How things are made matters: The effects of technology on the organization of work

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Abstract

Given a particular product to produce, firms have several alternative production technologies from which to choose. This paper examines the effect of production technologies, directly and indirectly through complexity and task interdependence, on outcomes essential to the organization of work. Our study uses online job vacancy postings in the U.S. manufacturing sector during 2017-2021 to analyze technical occupations (i.e., engineers, technicians, and operators) in plants that implement one of six primary technologies: subtraction, forming, molding, additive manufacturing, chemical, and assembly. Controlling for different forms of automation, location, and other factors, we find that the differences in the division of labor, specialization, and span of control among technologies are driven by differences in complexity. Additive manufacturing, chemical, and assembly are technologically more complex than forming, molding, and subtraction, and, as a result, they need more jobs to be designed, more tasks and skills to be bundled into a job, and fewer employees to be overseen by a manager. Moreover, each technology exhibits a distinct pattern of two forms of task interdependence—reciprocal and sequential, and therefore the effects on the three outcomes are more nuanced.

1 Introduction

Organizations across the world strive to improve process efficiency by continuously adopting new technologies and reorganizing the work accordingly. Emerging technologies, such as artificial intelligence, blockchain, and robots continue to reshape work across all industries (Bailey, 2022). Industrial robots have replaced workers in performing dangerous and mundane tasks with better precision, and the scope of tasks they can perform expands through the integration with artificial intelligence. The underlying technologies for transforming raw materials into finished goods in manufacturing, however, remain largely unchanged;[1] it is automation technology that has altered which tasks are performed by whom. Yet, these more fundamental processes have not received enough attention in the management literature.

Given a particular product and level of output, firms have several alternative production technologies from which to choose. There are six principal technologies for making goods: subtracting from a block of material, shaping material, pouring material into a mold, mixing chemical substances, adding layers of material, or assembling parts. The technology of production determines what tasks must be carried out to make a product. From making toys to assembling fuel nozzle tips, more than one technique can be deployed. A toy can be made by pouring heated liquid plastic into reusable molds or printing layers upon layers of material. In the former, molds of different shapes are needed to accommodate part geometry, and the solidified parts are assembled. In the latter, the entire toy can be made using a single printer. Thus, production technologies may have implications on how firms organize work, for instance, on what type of skills and how many workers are needed to operate the machines.

This illustrates the importance of technological choice for organizational design. First, more complex production technologies require more demanding tasks and higher skill levels (Ben-Ner et al., 2023). How does this affect how work is organized within an establishment? Second, extant studies have documented the effects of technological change on wages and employment, and yet the more enduring fundamental processes have received little attention, despite the fact that production technology is "sticky". Our data shows that 94.5 percent of plants implementing a primary technology still used the same technology a decade later.[2] Finally, labor costs comprise 24 percent of typical manufacturing costs, and an additional 20 percent is needed for engineering and research and development that involve technical

[1] For instance, the casting technology can be traced back to 4,000 B.C.E. after the discovery of copper (Groover, 2020), but the fundamental casting process remains unchanged today, wherein liquid metal is poured into a cast, the solidified part is removed, and post-processing is performed.

[2] See Appendix Table A1.

occupations (Groover, 2020). Given that almost thirteen million workers—fifteen percent of which are production workers—are employed in the manufacturing sector (United States Bureau of Labor Statistics, 2023), these fundamental technologies could have significant long-term impacts on the organization of work. Lacking evidence of how the characteristics of each production technology affect the organization of work, firms face uncertainty in choosing which process or combination of processes is best to produce goods. In this paper, we offer the first analysis of the effects of different production technologies in manufacturing on the division of labor and specialization, and other aspects of work at the establishment level.

We use the task-based approach in our analysis. We characterize tasks in terms of their function in the production process and their general attributes. Function corresponds to the phase in the process, such as product development, production, or process management. Task attributes include number, complexity, and interdependence.[3] A larger number of tasks (a longer production process) requires more distinct jobs, other things equal. Greater task complexity must be supported by more skilled workers, entailing greater specialization. Greater interdependence among tasks calls for broader jobs (multi-tasking) and less specialization.

Production technologies differ in the functions and attributes of the tasks they entail, such that, for example, one technology may require more development and design and fewer production tasks and entail fewer, more complex, and more interdependent tasks than another technology, throughout the entire production process or just in some phases. This implies different degrees of specialization and different combinations of occupations in different technologies.

We empirically examine the effects of different technologies of production, which are likely to yield heterogeneous effects on the division of labor and specialization in manufacturing. We use job postings by manufacturing plants over the course of five years. We analyze the data at the plant level under the assumption that this period is long enough for a plant to seek new hires for a representative sample of its workforce. Different turnover rates across occupations may cause biased representations in plants' workforce, but this would not affect the estimates of technology effects (unless occupational turnover varies systematically with technology). We use the five-year data to represent a snapshot of a plant's tasks and relate them to technologies across plants. We assume that the technology of production remains stable during the five-year period.

[3] This characterization summarizes Perrow's (1967) classification, which also includes routine and variability. We will discuss later other but closely related characterizations, including the now canonical nonroutine analytic, routine cognitive, nonroutine manual, routine manual, and interactive introduced by (Autor et al., 2003)

Using the near universe of job postings in the U.S. manufacturing for 2017-2021, we construct an analytical sample of plants for which we can ascertain a dominant technology of production, one of the six noted earlier. The sample contains 9,816 plants that belong to 3,070 firms and had 1,358,806 job postings. For each job posting, we identify occupation, task and skill requirements and their location in the production process. Using job posting level information, we construct plant-level measures of division of labor, specialization, and span of control. We distinguish technical occupations (engineers, technicians, and operators), managers, and support staff. Our principal analyses relate the various measures to the technology of production, automation in different phases, plant size, geographic location, firm characteristics, union coverage, and other variables.

We find that technologies that require more complex tasks (additive manufacturing, chemical, and assembly) entail a more detailed division of labor, deeper as well as wider specialization, and a narrower span of control than technologies that are relatively less complex (forming, shaping, subtraction). Technologies affect these outcomes indirectly through task complexity and, to a lesser extent, interdependence.

2 Related literature and theoretical framework

Division of labor has been recognized since antiquity as beneficial in organizations and in society at large.[4] Smith (1786) argued that a detailed division of labor has two advantages. "First, the improvement of the dexterity of the workmen, necessarily increases the quantity of the work he can perform; and the division of labour, by reducing every man's business to some one simple operation, and by making this operation the sole employment of his life, necessarily increases very much the dexterity of the workman... Secondly, the advantage which is gained by saving the time commonly lost in passing from one sort of work to another, is much greater than we should at first view be apt to imagine it. It is impossible to pass very quickly from one kind of work to another, that is carried on in a different place, and with quite different tools."

Babbage (1832) added to Smith's analysis the idea that tasks should be bundled into jobs according to the cost of the skills they require.[5] Stigler (1952), Yang and Borland (1991),

[4] Sun (2012) provides an analytical survey of economic thought on division of labor in different civilizations from antiquity to recent contributions.

[5] "That the master manufacturer, by dividing the work to be executed into different processes, each requiring different degrees of skill or of force, can purchase exactly that precise quantity of both which is necessary for each process; whereas, if the whole work were executed by one workman, that person must possess sufficient skill to perform the most difficult, and sufficient strength to execute the most laborious, of the operations into which the art is divided." (Babbage, 1832, ch. 19 para. 239).

Becker and Murphy (1992), and others include an additional factor: costs of communication and coordination among specialized workers. Communication and coordination may be hampered by technical difficulties involving complex tasks, which exacerbate asymmetric information and agency problems (Becker and Murphy, 1992). This suggests that greater task complexity is conducive to a less detailed division of labor and more multitasking. Interdependence among tasks increases the need for communication and coordination if the tasks are carried out by different individuals; hence it is also conducive to multi-tasking (Lindbeck and Snower, 2000). An increase in complexity strains the capacity of an individual to master it, requiring relatively narrow specialization based on extensive skills.

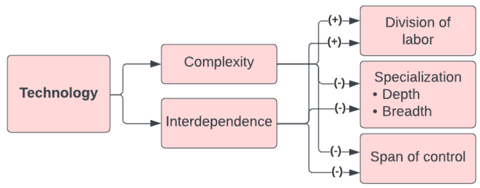
Much has changed since Smith's time. The production steps in the manufacturing of pins and other products remain the same, but many tasks are aided or carried out by machines. Several studies focused on ICT and computer-based technology, which were found empirically to favor specialization and relatively detailed division of labor, presumably because they facilitate communication and coordination (Borghans and ter Weel, 2006; Akçomak et al., 2011). Others argued that computerization has increased complementarity among workers' tasks, leading to demand for broadening of jobs (multitasking) to handle interdependence (Lindbeck and Snower, 2000), that is, to a less detailed division of labor (Caroli and Van Reenen, 2001). These studies, however, are at the industry level—information at the establishment level is hard to collect for more than a handful of establishments.

The relationship between technology and span of control has been studied by Hickson et al. (1969), Blau et al. (1976), Collins and Hull (1986), and others, inspired by Woodward (1965). The empirical studies were limited to around a hundred establishments and tested whether technological complexity (Woodward's classification, unit of mass and continuous based entailing increased complexity) affects the span of control and other organizational variables. The findings of this literature are inconsistent, and suggest that other factors such as establishment size and automation may be more important than technology.

Building on these literatures as well as on engineering literature, we develop a theoretical framework for understanding the effects of production technologies on the division of labor, specialization, and span of control. The framework is summarized in Figure 1.

Technologies of production differ in how they use inputs of labor, machines, and software to transform materials into products. These differences have implications for broad aspects of the production process, which we characterize in terms of flexibility, length, and integration. The degree of flexibility of the production process and the attributes of the output has been a central concept in the study of the effects of technology on work and

Figure 1: Theoretical framework



organization (Thompson, 1967; Sethi and Sethi, 1990; MacDuffie, 1995; Stabell and Fjeldstad, 1998; Akçomak et al., 2011). More flexible technologies require more deviations from rules and making contingent choices, as well as experimentation to ensure desirable outcomes than entailed by less flexible technologies. Greater flexibility contributes to a more complex production environment, with more complex tasks and greater interdependence, especially of the reciprocal type (Perrow, 1967; Sethi and Sethi, 1990; Lindbeck and Snower, 2000; Ben-Ner and Urtasun, 2013). In comparison, more rigid technologies are easier to manage, and the tasks are more clearly delineated.

The length of the production process reflects the number of steps required in the production process. The longer the process, the greater is the need for coordination among sequentially interdependent tasks. Process integration refers to the extent to which steps in the production process can be carried out independently from each other or are tightly coupled and not separable and are therefore interdependent. Longer processes and more integrated processes are more complex, with implications similar to those discussed in the previous paragraph.

In Figure 1 we indicate that technology complexity, manifested in task complexity and interdependence, affects the division of labor and specialization, and the span of control. Specifically, greater complexity requires more skills, that is, deeper specialization. This is tantamount to detailed division of labor. However, greater complexity calls for more and deeper skills to handle complex tasks as well as the independence arising from detailed division of labor (multiplicity of jobs). Interdependence requires that individuals in interacting jobs have some skills to understand also the jobs with which they interdependent.

To handle greater task complexity and interdependence, supervision and guidance need to be greater than in the case of more straightforward and independent jobs. This entails a narrower span of control reflected in more managers to interact with a given number of employees, and more engineers to interact with a given number of lower skill workers (Bell, 1967; Gittell, 2001). Woodward (1965) observes a curvilinear relationship between complexity and span of control. As plant complexity increases, the number of subordinates that a manager can effectively supervise tends to decrease as they need to devote more time to oversee complex tasks. This leads to fewer subordinates as complexity increases, but only up to intermediate levels. As tasks become too complex, however, managers will delegate more decision-making authority to subordinates and, consequently, the time to supervise each subordinate will decrease and the number of subordinates that can be effectively overseen increases.

We make a reasonable assumption that highly complex plants such as ones observed by Woodward (1965) comprise a disproportionately small number in our sample for two reasons. First, a company needs only a few highly complex plants, such as research and development centers, relative to the number of processing and assembly plants, as it would be inefficient to decentralize highly integrated conceptual tasks in various locations. Second, these plants are owned primarily by a handful of large companies. Thus, most manufacturing plants in our sample are likely to have low to intermediate complexity, and we would observe only the decreasing part of Woodward's curvilinear relationship. Based on these considerations, we propose the following hypotheses:

Hypothesis 1 *Technologies with higher complexity have (a) more detailed division of labor, (b) deeper specialization, and (c) narrower span of control.*

Hypothesis 2 *Technologies with greater task interdependence have (a) more detailed division of labor, (b) wider specialization, and (c) narrower span of control.*

To formulate specific hypotheses relative to the technologies discussed in this paper, we describe how the different technologies work, and how they differ in terms of flexibility, length, and integration. The principal manufacturing technologies were described in the Introduction; Table 1 provides more details, including keywords (terms) used to describe them (discussed later) and the type of materials used in them.

The last three rows of Table 1 describe our assessment of the extent of flexibility, length, and integration of the technologies. In sum, we assess that forming is relatively inflexible, and separable, molding and subtraction are more flexible, longer and separable, whereas the other three technologies are fairly integrated, with chemical long and inflexible, assembly with variable flexibility and length, and additive manufacturing most flexible and integrated and shortest of all. As a result of the differences in the three dimensions, we rank the complexity of manufacturing technologies based principally on their flexibility in process and output, and secondarily on length and integration.[6]

Forming is technologically not flexible as it typically consists of fewer production steps,

[6]See Appendix Figure B1 for the process flow of each production technology.

Table 1: Characteristics of production technologies

Characteristics	Forming	Molding	Subtraction	Chemical	Additive manufacturing (AM)	Assembly
Manufacturing processes description	Use of force to shape materials	Use of molds to shape raw materials	Reduction of blocks of material to desired shapes	Use of chemical reactions to transform organic and inorganic raw materials into a final product	Addition of successive layers of raw materials	Putting together intermediate parts to form a complete product
Keywords for technology identification – examples	Rolling, forging, extrusion, wire drawing, bending, spinning, stamping	Casting, molding, lay-up, thermoforming, hydroforming, vacuum forming, sintering	Turning, drilling, milling, cutting, broaching, sawing, water jet cutting, laser beam machining	NAICS code 325 instead of keywords	3d printing / additive manufacturing, powder bed fusion, binder jetting	Assembly and its variation
Materials	Metals	Metals, ceramics, polymers (liquid)	Metals, polymers, composites (wood)	Chemical substances	Polymers and metals, and other materials (powder, filaments)	Parts from other technologies
Flexibility – process and output	Low – requires specialized equipment; products have simple geometry	Medium – can produce parts with more complex geometry, but needs specialized equipment (a cast or mold)	Medium – can produce parts with more complex geometry, but needs specialized equipment (CNC)	Low – needs specialized equipment to produce specific products; not cost-effective to modify process	High – general-purpose technology	Low to high – depends on the types of parts being assembled
Length (number of production steps)	Short process	Medium-length process	Medium-length process	Long process	Short process	Varies, depending on the types of parts
Integration	Few, highly separable steps	Highly separable steps	Highly separable steps	Highly-integrated continuous flow	Production is integrated in a box	Varies, depending on the types of parts

Notes: The classification of technologies and keywords are based on Groover (2020) and Ulrich (n.d.). The discussion of flexibility is based on authors' judgement. In addition to keywords to identify technologies, we also use a negative list to exclude similar terms with unrelated meaning, such as forecasting, cutting edge, or IBM assembler (a programming language).

has a more limited choice of raw materials that can be processed (wires and sheets of metal), and produces simple products. It needs specialized equipment, such as benders, rollers, and cutters, that are set up according to the desired part geometry, thus making adjustments costly. Molding is more flexible than forming as it can process a wider variety of raw materials, such as plastic, rubber, or metal. It typically requires specialized equipment, such as a mold or cast, that are shaped and set up according to the desired product geometry. Molds and casts can be reusable or expendable depending on the specific process, and output flexibility can be moderately high as a new mold can be created with reasonable costs. Subtraction is also able to transform a wide variety of materials, such as wood, plastic, and metal, with more complex product geometry. It can be performed manually or aided by computer numerical control (CNC). A digital design and machine instructions are needed if a CNC is used. More complex product geometry and relatively low cost of a digital design allows for greater flexibility. Additive manufacturing is a versatile emerging technology that allows making products with highly complex geometry from a wide variety of materials. In this technology, a digital design is fed into a 3D printer to instruct it to add successive layers of material. Low cost of a digital design and customizable layers making it a highly flexible, short and integrated technology. Chemical manufacturing transforms materials into a product using elaborate processes (chemical reactions and purification) with highly specialized equipment. The sophistication of chemical reaction and purification steps makes it a highly complex technology. Finally, assembly sources parts from one or more other technologies. Flexibility of this technology depends on the parts being assembled. With the application of modular technology and robotic arms that are easily adjustable, this technology can be highly flexible.

In sum, additive manufacturing, chemical, and assembly require more complex parameters to adjust and we predict that they are more complex than forming, molding and subtraction. The differences in reciprocal interdependence among technologies follow the differences in complexity, generally because handling complexity demands more interactions, whereas sequential interdependence depends on the length and integration of tasks.

3 Empirical analysis

3.1 Data

Our data come from online job vacancy postings in the U.S. manufacturing sector from 2017 to 2021 collected by Burning Glass Technologies/Lightcast (BGT). 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), Deming and Noray (2020), and Ben-Ner et al. (2023), all of which provide extensive descriptions of the data. BGT uses machine learning algorithms to convert the text of job postings into strings of terms. This procedure considerably reduces the number of words employed to describe a job compared to the original text. We utilize BGT-annotated strings of terms, to which we refer as skillsets, to examine skills and tasks as demanded by employers.[7] We start from 9,229,007 manufacturing job postings that contain at least two terms. We focus on core manufacturing occupations that are directly impacted by the choice of technology: engineers, technicians, and operators, to which we refer collectively as ETO. These are occupations that are involved in the production process, and thus their tasks and skills are mostly impacted by technology. BGT classifies a six-digit Standard Occupational Classification (SOC) code to each job posting. For example, a "Machine Operator" is classified as 51-9199 (Production Workers, All Other) and an "Assembler" is

[7] For instance, the string of term for a job posting dated August 31, 2018, for Production Technician I in 3M located in Seattle, Washington contains cleaning, crucible, operations management, personal protective equipment (ppe), forklift operation, storage of products/inventory, packaging, and physical abilities.

classified as 51-2092 (Team Assemblers). We use these SOC codes to classify job postings into managers (11-0000), engineers (17-2000), technicians (17-3020 and 17-3030), and operators (49-0000 and 51-0000). Managers are further classified into technical managers—i.e., managerial occupations involved in the production phases—and non-technical managers.[8] In total, there are 3,849,793 manager and ETO job postings in our initial dataset.

From these job postings, we select establishments, to which we refer as plants, that have a valid firm identifier, a geolocation coordinate, and at least ten combined ETO postings across the five-year period.[9] A primary technology for each selected plant is identified by matching job titles and BGT-extracted terms with our list of keywords. We use regular expressions to allow for variability in wordings. The plant-level primary technology identification follows a two-step process. First, we identify forming, molding, subtraction, chemical, and additive manufacturing plants. A plant is assigned one of these primary technologies if the share of ETO job postings that contain terms from a particular technology is at least 20 percent of the overall ETO job postings, and the share is the largest among the six technologies.[10] Plants that do not meet these two criteria are classified as general plants. Second, among general plants, we apply at least 20 percent of ETO job postings with NAICS code 325 to identify chemical manufacturing plants. The remaining general plants are not included in the analyses of the present paper.[11]

Next, we assign a main NAICS code to a plant based on information available in job postings, which may have different NAICS codes (pre-assigned by BGT) although they originate from the same plant. Thus, we perform several steps to identify a plant-level NAICS code. First, we use the job posting-level 3-digit NAICS code that most frequently appears in a plant. Second, for plants within which all job postings do not have a NAICS code, we

[8] Job postings with SOC codes 11-1021 (General and Operations Managers), 11-3021 (Computer and Information Systems Managers), 11-3051 (Industrial Production Managers), 11-3061 (Purchasing Managers), 11-3071 (Transportation, Storage, and Distribution Managers), 11-9013 (Farmers, Ranchers, and Other Agricultural Managers), 11-9021 (Construction Managers), 11-9041 (Architectural and Engineering Managers), 11-9111 (Medical and Health Services Managers), and 11-9121 (Natural Sciences Managers) are classified as technical managers, whereas other SOC codes 11 are classified as non-technical managers.

[9] As a robustness check, we also try a minimum of 30 ETO postings per plant to investigate whether our analysis is affected by the size of ETO job postings. We replicate some analyses in this paper using this threshold.

[10] Examples of keywords that we use to identify the primary technology for these plants are in Table 1.

[11] Discussions with hiring HR managers suggest that plants that do not include clearly identifiable technologies in their job postings do so mainly because job applicants would know what kind of jobs are offered. They may be familiar in the local labor market, are familiar companies, or by visiting the website of the posting plant. Most plants do not include identifiable technologies, so we opted to omit these plants from our analysis and focus on plants with clearly identifiable technologies. As robustness checks, we visited the websites of 50 general plants and were able to identify their technologies and included them in analyses that showed no change in the findings.

take the most frequent plant-level 3-digit NAICS code from other plants within the same parent firm. Third, we match firms in the BGT dataset with Compustat to obtain parent firm-level NAICS codes. For firms where all plants do not have a NAICS code, we assign a parent firm-level 3-digit NAICS code that we obtain from the matching process.[12] We restrict our analytical sample to core manufacturing industries in NAICS codes 32 and 33.[13] Thus, our sample consists of primarily wood, chemical, plastic, rubber, metal processing, and electronic manufacturing plants.

Finally, we identify the commuting zone for each plant to obtain local market size data.[14] Based on this procedure, our analytical sample consists of 729,220 manager and ETO job postings from 9,816 plants. The number of plants included in our analytical sample by technology is identified in the first row of Table 2.

3.2 Measures

Our key outcome variables consist of plant-level measures of division of labor, specialization, and span of control. BGT identifies and cleans the job title for each job posting. A cleaned job title may appear as "Maintenance Technician" or "Production Supervisor". We use these job titles to construct a measure of division of labor by calculating the number of unique ETO job titles in a plant. The greater number of unique job titles indicates that workers are organized into more jobs, implying more detailed division of labor. However, more unique job titles may also be simply due to more job postings advertised by the same plant. Thus, we normalize this measure by dividing the number of unique ETO job titles by the number of ETO job postings.[15]

To measure specialization in a plant, we remove duplicate terms–which we refer to

[12]Some additive manufacturing plants have no NAICS associated with any job postings because they are service bureaus (contract manufacturers) that serve multiple industries (Ben-Ner et al., 2023). We assigned these plants to NAICS 33.

[13]We exclude NAICS 31 since these are "establishments that transform materials or substances into new products by hand or in the worker's home and those engaged in selling to the general public products made on the same premises from which they are sold, such as bakeries, candy stores, and custom tailors" and may use different manufacturing processes (United States Census Bureau, 2023).

[14]We match the county Federal Information Processing System (FIPS) codes in our dataset with Autor and Dorn's (2013) commuting zone dataset File [E7] in https://www.ddorn.net/data.htm.

[15]As a robustness check, we also calculate the number of unique skillsets. Each measure has its limitations. Job titles are highly unstructured, and it is difficult to determine whether two different but similar job titles from the same plant are essentially the same job. For example, in one plant machinist job postings are split based on levels into Machinist Level I and Machinist Level II, whereas in another plant, they are split based on work shifts into first and second shifts. It is almost impossible to manually determine whether similarly titled jobs are essentially the same. On the other hand, skillsets are more standardized, but two different jobs may have the same skillset due to high similarity in how they are advertised. The two measures thus overcome each other's limitations.

as tasks and skills, calculate the number of unique terms, and divide it by the number of unique job titles.[16] The greater this number in a plant, on average, the deeper and wider is specialization. Finally, our main span of control measure is the ratio of the number of ETO job postings to the number of technical manager job postings in a plant. A higher ratio implies a broader span of control.[17]

Our key independent variable, primary technology, is a vector of dummy variables for six production technologies. We do not directly measure flexibility, length, and integration of each production technology but measure their direct consequences: complexity and interdependence. We construct these measures by using the standard procedure in this literature, matching terms in job postings to a list of keywords that capture the measures of interest.[18] To construct our key measure of complexity, we develop a list of keywords to classify terms in ETO job postings into nonroutine analytic (e.g., "research", "analytical skills", and "root cause analysis"), routine cognitive (e.g., "calculation", "data entry", and "record keeping"), nonroutine manual (e.g., "equipment repair", "auto repair," and "engine repair"), and routine manual (e.g., "hand tools," "forklift operation," and "machine operation"). We then calculate the plant-level frequency of tasks and skills in each category and divide the number by the total number of tasks and skills to obtain four measures of intensity.[19] From these categories, we construct two aggregate measures. Cognitive complexity intensity is the difference between nonroutine analytic intensity and routine cognitive intensity, and manual complexity intensity is the difference between nonroutine manual intensity and routine manual intensity. Finally, the overall complexity intensity is the sum of cognitive complexity intensity and manual complexity intensity.[20]

We perform the same steps to construct our key measure of task interdependence, i.e., the overall interdependence intensity. Based on our list of keywords, tasks and skills among ETO job postings are classified into reciprocal (e.g., "teamwork/collaboration," "mentoring," and "negotiation skills") and sequential interdependence (e.g., "quality assurance and control," "leadership," and "supervisory skills"). Then, overall interdependence intensity is constructed by adding reciprocal and sequential interdependence intensity.

[16]These are words such as "packaging" or phrases such as "communication skills" and "supply chain knowledge", as well as technical skills that refer to brand names, such as "Oracle", or tools, such as "rubber mallets". We combine tasks (i.e., what a worker does) and skills (i.e., what a worker needs to know) together since we cannot distinguish them.

[17]As a robustness check, we also calculate the ratio of indirect employees to non-technical managers and the ratio of engineers to operators, which results will be explained later.

[18]See references in the Data subsection above.

[19]For example, if a plant has two ETO postings and each consists of two nonroutine analytic and two other tasks and skills, then the plant-level nonroutine analytic intensity is 50 percent.

[20]We use concepts and keywords developed in the literature cited above.

Unionization could affect how a plant is organized. For example, our data shows that subtraction has a larger union rate, whereas additive manufacturing has one of the lowest union rates, perhaps due to larger fractions of workers are highly skilled. Thus, more unionization in subtraction may confound our findings of less complexity—and hence less division of labor and specialization and wider span of control—in this technology. To address this concern, we match plants in the BGT dataset with a list of establishments that submit Form LM10 obtained from the Office of Labor Management Standards to construct a dummy that indicates whether a plant is unionized. [21]

Table 2: Descriptive statistics of key variables

Variable	*Primary technology*					
	Subtraction	*Forming*	*Molding*	*AM*	*Chemical*	*Assembly*
Number of plants	5,361	703	305	99	2,458	890
Number of postings per plant	93.96	72.33	82.11	161.08	270.59	110.23
	(175.82)	(92.20)	(169.22)	(297.32)	(659.55)	(267.63)
Complexity	-7.64	-5.10	-3.86	3.70	-1.78	-1.23
	(9.31)	(7.92)	(6.34)	(7.79)	(8.59)	(10.57)
Reciprocal interdependence	2.63	3.09	2.54	3.77	3.16	2.34
	(2.45)	(2.53)	(2.45)	(2.52)	(2.23)	(1.80)
Sequential interdependence	2.95	3.65	4.22	2.81	4.04	2.99
	(2.45)	(2.94)	(2.62)	(2.38)	(2.73)	(2.38)
Number of unique job titles/ETO posting	0.62	0.60	0.61	0.71	0.67	0.66
	(0.19)	(0.19)	(0.17)	(0.17)	(0.19)	(0.18)
Number of unique tasks and skills/job title	5.25	5.40	4.37	5.74	6.02	6.31
	(2.71)	(2.53)	(2.13)	(1.97)	(2.86)	(2.88)
Ratio of ETOs to technical managers	14.01	12.74	14.06	8.34	7.41	10.19
	(15.98)	(11.36)	(14.98)	(7.68)	(8.80)	(10.21)

Notes: Means and standard deviations (in parentheses) are shown, except for the number of plants. Variables are calculated for engineer, technician, and operator (ETO) job postings in 9,816 plants with a main NAICS 32 or 33. The ratio of ETOs to technical managers is calculated from 7,076 plants due to some plants not having technical manager job postings, causing indivisible values. Complexity = nonroutine analytical intensity − routine cognitive intensity + nonroutine manual intensity − routine manual intensity. Interdependence = reciprocal interdependence intensity + sequential interdependence intensity.

Descriptive statistics for the key measures are presented in Table 2. The most complex technology is additive manufacturing, followed by assembly and chemical, whereas subtraction is the least complex. Notably, complexity takes negative values when routine cognitive and manual tasks are greater than nonroutine tasks. Only additive manufacturing has a positive value, indicating higher nonroutine than routine tasks, whereas the other five technologies comprise of mainly manual tasks. Moreover, most technologies, except additive manufacturing, have greater sequential interdependence intensity, although the differences are not statistically significant. The three more complex technologies (i.e., additive manufacturing, chemical, and assembly) have more detailed division of labor, deeper specialization,

[21] Most of the unionized plants are in the general multi-technology category.

and narrower span of control. The relative magnitudes of these measures across technologies conform with our expectations.

Table 3: Correlation matrix

Variable	*Mean (SD)*	*1*	*2*	*3*	*4*	*5*
1. Complexity	-5.18 (9.52)	1				
2. Reciprocal interdependence	2.78 (2.37)	0.107	1			
3. Sequential interdependence	3.31 (2.61)	0.103	0.061	1		
4. Number of unique job titles/ETO posting	0.64 (0.19)	0.171	0.066	0.059	1	
5. Number of unique tasks and skills/job title	5.53 (2.77)	0.227	0.031	0.037	0.071	1
6. Ratio of ETOs to technical managers	11.58 (13.64)	-0.195	-0.054	-0.056	-0.206	-0.288

Notes: Means and standard deviations are calculated from 9,816 plants. Correlations are calculated from 7,076 plants due to some plants not having technical manager job postings causing indivisible values. Complexity = nonroutine analytical intensity − routine cognitive intensity + nonroutine manual intensity − routine manual intensity. Interdependence = reciprocal interdependence intensity + sequential interdependence intensity. All correlations are significant at $p < .01$.

Table 3 shows correlations among key variables in our model for all observations without distinction of technologies. The correlations (all statistically significant at $p < .01$) are consistent with our predictions. Plants with higher complexity and interdependence exhibit greater division of labor ($r_{complexity} = .171$, $r_{reciprocal} = .066$, $r_{sequential} = .059$), deeper and wider specialization ($r_{complexity} = .227$, $r_{reciprocal} = .031$, $r_{sequential} = .037$), and narrower span of control ($r_{complexity} = -.195$, $r_{reciprocal} = -.054$, $r_{sequential} = -.056$). This provides initial support for our hypotheses.

4 How technology affects complexity, interdependence, and the organization of work

To test the theoretical framework (Figure 1), we use multicategorical structural equation modeling (SEM). This approach is a mediation analysis in which we analyze whether complexity and interdependence mediates the effect of six distinct technologies on division of labor, specialization, and span of control. We cluster standard errors at the parent firm level to account for the nested structure of plants within a firm, violating the OLS assumption that observations are independent. Our data is structured at two levels. Plant level variables consist of a vector of technology dummy variables, complexity, interdependence, a vector of automation variables, plant size, local market size, union coverage, and 3-digit NAICS fixed effects, whereas parent firm level variable is the parent firm's size. We use standardized measures except for technology, union coverage, and NAICS fixed effects due to large differences in scales among variables in our model, which may cause SEM's estimation algorithm to be dominated by variables with larger variances. As our independent variable is categorical, we set subtraction as the reference group. Therefore, we describe the effects of the other technologies relative to subtraction in standardized measurement.[22]

We provide below the rationale for including several control variables in our analysis. First, our outcome variables may be directly impacted by the level of automation (as found in the literature reviewed earlier).[23] As different types of automation may affect our outcome variables differently, we construct six measures of automation.[24] Second, plant size may affect our outcome variables (as the abovementioned literature has argued).[25] We measure plant size by the number of all job postings in a plant. Third, each firm may have a different policy regarding the organization of work in plants that it owns. We measure the parent firm's size by the number of plants that the parent firm of a plant owns. Fourth, we include plant union coverage because different rates of unionization in different technologies might be the source of differences in how a plant is organized.[26]

Fifth, technological choice may be endogenous. A plant chooses a particular technology

[22] See Hayes and Preacher (2014) for a discussion on mediation analysis with a multicategorical independent variable.

[23] For instance, automation of routine tasks may reduce human tasks in routine cognitive and routine manual, increase complexity, and inflate its effect on the three outcome variables. Automation also decreases communication and coordination costs, such as in the case of a conveyor belt that moves work-in-process, which reduces the need for workers in the production line to interact with each other. This increases their productivity of the remaining tasks and leads to narrower specialization. However, automation may also create new tasks in which labor has a comparative advantage (Acemoglu and Restrepo, 2019), thus broadening their task scope (deeper and wider specialization).

[24] We split automation into ones that affect the entire process, pre-production and production. Automation in the pre-production phase, which is more conceptual, may complement workers' tasks and create a broader range of tasks, whereas production automation, which is more operational, tends to replace human tasks and lead to greater specialization. We rely on BGT-annotated skill clusters to classify types of automation. The entire process automation is divided into primary (i.e., skill clusters "Automation Engineering", "Machine Learning", and "Artificial Intelligence"), secondary (i.e., "Big Data"), and tertiary (i.e., "IT Automation"); pre-production automation contains tasks and skills from skill clusters "Drafting" and "Engineering Design"; and production automation is split into primary (i.e., "Computer Aided Manufacturing") and secondary (i.e., "Circuitry").

[25] Larger plants have more resources and they need more specialized workers to handle various tasks and responsibilities as a result of larger operations.

[26] As mentioned above, we use form LM10 to identify plants covered by unions. We acknowledge that form LM10 includes all transactions (payments and arrangements) from an employer to a union or officer, agent, shop steward, employee, or other representative of a union. This transaction may not always indicate the existence of labor union. Moreover, this dataset is at the firm-city level. However, unions may only cover certain occupations within a plant.

based on what kind of product it produces. Thus, comparing technologies should control for product characteristics. This cannot be achieved using the available data as there is no information on product varieties. We address this concern by controlling a plant's main 3-digit NAICS. Finally, per Smith (1786) that division of labor is affected by the extent of the market, we control for the local market size, as measured by the working age population of the commuting zone in which a plant is located.

4.1 Complexity

The SEM estimation result is shown in Table 4. The model demonstrates a good fit as SRMR and CFI are within acceptable levels (i.e., $SRMR < .08$ and $CFI > .90$).[27] Column 1 shows technology heterogeneity on complexity. All coefficients for complexity are positive and highly significant, indicating that subtraction is the least complex technology. Further inspection indicates that additive manufacturing has the greatest complexity among the six technologies. Columns 3, 4, and 5 show the relationships between complexity and key outcome variables, the second path of the role of complexity as a mediator. We find that complexity is positively associated with the number of unique job titles per ETO posting (implying more detailed division of labor), positively associated with the number of tasks and skills (implying deeper specialization), and negatively associated with the ratio of ETOs to technical managers (implying narrower spans of control, particularly for technical employees).

Finally, supporting Hypothesis 1, we find that all relative indirect effects of technology on division of labor, specialization, and span of control through complexity are highly significant, implying that differential levels of division of labor among the six technologies can be attributed to complexity. Moreover, additive manufacturing is strikingly different from the other technologies.

4.2 Task interdependence

We find mixed findings—-but are generally consistent with our technology characterization—-for task interdependence. Additive manufacturing and forming have more reciprocally interdependent tasks than subtraction, whereas molding and chemical are comparable (column 2). As for the second path, reciprocal interdependence can explain the variability in division of labor and specialization, but is not significant in explaining span of control. Molding and

[27] We do not rely on RMSEA since our multilevel mediation model has small degrees of freedom (df). In small df models, RMSEA should be used with caution as it too often falsely indicates a poor fitting model (Kenny et al., 2015), and SRMR and CFI should be relied more as they are less susceptible to small df (Shi et al., 2022).

Table 4: Structural equation model: Effects of technology on division of labor, specialization, and span of control through complexity and interdependence

Variable	*Dependent variable:*					
	Complexity	*Reciprocal interdependence*	*Sequential interdependence*	*Division of labor*	*Specialization*	*Span of control*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Complexity	-	-	-	0.143***	0.196***	-0.125***
				(0.022)	(0.019)	(0.016)
Reciprocal interdependence	-	-	-	0.049***	0.024	-0.017
				(0.018)	(0.016)	(0.014)
Sequential interdependence	-	-	-	0.028*	0.016	-0.013
				(0.016)	(0.016)	(0.015)
Forming	0.253***	0.141*	0.143	0.014	-0.110*	-0.049
	(0.059)	(0.076)	(0.091)	(0.077)	(0.061)	(0.051)
Molding	0.369***	-0.047	0.366***	0.008	-0.501***	0.087
	(0.069)	(0.126)	(0.091)	(0.096)	(0.076)	(0.087)
AM	0.793***	0.328**	-0.037	0.318***	-0.219***	-0.146**
	(0.078)	(0.137)	(0.124)	(0.117)	(0.084)	(0.066)
Chemical	0.287***	0.144	0.210***	0.170**	0.013	-0.247***
	(0.062)	(0.092)	(0.080)	(0.085)	(0.072)	(0.070)
Assembly	0.258***	-0.088*	-0.011	0.159**	0.069	-0.113***
	(0.067)	(0.045)	(0.054)	(0.064)	(0.050)	(0.039)
Indirect effects:						
Forming → Complexity → DV	-	-	-	0.036**	0.050**	-0.032**
				[0.022, 0.051]	[0.031, 0.069]	[-0.045, -0.019]
Molding → Complexity → DV	-	-	-	0.053**	0.073**	-0.046**
				[0.035, 0.073]	[0.050, 0.097]	[-0.064, -0.031]
AM → Complexity → DV	-	-	-	0.113**	0.156**	-0.099**
				[0.085, 0.144]	[0.123, 0.190]	[-0.126, -0.074]
Chemical → Complexity → DV	-	-	-	0.041**	0.056**	-0.036**
				[0.024, 0.059]	[0.034, 0.081]	[-0.052, -0.021]
Assembly → Complexity → DV	-	-	-	0.037**	0.051**	-0.032**
				[0.021, 0.054]	[0.031, 0.071]	[-0.046, -0.019]
Forming → Reciprocal interdependence → DV	-	-	-	0.007**	0.003**	-0.002
				[0.001, 0.015]	[0.000, 0.008]	[-0.007, 0.001]
Molding → Reciprocal interdependence → DV	-	-	-	-0.002	-0.001	0.001
				[-0.011, 0.006]	[-0.006, 0.003]	[-0.003, 0.005]
AM → Reciprocal interdependence → DV	-	-	-	0.016**	0.008**	-0.006
				[0.004, 0.033]	[0.001, 0.019]	[-0.017, 0.003]
Chemical → Reciprocal interdependence → DV	-	-	-	0.007**	0.004	-0.003
				[0.001, 0.015]	[0.000, 0.009]	[-0.008, 0.001]
Assembly → Reciprocal interdependence → DV	-	-	-	-0.004**	-0.002	0.002
				[-0.009, -0.001]	[-0.006, 0.000]	[-0.001, 0.005]
Forming → Sequential interdependence → DV	-	-	-	0.004**	0.002	-0.002
				[0.000, 0.009]	[-0.001, 0.007]	[-0.007, 0.002]
Molding → Sequential interdependence → DV	-	-	-	0.010**	0.006	-0.005
				[0.001, 0.021]	[-0.002, 0.016]	[-0.016, 0.005]
AM → Sequential interdependence → DV	-	-	-	-0.001	-0.001	0.000
				[-0.008, 0.005]	[-0.006, 0.004]	[-0.004, 0.005]
Chemical → Sequential interdependence → DV	-	-	-	0.006**	0.003	-0.003
				[0.001, 0.013]	[-0.001, 0.009]	[-0.009, 0.003]
Assembly → Sequential interdependence → DV	-	-	-	0.000	0.000	0.000
				[-0.003, 0.002]	[-0.002, 0.002]	[-0.002, 0.002]
N of plants				7,093		
SRMR				0.006		
CFI				0.966		

Notes: Coefficients above are estimated using multicategorical structural equation modeling with the *lavaan* package in R. Standard errors (in parentheses) are clustered at the parent firm level. Regression includes five measures of automation intensity, number of postings per plant, number of plants per firm, commuting zone's population of working age, union status, and 3-digit NAICS as control variables. Non-unionized subtraction plants in NAICS 33 are the reference group. All variables are standardized, except dummies for primary technology, union status, and NAICS. Analysis is performed on plants with main NAICS 32 and 33. The number of samples is smaller than our initial sample size due to indivisible values of span of control, as not all plants in our sample have technical manager job postings. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

chemical have more sequentially interdependent tasks than subtraction, whereas forming, assembly, and additive manufacturing are comparable. Notably, although the coefficient for additive manufacturing is not statistically significant, it is the lowest among the other four due to the short production process (i.e., production in a box). Sequential interdependence is a significant mediator only for division of labor.[28]

As we show in the following section (Figure 3), reciprocal and sequential interdependence do not go hand in hand. A complex but short production process such as additive manufacturing will have high reciprocal, but low sequential, interdependence. On the other hand, a long and elaborate process, such as chemical manufacturing, will have medium-to-high reciprocal and sequential interdependence. Forming and molding have clear, specific steps, in which production follows a particular sequence, thus exhibiting low reciprocal but high sequential interdependence.

In sum, our findings suggest that (1) reciprocal and sequential interdependence are associated with variations in division of labor, (2) reciprocal and sequential interdependence explain the mechanism through which different technologies have different extents of division of labor (i.e., Hypothesis 2(a) is supported), (3) only reciprocal interdependence that is significant in explaining specialization (i.e., Hypothesis 2(b) is weakly supported), and (4) we do not find evidence for the role of both task interdependence in mediating the effect of technology on span of control (i.e., Hypothesis 2(c) is not supported).

Although Table 4 does not show coefficients for control variables, several are potentially important in affecting the key outcomes.[29] Our study shows that automation across the entire process (primary) and in pre-production is positively associated with overall complexity and negatively associated with interdependence.[30] Primary production automation has negative associations with plant complexity, whereas secondary production automation has a positive effect.[31] We also find that larger plants are associated with more complexity and interdependence. Lastly, our findings support the notion that the extent of the market limits that division of labor (in a broad sense) as local market size is associated with more detailed division of labor (narrowly defined as job titles), deeper specialization, and narrower span of control.

[28] We follow Hayes and Preacher (2014) that suggest "[e]vidence that at least one relative indirect effect is different from zero supports the conclusion that M mediates the effect of X on Y."

[29] See Appendix Table A2 for covariate coefficients obtained from structural equation model estimation.

[30] Perhaps because this type of automation enhances human tasks, which shifts workers to more complex tasks and consequently increases their job complexity but also reduces sequential interdependence.

[31] Perhaps due to different levels of adoption of the two types of automation across technologies. Computer adaptive manufacturing is primarily used in subtraction, whereas circuitry in assembly plants. Investigation of the effects of different types of automation on the organization of work is the focus of a companion study.

5 Heterogeneity of technology

Our findings above demonstrate that technologies differ in their levels of complexity and interdependence, which further affects how workers are organized. The following sections provide a more detailed examination of each production technology. We first investigate how each technology differs regarding complexity and task interdependence, and later discuss the implications for division of labor, specialization, and span of control. We regress the outcome variables on production technologies with the same control variables as the previous model and introduce more detailed measures to investigate the source of variation further. Finally, standard errors in the following models are clustered at the parent firm's level to consider dependency of observations from the same firm.

5.1 Technology and plant complexity

Table 5: Regression analysis of complexity on primary technology

Variable	*Dependent variable:*							
	Number of unique terms/ETO posting		*Cognitive complexity*		*Manual complexity*		*Overall complexity*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Forming	-0.059	-0.024	-0.419*	0.357*	2.957***	1.766***	2.741***	2.123***
	(0.140)	(0.111)	(0.239)	(0.210)	(0.430)	(0.383)	(0.559)	(0.471)
Molding	-0.611***	-0.657***	-0.765***	-0.098	4.545***	3.118***	3.837***	3.020***
	(0.157)	(0.130)	(0.254)	(0.238)	(0.509)	(0.523)	(0.531)	(0.595)
AM	0.793***	0.264	5.268***	3.785***	6.078***	3.534***	10.935***	7.319***
	(0.182)	(0.185)	(0.901)	(0.668)	(0.580)	(0.570)	(1.154)	(0.825)
Chemical	0.782***	0.306*	-0.245	-0.074	6.105***	3.571***	5.244***	3.498***
	(0.170)	(0.171)	(0.271)	(0.341)	(0.778)	(0.789)	(0.827)	(0.852)
Assembly	0.864***	0.347***	4.245***	2.312***	2.163***	-0.779***	6.275***	1.533***
	(0.111)	(0.116)	(0.428)	(0.403)	(0.307)	(0.295)	(0.624)	(0.572)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,816	9,816	9,816	9,816	9,816	9,816	9,816	9,816
R^2	0.041	0.127	0.081	0.264	0.126	0.265	0.107	0.284
Adjusted R^2	0.040	0.124	0.080	0.262	0.126	0.263	0.106	0.282

Notes: Standard errors (in parentheses) are clustered at the firm level. All regressions include five measures of automation intensity, number of postings per plant, number of plants per firm, commuting zone's population of working age, union status, and 3-digit NAICS as control variables. Subtraction is the reference group. Sample includes 9,816 plants (703 forming plants, 305 molding plants, 5,361 subtraction plants, 99 AM plants, 2,458 chemical plants, and 890 assembly plants. Cognitive complexity = nonroutine analytic intensity − routine cognitive intensity. Manual complexity = nonroutine manual intensity − routine manual intensity. Overall complexity = cognitive complexity + manual complexity. The intensity measures are constructed by dividing the number of ETO tasks and skills related to each complexity category divided by the total number of ETO tasks and skills in a plant, taking into account the frequency of each task/skill. *p<0.1; **p<0.05; ***p<0.01.

Table 5 shows the association of production technologies with plant complexity. We estimate four measures of complexity: the number of plant-level unique terms normalized by the number of ETO postings, cognitive and manual complexity measures, and their aggregates. Technologies exhibit a wide variation in complexity, as indicated by the significance of the majority of technology coefficients, even after controlling several variables–plant size, parent firm's size, local market size, union coverage, and product variety. The first measure indicates the heterogeneity of skills and tasks performed in a plant. A more complex plant will have more heterogenous terms in its job postings due to more variety of tasks performed and skills required to perform them. Our alternative measures of complexity generally show consistent results.

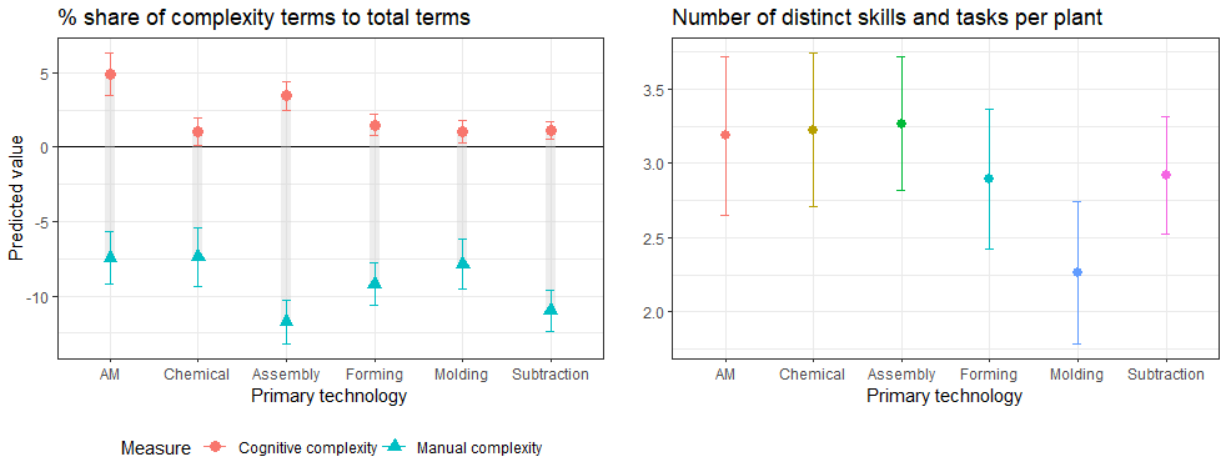
Supporting our prediction, additive manufacturing, chemical, and assembly are technologically more complex with more diverse plant-level unique tasks and skills. This variation becomes weaker after introducing covariates, but the signs remain consistent (column 2). With respect to our key measure of complexity, columns (7) and (8) show that relative to subtraction, the other five technologies have higher levels of overall complexity, with additive manufacturing exhibiting the highest level. The magnitudes decrease and R^2 shows a meaningful increase after covariates are introduced, indicating plant-level complexity is a mix of various factors, and yet technologies have incremental validity over the others. The cognitive and manual components show more variations [columns (3)-(6)]. Only additive manufacturing and assembly consistently show high cognitive complexity, whereas the other three technologies exhibit equal or lower levels compared to subtraction. Manual complexity shows more consistent results, albeit the coefficient for assembly switch signs after introducing covariates.[32] Next, we proceed to depict the predicted value of complexity in each technology, holding the covariates at their mean values. Hence, Figure 2 below shows the predicted value of complexity for typical plants in each technology.

Panel (a) visualizes the predicted values of cognitive and manual complexity. Additive manufacturing has the highest cognitive complexity intensity with nonroutine cognitive being five percent more frequent than routine cognitive terms. On the other end, molding and chemical have almost equal intensity of nonroutine and routine cognitive complexity terms. Subtraction and assembly have the lowest manual complexity intensity, with larger than ten percent of terms associated with more routine than nonroutine manual tasks.[33] Panel (b) depicts the predicted values of the number of unique tasks and skills, estimated from column 2 of Table 5. The values represent the expected number of unique tasks and skills

[32]Perhaps, this is due to assembly plants being highly automated, which increases their process complexity. After controlling for five automation intensity measures, the remaining complexity explainable by production technology becomes much lower. This highlights the importance of controlling levels of automation in examining manufacturing technologies, as the two are closely intertwined.

[33]As we mentioned above, the negative values exist because there are higher numbers of tasks and skills related to routine manual—-the subtrahend for manual complexity-—than nonroutine manual.

Figure 2: Predicted values of plant complexity



(a) Number of unique tasks and skills/ETO posting

(b) Cognitive and manual complexity

Notes: Panel (a) is based on model (2), and panel (b) on models (4) and (6) in Table 5. Each point represents a predicted value for each technology while keeping other variables (i.e., intensity of automation, number of job postings per plant, parent firm's number of plants, and commuting zone's working age population) at their mean values. Whiskers represent 95-percent confidence intervals based on robust standard errors clustered at the parent firm level. The sample includes 9,816 plants (703 forming plants, 305 molding plants, 5,361 subtraction plants, 99 AM plants, 2,458 chemical plants, and 890 assembly plants) within NAICS 32 and 33. Cognitive complexity = nonroutine analytic − routine cognitive; more positive values indicate more nonroutine analytic task intensity at the plant level. Manual complexity = nonroutine manual − routine manual; more negative values indicate more routine manual task intensity at the plant level.

in each technology for the average levels of automation intensity, plant size, parent firm's size, and local market size. The order of values is generally consistent with our technology characterization in Table 1, based on which additive manufacturing, chemical, and assembly have more tasks and skills relative to forming, molding, and subtraction.

The findings suggest that additive manufacturing is among the most complex technologies. We also find that assembly requires comparatively more tasks and skills that are cognitively complex but also manually routinized. We interpret this as due to these plants being technologically advanced with the application of robots on the shop floor, such as in microchip or car assembly plants (e.g., Krzywdzinski, 2021).

5.2 Technology and task interdependence

We now examine the determinants of the two types of interdependence, sequential and reciprocal. Table 3 indicates that task interdependence and complexity are correlated. A simple process requires fewer interactions, in which an output of a worker becomes an input for another, thus exhibiting sequential interdependence. In contrast, in a more complex process, more workers need to work together to accomplish a common goal, and their jobs require more back and forth interactions with coworkers. Thus, more complex technologies will have higher reciprocal interdependence than—-but comparable sequential interdependence with—-less complex technologies. Table 6 and Figure 3 show the regression results and predicted values for the effects of technologies on task interdependence measures, respectively.

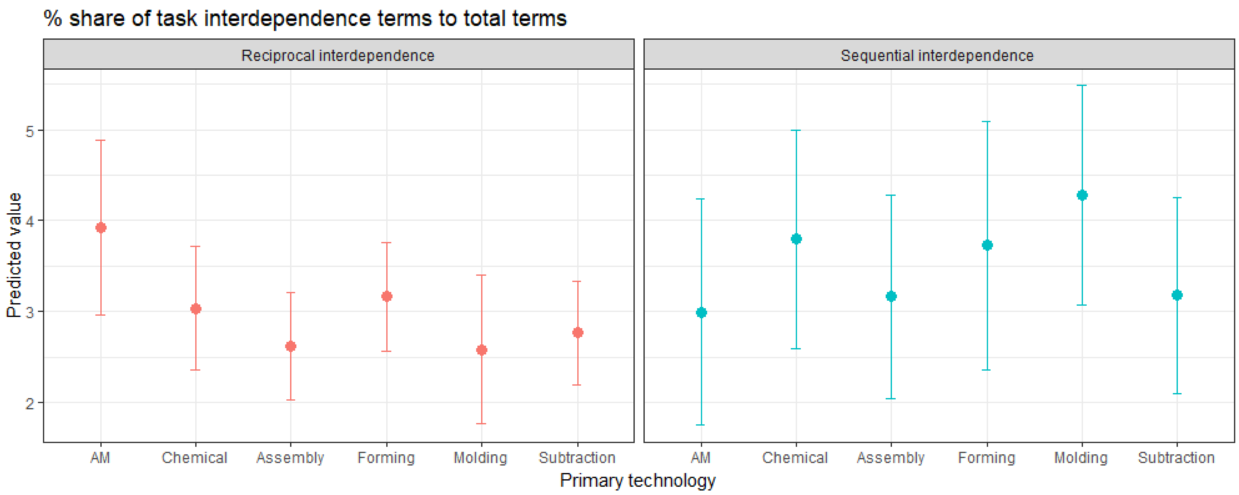
Table 6: Regression analysis of task interdependence on primary technology

Variable	*Dependent variable:*					
	Reciprocal interdependence		*Sequential interdependence*		*Overall interdependence*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Forming	0.457*	0.396	0.702***	0.549***	1.159***	0.945***
	(0.249)	(0.259)	(0.216)	(0.171)	(0.238)	(0.227)
Molding	-0.097	-0.185	1.272***	1.095***	1.175***	0.911***
	(0.321)	(0.341)	(0.300)	(0.295)	(0.186)	(0.209)
AM	1.137**	1.157***	-0.140	-0.187	0.997***	0.970***
	(0.459)	(0.442)	(0.409)	(0.400)	(0.289)	(0.293)
Chemical	0.526*	0.271	1.088***	0.617***	1.614***	0.888***
	(0.314)	(0.338)	(0.141)	(0.199)	(0.242)	(0.220)
Assembly	-0.298**	-0.146	0.044	-0.011	-0.253**	-0.156
	(0.148)	(0.150)	(0.092)	(0.094)	(0.105)	(0.114)
Control variables	No	Yes	No	Yes	No	Yes
Observations	9,816	9,816	9,816	9,816	9,816	9,816
R^2	0.015	0.035	0.037	0.053	0.041	0.064
Adjusted R^2	0.015	0.032	0.036	0.050	0.040	0.061

Notes: Standard errors (in parentheses) are clustered at the firm level. All regressions include five measures of automation intensity, number of postings per plant, number of plants per firm, commuting zone's population of working age, union status, and 3-digit NAICS as control variables. Subtraction is the reference group. Sample includes 9,816 plants (703 forming plants, 305 molding plants, 5,361 subtraction plants, 99 AM plants, 2,458 chemical plants, and 890 assembly plants. Overall interdependence = reciprocal interdependence + sequential interdependence. The intensity measures are constructed by dividing the number of ETO tasks and skills related to each interdependence category divided by the total number of ETO tasks and skills in a plant, taking into account the frequency of each task/skill. *p<0.1; **p<0.05; ***p<0.01.

The regression table indicates that additive manufacturing is the most reciprocally interdependent technology, whereas the other five technologies are comparably similar to subtraction. On the other hand, forming, molding, and chemical are sequentially more interdependent, whereas additive manufacturing and assembly are comparable to subtraction. Finally, the overall interdependence measure indicates that chemical, forming, molding, and additive manufacturing have significantly higher levels of interdependence, whereas assembly is lower than subtraction. Figure 3 shows that most technologies have overlapping confidence intervals of reciprocal interdependence intensity, yet additive manufacturing still has the highest predicted values of between 3 to 5 percent. On the other hand, two complex technologies (i.e., additive manufacturing and assembly) have comparably lower sequential interdependence than forming, molding, and assembly. We discuss further our interpretations of these findings below.

Figure 3: Predicted values of task interdependence



Notes: Figures are based on models (2) and (4) in Table 6. Each point represents a predicted value for each technology while keeping other variables (i.e., intensity of automation, number of job postings per plant, parent firm's number of plants, and commuting zone's working age population) at their mean values. Whiskers represent 95-percent confidence intervals based on robust standard errors clustered at the parent firm level. The sample includes 9,816 plants (703 forming plants, 305 molding plants, 5,361 subtraction plants, 99 AM plants, 2,458 chemical plants, and 890 assembly plants) within NAICS 32 and 33.

In general, we find that the pattern of task interdependence is more nuanced. The results support the conclusion that more complex technologies are reciprocally more interdependent, and sequential interdependence also shows meaningful variations across technologies that goes on the opposite direction. Additive manufacturing has a shorter process and thus sequentially less interdependent; chemical manufacturing requires a long, elaborate process to perform chemical reactions and purification, each needs to be carried out in a specific order, and thus it has higher sequential interdependence; forming and molding (collectively termed netshape processes) are performed in steps that adhere to a specific order, and consequently, tasks are more sequentially interdependent. Finally, subtraction and assembly exhibit comparable sequential interdependence to additive manufacturing. We interpret this as a consequence of more automation and machinery implemented in the two technologies (e.g., robotic arms in assembly and CNC in subtraction), which makes labor tasks to be more independent. In sum, these findings demonstrate that the two types of interdependence must be considered separately as they may not go hand in hand.

5.3 Technology, division of labor, and specialization

Plant complexity has implications on how jobs are organized in a plant. More complex technologies require more parameters to adjust and more diverse and cognitively complex skills and tasks for workers. In turn, they require more jobs to carry out the tasks while simultaneously more tasks and skills are bundled in a job. Table 7 indicates that manufacturing technologies vary in how jobs are designed. As discussed above, plants with more complex technologies consist of more diverse (i.e., unique) tasks and skills. Not surprisingly, these plants also organize workers in more jobs, and each job consists of more tasks and skills. Additive manufacturing, chemical, and assembly have more unique jobs than subtraction, as measured by unique job titles (column 2) and skillsets (column 4). The average job in these three technologies also consists of more unique tasks and skills relative to subtraction (i.e., deeper specialization). Forming is similar to subtraction with respect to the number of unique tasks and skills per job title, whereas the coefficient for molding is significantly lower. Substituting unique skillsets for unique job titles yields similar results.

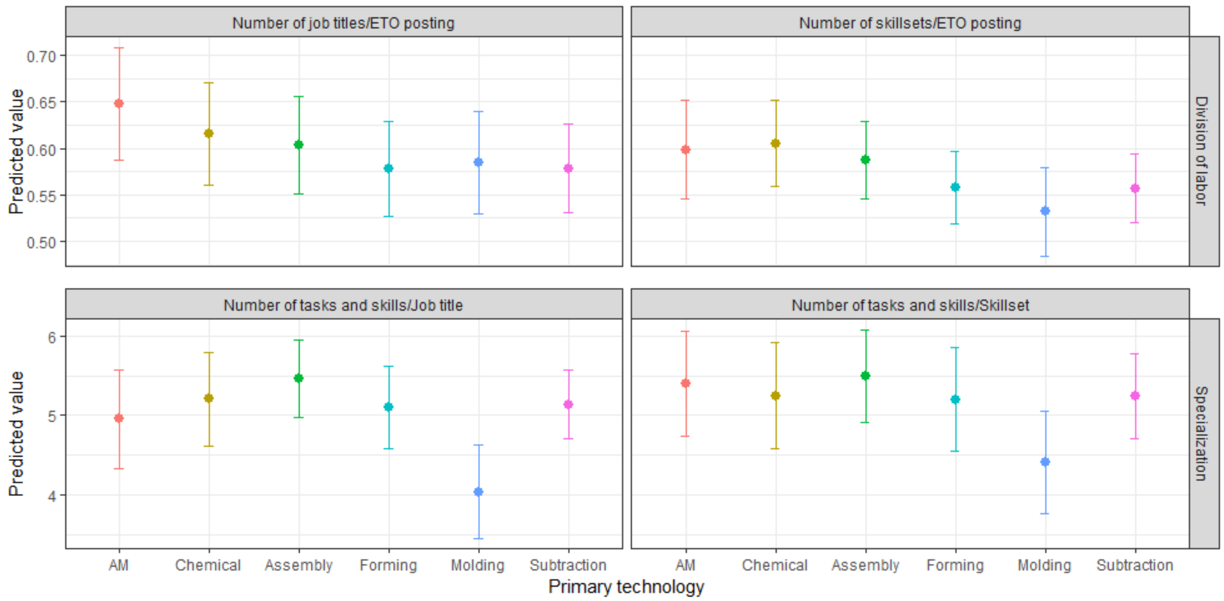
Table 7: Regression analysis of division of labor and specialization on primary technology

Variable	*Dependent variable:*							
	Division of labor				*Specialization*			
	Number of unique job titles/ETO posting		*Number of unique skillsets/ETO posting*		*Number of unique tasks and skills/job title*		*Number of unique tasks and skills/skillset*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Forming	-0.028*	-0.001	-0.019	0.001	0.146	-0.042	0.056	-0.043
	(0.015)	(0.013)	(0.014)	(0.012)	(0.196)	(0.159)	(0.164)	(0.133)
Molding	-0.011	0.006	-0.033**	-0.025	-0.886***	-1.102***	-0.726***	-0.839***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.225)	(0.197)	(0.194)	(0.164)
AM	0.084***	0.069***	0.070***	0.042**	0.487*	-0.186	0.711***	0.157
	(0.020)	(0.020)	(0.020)	(0.020)	(0.258)	(0.229)	(0.205)	(0.200)
Chemical	0.041***	0.037**	0.057***	0.049***	0.766***	0.070	0.645***	-0.0004
	(0.013)	(0.015)	(0.014)	(0.015)	(0.173)	(0.210)	(0.171)	(0.197)
Assembly	0.033***	0.025**	0.056***	0.031***	1.058***	0.325**	0.834***	0.257**
	(0.011)	(0.012)	(0.010)	(0.011)	(0.132)	(0.130)	(0.108)	(0.112)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	9,816	9,816	9,816	9,816	9,816	9,816	9,816	9,816
R2	0.015	0.040	0.026	0.061	0.026	0.123	0.023	0.118
Adjusted R2	0.014	0.038	0.026	0.059	0.026	0.120	0.023	0.116

Notes: Standard errors (in parentheses) are clustered at the firm level. All regressions include five measures of automation intensity, number of postings per plant, number of plants per firm, commuting zone's population of working age, union status, and 3-digit NAICS as control variables. Subtraction is the reference group. Sample includes 9,816 plants (703 forming plants, 305 molding plants, 5,361 subtraction plants, 99 AM plants, 2,458 chemical plants, and 890 assembly plants). *p<0.1; **p<0.05; ***p<0.01.

Figure 4 depicts the predicted values of division of labor and specialization from columns (2), (4), (6), and (8) of Table 7. A consistent pattern emerges from the four panels. More complex technologies are also characterized by greater division of labor (i.e., more unique job titles and unique skillsets per ETO job posting) and deeper and wider specialization (i.e., more tasks and skills per job title or skillset), although the 95-percent confidence intervals highly overlap. Around 55 to 60 percent of ETO job postings in all technologies are unique, and an average ETO job consists of around four to five tasks and skills.

Figure 4: Predicted values of division of labor and specialization



Notes: Division of labor figures (i.e., top figures) are based on models (2) and (4), and specialization figures (i.e., bottom figures) on models (6) and (8) in Table 7. Each point represents a predicted value for each technology while keeping other variables (i.e., intensity of automation, number of job postings per plant, parent firm's number of plants, and commuting zone's working age population) at their mean values. Whiskers represent 95-percent confidence intervals based on robust standard errors clustered at the parent firm level. The sample includes 9,816 plants (703 forming plants, 305 molding plants, 5,361 subtraction plants, 99 AM plants, 2,458 chemical plants, and 890 assembly plants) within NAICS 32 and 33. A skillset is a string of terms annotated by Burning Glass Technology that reflects the content of a job posting.

Collectively, these findings support our classification of production technologies with respect to division labor and specialization. First, we find that more jobs are designed in plants with more complex technologies, evidence of more detailed division of labor. Second, workers in highly complex technologies need to attend to multifaceted parameters, which tend to increase the number of tasks they perform and skills with which they are equipped. More tasks and skills are thus bundled into a job for workers in these plants, evidence of deeper and wider specialization in more technologically complex plants.

5.4 Technology and span of control

We predict that plant complexity is negatively associated with the number of subordinates an average manager supervises. Table 8 shows that more complex technologies have narrower spans of control; additive manufacturing and chemical exhibit lower ratios of non-managers to managers relative to subtraction (column 2). Further investigation reveals that this variation stems from core manufacturing employees (i.e., technical managers, engineers, technicians, and operators; column 4). On the other hand, the coefficients for indirect employees to non-technical managers show weaker significance, implying less variation across technologies (column 6). Finally, more complex technologies are also associated with higher ratios of engineers to operators, indicating more high-skilled workers needed to support operators in more technologically complex plants (column 8).

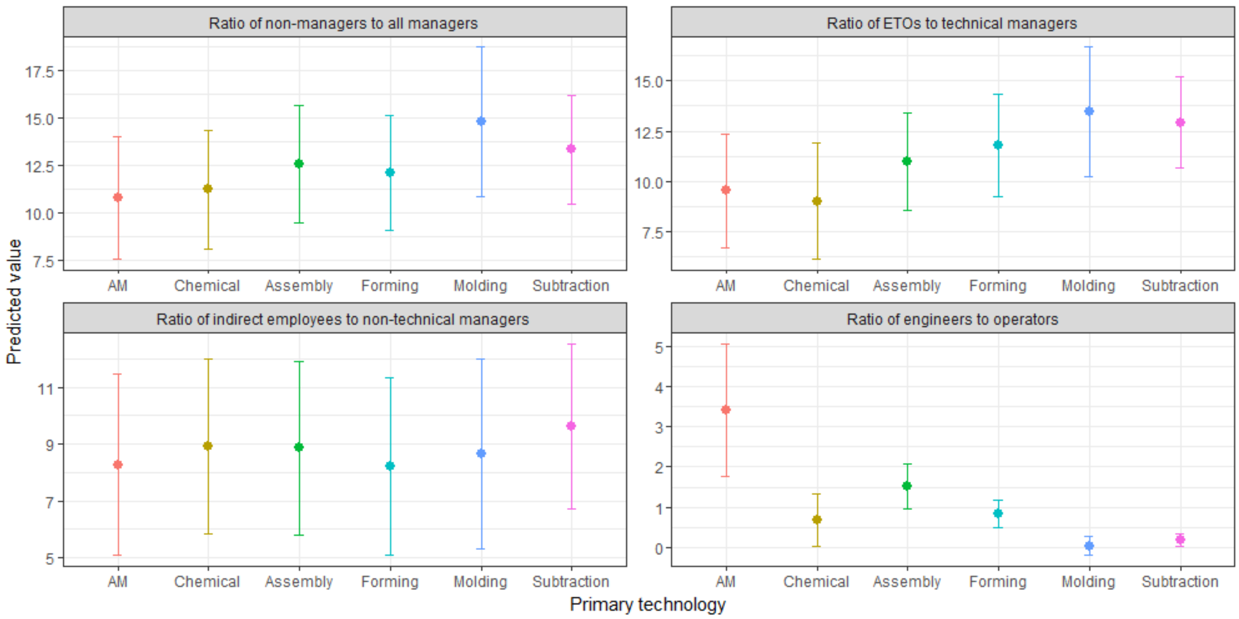
Table 8: Regression analysis of span of control on primary technology

	Dependent variable:							
Variable	*Ratio of non-managers to all managers*		*Ratio of ETOs to technical managers*		*Ratio of indirect employees to non-technical managers*		*Ratio of engineers to operators*	
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*	*(8)*
Forming	-0.584	-1.268*	-1.263*	-1.153*	-0.028	-1.418**	0.378**	0.663***
	(0.843)	(0.764)	(0.685)	(0.701)	(0.927)	(0.670)	(0.185)	(0.182)
Molding	1.515	1.429	0.054	0.506	-0.166	-0.958	-0.351***	-0.142
	(1.506)	(1.389)	(1.113)	(1.216)	(0.726)	(0.828)	(0.084)	(0.104)
AM	-4.628***	-2.576***	-5.666***	-3.405***	-1.768***	-1.357**	3.931***	3.239***
	(0.830)	(0.799)	(0.930)	(0.913)	(0.681)	(0.680)	(0.917)	(0.836)
Chemical	-4.346***	-2.120***	-6.599***	-3.923***	-0.849*	-0.703	1.024***	0.504
	(0.627)	(0.685)	(0.639)	(0.965)	(0.481)	(0.589)	(0.169)	(0.330)
Assembly	-2.731***	-0.787	-3.817***	-1.950***	-1.201**	-0.755	2.131***	1.339***
	(0.660)	(0.641)	(0.530)	(0.537)	(0.542)	(0.541)	(0.286)	(0.280)
Control variables	No	Yes	No	Yes	No	Yes	No	Yes
Observations	8,237	8,237	7,076	7,076	7,123	7,123	9,536	9,536
R2	0.024	0.060	0.046	0.071	0.002	0.027	0.046	0.102
Adjusted R2	0.023	0.056	0.046	0.067	0.002	0.023	0.046	0.099

Notes: Standard errors (in parentheses) are clustered at the firm level. All regressions include five measures of automation intensity, number of postings per plant, number of plants per firm, commuting zone's population of working age, union status, and 3-digit NAICS as control variables. Subtraction is the reference group. The number of samples for each dependent variable differs due to indivisible values. Technical managers include job postings with SOC codes 11-1021 (General and Operations Managers), 11-3021 (Computer and Information Systems Managers), 11-3051 (Industrial Production Managers), 11-3061 (Purchasing Managers), 11-3071 (Transportation, Storage, and Distribution Managers), 11-9013 (Farmers, Ranchers, and Other Agricultural Managers), 11-9021 (Construction Managers), 11-9041 (Architectural and Engineering Managers), 11-9111 (Medical and Health Services Managers), and 11-9121 (Natural Sciences Managers). Non-technical managers include SOC code 11 other than technical managers. All managers include technical and non-technical managers. Non-managers include job postings other than managers. Indirect employees include job postings other than managers, engineers, technicians, and operators. *p<0.1; **p<0.05; ***p<0.01.

Figure 5 illustrates the predicted values of span of control measures calculated from columns (2), (4), (6), and (8) of Table 8. A technical manager in an average subtraction plant can supervise almost 1.5 as many ETOs as a chemical plant and an additive manufacturing plant. On the other hand, the confidence intervals for the ratio of indirect employees to non-technical managers highly overlap, indicating less impact of technology to occupations not directly related to the production process. Eight indirect employees are supervised by an average manager in all technologies. Finally, this figure shows that the expected ratios of engineers to operators for additive manufacturing and assembly are larger than one, indicating that they require more engineers than operators. In contrast, the other lower complex technologies show the opposite pattern.

Figure 5: Predicted values of span of control



Notes: Figures are based on models (2), (4), (6), and (8) in Table 8. Each point represents a predicted value for each technology while keeping other variables (i.e., intensity of automation, number of job postings per plant, parent firm's number of plants, and commuting zone's working age population) at their mean values. Whiskers represent 95-percent confidence intervals based on robust standard errors clustered at the parent firm level. The sample includes plants within NAICS 32 and 33. The number of samples for each figure differs due to indivisible values. See Table 8 for more details.

These findings confirm our predictions that more complex technologies require narrower spans of control. A manager's time to oversee subordinates positively correlates with task complexity. Consequently, the number of subordinates that can be effectively managed is inversely related to task complexity. This aligns with our findings that there are fewer non-managers to managers in more complex technologies. More importantly, the variability in the cost of supervision is driven by occupations that are directly affected by the choice of technology; the number of engineers, technicians, and operators per technical manager is lower for these technologies. We also examine the ratio of indirect employees to non-technical managers as a placebo test. The impact of technology should be less prevalent for these occupations since they are not directly involved in the production process. Indeed, Figure 5 confirms that confidence intervals for the ratio of indirect employees to non-technical managers highly overlap across technologies. Finally, our findings suggest that operators in more complex technologies require more support from engineers, indicating more complex tasks in these technologies.

6 Conclusion

In the management and organization theory literature on work, distinctions among establishments based on complexity and interdependence of their technologies have a long history. In the economics literature, during the last two decades the focus was on distinctions between routine and nonroutine manual and cognitive tasks in occupations in relation to technology represented by degrees of computerization. More recently, attention has shifted to the effects of automation, robotics, and AI on workers' skills. In these varied analyses, little attention has been paid to how things are made beyond generalities such as industry, size of operation, and rarely general attributes such as batch versus continuous processes (ascribed but not measured).

This approach to research on the organization of work is appropriate but insufficient. How things are made matters to how work is organized. There are several likely reasons why management and economics researchers have yet to engage in analysis of concrete and empirically prominent technologies. Information about production technologies is not available in datasets used in research, and their investigation draws on knowledge from other fields. Establishment level research therefore requires a different approach to collecting and classifying information.

Work is increasingly a topic of wide interest and concern. "The future of work" is a frequently used phrase in academic research, policy conversations, and in exchanges among people wondering what they will be doing in the future. We have shown in our analyses that automation, AI, and robotics do matter, but so does the way things are made. Controlling for automation, AI, and robotics and many other factors, we have shown that there are important differences in division of labor, specialization, and span of control among key technologies of production. Based on engineering literature, we identified flexibility, length, and integration of the production process as key determinants of complexity and interdependence among tasks, jobs and phases in the production process. Whereas we used flexibility, length, and integration to explain work organization, we did not measure them. It is a topic that we leave for future research. We measured, however, their presumed consequences, multiple facets of complexity and interdependence. We also measured, in multiple ways, key aspects of organization of work: division of labor, specialization, and span of control.

We found a strong relationship between technology of production and complexity, and a nuanced link to sequential and reciprocal interdependence, and from there to three measures of work organization we used. Additive manufacturing, the newest of manufacturing technologies, generally followed by chemical and assembly establishments, are the most complex and have more detailed division of labor, deeper and wider specialization, and lower span of control. Plants that rely primarily on subtraction, the most common technology of production, followed by those using forming and molding, are the least complex, with less division of labor and narrower specialization, and wider span of control. We have measured the organization of work for the combined group of technical workers–engineers, technicians, and operators–for conciseness.

The source of the data that allowed investigating matters heretofore unexplored in academic research in the domain of this paper is its major strength. But this source, job vacancy postings, also has limitations. Job postings are reflections of employer demand rather than a snapshot of what happens in a plant. We considered five years' worth of job postings to capture a wider cross section of jobs, but this is only a partial substitute for a full accounting of what goes on in a plant. Another limitation is the absence of identifiable technology of production in many postings, which forced us to look only where we can identify the primary technology. We conducted various robustness checks, but this is a limitation that can only be overcome with surveys and interviews with plant representatives.

Our research has identified important relationships that managers should consider in their design of jobs along the entire production process, in hiring, and training of workers. Our findings suggest important contingencies associated with the technology of production, strongly advising against the idea of an optimal division of labor, specialization, or span of control. Of course, technology of production is not the only factor that affects the organization of work. In a separate analysis not shown here, we find that automation and size matter, too, in specific ways. In doing this, we part ways with the broad, single variable, concept of automation, that has dominated the literature. We show that different types of automation (including AI and robotics) in different phases of the production process have different effects on the organization of work. This is a fertile space for future research.

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A Appendix tables

Table A1: Technological paths

Primary technology (beginning)	*Primary technology (end)*						*Total*
	AM	*Assembly*	*Chemical*	*Forming*	*Molding*	*Subtraction*	
AM	**15**	1	2	0	0	0	18
	(83.33%)	(5.56%)	(11.11%)	(0.00%)	(0.00%)	(0.00%)	(100%)
Assembly	0	**34**	6	3	0	14	57
	(0.00%)	**(59.65%)**	(10.53%)	(5.26%)	(0.00%)	(24.56%)	(100%)
Chemical	0	2	**1,110**	1	2	17	1,132
	(0.00%)	(0.18%)	**(98.06%)**	(0.09%)	(0.18%)	(1.50%)	(100%)
Forming	0	0	6	**46**	1	5	58
	(0.00%)	(0.00%)	(10.34%)	**(79.31%)**	(1.72%)	(8.62%)	(100%)
Molding	0	0	0	2	**17**	5	24
	(0.00%)	(0.00%)	(0.00%)	(8.33%)	**(70.83%)**	(20.83%)	(100%)
Subtraction	1	9	14	11	7	**656**	698
	(0.14%)	(1.29%)	(2.01%)	(1.58%)	(1.00%)	**(93.98%)**	(100%)

Notes: A primary technology is assigned if a plant has at least 20 percent job postings associated with a technology and it is the largest proportion among the six technologies. Beginning primary technology is calculated from period 2013-2017. Ending primary technology is calculated from period 2018-2022. Total number of plants that stayed in a particular technology during 2013-2022 is 1,878 (94.5 percent). Narrowing the aggregation period to 3 years (i.e., 2013-2015 vs. 2020-2022) yields a similar result. All plants are in manufacturing (NAICS 31-33).

Table A2: Control variables used in structural equation modeling

Variable	*Dependent variable:*					
	Complexity	*Reciprocal interdependence*	*Sequential interdependence*	*Division of labor*	*Specialization*	*Span of control*
	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*
Entire process automation intensity (primary)	0.058***	-0.005	-0.034***	0.037*	0.087***	-0.026*
	(0.012)	(0.012)	(0.012)	(0.020)	(0.019)	(0.014)
Entire process automation intensity (secondary)	-0.014*	0.029*	-0.011	0.010	0.034	-0.017***
	(0.008)	(0.015)	(0.008)	(0.018)	(0.023)	(0.006)
Entire process automation intensity (tertiary)	0.015**	0.001	-0.020**	0.050***	0.064***	-0.024***
	(0.006)	(0.009)	(0.009)	(0.009)	(0.014)	(0.003)
Pre-production automation intensity	0.334***	-0.035**	-0.085***	-0.002	0.014	-0.020
	(0.023)	(0.014)	(0.015)	(0.019)	(0.019)	(0.014)
Production automation intensity (primary)	-0.243***	-0.012	-0.006	0.063***	-0.091***	0.055***
	(0.021)	(0.019)	(0.016)	(0.017)	(0.012)	(0.021)
Production automation intensity (secondary)	0.045***	-0.060***	-0.049***	-0.015	0.043***	0.034***
	(0.013)	(0.011)	(0.011)	(0.014)	(0.013)	(0.012)
Number of job postings	0.089***	0.073***	-0.017**	-0.078***	-0.262***	-0.022***
	(0.011)	(0.014)	(0.008)	(0.014)	(0.027)	(0.008)
Commuting zone's population of working age	0.034***	-0.026*	0.020	0.068***	0.039***	-0.051***
	(0.013)	(0.014)	(0.013)	(0.015)	(0.014)	(0.011)
Parent firm's number of plants	0.040	0.028	0.034	0.058*	-0.010	-0.019
	(0.038)	(0.020)	(0.024)	(0.031)	(0.017)	(0.018)
Union	-0.299**	-0.059	0.115	0.376**	-0.218	-0.308**
	(0.136)	(0.205)	(0.241)	(0.172)	(0.145)	(0.128)
NAICS 321	-0.404	0.517*	0.299	0.097	-0.871***	0.046
	(0.263)	(0.290)	(0.318)	(0.255)	(0.310)	(0.182)
NAICS 322	0.072	0.626**	0.071	-0.199	-0.789**	0.261
	(0.253)	(0.290)	(0.254)	(0.306)	(0.327)	(0.195)
NAICS 323	-0.044	0.189	-0.131	0.109	-1.017***	0.478*
	(0.252)	(0.322)	(0.269)	(0.286)	(0.321)	(0.270)
NAICS 324	-0.015	0.382	-0.075	0.114	-0.675**	0.009
	(0.264)	(0.322)	(0.243)	(0.268)	(0.329)	(0.178)
NAICS 325	0.121	0.364	0.317	0.383	-0.634**	0.054
	(0.241)	(0.263)	(0.224)	(0.240)	(0.306)	(0.170)
NAICS 326	-0.106	0.435	0.271	0.019	-0.924***	0.199
	(0.250)	(0.291)	(0.253)	(0.249)	(0.315)	(0.170)
NAICS 327	-0.319	0.087	0.050	0.119	-0.652**	0.104
	(0.278)	(0.279)	(0.314)	(0.266)	(0.313)	(0.176)
NAICS 331	-0.321	0.234	0.076	0.320	-0.711**	0.193
	(0.260)	(0.262)	(0.229)	(0.255)	(0.309)	(0.178)
NAICS 332	-0.091	0.481*	0.188	0.394*	-0.781***	0.083
	(0.236)	(0.256)	(0.223)	(0.232)	(0.301)	(0.166)
NAICS 333	-0.133	0.360	0.098	0.270	-0.754**	0.207
	(0.237)	(0.262)	(0.221)	(0.234)	(0.304)	(0.170)
NAICS 334	0.207	0.310	0.176	0.338	-0.738**	0.045
	(0.235)	(0.253)	(0.220)	(0.235)	(0.301)	(0.161)
NAICS 335	-0.172	0.457	0.271	0.162	-0.770**	0.187
	(0.252)	(0.287)	(0.231)	(0.241)	(0.313)	(0.202)
NAICS 336	-0.016	0.260	0.280	0.304	-0.973***	0.195
	(0.235)	(0.255)	(0.234)	(0.236)	(0.302)	(0.168)
NAICS 337	-0.311	0.537	0.317	0.315	-1.113***	-0.113
	(0.270)	(0.353)	(0.276)	(0.258)	(0.313)	(0.187)
NAICS 339	0.247	0.292	0.293	0.376	-0.757**	0.069
	(0.250)	(0.265)	(0.232)	(0.249)	(0.312)	(0.182)

Notes: Coefficients above are estimated using multicategorical structural equation modeling with the *lavaan* package in R. Standard errors (in parentheses) are clustered at the parent firm level. All variables are standardized, except dummies for union status and NAICS. Analysis is performed on plants with main NAICS 32 and 33. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

B Appendix figures

Figure B1: Production technology flowchart