufacturing technology entails more complex tasks for core manufacturing occupations, as well as slightly more interdependence among tasks. AM demands greater skills of all kinds: cognitive, social and technical. Practically all types of technical skills are in greater demand under AM than TM. These findings suggest that AM is an enskilling technology. The skill gains are not experienced only by engineers, but also by technicians and operators.

The relative newness of the AM technology may be a contributing factor to the greater task complexity and skill requirements. The knowledge is not routine, procedures are not tested, and the application to many products is novel and experimental. On the other hand, the features that distinguish AM from TM, particularly the tight linkages across the nodes of the production process that broaden the scope of tasks and the possibility to customize by tailoring design and materials close to customer needs, entail considerable complexity and broad skills are unlikely to be tempered by time.

These findings have considerable policy implications. If additive manufacturing is indeed poised to become a dominant technology, as many observers predict, our findings suggest that workers will be required to add skills beyond what is required of them in many workplaces. Our findings are based on a very narrow segment of the manufacturing sector, the more advanced and that which produces more complex products. It is quite possible, however, that production of simple products by AM methods requires fewer skills than production of comparable products under TM.

AM automates production, and it is very likely that it requires fewer workers, especially operators, than TM to product the same amount of output. We were unable to examine this issue with our dataset, although one possible hint that this may be so emerges from the lower proportion of AM operators among AM production worker postings as compared to TM postings (Table 1).

In future work we will explore three matters. First, we will expand the characterization of task attributes and skills to include all terms that are used in job postings. Second, we will explore in depth the relationship between task attributes and skills – how different skills combine to carry out task of different degrees of complexity and interdependence. Third, we will examine differences in specific activities and tasks between AM and TM, as well as in specific skill requirements.

References

Acemoglu, Daron, and David Autor. "Skills, tasks and technologies: Implications for employment and earnings." In *Handbook of labor economics*, vol. 4, pp. 1043-1171. Elsevier, 2011.

Alabdulkareem, Ahmad, Morgan R., Lijun Sun, Bedoor AlShebli, César Hidalgo, and Iyad Rahwan. "Unpacking the polarization of workplace skills." Science advances 4, no. 7 (2018): eaao6030.

Autor, David H., and Michael J. Handel. "Putting tasks to the test: Human capital, job tasks, and wages." *Journal of Labor Economics* 31, no. S1 (2013): S59-S96.

Autor, David H., Frank Levy, and Richard J. Murnane. "The skill content of recent technological change: An empirical exploration." *Quaterly Journal of Economic* 118, no. 4 (2003): 1279-1333.

Baumers, Martin, Phill Dickens, Chris Tuck, and Richard Hague. "The cost of additive manufacturing: machine productivity, economies of scale and technology-push." *Technological forecasting and social change* 102 (2016): 193-201.

Ben-Ner, Avner, Fanmin Kong, and Stéphanie Lluis. "Uncertainty, task environment, and organization design: An empirical investigation." *Journal of Economic Behavior & Organization* 82, no. 1 (2012): 281-313.

Ben-Ner, Avner, and Ainhoa Urtasun. "Computerization and skill bifurcation: the role of task complexity in creating skill gains and losses. "*ILR Review* 66, no. 1 (2013): 225-267.

Ben-Ner, Avner, and Enno Siemsen. "Decentralization and localization of production: The organizational and economic consequences of additive manufacturing (3D Printing)." *California Management Review* 59, no. 2 (2017): 5-23.

Bloom, Nicholas, and John Van Reenen. "Why do management practices differ across firms and countries?." *Journal of economic perspectives* 24, no. 1 (2010): 203-24.

Brynjolfsson, Erik, and Tom Mitchell. "What can machine learning do? Workforce implications", *Science*, 358, no. 6370, (2017): 1530-1534

Brynjolfsson, Erik, Tom Mitchell, and Daniel Rock. "What can Machines Learn and What does it mean for Occupations and Industries." In *AEA Projects and Proceedings*. 2018.

Campbell, Donald J. "Task complexity: A review and analysis." *Academy of management review* 13, no. 1 (1988): 40-52.

Börner, Katy, Olga Scrivner, Mike Gallant, Shutian Ma, Xiaozhong Liu, Keith Chewning, Lingfei Wu, and James A. Evans. "Skill discrepancies between research, education, and jobs reveal the critical need to supply soft skills for the data economy." *Proceedings of the National Academy of Sciences* 115, no. 50 (2018): 12630-12637.

Deming, David, and Lisa B. Kahn. "Skill requirements across firms and labor markets: Evidence from job postings for professionals." *Journal of Labor Economics* 36, no. S1 (2018): S337-S369.

Eyers, Daniel R., Andrew T. Potter, Jonathan Gosling, and Mohamed M. Naim. "The flexibility of industrial additive manufacturing systems." *International Journal of Operations & Production Management* 38, no. 12 (2018): 2313-2343.

Falck, Ann-Christine, Roland Örtengren, Mikael Rosenqvist, and Rikard Söderberg. "Basic complexity criteria and their impact on manual assembly quality in actual production." *International Journal of Industrial Ergonomics* 58 (2017): 117-128.

Ferreira, Maria, Andries de Grip and Rolf van der Velden. "Does informal learning at work differ between temporary and permanent workers? Evidence from 20 OECD countries." Labour Economics, 55 (2018): 18-40.

Foss, Nicolai J., and Keld Laursen. "Performance pay, delegation and multitasking under uncertainty and innovativeness: An empirical investigation." *Journal of Economic Behavior & Organization* 58, no. 2 (2005): 246-276.

Frank, Morgan R., David Autor, James E. Bessen, Erik Brynjolfsson, Manuel Cebrian, David J. Deming, Maryann Feldman, Matthew Groh, José Lobo, Esteban Moro, Dashun Wang, Hyejin Youn, and Iyad Rahwan, "Toward understanding the impact of artificial intelligence on labor," *Proceedings of the National Academy of Sciences*, March 25, 2019 https://doi.org/10.1073/pnas.1900949116.

Friesike, Sascha, Christoph M. Flath, Marco Wirth, and Frédéric Thiesse. "Creativity and productivity in product design for additive manufacturing: Mechanisms and platform outcomes of remixing." *Journal of Operations Management* (2018).

Gathmann, Christina, and Uta Schönberg. "How general is human capital? A task-based approach." *Journal of Labor Economics* 28, no. 1 (2010): 1-49.

Gully, Stanley M., Dennis J. Devine, and David J. Whitney. "A meta-analysis of cohesion and performance: Effects of level of analysis and task interdependence." *Small group research* 26, no. 4 (1995): 497-520.

Ham, Dong-Han, Jinkyun Park, and Wondea Jung. "Model-based identification and use of task complexity factors of human integrated systems." *Reliability Engineering & System Safety* 100 (2012): 33-47.

Hedenstierna, Carl Philip T., Stephen M. Disney, Daniel R. Eyers, Jan Holmström, Aris A. Syntetos, and Xun Wang. "Economies of collaboration in build-to-model operations." *Journal of Operations Management* (2019):1-23.

Hershbein, Brad, and Lisa B. Kahn. "Do recessions accelerate routine-biased technological change? Evidence from vacancy postings." *American Economic Review* 108, no. 7 (2018): 1737-72.

Jiang, Ruth, Robin Kleer, and Frank T. Piller. "Predicting the future of additive manufacturing: A Delphi study on economic and societal implications of 3D printing for 2030." *Technological Forecasting and Social Change* 117 (2017): 84-97.

Lazear, Edward P. "Firm-specific human capital: A skill-weights approach." *Journal of political economy* 117, no. 5 (2009): 914-940.

Lipson, Hod, and Melba Kurman. *Fabricated: The new world of 3D printing*. John Wiley & Sons, 2013.

Liu, Peng, and Zhizhong Li. "Task complexity: A review and conceptualization framework." *International Journal of Industrial Ergonomics* 42, no. 6 (2012): 553-568.

Matthes, B., Christoph, B., Janik, F, Ruland, M. Collecting information on job tasks – an instrument to measure task required at the workplace in a multi-topic survey, Journal of Labour Market Research, 47 (2014):273-297.

Modestino, Alicia S., Daniel Shoag and Joshua Balance. "Downskilling: Changes in employer skill requirements over the business cycle," *Labor Economics* 41 (2016): 333-347.

National Academies of Sciences. *Information technology and the workforce: Where are we and where do we go from here?* National Academy of Science, Washington, D.C. (2017).

Niaki, Mojtaba Khorram, and Fabio Nonino. *The Management of Additive Manufacturing*. Springer, 2018.

Osterman, Paul. "Choice of employment systems in internal labor markets." *Industrial Relations* 26, no. 1 (1987): 46-67.

Perrow, Charles. *Complex organizations; A critical essay*. 3rd ed. Random House, New York. 1982.

Prendergast, Canice, 2002. “The tenuous trade-off between risk and incentives,” *Journal of Political Economy* 101, 1071–1102.

Saavedra, Richard, P. Christopher Earley, and Linn Van Dyne. "Complex interdependence in task-performing groups." *Journal of applied psychology* 78, no. 1 (1993): 61.

Syverson, Chad. "What determines productivity?." *Journal of Economic literature* 49, no. 2 (2011): 326-65.

Thompson, James D. *Organizations in action: Social science bases of administrative theory*. 1967.

Tambe, Prasanna. "Big data investment, skills, and firm value." *Management Science* 60, no. 6 (2014): 1452-1469.

Tambe, Prasanna, and Lorin M. Hitt. "Job hopping, information technology spillovers, and productivity growth." *Management science* 60, no. 2 (2013): 338-355.

Tofail, Syed AM, Elias P. Koumoulos, Amit Bandyopadhyay, Susmita Bose, Lisa O’Donoghue, and Costas Charitidis. "Additive manufacturing: Scientific and technological challenges, market uptake and opportunities." *Materials today* 21, no. 1 (2018): 22-37.

Zairi, Mohamed. "Supplier partnerships for effective advanced manufacturing technology implementation: A proposed model." *Integrated Manufacturing Systems* 9, no. 2 (1998): 109-119.

Zanoni, Simone, Milad Ashourpour, Andrea Bacchetti, Massimo Zanardini, and Marco Perona. "Supply chain implications of additive manufacturing: a holistic synopsis through a collection of case studies." *The International Journal of Advanced Manufacturing Technology* (2019): 1-16.

Zuboff, Shoshana. *In the Age of the Smart Machine. The Future of Work and Power*, Basic Books (1998).