EFFECTS OF NEW TECHNOLOGIES ON WORK: THE CASE OF ADDITIVE MANUFACTURING

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The authors study the effects on work of additive manufacturing (AM), an emerging technology that may replace significant segments of traditional manufacturing (TM). Compared to TM, AM is more integrated and offers greater flexibility in design, materials, and customizability; thus, it should entail more demanding tasks and higher skill levels. The authors analyze vacancies for AM and TM workers, focusing on plants that posted vacancies in both technologies to control for factors that may affect the content of job postings. Findings show that AM jobs are more complex (with more non-routine analytic and less routine cognitive content) in comparison to TM jobs, and AM jobs require more high-level technical skills and more reasoning skills. The relative differences are larger for lower-skill workers (operators) than for high-skill workers

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(engineers). The authors conclude that AM is an upskilling technology that is skill biased in favor of low-skill workers and therefore reduces the skill gap.

Technology affects workers' tasks and demand for skills in diverse ways. Computerization, introduced widely since the 1980s, has reduced the routine content of tasks and enhanced non-routine cognitive tasks, enriching high-skill workers' tasks and productivity more than that of low-skill workers. This shift has increased the skill gap and wage inequality. Artificial intelligence, robots, and additive manufacturing are more recently introduced general-purpose technologies. These substantially automated technologies have raised concerns about the future of work. Will these technologies simplify the task content of jobs and reduce the demand for skills for most workers, leaving only a few high-skill workers who design, develop, and program machines? Currently, empirical evidence concerns primarily robots, and findings are mixed (Borjas and Freeman 2019; Dixon, Hong, and Wu 2021; McGuinness, Pouliakas, and Redmond 2021).

This article provides the first evidence on the effects of one emerging technology, additive manufacturing (AM), on work. AM deployment in industry is currently limited but is rising rapidly and is predicted to transform manufacturing, supply chains, the geography of production, and more. AM is a computer-based integrated process in which layers of plastics, metals, and other materials are deposited to generate a complete part or product with complex geometry. Its flexibility enables extensive customizability, which entails many product-dependent choices and requires experimentation—more so than the subtractive, mold-based or forming processes used in traditional manufacturing (TM). We explore three central questions at the job level: 1) How do tasks in AM and TM compare? 2) How do skill requirements between the two compare? 3) How do the effects of AM differ between lower- and higher-skill occupations?

We develop a framework to analyze how technology affects tasks and skill requirements. We emphasize product flexibility and process integration, and we analyze how these affect task content of jobs in different occupations as well as workers' skill requirements. We argue that AM is more flexible and more integrated than TM, implying a more complex task environment for most workers: more non-routine analytic, less routine cognitive, less sequentially and more reciprocally interdependent tasks. This task environment requires higher-level technical and cognitive skills as compared to TM skill requirements.

Our empirical investigation uses data on manufacturing vacancy postings from January 1, 2014, to January 31, 2022, assembled by Burning Glass Technologies. The content of job postings reflects what employers want workers to do and know. We extract task and skill information by matching terms included in job postings to a set of predetermined keywords that describe particular tasks and skills. The content of job postings reflects not only differences implied by technology but also by unobservable factors such as management philosophy and style of writing postings. To control for such unobserved heterogeneity, instead of using propensity score matching or similar techniques, we focus on plants that posted both AM and TM jobs (at least five in each technology) in core occupations. This within-plant matching permits identification of the effects of technology on tasks and skill requirements, using variations within a plant over time and between plants after controlling for plant fixed effects. We find that AM increases job complexity and raises skill demand, at least as much for lower-skill workers as for higher-skill workers.

A Theoretical Framework for Analyzing the Effects of Technology on Work

The production process brings together workers, machines, and software to transform materials into products. Using the task framework, Acemoglu and Restrepo (2019: 6) described a manufacturing process as follows: "Production requires the completion of a range of tasks. The production of a shirt, for example, starts with a design, then requires the completion of a variety of production tasks, such as the extraction of fibers, spinning them to produce yarn, weaving, knitting, dyeing, and processing, as well as additional nonproduction tasks, including accounting, marketing, transportation, and sales. Each one of these tasks can be performed by human labor or by capital (including both machines and software). The allocation of tasks to factors determines the task content of production."

A large literature grounded in this framework has analyzed the effects of technology on tasks and skill requirements. Many analyses focus on the effects of computerization. The dominant explanation was put forth by Autor, Levy, and Murnane (2003), who argued that computers take over the execution of routine tasks and complement the efforts of workers who carry out non-routine analytical and interactive tasks. They found that computerization is greater in industries historically intensive in routine tasks, and that computerization increases the incidence of non-routine analytical and interactive tasks and reduces the incidence of routine tasks. Spitz-Oener (2006) extended this argument and provided direct evidence on skills from employee surveys and showed that skills, assessed through task requirements, have become more complex, especially in occupations that have experienced more rapid computerization. Borghans, ter Weel, and Weinberg (2014) found that computerization increased demand for "soft" people skills. Ben-Ner and Urtasun (2013) found that job complexity before computerization positively affects adoption of computerization, as well as subsequent gains in task complexity, gain in complex (cognitive and technical) skills, and loss of some skills. Acemoglu and Restrepo (2019) showed that technology changes the task content of jobs by replacing workers in some tasks and by creating new tasks in which workers have a comparative advantage.

The literature on the effects of computerization focused on the replacement of routine tasks and the enhancement of non-routine tasks by software and computerized machines, including robots and automation. Most manufacturing is now substantially computerized. To evaluate the impact of various technologies or techniques of production on work, it is necessary to examine features in addition to their degrees of reliance on computers. We suggest product *flexibility* and process *integration*. These have been central in the study of the effects of technology on work organization by Thompson (1967), Sethi and Sethi (1990), MacDuffie (1995), Stabell and Fjeldstad (1998), Akçomak, Borghans, and ter Weel (2011), and others.

Technologies of production differ in terms of flexibility in product characteristics, materials, and customizability. Greater flexibility entails numerous exceptions and choices and requires more experimentation with alternative specifications of parameters to ensure desirable outcomes. This experimentation results in more non-routine tasks and greater job complexity. The execution of such tasks demands greater technical and reasoning skills than are needed in less complex jobs (Perrow 1972; Sethi and Sethi 1990; Lindbeck and Snower 2000; Ben-Ner and Urtasun 2013).

The production process consists of a sequence of tasks. Tasks may be discrete and separable from each other (as in the example of shirt making) or closely linked and integrated with each other (as in the production of chemicals). Separable tasks may be carried out by more than one worker, all of whom utilize narrow skill sets (Borghans and ter Weel 2006), with their sequentially interdependent work coordinated by managers. In integrated technologies, several adjacent tasks are combined into a single job, with reduced sequential interdependence and less need for coordination between them (Thompson 1967; Stabell and Fjerdstad 1998; Lindbeck and Snower 2000).

This theoretical framework suggests that the more flexible and the more integrated a technology, the greater the complexity of workers' jobs, implying demand for more technical and reasoning skills. Additional task attributes and skill requirements may be affected by specific aspects of technology. We turn now to describe AM and TM and to evaluate differences in flexibility and integration and their implications for workers' tasks and demand for skills.

Both AM and TM are computer-based but differ radically in how they transform materials into products. TM entails 1) subtraction from a solid block by filing, turning, milling, and grinding; 2) forming or forging using presses; or 3) casting or injecting materials into product-specific limited-use molds; subtractive methods are most common. Distinct components, produced separately, are assembled into a product through fitting, welding, and similar methods. In AM, materials are deposited layer by layer to build up a part or a finished product in a build space or a vat, without a mold. The layers consist of a single material, usually polymers or metals, but combinations of multiple materials with differing properties (conductivity, rigidity, and color) are feasible. The layers are fused together and solidified through heating, cooling, or optical energy. The process is directed by computer software. Specific AM techniques differ in how the layers are deposited, joined, and solidified; the speed of production; the size of the product; materials used; product geometric complexity; finishing; and other parameters. Post-processing is required.[1]

AM and TM transform materials into products in a similar sequence of activities. These include, as quoted earlier from Acemoglu and Restrepo (2019), development, design, and choice of materials based on customer demand; identification of production processes for various parts; assembly, inspection, and shipping to the customer; with support services by management, human resources, and other functions. However, key differences occur between AM and TM in the design, development, and materials choice stage and in the production stage. AM product design options are much greater than in any of the TM techniques, offering substantially more flexibility (Ben-Ner and Siemsen 2017; Quinlan and Hart 2020), which permits extreme customizability (Jiang, Kleer, and Piller 2017). AM production is much more integrated, being performed in one machine, whereas TM entails a longer sequence of multiple steps and multiple parts to create one component (Rehnberg and Ponte 2018).

Two products made by AM and TM are illustrated in Online Appendix (OLA) A, Figure OA.1. (Hereafter, numbering for Online Appendix material is prefaced with an "OA.") The first example is a fuel nozzle tip for jet engines, and the second is an air duct for cooling thermal printers. When produced by TM, these products require the separate production of 20 and 8 parts, respectively (most by subtractive methods, some by casting), and assembly to achieve desired geometric properties. In AM, these products are made of a single piece in compact machines like those shown in OLA A, Figure OA.2. Current applications of AM are concentrated in geometrically complex products, customized products and tools, products that require multiple materials, and rapid prototyping of TM products (see OLA A, Figure OA.3).

The differences in the flexibility and integration features of AM and TM have significant implications for workers' tasks and skills. The exploitation of flexibility presents challenges to engineers in ideation, research, design, and product development to ensure product strength, durability, cost, and other objectives. This process requires experimentation, testing, and holistic analysis of results. The same phases occur in TM, but AM solutions are drawn from a larger solution space, implying more non-routine and variable tasks, which therefore require higher-level technical and reasoning skills than in TM (Friesike, Flath, Wirth, and Thiesse 2018; Zanoni et al. 2019).

[1]AM was introduced in the 1980s for prototyping and producing replacement parts. In recent years, AM capabilities have expanded dramatically in terms of the parameters noted in the text.

The greater flexibility in AM also entails more complex technical and cognitive tasks for AM operators and technicians. They handle different materials, develop or implement varying support structures in the build space where the products are deposited, remove and inspect them, and do some or all required post-processing. These tasks are more variable and less routine than tasks in TM. Less product flexibility results in fewer changes from established routines and less experimentation. Consequently, AM operators and technicians must possess technical and reasoning skills that exceed those of their TM counterparts.

The greater integration of the AM production process—carried out mostly in one machine—implies that one AM worker is engaged with most of it and must understand the relationship between materials, production process, and the product.[2] In TM, workers usually focus on one phase of the production process. For example, investment casting, used for making parts with relatively complex geometry, consists of several steps. A pattern is produced from which the mold (master die) is made, from which complementary wax patterns are produced and combined to create the mold that represents the product. This wax mold is then used to make ceramic molds, into which molten metal is poured, afterward hardened, and then the ceramic mold is removed to reveal the product. These multiple tasks are carried out by workers located in different parts of a plant and whose work is sequentially interdependent. In AM, sequential interdependence in production is reduced and is internalized in one job (carried out by an operator or technician).

Because of more extensive and frequent experimentation in AM, engineers need to consult with each other on the materials, design, and production process suitable for a particular set of parameters. Engineers also need to consult with and receive feedback from operators and technicians about the feasibility of support structures, fragility of products, and issues that arise in removal from the build space. This level of communication requires exchanges between engineers and production workers, that is, reciprocal interdependence between them. For this process to be effective, they should understand each other's tasks, specifically, they should possess some of each other's skills. Interdependence requires communication and social skills to interact effectively with other workers. The two technologies require interactions, albeit of somewhat different kinds, but no suggestion of significant difference in people skills.

We summarize the foregoing discussion in several hypotheses. In line with the task framework, we hypothesize separately the effects of AM relative to TM on the nature of tasks and the demand for skills required to support the execution of such tasks.

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[2]Post-processing may be done by AM workers. If the removal of the product from the support structure is complicated or the product is combined with other products to create a part, post-processing may involve TM workers.

Tasks. Compared to TM tasks, AM tasks are **(T1)** cognitively more complex, **(T2)** less complex manually, **(T3)** more reciprocally interdependent, and **(T4)** less sequentially interdependent.

Technological change may induce upskilling of both lower- and higher-skill workers, de-skilling of both, bifurcated effects, and mixed effects with increases in demand for some skills and decreases in demand for other skills. In OLA B, we present a model (based on Lucas 1988) of alternative possibilities of technology-induced skill change relative to initial skill level. Our discussion above implies that effects of AM on demand for various skills are in the same direction for low- and high-skill occupations. Our theoretical framework, however, is not sufficiently specific to predict the relative change in demand for skills by occupations.

Skills. Compared to TM, AM demand **(S1)** for technical engineering skills is greater, **(S2)** for operations skills is lower, **(S3)** for reasoning skills is greater, and **(S4)** for people skills is similar.

Differences between AM and TM tasks and skills may be inflated by the newness of AM. Newness may entail learning about the optimal task content and skill requirements, which may be reflected in hoarding skills to handle unexpected demands (Autor 2013; Zanoni et al. 2019; Quinlan and Hart 2020). We conjecture that the differences between AM and TM in tasks and skills may moderate over time.

In the comparison of AM and TM we assumed, implicitly, that they are deployed in similar contexts. Companies that have advanced technical capabilities are more likely to introduce a new technology such as AM in addition to TM (Rehnberg and Ponte 2018), if they judge that the new technology promises a favorable benefit–cost relationship (Bresnahan, Brynjolfsson, and Hitt 2002). In our empirical analysis, we focus on postings made by plants that use AM in addition to TM. We do not model their choice but analyze differences in tasks and skills conditional on the use of both AM and TM.[3]

Data and Measures

To understand differences in tasks and skills between AM and TM, we study the views of employers as expressed in the content of job vacancy postings. Our data set consists of online job postings in the US manufacturing sector from January 1, 2014, to January 31, 2022. The data were collected by Burning Glass Technologies (BGT), a labor market analysis consulting firm.

[3]An ideal approach would be to model adoption separately, but doing so is often not feasible for new technologies with very low initial adoption rates. For a similar situation concerning adoption of robotics, see Dixon, Hong, and Wu (2021).

BGT scrapes vacancy postings from more than 40,000 online job boards and company websites. It removes duplicate postings and systematically classifies the information contained in the postings, including occupation, tasks, requisite skills, education, certification, and experience, as well as employer name, industry, and location. BGT data have been used to analyze jobs and skills in several recent articles, including Hershbein and Kahn (2018), Deming and Kahn (2018), Börner et al. (2018), and Deming and Noray (2020), all of which provided extensive descriptions of the data; hence, we do not repeat it here. These and other authors (e.g., Atalay, Phongthiengtham, Sotelo, and Tannenbaum 2020) suggested that job postings are a useful source of information about workers' tasks and skills for comparisons across occupations, industries, and over time.

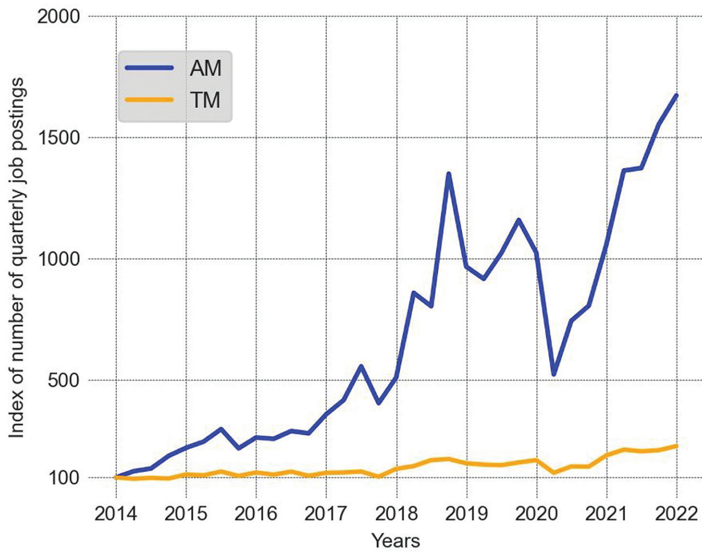
We classify a posting as AM if it contains terms such as "additive manufacturing" and/or "3D printing." This criterion does not account for all new AM hires, as some postings may not mention AM but have the intention to provide AM training after hiring. Similarly, current employees may be trained for AM without recourse to external hiring (Behaghel, Caroli, and Walkowiak 2012). Our identification of AM postings is likely to result in an undercount of new AM jobs, but we do not judge this as a source of bias in findings. All other postings are classified as TM. TM consists of several techniques; later in this article, in the section titled Extensions and Robustness Checks, we compare AM with various TM techniques, showing that the main findings are not affected by the aggregation into TM.

We focus on core manufacturing occupations: engineers (2010 Standard Occupational Classification [SOC] code 17-2000), technicians (SOC 17-3020 and 17-3030), operators (SOC 49-0000 and 51-0000), and managers (SOC 11-0000). Engineers are high-skill workers, operators are low-skill workers, and technicians are middle-skill workers. Managers may be business or operations oriented, with many in the high-skill category.

In total, 7,684,467 vacancies were posted between January 1, 2014, and January 31, 2022, in the four occupations in manufacturing (North American Industry Classification System [NAICS 31-33]) in the BGT data set. We focus on postings that contain at least two terms (excluding job title) made by establishments with a valid firm identifier and an address: 5,553,317 postings, of which 18,249 are in AM. Figure 1 presents the evolution of AM and TM postings in this sample. Very few AM postings appear prior to 2014; the number of AM postings accelerated around 2016, whereas TM postings exhibited a much more modest increase; the pandemic period was marked by variability in both AM and TM postings.

We identify establishments (plants) by geolocation coordinates and company name. Numerous plants posted just a few vacancies during the sample period (because the establishments had low demand for new workers, exited, changed names, or moved). Following others who work with BGT data, we use plants that posted a certain minimum number of vacancies. For plants that posted only AM jobs or only TM jobs—"pure AM" and

Figure 1. Quarterly Evolution of Additive Manufacturing (AM) and Traditional Manufacturing (TM) Job Vacancies: Managers, Engineers, Technicians, and Operators, 01/2014–01/2022



Source: Authors' analysis of Burning Glass Technologies data.
Notes: The chart represents the index of number of quarterly job postings, first quarter of 2014 = 100 (87 postings in AM and 123,101 postings in TM).

"pure TM" plants, respectively—we require a minimum of five total postings in the four occupations. For plants that posted jobs in both technologies—"hybrid AM-TM" plants—we impose a minimum of five postings in *each* technology. This minimum is intended to detect sustainable operations.[4]

Table 1 provides information about the three types of plants that meet the inclusion criteria. Most plants and postings are from pure TM plants. Our sample contains only a handful of pure AM plants. Most postings by hybrid plants are in TM. Hybrid plants hire many more engineers (approximately 38% of their postings in our four occupations) than pure TM plants hire (16% of postings).[5] Hybrid plants are larger, as indicated by many more postings per plant than pure TM plants (799 vs. 32). Pure TM plants are distributed across the manufacturing sector, whereas hybrid plants operate in various industries, with concentration in aerospace, medical devices, automotive and parts manufacturing, and they belong to technologically

[4]According to the US Bureau of Census ECNLOCMFG2012 data set, of all 297,171 NAICS 31-33 manufacturing plants in 2012, 30,203 employed four or fewer employees. Five postings in eight years seems sufficient as the basis for a viable operation in a plant. We conduct robustness checks with higher numbers of postings.

[5]Turnover rates may vary across occupations and types of plants, resulting in different job posting rates. This finding is not material to our analysis, and we do not explore it further in this article.

Table 1. Number of Plants, Firms, and Job Postings, by Occupation and by Plant Type, 01/2014–01/2022

	A. Pure AM plants	*B. Pure TM plants*	*C. Hybrid AM-TM plants*		*Total*
Number of plants	39	119,827	700		120,566
Number of firms	34	31,357	297		31,688
	AM postings	*TM postings*	*AM postings*	*TM postings*	*Total*
Manager	80	1,433,220	2,437	233,820	1,669,557
Engineer	91	607,880	6,302	205,328	819,601
Technician	46	289,034	1,009	29,365	319,454
Operator	78	1,537,169	1,348	79,646	1,618,241
Total	295	3,867,303	11,096	548,159	4,426,853

Notes: Pure AM plants posted only AM jobs, pure TM plants posted only TM jobs, and hybrid AM-TM plants posted both AM and TM jobs during the sample period. The sample is restricted to pure AM and pure TM plants that posted at least 5 jobs and hybrid plants that posted at least 5 AM and 5 TM jobs in the four occupations. Each plant belongs to a firm; some firms have multiple plants.

more advanced and larger firms. Within hybrid plants, 57% of AM postings are for engineers, compared to 37% for TM. Pure AM plants are mostly contract manufacturers; the share of engineer postings in these plants is slightly less than one-third, lower than in hybrid plants but twice as high as in pure TM plants. We do not study what is done in individual plants, but information about several hybrid plants suggests that TM workers in the four occupations are engaged in various aspects of making products, from design, production planning, and purchasing, to setting up of tools and machines, maintenance, production, quality control, data analysis, marketing, logistics, and more; some TM workers do post-processing for AM products. AM workers in the four occupations are engaged in similar activities as TM workers, producing parts or products for external customers within and outside the company (such as components in airplanes and printers as illustrated in OLA A, Figure OA.1) and internal customers (such as prototyping and making jigs and fixtures for use in TM production).

Job postings reflect differences in job requirements. We are interested in evaluating differences that arise from technological differences between AM and TM. Differences in tasks and skill requirements across plants may arise from unobservable approaches to the design of jobs (Bloom and Van Reenen 2007; Brenčič and Norris 2009; Feng and Valero 2020), differences in the quality and productivity of workers (Syverson 2011), and differences in the style of postings. To identify the effects of technology, we focus on vacancies posted by hybrid AM-TM plants; this eliminates plant-level fixed effects associated with unobservable heterogeneity. Thus, our analytical sample consists of 700 plants that posted at least 5 AM and 5 TM vacancies each, with 559,255 postings in total, of which 11,096 were AM jobs (see Table 1). This method of matching technologies within plants permits causal inference of the effects of AM relative to TM when we cannot implement empirically a two-step model whereby choice of technology precedes analyses of differences associated with technology.[6] In the extensions and robustness analyses, we use all observations listed in Table 1 as well as various subsamples.

Task Attributes and Skills

We identify task attributes and skills that meet four overlapping criteria: 1) are directly related to our hypotheses, 2) are widely used in the related literature, 3) provide a broad outlook on AM and TM, and 4) may be used for validity and placebo tests.

The theoretical framework highlights the centrality of job complexity and interdependence. We capture complexity through non-routine analytic, routine cognitive, non-routine manual, and routine manual tasks and skills that have been widely used in the literature, with non-routine reflecting greater complexity and routine lesser complexity. Interdependence may be reciprocal and sequential (the literature combines the two into interactivity).

We classify skills into four categories: 1) engineering (consisting of development, design, and materials), 2) operations (inventory, tooling, maintenance, automation, and production), 3) support (administration, management, finance, and so forth), and 4) general skills, classified into reasoning (cognitive skills and creativity) and people skills (social skills and character). These skills are required in varying degrees across the range of jobs; engineering skills are core skills for engineers, operations skills are core for operators, support skills are central to managers' jobs, and general skills are needed in all occupations. We have proposed hypotheses about engineering, operations, and general skills, but include support skills to provide a richer picture of differences across jobs and technologies and for use in some tests.

Measures

BGT uses machine-learning algorithms to convert the text of job postings into strings of terms. These are words such as "creativity" or phrases such as "problem solving" and "electrical schematics design," as well as technical skills that refer to brand names, such as "Microsoft Office." This procedure considerably reduces the number of words employed to describe a job compared to the original text. An example of a job posting and its counterpart in BGT terms is presented in OLA A, Figure OA.4.

The BGT terms in each posting are the raw material from which we construct our measures of task attributes and demand for skills, using the keyword approach. This approach has been applied to source materials that

[6]Matching approaches that deal with similar situations include the widely used propensity score matching and coarsened exact matching (Iacus, King, and Porro 2012). The latter was used by Dixon, Hong, and Wu (2021) to identify the effects of robots on outcomes. Our within-plant matching, not commonly available to researchers, offers clear advantages associated with location, industry, management, plant size, and other variables being the same for both technologies.

describe the content of jobs, such as job descriptions, vacancy postings, Dictionary of Occupational Titles (DOT) and O*NET, and employee and employer surveys. The source material is matched to lists of keywords that describe skills or tasks. The common measure is based on the count of terms that match keywords. For example, Autor et al. (2003) considered a task as routine cognitive if the DOT task description contains the keywords "set limits," "tolerances," or "standards," and as routine manual if it contains "finger dexterity." Spitz-Oener (2006) matched terms in job surveys to lists of keywords to measure the strength of several task attributes. Similarly, Deming and Kahn (2018), Deming and Noray (2020), and Börner et al. (2018) used BGT data to measure diverse skills. Atalay et al. (2020) measured skills by matching terms extracted from newspaper job ads to keywords. We follow the approach and keyword lists developed by these authors.

Measures can be created based on 1) the count of matched terms (Deming and Kahn 2018; Deming and Noray 2020), 2) a binary variable that captures the presence of any matched term (Autor et al. 2003), 3) the share of matched terms in the total number of keywords in a list (Spitz-Oener 2006), and 4) the share of matched terms in the total number of terms in a job posting (Michaels, Rauch, and Redding 2019; Atalay et al. 2020). The count of terms measure is straightforward: If, say, engineers in AM have more terms related to engineering skills than do TM engineers, then these skills are more important for AM engineers. The binary measure is suited for cases with few terms. The share of matched terms in the number of keywords is the same for purposes of comparing AM and TM (both have the same denominator). The share of matched terms in the total number of terms in a posting reflects the relative importance of different measures, so, for example, a higher share of engineering skills for AM engineers implies that, relative to other skills, it is more important in AM than in TM. The difference between the share and count measures is that the shares add up to unity (if all terms are accounted for in keyword lists), so not all measures can be greater in one technology as compared to the other, whereas with the count measure, all measures can be larger in one technology than in the other (on average, we account for 57.8% of terms in job postings). We use the share measure as our leading measure but replicate the main analyses using the count and binary measures.

We construct measures for each task and skill using keyword lists from Spitz-Oener (2006), Deming and Kahn (2018), Deming and Noray (2020), Atalay et al. (2020), and BGT classifications of technical terms. Appendix Table A.1 (referring to a brief appendix that falls at the end of the article text rather than part of the Online Appendix) presents the principal keyword lists, with more details in OLA A, Table OA.1. The keywords for task attributes are exclusive to each attribute, and the keywords for skills are exclusive to each skill. However, some keywords are used to identify both tasks and skills. This overlap is unavoidable in the search for meaning in a limited word space; this precludes an analysis of the relationship between skills and task attributes. Terms that identify AM are not included in the measures.

In sum, we create measures for each job posting by matching terms to keywords, adding up the number of matches for each task attribute and skill to obtain the count measures, then dividing by the total number of terms in the posting and multiplying by 100 to obtain the share measures. For example, in the job posting in OLA A, Figure OA.4, the measure of the task attribute routine manual is 23.08: three matched terms ("material handling equipment," "machine operation," and "equipment maintenance") divided by 13 (the number of terms in the posting) times 100.

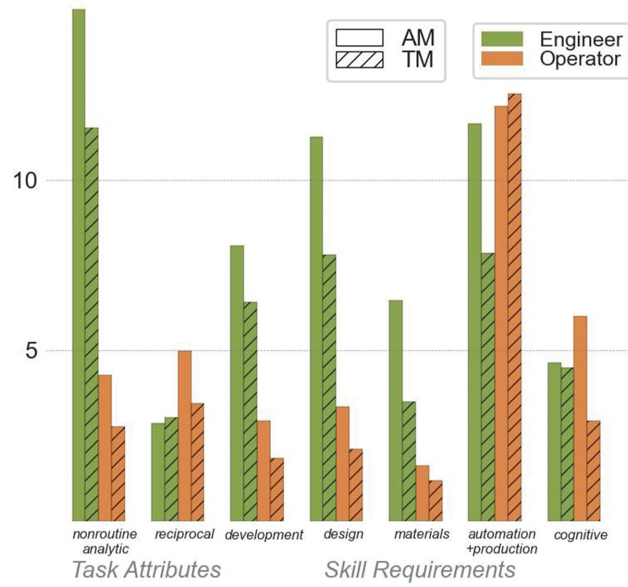
Empirical Analysis

We start with an overview of select task attribute and skill requirement measures for engineers and operators. Figure 2 presents share measures and Figure 3 presents count measures for the analytical sample of hybrid AM-TM plants for the entire sample period. The purpose of these figures is to provide a broad overview of the key differences in task attributes and demand for skills between AM and TM for high-skill and low-skill occupations, and to highlight what the share and count measures may capture. The share and the count measures convey the same picture, with two insignificant differences (in reciprocal interdependence for engineers and in automation+production for operators). The non-routine analytic task content is much larger for engineers than for operators, as one would expect, and it is larger in AM than in TM for both occupations. The key engineering skills are more important for engineers than for operators, again as expected, and the demand for them is greater in AM than in TM in both occupations. Reciprocal interdependence is greater in AM only for operators, and so is the demand for cognitive skills. Automation and production skill requirements are greater for AM engineers than for TM counterparts; the picture is less clear for operators.

This summary suggests there may be significant differences between the two technologies in the key occupations. Next, we turn to an examination of means of all measures for the four occupations. These findings are visualized in Figures A.1 and A.2, with means, standard deviations, and *p* value of *t*-test of equality between AM and TM means shown in Tables A.2 and A.3.

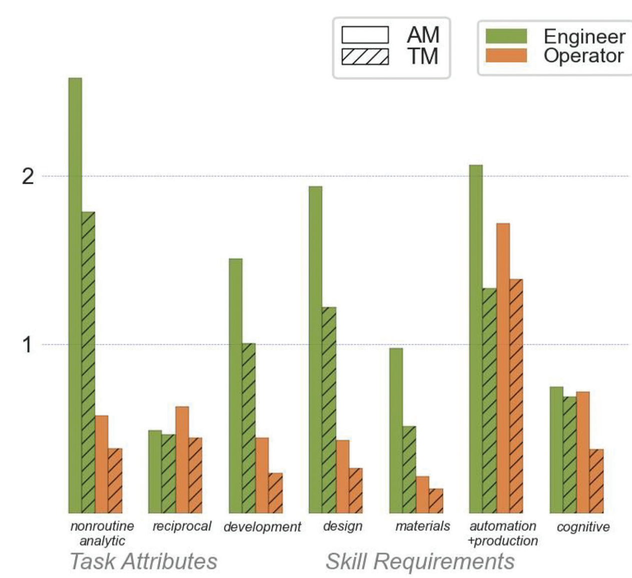
Non-routine analytic is greater in AM, whereas routine cognitive is larger in TM for engineers and operators (nonsignificant for managers and technicians). The differences regarding manual tasks are mostly reversed: non-routine manual is greater in TM (nonsignificant for engineers) and routine manual is greater in AM for managers and engineers but not for operators (nonsignificant for technicians). Thus, the means suggest that cognitive tasks may be more complex and manual tasks may be less complex in AM. Reciprocal interdependence is larger in AM only for the lower-skill occupations, whereas sequential interdependence is significantly lower in

Figure 2. Plant Level Means of Select Task and Skill Measures as Shares for Engineers and Operators, by AM and TM, Hybrid AM-TM Plants, 01/2014–01/2022



Notes: See Notes to AppendixTable A.2, from which this figure is derived.

Figure 3. Plant Level Means of Select Task and Skill Measures as Counts for Engineers and Operators, by AM and TM, Hybrid AM-TM Plants, 01/2014–01/2022



Notes: See Notes to OLA A, Table OA.2, from which this figure is derived.

AM for the higher-skill occupations and higher for the lower-skill ones. Regarding skills (as shown in Table A.3), engineering skill requirements are larger in AM than in TM for the three skill groups. For operations, the skill group of inventory, tooling, and maintenance shows substantially larger values in TM than in AM. For the automation and production group, AM is larger except for operators. In support, the administration-management-finance-business group is similar in AM and TM (except for the larger value for AM operators). For the machine learning (ML) and software group, TM values are somewhat larger (significant for engineers). In the third group, which includes computer support and data management, TM values are significantly larger. Finally, cognitive skills and creativity (reasoning skills) are somewhat larger in AM. Social skills and character are greater for TM managers and engineers, but similar for the lower-skill occupations.[7]

The comparison of means of plant means does not account for the fact that not all plants had both AM and TM vacancies in the same occupation. The number of postings and the number of plants that posted them are reported in the last two rows of Tables A.2 and A.3. Of the 700 hybrid plants, 391 posted vacancies for AM managers (2,437 vacancies), and 688 plants sought TM managers (233,820 vacancies). A similar pattern is observed for postings for other occupations. To conduct a within-plant within-occupation comparison of means, we drop observations without counterparts in the other technology in the same occupation in the same plant. The resulting sample is slightly smaller, as shown in the last two rows of OLA A, Tables OA.4 and OA.5; for example, in the matched sample 578 plants have both AM and TM engineers, 6,224 and 198,404 each, as compared with 6,302 AM engineers in 588 plants and 205,328 TM engineers in 669 plants in the full hybrid plants sample. To exploit the matched aspect of this sample, we conduct a non-parametric test, an extension of the Wilcoxon test (described in the notes to OLA A, Tables OA.4 and OA.5) that takes into consideration the unequal number of AM and TM postings in each plant. The p values of the z-scores are presented in the tables.

The occupation-matched within-plant means are similar to the unrestricted, and the tests of equality yield similar conclusions. Next, we turn to regression analysis to account for differences in tasks and skills over time and for common effects across occupations and technologies within plants.

Regression Analysis at the Job Posting Level

Consider the following baseline regression:

$$y_j = \beta_1 AM_j + \sum_{o=1}^{3} \beta_{2_o} x_{oj} + \beta_3 Year_j + \sum_{p=1}^{699} \beta_{4p} z_{pj} + \alpha + u_j \tag{1}$$

[7]Summary statistics for the count measures are presented in OLA A, Tables OA.2 and OA.3, with visualization in OLA A, Figures OA.5 and OA.6. The differences between AM and TM are consistent with the differences reflected in the share measures.

where y_j is the measure of a task attribute or skill requirements in job posting j. The coefficient β_1 on AM_j estimates the difference between AM and TM (the omitted dummy variable). We capture occupational differences using three occupation dummies x_{oj} with o = *Manager, Engineer, Technician* (*Operator* is omitted). To control for possible changes over time,[8] we use a year linear trend $Year_j$ ($Year^2$ was statistically insignificant). We include 699 plant dummies z_{pj} (p indexes plants) to control for plant fixed effects. The model includes an intercept α.

The effect of AM relative to TM may differ among occupations, so to confine comparisons to within-occupation, we add interaction terms between AM_j and the four occupation dummies x_{oj} (AM_j is omitted). The effects of AM may change over time, so we interact AM_j with $Year_j$. Occupations may change over time, so we interact $Year_j$ with the four occupation dummies x_{oj} ($Year_j$ is omitted). It is also possible that the AM occupation effects vary over time, so we add interaction terms $AM_j \times Year_j \times x_{oj}$ ($AM_j \times Year_j$ is omitted). The full model is as follows:

$$y_j = \sum_{o=1}^{4} \beta_{1o} AM_j x_{oj} + \sum_{o=1}^{4} \beta_{2o} AM_j Year_j x_{oj} + \sum_{o=1}^{4} \beta_{3o} Year_j x_{oj} + \sum_{o=1}^{3} \beta_{4o} x_{oj} + \sum_{p=1}^{699} \beta_{5p} z_{pj} + \alpha + u_j \tag{2}$$

OLA A, Tables OA.6 and OA.7 display the estimation results of the three nested models: Model (i.e., column) A implements Equation (1) and identifies the overall AM effect on y controlling for differences among occupations, years, and plants. Model B adds two-way interactions between technology and occupations and time trend, so the AM effect on y varies with occupation and the time trend. Model C estimates Equation (2), adding the three-way interactions, and thus identifying the AM effect in each occupation and year off variations in task attributes and skills among plants. The estimates in model A suggest that non-routine analytic is higher, whereas non-routine manual and routine cognitive are both lower in AM. Reciprocal interdependence does not differ, but sequential interdependence is lower in AM. All engineering skills are higher in AM, and so are higher-level automation and production skills, but the basic operations skills are lower in AM. In support skills, AM effects are mixed. AM is higher in cognitive and creative skills and lower in character and social skills. The estimates on the occupation dummies indicate an expected hierarchy for most dependent variables; for example, non-routine

[8]In addition to the newness of AM, there may be time effects common to AM and TM. For instance, employers tend to lower their demand for higher skills when unemployment rates are low (Modestino, Shoag, and Ballance 2016). Our focus on hybrid AM-TM plants controls for the local labor market conditions from which AM and TM workers are hired.

cognitive task content is the highest for engineers, followed by managers, technicians, and operators.

The results in models B and C are similar for most dependent variables, and the estimates on the triple interactions are mostly statistically insignificant. We return to this issue later. The likelihood ratio tests comparing the three models are listed in the B and C columns. Model B is better than model A for all dependent variables. Model C dominates model B for several measures, and we use it for interpretation. Tables 2 and 3 present the OLS estimates for this model for task attributes and skills, respectively.

The results of this complex model are difficult to interpret. To aid interpretation, we calculate estimated semi-elasticities of each measure with respect to AM, separately for each occupation, evaluated at the means of the explanatory variables in the last year of the sample period (2021), which has the most observations in AM. Semi-elasticities permit comparison of size effects across occupations and measures. Figure 4 presents the task attributes. We see a substantial increase in non-routine analytic and decrease in routine cognitive under AM in all occupations. The largest relative gain is for operators. An opposite and more moderate effect is registered for manual complexity. These findings support hypotheses T1 and T2. The AM effect on reciprocal interdependence is positive for engineers and nonsignificant for the rest. The AM effect on sequential interdependence is significantly negative for engineers and nonsignificant for the rest. These findings weakly support T3 and T4.

We summarize the estimates from Table 3 with the semi-elasticities presented in Figure 5. AM demands more of the three engineering skills in all four occupations. This finding supports hypothesis S1. We observe a loss of basic operations skills (inventory, tooling, and maintenance) in AM for all four occupations, supporting hypothesis S2. A gain in production and automation skills for managers, engineers, and technicians, but a loss for operators, leads to mixed support for hypothesis S2. Regarding support skills, we see small losses in AM (with a minor exception, operators' large gain in the first group, on a quite low base level). We had no hypothesis stated for support skills. The effect of AM on demand for reasoning skills is positive, except for engineers, thus mostly supporting hypothesis S3. AM effects on social skills and character are negative for the higher-skill occupations and non-negative for the lower-skill occupations, resulting in a mixed outcome on S4.

Overall, the most substantive and statistically significant results suggest greater analytical–cognitive task complexity and gains in engineering skills for engineers and operators. The proportionate difference is larger for operators than for engineers. Operators lost manual complexity, as well as some production and automation skills; engineers gained such skills. Managers and technicians track, with more mixed results, engineers and operators, respectively. No weighting is available to compare the changes

Table 2. Relationship between Technology and Task Attributes (Share Measures) in Hybrid AM-TM Plants, 01/2014–01/2022, OLS Estimations

	Complexity				*Interdependence*	
Dependent variables	*Non-routine analytic*	*Non-routine manual*	*Routine cognitive*	*Routine manual*	*Reciprocal*	*Sequential*
AM × Manager	1.95***	−0.09	−0.10	1.39***	−0.08	−0.97***
	(0.39)	(0.06)	(0.09)	(0.44)	(0.26)	(0.29)
AM × Engineer	2.51***	0.02	−0.37***	0.23	−0.17	−1.04***
	(0.38)	(0.09)	(0.08)	(0.20)	(0.14)	(0.15)
AM × Technician	1.55**	−1.75***	−0.60**	0.30	0.53	0.66**
	(0.72)	(0.36)	(0.28)	(0.95)	(0.45)	(0.34)
AM × Operator	1.99***	−1.63***	−0.98***	−1.76**	1.56***	−0.43
	(0.40)	(0.28)	(0.18)	(0.68)	(0.34)	(0.37)
AM × Manager × Year	−0.23	0.02	−0.07**	0.25**	0.03	0.26**
	(0.16)	(0.03)	(0.04)	(0.13)	(0.10)	(0.11)
AM × Engineer × Year	−0.09	0.09**	0.01	−0.07	0.20***	0.07
	(0.14)	(0.04)	(0.03)	(0.08)	(0.06)	(0.05)
AM × Technician × Year	0.20	0.14	−0.08	−0.10	−0.22	−0.11
	(0.19)	(0.12)	(0.10)	(0.28)	(0.15)	(0.13)
AM × Operator × Year	−0.27	−0.11	0.03	0.41*	−0.46***	0.35
	(0.17)	(0.10)	(0.08)	(0.25)	(0.13)	(0.23)
Manager × Year	−0.09***	0.00	0.01	−0.03**	0.07***	0.05***
	(0.02)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
Engineer × Year	−0.02	0.00	0.00	−0.03	0.06***	−0.02
	(0.05)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)
Technician × Year	−0.23***	0.01	0.04	0.11	0.05	0.03
	(0.07)	(0.04)	(0.03)	(0.08)	(0.04)	(0.03)
Operator × Year	−0.03	0.01	0.02	−0.03	0.05	0.00
	(0.03)	(0.05)	(0.02)	(0.09)	(0.03)	(0.03)
Manager	2.64***	−3.71***	−0.84***	−7.14***	1.66***	0.99***
	(0.13)	(0.21)	(0.09)	(0.32)	(0.12)	(0.13)
Engineer	9.46***	−3.41***	−0.51***	−6.55***	−0.06	−0.55***
	(0.22)	(0.20)	(0.11)	(0.34)	(0.16)	(0.14)
Technician	2.69***	−0.83***	0.60***	−1.60***	−0.04	−1.23***
	(0.25)	(0.23)	(0.15)	(0.35)	(0.15)	(0.16)
Intercept	2.51***	6.63***	1.60***	9.82***	3.77***	4.24***
	(0.14)	(0.18)	(0.08)	(0.29)	(0.11)	(0.11)
Adjusted R^2	0.1871	0.1699	0.0380	0.2166	0.0669	0.0672
Mean	7.97	1.16	1.22	3.89	4.04	3.80
SD	10.07	4.02	3.77	7.51	5.97	6.04

Notes: Measures as shares (count of matched terms)/(total count of terms) in a posting multiplied by 100. The table shows estimates of model C that correspond to Equation (2) in the article. *Year* is demeaned to reduce multicollinearity. Standard errors (in parentheses) clustered by plant to account for overdispersion. The sample is sample C (Hybrid AM-TM plants) in Table 1, with a total of 559,255 postings. For variable definitions, see text. OLS, ordinary least squares.
***p <0.01; **p <0.05; *p <0.1.

for engineers and operators, but our assessment is that AM did not disadvantage operators relative to engineers. We examine this issue in greater detail in the final section, but the answer to our empirical question is that our findings suggest that AM is not biased against low-skilled workers.

Table 3. Relationship between Technology and Skill Requirements (Share Measures) in Hybrid AM-TM Plants, 01/2014–01/2019, OLS Estimations

	Engineering			*Operations*		*Support*			*Reasoning*		*People*	
Dependent variables	*Develop*	*Design*	*Materials*	*Invent+tool+ mainten*	*Automat+ production*	*Adm+manag+ finan+bus*	*ML+ software*	*Data+office+ technical*	*Cognitive*	*Creativity*	*Social*	*Character*
AM × *Manager*	2.28***	2.41***	1.89***	−2.16***	2.03***	0.49	−0.72***	−2.06***	1.99***	0.05	−1.01***	−3.38***
	(0.32)	(0.31)	(0.26)	(0.33)	(0.41)	(0.72)	(0.28)	(0.23)	(0.37)	(0.15)	(0.28)	(0.35)
AM × *Engineer*	1.45***	3.22***	2.85***	−1.07***	4.13***	−0.03	−1.96***	−0.80***	0.35	0.20**	−0.83***	−1.06***
	(0.28)	(0.48)	(0.44)	(0.23)	(0.42)	(0.23)	(0.35)	(0.23)	(0.22)	(0.09)	(0.20)	(0.19)
AM × *Technician*	1.69**	1.43***	1.19**	−4.85***	3.69***	0.83*	−0.63	−2.00***	0.92**	0.51**	−0.06	2.29***
	(0.73)	(0.52)	(0.59)	(1.04)	(0.84)	(0.45)	(0.42)	(0.70)	(0.45)	(0.20)	(0.56)	(0.73)
AM × *Operator*	1.63***	1.59***	0.89*	−7.61***	0.57	2.36***	−0.33	−0.23	2.97***	0.16	1.37***	0.67
	(0.34)	(0.41)	(0.54)	(0.72)	(0.99)	(0.82)	(0.28)	(0.57)	(0.42)	(0.15)	(0.37)	(0.50)
AM × *Manager* × *Year*	−0.34***	−0.28*	−0.12	−0.01	−0.32**	0.62***	−0.13	0.16	0.00	−0.05	−0.17	0.13
	(0.13)	(0.15)	(0.10)	(0.15)	(0.15)	(0.23)	(0.14)	(0.13)	(0.11)	(0.05)	(0.12)	(0.15)
AM × *Engineer* × *Year*	−0.08	−0.18	−0.17	−0.14	−0.03	−0.06	0.13	0.21**	−0.09	−0.06*	0.01	0.01
	(0.11)	(0.16)	(0.13)	(0.09)	(0.15)	(0.09)	(0.10)	(0.09)	(0.07)	(0.04)	(0.08)	(0.08)
AM × *Technician* × *Year*	−0.37*	0.12	−0.04	−0.46	0.39	−0.09	0.22	0.02	−0.15	−0.05	0.01	−0.20
	(0.22)	(0.22)	(0.16)	(0.33)	(0.35)	(0.16)	(0.16)	(0.28)	(0.14)	(0.10)	(0.22)	(0.27)
AM × *Operator* × *Year*	−0.11	−0.14	−0.09	0.35	−0.40	0.48*	0.34***	−0.18	−0.17	−0.03	−0.18	0.33
	(0.13)	(0.15)	(0.15)	(0.28)	(0.44)	(0.26)	(0.12)	(0.23)	(0.16)	(0.06)	(0.14)	(0.46)
Manager × *Year*	0.01	−0.03**	0.01	0.04	−0.03	−0.06*	0.10***	−0.07**	0.02	0.03***	−0.05**	0.07***
	(0.02)	(0.01)	(0.02)	(0.03)	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)	(0.02)
Engineer × *Year*	0.08***	−0.07*	0.04	−0.04	−0.08**	−0.01	0.09**	−0.21***	−0.01	0.03***	−0.08***	−0.03
	(0.02)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.02)	(0.01)	(0.03)	(0.02)
Technician × *Year*	−0.03	−0.25***	−0.19***	0.23*	0.09	−0.02	−0.20***	0.00	−0.05	0.02	−0.11*	0.11**
	(0.04)	(0.06)	(0.06)	(0.12)	(0.07)	(0.05)	(0.06)	(0.07)	(0.04)	(0.01)	(0.07)	(0.05)
Operator × *Year*	0.03	−0.09***	−0.02	−0.08	0.00	−0.08	−0.10**	−0.12**	0.02	0.04***	−0.12***	−0.02
	(0.02)	(0.03)	(0.02)	(0.14)	(0.09)	(0.05)	(0.04)	(0.06)	(0.03)	(0.01)	(0.04)	(0.05)
Manager	0.34***	−0.64***	−0.26***	−9.25***	−9.42***	8.71***	1.38***	−1.71***	1.01***	0.48***	3.19***	3.32***
	(0.11)	(0.15)	(0.10)	(0.46)	(0.43)	(0.27)	(0.20)	(0.21)	(0.10)	(0.04)	(0.19)	(0.21)

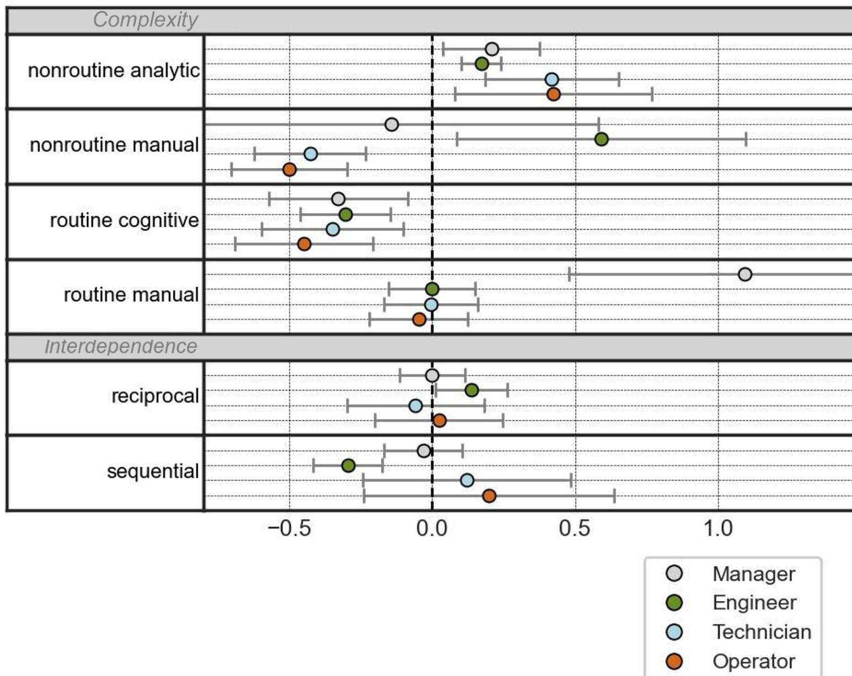
(continued)

Table 3. Continued

	Engineering			*Operations*		*Support*			*Reasoning*		*People*	
Dependent variables	*Develop*	*Design*	*Materials*	*Invent+tool+ mainten*	*Automat+ production*	*Adm+manag+ finan+bus*	*ML+ software*	*Data+office+ technical*	*Cognitive*	*Creativity*	*Social*	*Character*
Engineer	4.47***	5.80***	2.97***	−10.12***	−6.53***	−0.28	3.92***	−1.63***	1.82***	0.36***	1.79***	−0.80***
	(0.16)	(0.21)	(0.24)	(0.44)	(0.48)	(0.20)	(0.21)	(0.22)	(0.15)	(0.05)	(0.21)	(0.20)
Technician	1.87***	1.87***	1.10***	−0.87*	−4.43***	−1.44***	1.10***	1.98***	0.68***	0.10	0.67***	−1.01***
	(0.28)	(0.20)	(0.16)	(0.45)	(0.47)	(0.19)	(0.25)	(0.31)	(0.18)	(0.07)	(0.21)	(0.22)
Intercept	1.31***	1.23***	1.38***	16.06***	12.25***	7.04***	1.90***	5.90***	2.45***	0.55***	5.27***	6.24***
	(0.10)	(0.13)	(0.12)	(0.38)	(0.39)	(0.19)	(0.14)	(0.18)	(0.10)	(0.04)	(0.17)	(0.17)
Adjusted R^2	0.1425	0.1799	0.1948	0.1723	0.1978	0.2016	0.1002	0.0744	0.0863	0.0625	0.1097	0.0874
Mean	4.06	4.53	2.39	7.38	5.72	8.60	5.02	5.44	3.93	0.69	6.91	6.42
SD	7.14	8.70	6.63	11.94	10.65	10.59	9.55	8.75	5.87	2.41	7.72	8.04

Notes: Measures as shares (count of matched terms)/(total count of terms) in a posting multiplied by 100. The table shows estimates of model C that correspond to Equation (2) in the article. *Year* is demeaned to reduce multicollinearity. Standard errors (in parentheses) clustered by plant to account for overdispersion. The sample is sample C (Hybrid AM-TM plants) in Table 1, with a total of 559,255 postings. For variable definitions, see text. ML, machine learning; OLS, ordinary least squares.
***p <.01; **p <0.05; *p <0.1.

Figure 4. Estimates of Semi-Elasticities of AM for Task Attributes, from OLS Regressions, Hybrid AM-TM Plants, 01/2014–01/2022



Notes: Based on estimates in Table 2. Whiskers represent 95% confidence intervals. OLS, ordinary least squares.

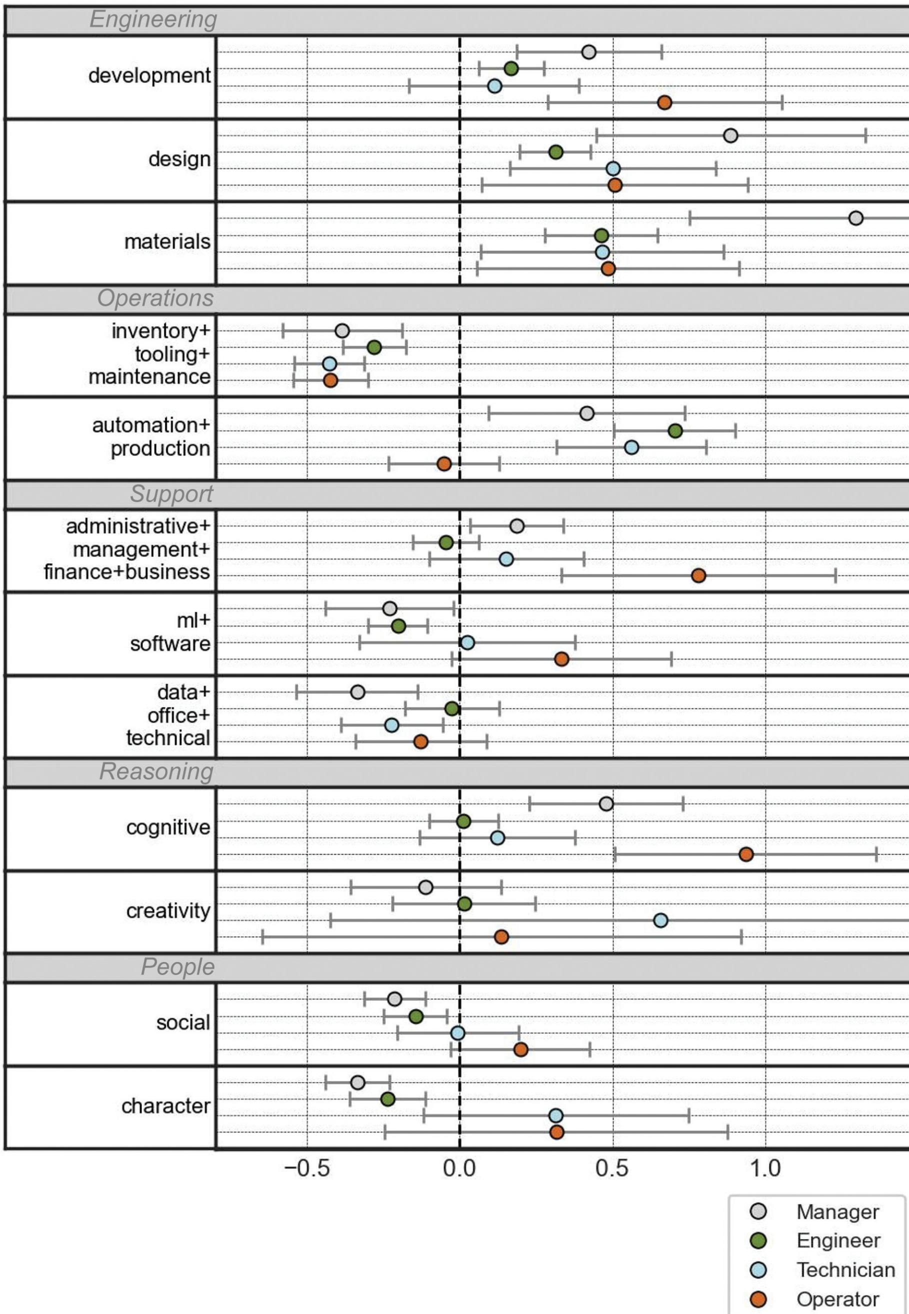
Extensions and Robustness Checks

In this section, we check whether the conclusions drawn from the main analyses are robust to alternative estimation methods, alternative measures, new samples as well as subsamples of the analytical sample, and specific TM techniques and robotics. We also conduct placebo tests, investigate whether task attributes and skill requirements have changed during the sample period, and present a decomposition analysis.

Plant Characteristics Instead of Plant Fixed Effects

We estimate Equation (2) controlling for plant characteristics instead of plant dummies. Plant characteristics include the number of plants owned by the parent firm, the total number of vacancies in the four occupations during the sample period (proxy for plant size), the ratio of the number of engineer postings to the sum of engineer, technician, and operator postings (proxy for technological complexity), a variable that identifies postings made by service bureaus, and the plant's 4-digit NAICS. The results, presented in OLA A, Figures OA.7 and OA.8, are very similar to those in Figures 4 and 5.

Figure 5. Estimates of Semi-Elasticities of AM for Skill Requirements from OLS Regression, Hybrid AM-TM Plants, 01/2014–01/2022



Notes: Based on estimates in Table 3. Whiskers represent 95% confidence intervals. OLS, ordinary least squares.

Alternative Measures

Count of Matched Terms

We estimate a Poisson regression that accounts for the count nature of the dependent variable and for the fact that the distribution of some measures is skewed toward zero. OLA A, Tables OA.8 and OA.9 provide estimates for the exponentiated version of Equation (2),[9] and OLA A, Figures OA.9 and OA.10 present the (constant) semi-elasticities that parallel Figures 4 and 5. The two sets of figures are very similar.

Binary Variable Measure

We create a variable that equals 0 if no terms in a posting match any of the keywords for a particular task or skill, and 1 otherwise. The estimated semi-elasticities from a logit estimation are plotted in OLA A, Figures OA.11 and OA.12, which are similar to Figures 4 and 5.

In sum, the findings of this article are largely independent of the choice of a specific measure.

Alternative Samples

The 150 Largest Hybrid Plants by Number of AM Postings

This subsample accounts for almost half of the hybrid plants and more than half of postings.[10] The semi-elasticities in OLA A, Figures OA.13 and OA.14 are similar to those in Figures 4 and 5.

Service Bureaus

These are contract manufacturers that use both AM and TM to make customized small-run parts and products for small and large firms. Service bureaus are small to medium size with a few hundred employees.[11] We identified 16 such firms with 59 plants (27 hybrid, included in the analytical sample, 2 pure AM and 30 pure TM). The number of AM and TM postings in this sample is much more balanced: 943 AM postings (339 managers, 274 engineers, 122 technicians, and 208 operators) and 1,856 TM postings (793 managers, 251 engineers, 163 technicians, and 649 operators). We estimate regressions with firm dummies (plant dummies overlap with technology in single-technology plants) and plant characteristics. Overall semi-elasticities are presented in OLA A, Figures OA.15 and OA.16. With a much smaller

[9] $y_j = \exp(\sum_{o=1}^{4} \beta_{1_o} AM_j x_{oj} + \sum_{o=1}^{4} \beta_{2_o} AM_j Year_j x_{oj} + \sum_{o=1}^{4} \beta_{3_o} Year_j x_{oj} + \sum_{o=1}^{3} \beta_{4_o} x_{oj} + \sum_{p=1}^{699} \beta_{5_p} z_{pj} + \alpha + u_j)$

[10] The total number of AM postings in this subsample is 6,522 (1,532 managers, 3,681 engineers, 627 technicians, and 682 operators), and of TM postings is 208,609 (77,207 managers, 93,054 engineers, 11,204 technicians and 27,144 operators).

[11] See, for example, one company's description of its services: https://www.protolabs.com/resources/blog/online-manufacturing-platform-can-offer-best-of-both-worlds-service-bureau-and-supplier-network/.

sample, yearly estimates are less precise than those presented in Figures 4 and 5. The positive difference between AM and TM in non-routine analytic task content found in the larger sample shrinks in the service bureaus sample. Differences in the three engineering skills are similar in the two samples. Basic operations skills, which are estimated to be lower in AM than in TM in the analytical sample, are more similar in service bureaus, whereas the demand for higher operations skills is lower for AM engineers in service bureaus, contrary to what we found in the analytical sample. Cognitive skills are larger in AM only for operators in service bureaus, whereas in the analytical sample this was true for most occupations. However, creativity demands are significantly larger in AM than in TM, except for managers, in service bureaus, whereas in the analytical sample they were more similar. Social skills are lower for AM operators in service bureaus but greater in the analytical sample. Although more muted, most differences between AM and TM in tasks and skills identified in the hybrid plants sample are sustained in firms that operate in competitive niches producing similar customized products in AM and TM.

The 50 Largest Manufacturing Firms with Hybrid Plants

We identify the 50 largest firms (by the number of postings) that have hybrid plants; these include most of the largest US manufacturing firms. We create a sample that includes their pure TM plants in addition to their hybrid plants.[12] We estimate regressions with firm dummies and plant characteristics. Estimated semi-elasticities are in OLA A, Figures OA.17 and OA.18, which show stronger AM effects than those identified in the analytical sample.

A Sample with Approximately 4.4 Million Postings

This sample is described in Table 1. We use regression with plant characteristics; estimated semi-elasticities in OLA A, Figures OA.19 and OA.20 are similar to those based on the hybrid plants sample (with stronger AM skill effects).

Comparisons across Samples

We found that the differences between AM and TM are detected in various samples, with minor variation. But do tasks and skills vary across types of firms and plants? We compare select tasks and skills for engineers and operators in AM and TM across three samples: the largest 50 firms, the analytical sample of hybrid plants, and the service bureaus. OLA A, Figures OA.21 and OA.22 show the average of plant means of share measures and

[12]These firms had 5,975 AM postings (1,216 managers, 3,601 engineers, 506 technicians, and 652 operators) and 1,209,938 TM postings (499,489 managers, 318,695 engineers, 73,333 technicians, and 318,421 operators).

OLA A, Figures OA.23 and OA.24 present count measures. We comment below about differences across samples within AM and TM; comparison between the two technologies was carried out for each sample just above.

Non-routine analytical task content and engineering skill requirements are greater in the 50 largest firms and in hybrids than in service bureaus for AM engineers and to a limited degree for TM engineers and operators; the differences effectively disappear for AM operators. The demand for cognitive skills does not vary much across samples. Reciprocal interdependence is greater for operators in the largest 50 firms and hybrid plants than in service bureaus, but the pattern is reversed for engineers. The demand for automation and production is greatest in service bureaus, across the board. These comparisons suggest that the larger firms place greater technical demands on engineers than do service bureaus in both technologies, whereas service bureaus emphasize automation and production skills for both AM and TM engineers. As noted earlier, in all three samples and for both occupations, AM is more complex and skill demanding than TM.

Specific TM Techniques and Robotics

In the analyses presented so far, we did not distinguish among types of TM techniques, so our findings reflect differences between AM and TM on average across techniques. Next, we identify skills linked to specific TM techniques and compare them to AM (a minority of postings mention technique-specific skills). The results are presented in OLA C. We summarize key results here. AM increases cognitive task complexity and reduces manual task complexity relative to TM without technique mention as well as relative to specific techniques, with an exception, in part, for molding. AM increases reciprocal interdependence for operators and reduces sequential interdependence for engineers. AM increases engineering and automation and production skill requirements and reduces other operations skill demands (inventory, tooling, maintenance) relative to TM. We see a statistically marginally significant increase in demand for cognitive skills (and a smaller one for creativity) in AM and a mixed and mostly statistically marginal effect on people skills relative to TM in general and specific techniques. Molding, a TM technique, appears to have effects that are more similar to AM than other techniques.

Robotics is used in diverse applications in various stages of the production process. We examine the effect of AM and TM with and without robotics on tasks and skills for engineers and operators. OLA C shows a greater demand for robotics skill in AM than in TM (for example, 8.8% of AM operators are required to have robotics skills as compared to 1.95% of TM operators). The key conclusion of this analysis is that the inclusion of robotics does not affect the relative impact of AM on tasks and skills. The addition of robotics to TM does not increase cognitive complexity relative to AM, with or without robotics; similarly, TM with robotics does not require greater high-level skills than AM (with or without robotics) but instead requires less.

Placebo and Validity Tests

Considerable heterogeneity occurs in the manager occupation, which includes engineering, general, and other kinds of managers who need different types of skills and are affected differently by technology. We expect that 1) managers with more technical jobs will have more non-routine analytic tasks and require more engineering skills than managers in less technical jobs have, 2) AM will increase non-routine analytical content of tasks and demand for development and design engineering skills for technical managers, and 3) AM will not affect demand for management and business skills.

We use the first point as validation of our measures and the second and third points as placebo tests in the identification of the AM (treatment) effect. We would have preferred to use clear-cut technical and non-technical managers for these tests, but our sample includes too few AM postings in some sub-occupations. These sub-occupations include the most and the least technical managers—engineering and general managers, respectively—with marketing and industrial production managers between these two. We created a sample of matched within-plant AM and TM postings in these sub-occupations.[13]

OLA A, Table OA.10 presents summary statistics for the task and skill measures noted above. Concerning the validity test, we observe that general managers in both AM and TM have much lower values for measures of *non-routine analytic, development,* and *design* in comparison to engineering managers, with the other sub-occupations showing intermediate values. This finding is as expected in point 1 above. Regarding the placebo test in point 2, these measures are, as expected, larger in AM than in TM for technical managers, mostly statistically significant and, as expected, not different for general managers. Concerning the placebo test in point 3, requirements for management and business skills are similar in AM and TM, except for marketing managers and a small difference for industrial managers.

Changes over Time

AM is a new technology and managers may need to learn how to structure jobs and determine skill requirements. Risk-averse managers may play it safe by asking for more skills than necessary. In the regression analyses, we controlled extensively for time effects. Tables 2 and 3 show the estimates on the occupational interactions between *Year* and *AM*. The estimates have a mix

[13]We tallied 234 AM and 2,133 TM postings for general managers in 70 plants, 890 AM and 23,906 TM for marketing managers in 149 plants, 294 AM and 3,499 TM industrial managers in 117 plants, and 287 AM and 10,758 TM for engineering managers in 105 plants.

of positive and negative signs, most are statistically insignificant. We found no measure for which a trend can be clearly identified as indicated by tests of the significance of the net effect of time on semi-elasticities for all measures in OLA A, Table OA.11. This outcome is evidence of no newness effect.

OLA A, Figures OA.25 to OA.32 present the annual plant means of each of the measures by occupation, for AM on the left and TM on the right. Generally, TM, with tens of thousands of observations per year, is more stable for all measures and occupations than AM, which in its early years has only dozens of observations. The fluctuations in AM measures are mostly mild, and no obvious trends appear.

To test whether the more mature AM technology differs from TM, we create a sample for the last three years, using the same criteria we used for the entire sample, focusing on postings made by plants that had at least five AM and at least five TM postings during 01/2019 to 01/2022. The sample has 413 hybrid plants with 5,854 AM and 164,892 TM postings. We replicate the main analysis and present the semi-elasticities in OLA A, Figures OA.33 and OA.34. The values are very similar to those in Figures 4 and 5. The findings reported and discussed earlier stand, suggesting that differences are not affected by the newness of AM.

Decomposition Analysis

We decompose the grand means of tasks and skills into occupational distribution differences and technology differences. We use the share of postings for the occupational decomposition method (e.g., Spitz-Oener 2006) in panel A of OLA A, Table OA.12 and the Blinder-Oaxaca regression method in panel B.[14] The results are similar, suggesting that the overall difference in several tasks and skills between AM and TM is attributable in part to technology differences and in part to varying occupational weights between technologies in the total number of postings. For example, in panel A, 53% of the overall difference in *non-routine analytic* are attributable to occupational differences and 47% to technology differences; in panel B, 31% are attributable to occupational differences. The share attributable to technology difference corresponds approximately to the semi-elasticities presented in Figures 4 and 5, such that higher semi-elasticities in the four occupations correspond to a greater share of mean differences attributable to technology.

[14]The proportion of job postings for occupations in AM and TM in Table 1 shows that in AM, 22% of postings are for managers, 57% for engineers, 9% for technicians, and 12% for operators, as compared to 43%, 37%, 5%, and 15%, respectively, in TM. The higher proportion of managers in TM may reflect, in part, the administration infrastructure of a plant that AM does not require separately and specifically. In part, it may also reflect the need for more management in long separable technologies with coordination needs that are largely absent in AM.

Discussion and Conclusions

The use of additive manufacturing, a new manufacturing technology, is increasing rapidly. We analyzed the content of recent job postings in the US manufacturing sector, distinguishing among multiple task attributes and technical and general skill requirements, separately for a selection of occupations. We found that AM entails more cognitively complex jobs and requires greater high-level skills. The gains in complexity and skills are slightly skewed in favor of lower-skill workers; however, they lose some lower-level operational skills.

Specifically, focusing on engineers and operators, the high- and low-skill workers in manufacturing, we found that AM jobs are more complex: They have both more non-routine analytic content and less routine cognitive content. The gain in non-routine analytic content is higher for operators than for engineers (semi-elasticity of 0.42 compared to 0.17 in Figure 4, difference significant at p value = 0.08), and the reduction in routine cognitive content is greater (−0.45 compared to −0.30, p value = 0.16). A decline in manual complexity is experienced by operators, probably because of fewer manual tasks. As displayed in Figure 5, AM operators gained relatively more high-level technical engineering skills than engineers (semi-elasticities of 0.67 compared to 0.17, 0.51 compared to 0.31, and 0.48 compared to 0.46, p values = 0.01, 0.19, and 0.46 for skills development, design, and materials, respectively). Engineers' smaller gain is, however, from a substantially higher baseline than operators. This result is upskilling, with greater gains for low-skill workers.

AM operators lose basic operations skills (such as tooling and maintenance) more than engineers (−0.42 compared to −0.28, p value = 0.04) and have no gain in automation and production skills, whereas engineers gain (−0.05 compared to 0.70, p value = 0.00). This de-skilling effect in operations skills is consistent with operators' moderate shift from manual to cognitive tasks noted above, which is also reflected in an increase in cognitive skills and creativity for AM operators substantially larger than that for engineers (0.94 compared to 0.01 with p value = 0.00, and 0.14 compared to 0.01 with p value = 0.38). Social skills and character differences between AM and TM are small.[15] These findings are robust to the use of alternative measures, samples, and estimation methods and to whether we compare AM to TM in general or to specific techniques. The upskilling effect of AM that favors low-skill workers is in contrast with the bifurcated effect of computerization in manufacturing and other parts of the economy, which resulted in upskilling of high-skill workers and less skill gains or actual skill loss for lower-skill workers (Ben-Ner and Urtasun 2013).

[15]In terms of OLA B, Figure OB.1, operators' skill change is represented by line 3 for high-level and reasoning skills, which is steeper than line 6, which represents high-level and reasoning skills change for engineers. Operations skill change for operators is represented by line 1.

The findings accord with our hypotheses, which we derived from a theoretical framework that emphasizes the implications for work of two features of technology: product flexibility and process integration. Product flexibility is reflected in the range of options for multiple parameters that define a product: weight, geometry, strength, and so on. Such flexibility requires greater high-level engineering skills of engineers, but has similar effects on operations workers, technicians, and operators, who need to contend with experimentation, evaluation of outcomes, and provision of feedback for changes and improvement. The AM production process is much more integrated than TM, as it is much shorter. This implies that an AM worker handles the process from materials to the final product, whereas in TM, workers handle only parts of the process, hence AM demands broader skills than does TM. These considerations led to the hypotheses that AM jobs are more complex and require greater skills, as compared to TM.

These effects may have broad implications for wages and work organization. Greater job complexity and higher technical skills are likely to demand higher wages, with a larger increase for low-skill workers. Complexity is an important determinant of workplace organization, as it entails greater worker decision-making autonomy, less monitoring, and more incentives (Perrow 1972; Prendergast 2002; Ben-Ner, Kong, and Lluis 2012), leading to more "holistic" or "high road" work organization (MacDuffie 1995; Lindbeck and Snower 2000). These effects may be combined with those of greater skills in engendering organizational change toward greater decision-making autonomy (Caroli and Van Reenen 2001).

Our study has several limitations. Like the rest of the literature, our measure of demand for skills reflects mentions of skills in job postings, but this does not necessarily imply equal importance. We partially addressed this concern by comparing postings in the same occupations made by the same plants, which are likely to reflect similar biases across multiple postings. In the same vein, we did not assign weights or prices to individual skills to compare the total value of skills in the two technologies. Another limitation of this method is that job postings, especially in the summary form that we used, do not capture the full richness of tasks and activities in the workplace. Concepts such as interdependence are hard to measure through this method and may only be understood through surveys of employers and employees, detailed job descriptions, and case studies.

An important limitation of our study is the focus on individual jobs rather than on the production process or value chain in its entirety. This approach, which is the cornerstone of the literature, analyzes tasks and skills associated with jobs. The production process entails tasks that complement each other and that can be combined into jobs in diverse ways and require different combinations of tasks. To fully understand the implications of various technologies for work, it is necessary to analyze the entire production processes, from end to end, to understand how technologies differ in terms of division of labor and specialization. In this article, we characterized the tasks and skills of workers in different occupations; we analyzed within-plant differences, but we did not examine the production process. Future research on the implications of technology on work organization should address the entire value chain and the parts that are housed in distinct establishments.

Adoption of robotics is changing the role of workers and the content of their tasks in all production technologies. In this article, we only touched on this matter, finding that the use of robotics does not seem to significantly change the task attributes and skill requirements in AM and in TM. A study that focuses on production processes with and without robotics would inform better about the roles, tasks, and skills of workers in the two types of technology environments.

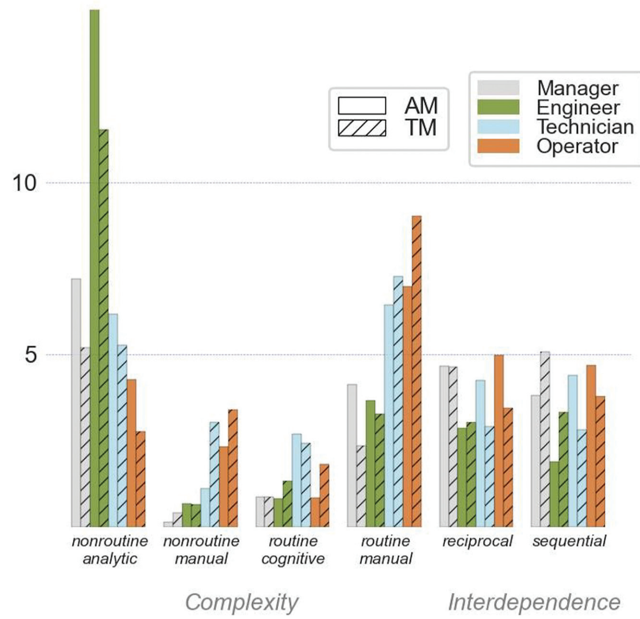
AM is employed in few plants, so our comparison necessarily evaluated a disparate number of observations in the two technologies. In our robustness tests, we analyzed service bureaus, which have more balanced numbers of postings in AM and TM and obtained similar but less sharp differences in task content and skill requirements. We also analyzed other samples and subsamples of our analytical sample and found results similar to the main results.

Important considerations remain to be studied. Our data do not contain information about output; hence, we could not investigate whether AM is labor saving, which is a major concern when considering the potential labor displacement effect of new technologies.[16] Another consideration is whether AM changes the relative employment shares of different occupations. Among non-managers, 65% of postings in TM during the eight-year sample period were for engineers, whereas in AM the percentage was 73. This difference may reflect a less production-worker intensive process in AM, or a higher-skill intensive pre-production process. These points are cardinal concerns that should be addressed in future research.

[16]Felice, Lamperti, and Piscitello (2021) argued that the effect of AM on employment is positive and found supportive evidence in connecting industry-level AM patent activity and employment. This view is shared, for example, by the consulting firm A.T. Kearney (2018). Dixon, Hong, and Wu (2021) found positive effects of robots on employment. Whether these findings are associated with increased demand for products made by firms using new technologies, or these technologies are more labor intensive despite automation, is an open question.

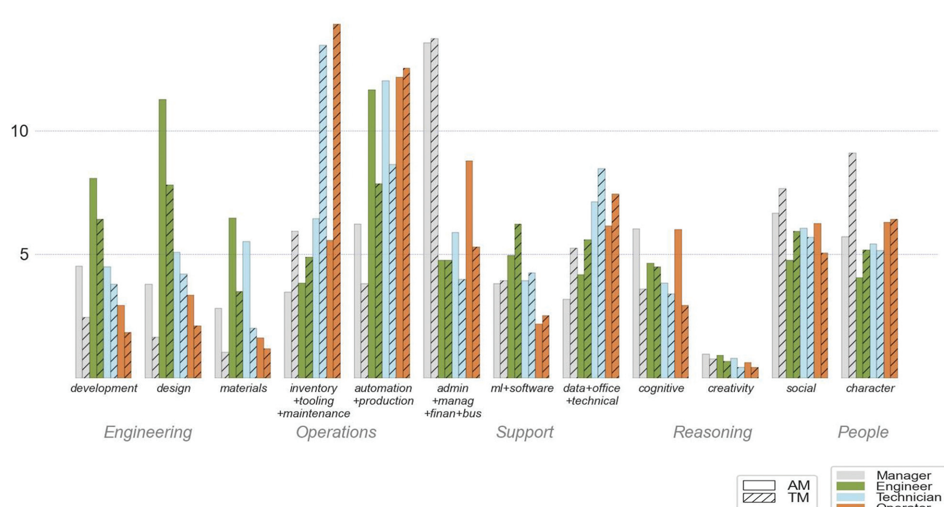
Appendix

Figure A.1. Plant Level Means of Task Attributes (Share Measures), Hybrid AM-TM Plants, by Occupation and Technology, 01/2014–01/2022



Notes: See notes to Table A.2, from which this figure is derived.

Figure A.2. Plant Level Means of Skill Requirements (Share Measures), Hybrid AM-TM Plants, by Occupation and Technology, 01/2014–01/2022



Notes: See notes to Table A.3, from which this figure is derived.

Table A.1. Keywords for Task Attributes and Skill Requirements

Task attributes
Complexity (*source:* authors, based on Spitz-Oener 2006 and Atalay et al. 2020)
Non-routine analytic: abstract, advanced, analy, complex, design, evaluat, flexib, interpret, research, sketch, synthes;
Non-routine manual: repair;
Routine cognitive: bookkeep, calcul, compar, copy, correct, data, measur, record;
Routine manual: assembl, control, drill, equip, feed, install, maintain, operat, tool.
Interdependence (*source:* authors, based in part on Spitz-Oener 2006 and Atalay et al. 2020's keywords for non-routine interactive)
Reciprocal: advis, agree, assist, bargain, coach, collaborat, conflict, consult, coordinat, counsel, feedback, group, mentor, negotiat, persua, social, teach, team, train, trust;
Sequential: accuracy, appraisal, assurance, authority, command, compliance, controller, direct, kpi, leader, metrics, monitor, protocol, report, routin, rule, standard, supervis, surveillance.
Skill requirements
Engineering (*source:* BGT families and clusters, and some keywords)
Development, **design**, **materials**.
Operations (*source:* BGT families and clusters)
Inventory, **tooling**, **maintenance**, **automation**, **production**.
Support (*source:* Deming and Noray 2020)
Administrative, **management**, **finance**, **business**, **machine learning**, **software**, **data**, **office**, **technical support**.
Reasoning (*source:* Deming and Kahn 2018 in the version used by Atalay et al. 2020)
Cognitive: analytical, cognitive, critical thinking, math, problem solving, research, statistics; **Creativity**: creativ.
People (*source:* Deming and Noray 2020)
Social: collaboration, communication, listening, negotiation, persua, present, social, team; **Character**: detail-oriented, energetic, goal setting, initiative, meeting deadlines, multi-tasking, organizational skills, planning, positive disposition, prioritizing tasks, self-motivation, self-starter, time management.

Sources: Listed in parentheses.
Notes: We use stems for words when the source does so. For more details, see OLA A, Table OA.1. BGT, Burning Glass Technologies.

Table A.2. Summary Statistics of Task Attributes (Share Measures), Hybrid AM-TM Plants Job Postings, 01/2014–01/2022

	Manager		*Engineer*		*Technician*		*Operator*	
Task attributes	*AM*	*TM*	*AM*	*TM*	*AM*	*TM*	*AM*	*TM*
Complexity								
Non-routine analytic	7.19***	5.19	15.36***	11.52	6.17*	5.28	4.26***	2.77
	(3.00)	(5.88)	(4.92)	(8.85)	(1.76)	(5.74)	(1.23)	(4.22)
Non-routine manual	0.13***	0.40	0.68	0.65	1.11***	3.02	2.34***	3.40
	(0.10)	(1.24)	(0.63)	(1.55)	(0.48)	(3.49)	(0.72)	(4.47)
Routine cognitive	0.87	0.86	0.81***	1.33	2.68	2.42	0.83***	1.82
	(0.95)	(2.21)	(0.82)	(2.57)	(0.78)	(3.29)	(0.37)	(3.21)
Routine manual	4.12***	2.34	3.66*	3.29	6.43	7.25	6.98***	9.01
	(1.64)	(3.66)	(2.43)	(4.25)	(1.65)	(6.24)	(2.21)	(8.46)
Interdependence								
Reciprocal	4.67	4.65	2.87	3.03	4.25***	2.92	4.98***	3.44
	(2.36)	(4.98)	(1.94)	(3.94)	(0.89)	(4.08)	(1.16)	(4.64)
Sequential	3.82***	5.06	1.90***	3.32	4.39***	2.81	4.68**	3.78
	(2.52)	(5.46)	(1.43)	(4.21)	(0.73)	(3.50)	(1.32)	(5.18)
Number of job postings	2,437	233,820	6,302	205,328	1,009	29,365	1,348	79,646
Number of plants	391	688	588	669	262	607	309	628

Notes: Measures as shares (count of matched terms)/(total count of terms) in a posting multiplied by 100. Means of plant level means and standard deviations (in parentheses). The significance is from two-tailed unequal variances *t*-tests of mean differences. The sample is sample C (Hybrid AM-TM plants) in Table 1. For variable definitions, see text.
$^{***}p > 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$.

Table A.3. Summary Statistics of Skill Requirements (Share Measures), Hybrid AM-TM Plants Job Postings, 01/2014–01/2022

	Manager		*Engineer*		*Technician*		*Operator*	
Skill requirements	*AM*	*TM*	*AM*	*TM*	*AM*	*TM*	*AM*	*TM*
Engineering								
Development	4.52***	2.45	8.07***	6.41	4.49*	3.78	2.95***	1.85
	(2.33)	(4.20)	(3.99)	(6.39)	(1.64)	(4.34)	(1.06)	(3.27)
Design	3.78***	1.64	11.25***	7.79	5.08	4.21	3.35***	2.11
	(2.16)	(3.55)	(4.44)	(7.87)	(1.41)	(5.21)	(1.07)	(3.61)
Materials	2.82***	1.03	6.46***	3.50	5.51***	2.00	1.63	1.18
	(1.50)	(2.29)	(3.77)	(4.93)	(0.97)	(3.07)	(0.64)	(2.48)
Operations								
Invent+tool+mainten	3.46***	5.92	3.84***	4.89	6.44***	13.44	5.57***	14.28
	(2.14)	(8.54)	(2.80)	(6.26)	(2.14)	(9.63)	(2.14)	(11.96)
Automat+production	6.22***	3.80	11.65***	7.85	12.00***	8.63	12.16	12.51
	(2.77)	(5.53)	(4.83)	(7.55)	(3.04)	(7.49)	(3.23)	(11.86)
Support								
Adm+manag+finan+bus	13.53	13.71	4.77	4.77	5.87***	3.99	8.78***	5.30
	(4.30)	(10.04)	(3.10)	(5.45)	(1.21)	(4.61)	(1.66)	(6.64)
ML+software	3.81	3.93	4.95***	6.22	3.92	4.25	2.17	2.53
	(2.46)	(5.65)	(2.82)	(7.56)	(0.95)	(5.43)	(0.93)	(4.33)
Data+office+technical	3.19***	5.24	4.17***	5.58	7.12***	8.45	6.15***	7.45
	(1.91)	(6.61)	(2.62)	(6.43)	(2.09)	(7.23)	(1.84)	(7.89)
Reasoning								
Cognitive	6.02***	3.60	4.63	4.48	3.85	3.40	6.00***	2.94
	(1.99)	(4.26)	(2.67)	(4.64)	(1.03)	(3.75)	(1.26)	(3.98)
Creativity	0.95	0.76	0.93***	0.68	0.79**	0.44	0.63	0.43
	(0.59)	(1.71)	(0.88)	(1.53)	(0.36)	(0.82)	(0.34)	(0.93)
People								
Social	6.65***	7.65	4.77***	5.92	6.04	5.69	6.23***	5.04
	(2.47)	(6.18)	(2.48)	(5.34)	(1.32)	(5.39)	(1.52)	(5.30)
Character	5.71***	9.09	4.06***	5.16	5.41	5.14	6.30	6.42
	(2.62)	(7.29)	(2.22)	(5.39)	(1.71)	(4.78)	(1.77)	(6.56)
Number of job postings	2,437	233,820	6,302	205,328	1,009	29,365	1,348	79,646
Number of plants	391	688	588	669	262	607	309	628

Notes: See notes to Table A.2. ML, machine learning.
***$p > 0.01$; **$p < 0.05$; *$p < 0.1$.

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