Not all Technological Change is Equal: Disentangling Labor Demand Effects of Automation and Parts Consolidation

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Abstract

We separate and directly measure the labor-demand effects of two simultaneous forms of technological change—automation and parts consolidation. We collect detailed shop-floor data from four semiconductor firms with different levels of automation and parts consolidation. For each process step, we collect task data and measure operator skill requirements, including operations and control, near vision, and dexterity requirements using the O*NET survey instrument. We then use an engineering process model to separate the effects of the distinct technological changes on these process tasks and operator skill requirements. Within an occupation we show that aggregate measures of technological change can mask the opposing skill biases of multiple simultaneous technological changes. In our empirical context, automation polarizes skill demand as routine, codifiable tasks requiring low and medium skills are executed by machines instead of humans, while the remaining and newly created human tasks tend to require low and high skills. Parts consolidation converges skill demand as formerly divisible low and high skill tasks are transformed into a single indivisible task with medium skill requirements and higher cost of failure. We propose a new theory for the differential labor effects of technological changes on tasks, and hence jobs. Understanding these differential effects of technologies on labor outcomes is a critical first step toward analyzing the impact of emerging technological changes on labor demand, and eventually markets.

1. Introduction

A sizable literature has emerged around the influence of technological change on employment, wages, and skill demand of labor (Card and DiNardo 2002, Autor et al. 2003, Bartel et al. 2007, Vivarelli 2014, Ales, Kurnaz, Sleet 2015, Acemoglu and Restrepo 2017). A core concern of this literature has been the relationship between technological change and increases and decreases in demand for particular skills. For example, studies have highlighted skill-biased technological change (SBTC) that heterogeneously affects relative productivity of different types of labor and, hence, increases demand for certain (typically higher-skilled) labor while decreasing demand for other (typically middle- or lower-skilled) forms (Autor, Katz and Kearny 2008, Acemoglu and Autor 2011, Autor and Dorn 2013). These studies suggest that computational and automation technology is a key driver of increases in demand for high skills relative to "middle skills", causing wage inequality between skill groups.

While scholars have recognized that multiple forms of technological change can occur concurrently (Goldin and Katz 1998), the SBTC literature has not sought to separately measure simultaneous technological changes. Traditional methods have difficulty separately measuring the effects of simultaneous technological changes given available data, as aggregate observations capture the joint effect of all simultaneous changes. Furthermore, because of data availability, the literature has not directly measured the effect of technological change (past, current, or emerging) on labor demand, instead relying on indirect measures of technological change (e.g. capital) and then relating these to labor outcomes. Such approaches may conflate the effects of different technologies with opposing labor implications.

Directly measuring the effects of different simultaneous technological changes on the demand for labor skill is relevant for labor economics, management, and policy. Technologies that affect demand for different types of skills may necessitate different training or other responses by firms and policymakers. There is historical evidence in the engineering literature of widespread simultaneous technological changes across a range of industries (Abernathy and Utterback 1978). Examples include process changes in the 19th to mid-20th centuries driven by simultaneous innovations in machine tooling, materials and electrification (Rosenberg 1963, David 1985, Hounshell 1984). More modern cases range from the simultaneous adoption of broadband technology and automation across industries (Gramlich 1994, Koutroumpis 2009), to simultaneous parts consolidation (Lecuyer 1999) and automation (Pillai et al. 1999) in semiconductors, to simultaneous automation (Jamshidi et al. 2010) and adoption of additive manufacturing (Mueller 2012) in aerospace. These distinct technological changes may not only produce competing designs from a consumer perspective, but also variations in the factor (e.g. labor) content of production (Anderson and Tushman 1990). Moreover, simultaneous technological changes can be complementary or occur independently from each other, and different combinations of technologies can be implemented by different firms or regions (e.g. Chung and Alcacer 2002, Fuchs and Kirchain 2010, Fuchs et al. 2011, Fuchs, Kirchain, and Liu 2011).

To separate and measure the labor demand implications of simultaneous technological changes, we use engineering process modeling. Our engineering models enable us to determine the quantity and skills of laborers needed to produce a given amount of output, conditional on a particular set of production technologies and operating parameters. We focus on operator jobs, which in our context require in the U.S. a high school education, and overseas sometimes require less. This shop-floor operator focus helps us characterize how technological change affects skill demand within a population with low workforce participation (BLS 2018) and historic vulnerability to technological displacement in aggregate (Autor and Dorn 2013, Acemoglu and Restrepo 2017).

Our engineering process model is a *process-based cost model* (PBCM), which unpacks the firms' production function into individual steps, and uses existing data and technical knowledge to simulate each step (with data for some steps disaggregated still further into the detailed tasks within a step). PBCMs have been used for over 10 years in engineering and management to understand the effects of technological decisions on factor demands and costs prior to large-scale investments (Field, Roth, Kirchain 2007, Fuchs et al. 2008). These models have informed engineering and production decisions in multiple industries (Field, Roth, Kirchain 2007, Huang et al. 2018, Laureijs et al. 2018). We extend these modeling techniques to include a detailed portrayal of labor skill requirements per process step. For our purposes, PBCM has the following advantages: (1) it allows us to recover economic production functions without relying on simplifications and structural assumptions for mathematical convenience that may not be well supported by the nature of a technology or production process (Chenery 1949, Lave 1966, Pearl and Enos 1975), (2) it makes use of production step-level inputs rather than aggregate data, allowing us to map technical characteristics (such as the level of automation) directly to the production tasks and associated labor consequences, and (3) it allows us to disentangle the labor demand implications of simultaneous technical changes by constructing counterfactuals of independently applied combinations of technologies to the production process that are technically feasible but are not observed in historical firm operations, including emerging technologies that do not exist yet in large-scale production.

We focus on disentangling two examples of technological change: automation, and parts consolidation. Automation is a process innovation that reflects the reallocation of tasks from human operators to technical systems (Frohm et al. 2008). Parts consolidation is a product innovation involving the redesign of a product that allows multiple formerly discrete parts to be fabricated as a single component (Schwedes 2001). Note that while parts consolidation is a product innovation, it also requires reorganization of the production process and associated tasks. These two technological changes occur simultaneously with each other in industrial and technological contexts as diverse as semiconductors (Lecuyer 1999, Pillai et al. 1999), aerospace (Jamshidi et al. 2009, Lyons 2014) and automobiles (Fuchs et al. 2008, Shimokawa et al. 2012). We focus on a subset of the semiconductor industry, specifically, optoelectronics. In optoelectronics, there exists a broad range of functionally homogenous but competing designs with different levels of parts consolidation, as well as different levels of automation in their production.

Building on previous process-based cost modeling (Fuchs et al. 2011), we collect data from four firms representative of leading capabilities and 42-44% of production volume across the industry for five different designs, which represent the range of automation and parts consolidation across the industry. Our data includes detailed operational inputs (e.g. machine prices, cycle times, yields, downtimes, material usage, operator time, etc.) for 481 process steps, totaling over 9000 inputs; upper and lower bounds for these operational inputs; employee education and experience requirements; and three measures of employee skill requirements (using the Department of Labor sponsored O*NET Content Model (2017)) for direct line operators.

Using direct measures of the effect of technological change on labor demand, we find that aggregate measures of technological change can mask the opposing skill biases of multiple simultaneous changes. Our paper makes five main contributions: (1) We directly measure the influence of technological changes on demand for labor characteristics of manufacturing shop-floor operators in terms of detailed heterogeneous skill requirements. (2) We disentangle the effects of two different types of simultaneous technological change—process automation and parts consolidation. (3) Where most of the SBTC literature has focused on demand shifts between occupations, we capture the effects of technological change within an occupation. (4) Through these methodological contributions, we find evidence of heterogeneous effects of differing technologies on the demand for labor skill. Empirically, we find that automation polarizes while parts consolidation can converge skill requirements for operators. These results suggest that understanding the differential effects of technologies on labor outcomes may be key to analyzing the impact of emerging technological changes on labor demand, and eventually markets. (5) Drawing from our empirical findings, we propose a new theory for the differential labor effects of technological changes in which automation leads to task substitution, parts consolidation to task elimination and transformation, and both sometimes require task creation.

2. Literature Review

A significant literature has emerged on the influence of technological change on wage and employment inequality, especially in manufacturing, with skill-biased technological change (SBTC) a proposed driver (Card and DiNardo 2002). SBTC occurs when a technology has a heterogeneous effect on the marginal product of different types of labor (Card and DiNardo 2002, Bartel et al. 2004) or when technology enables substitution between certain types of labor and other factors of production (Brynjolfsson and Hitt 1995, Dewan and Min 1997, Bresnahan et al. 2002). Skill-biased technological change has been associated with high returns to skill, particularly in the case of the automation of routine tasks (Autor et al. 2003, Autor and Dorn 2013), and with information technology adoption both across the economy (Bresnahan et al. 2002, Michaels et al. 2014, Atasoy et al. 2016) and on the factory floor (Bartel et al. 2007). Organizational change and management innovations can also lead to heterogeneous worker productivity effects (Caroli and van Reenen 2001, Ichniowski and Shaw 2009). Detailed characteristics of a technology have relevance for its productivity and hence labor implications (Bartel et al. 2004), such as the types of tasks susceptible to automation (Autor, Levy and Murnane 2003). Despite the importance of individual technological characteristics and evidence of technological heterogeneity within the literature, past work in SBTC has not sought to separate the potentially different labor effects of simultaneous technological changes. The existing literature linking technological change and labor outcomes is also primarily focused on the effects of historical technological change on labor market outcomes, and thus may also face challenges anticipating the consequences of emerging technologies for labor demand.

In order to characterize labor effects of SBTC, the literature draws heavily (but not solely) on education as a measure of skill (Autor, Levy and Murnane 2003, Acemoglu and Autor 2011, Carneiro and Lee 2011, Autor and Dorn 2013). Different technological changes may have important, heterogeneous effects on skill requirements within the same educational category (e.g. manufacturing jobs with all the same low educational requirements). Other skill measures include past wages (Autor, Levy and Murnane 2003, Autor and Dorn 2013), with the potential to mask important worker reallocations and other labor force shifts (Lane 2005). A few studies have collected detailed technical and operation skill and training information on machine operators (Bartel et al. 2004, Bartel et al. 2007): this past work describes the effects of technological change on manufacturing operator skills, but measures these effects indirectly, through firm-level surveys of whether specific skills become more or less important to operators in aggregate. These studies suggest a direction of the effect of technological change but, lacking measures for differences in the level of skill required and the share of operators affected, not its magnitude, as well as possibly overlooking multimodal effects of technological change within the same skill (i.e. rather than a bidirectional skewing of skill requirements). In addition to education and wage as intermediaries for skill, a literature has also emerged suggesting that technological change may substitute for labor in certain types of tasks, potentially replacing “routine” labor while increasing demand for cognitive work (Autor 2013). This task approach to measuring technological change is relevant within jobs of the same educational or wage band and may reflect labor substitution effects not measured by education or wage.

When characterizing labor demand, the literature uses production functions that are often subject to restrictive assumptions (e.g. time-constant factor share and degree of factor substitution) that are potentially implausible during periods of fundamental technological change (Chenery 1949, Lave 1966, Pearl and Enos 1975, Wibe 1984, Smith 1986). Whereas classical production functions are limited to historic factor substitutions captured by statistical data (Pearl and Enos 1975), engineering process-based models and data make it possible to explicitly map current and future technological change—including expected future design decisions—to production processes and operations at scale, including the heterogeneity of equipment, labor and material inputs (Pearl and Enos 1975, Fuchs and Kirchain 2010). Previous work (Fuchs and Kirchain 2010, Fuchs et al. 2011, Fuchs 2014) use engineering models to show how shifting from a developed to a developing country changes which advanced products it is profitable for firms to pursue, thus questioning traditional assumptions in gains from trade. Whitefoot et al. (2017) use engineering models combined with oligopolistic equilibrium models to estimate the influence of energy efficiency regulations on technology adoption and tradeoffs with other product characteristics without conflating unobserved characteristics that are difficult to address econometrically (Whitefoot et al. 2017). To-date, however, these methods have not been used to study the implications of technological change on labor outcomes or disentangle the different implications of different forms of technological change.

3. Methods: Engineering Process-Based Cost Modeling

Engineering process-based cost models (PBCMs) simulate the consequences of technological changes at each step based on firm production plans, information from similar processes at different scale or in different contexts, basic scientific principles, and observations of production activities before and after a technological change (Fuchs, Ram, Bruce and Kirchain 2006). We use a PBCM to characterize the production functions of several functionally homogenous goods and generate technically feasible designs that capture current and future parts consolidation separately from other changes to the production process (particularly automation) and inputs, such as factor prices (Field, Kirchain and Roth, 2007).

PBCMs unpack the aggregate production function into individual manufacturing steps. Specifically, PBCMs map design (e.g. geometry, material, process) decisions to process inputs per step (e.g. cycle time, labor usage, equipment type, yields) to operations at scale and, given input prices, to cost (see Appendix 1: Equations for a functional characterization of the PBCM). While they have not been used to do so in the past, these models can easily and flexibly characterize labor inputs at very fine levels of required skills, training, and competencies (e.g., workers with fine motor skills or those with training in chemical vapor deposition). One output of the PBCM is operator labor required per production step at a given production volume (see Appendix 1). We also collect skill ratings reflecting the minimum capabilities for an employee to perform the tasks associated with each production step. We measure these skills along the O*NET rating scale of difficulty for each of three skill dimensions: finger dexterity, near vision, and equipment operations and control (O*NET Online), described further in Section 5.2.

For each technology, design, and process configuration, we use our PBCM to estimate the quantity of labor demanded (i.e. required inputs for operations at scale) at differing levels of rated skill difficulty. With this information, we are able to estimate the change in skill demand as measured by the level of skill requirements for each production process step. We use the sum of labor required across production steps with a given skill level (1-5) and type (i.e, dexterity, vision, operations and control) to estimate the total quantity of labor required at that skill level (e.g. the number of operators at dexterity level 1). This information is used to generate quantitative (i.e. production process level) estimates of the direction(s) and magnitude of technological change effects on labor skill demand. However, our PBCM does not incorporate the market equilibrium interactions among firms and workers. Thus, we are able to directly capture the effect of technological change on shifts in labor demand but not on equilibrium production volumes and labor quantity.

4. Technology and Industrial Context

4.1 Disentangling Simultaneous Technological change: Parts Consolidation and Automation

Parts consolidation occurs when multiple formerly discrete parts are designed and fabricated as one component (Schwedes 2001, Johnson and Kirchain 2009). As such, parts consolidation is a product innovation with many process implications. Parts consolidation is generally enabled by fundamental technological advances in design (e.g. topology optimization), materials (c.f. composites or strained silicon), and processes (e.g. additive manufacturing or e-beam lithography). Ongoing efforts for parts consolidation are common across a wide range of industries, including automobiles, (Fuchs et al. 2008, Johnson and Kirchain 2009), aerospace (Lyons 2014), and both electronic (Lecuyer 1999), and photonic (Fuchs and Kirchain 2010, National Academy of Sciences 2013, Yang et al. 2015) semiconductors. Table 1 provides examples of parts consolidation across several industries.

Table 1 Examples of Parts Consolidation by Industry and Number of Parts Consolidated

Industry	Example	Parts Consolidated
Aerospace (Thompson et al 2016)	Additive manufacturing: fuel nozzles and engines	18 parts to 1 (nozzle) 855 parts to 12 (engine)
Automotive (Fuchs et al 2008)	Steel to polymers: auto bodies	250 to 62
Electronics (Moore 1995)	Monolithic integration: transistors	120 parts to 1
Optoelectronics (NAS 2013)	Monolithic integration: lasers	20 parts to 3

The engineering literature on parts consolidation, and parts count reduction more broadly, suggests process-level consequences including reduced assembly and more complex component fabrication. (Fuchs et al. 2008, Johnson and Kirchain 2009, Yang et al. 2015, Liu 2016). These consequences may generate skill-biased changes in labor demand by altering the skill content of remaining (or newly created) production tasks. They may also shift the ratio of tasks with already heterogeneous skill content, driving relative increases or decreases in labor demand for some types of skills.

Automation consists of the transition of tasks, historically in manufacturing, from human workers to machines (Frohm et al. 2008). Automation is a largely process-based (rather than product design, as in parts consolidation) strand of technological change, including structuring production systems to enable automated or remote management of machine activities (Carpanzano and Jovane 2007). Automation is often described within the literature as skill-biased, principally eliminating manual or routine jobs and increasing demand for higher-skilled labor (Autor and Dorn 2013): the shift in task ratios driven by parts consolidation, however, may affect different jobs and thus demand for different types of labor.

4.2 Empirical Setting: The Optoelectronic Semiconductor Industry

Optoelectronic devices combine electronics and photonics (light) to send and receive information in a variety of applications, including throughout the communications and computing industries (Lebby and Hartman 1995). The global optoelectronics industry is anticipated to reach $55 billion in revenue by 2020 (MarketsandMarkets 2017), and over time, due to its increased bandwidth and reduced energy use, optics is increasingly expected to replace traditional electronics (NAS 2013). The optoelectronics industry is a particularly interesting case for studying simultaneous technological changes, and simultaneous parts consolidation and automation in particular: the optoelectronic device[1] we study features competing designs with different levels of parts consolidation, as well as different levels of production process automation. At all levels of parts consolidation for our case technology, the products are perfect substitutes in today's marketplace; although the most consolidated designs may have performance advantages (specifically, smaller size) in other markets in the long term (Fuchs and Kirchain 2010, NAS 2013), the designs in today's market have the same performance requirements, including a standard sized packaging that fits into devices for use.

Past work and our own interviews with firms suggest that competition in the specific optoelectronic devices we study is driven primarily by price (Fuchs and Kirchain 2010, Personal Interviews with Industry Leaders).[2] Prior research (Fuchs et al. 2011) also suggests that a low-cost leader does not exist among products with different levels of parts consolidation, allowing heterogeneous designs to persist in the industry. However, location (hence, labor costs and capabilities)[3] (Fuchs and Kirchain 2010) or technical capabilities could drive a firm-specific cost advantage for certain levels of parts consolidation, allowing the variation in parts consolidation important to our study.

Automation levels also vary across the industry: Some firms in our sample require operators to perform extensive visual inspections throughout the production process, while others rely more on automated testing equipment. Some component attachment and other subassembly is performed physically in one participant firm, while automated in others. These differences may be driven by location-specific labor costs and capabilities, which affect the viability and costs of automation and shift the optimal process configuration (Fuchs and Kirchain 2010). Hence, for example, a firm located in Southeast Asia with a low level of automation could compete with a highly automated firm in North America.

[1] The specific device is not identified to protect the confidentiality of participating firms.
[2] Industry interviews also suggest some competition around serving client-firm needs, but customization is typically around form factor and hence independent of internal component parts consolidation.
[3] The optoelectronics industry has historically witnessed offshoring from the United States toward East Asia, driven by cost. Our study includes facilities in the U.S., Developed and Developing East Asia and Western Europe.

As in electronic semiconductors (Klepper 2010), in optoelectronic semiconductors, parts consolidation occurs through “integration.” The industry contains low parts consolidation designs with individual discrete components mounted onto a semiconductor wafer and wire-bonded to each other; medium parts consolidation (called “hybrid” integration by the industry) with some formerly discrete parts fabricated together as single components and then assembled together through bonding; and finally, high parts consolidation (called monolithic integration), which involves “growing” multiple components on or within a wafer using semiconductor fabrication and etching techniques rather than attaching them using assembly techniques (NAS 2013, Yang et al. 2016).

Production of an optoelectronic device can take over 150 process steps and require more than 65 different machines. These process steps can be broken into four main categories: fabrication, subassembly, and final assembly (see Figure 1), with testing throughout the other three categories. Fabrication requires semiconductor processes such as deposition, lithography, and etching; for example, operators may load wafers into lithography machines or monitor gas pressure during material deposition. Sub-assembly of these fabricated components into the desired device occurs through a series of steps; for example, operators may manually attach components to a substrate, calibrate and monitor automated component bonding processes or load batches onto a curing belt. In final assembly, the device is packaged into a standardized “form factor” that allows it to interface with the rest of the communications or computing system. In this step, operators may attach optical fibers or screw together packaging cases. The fourth category of process steps, testing, occurs throughout each of these stages of the production process; operators may visually inspect components or the finished product through microscopes or prepare and monitor large scale automated testing processes such as thermal stress testing.

Parts consolidation increases the share of production activity in fabrication and reduces the number of subassembly steps, as there are fewer components to assemble. While testing remains important (perhaps more so with potentially greater costs of component failure from merged process steps), the number of opportunities for testing steps in the process flow can also decrease. Final assembly steps are less affected, as the final packaging currently remains largely the same across designs. Automation of production tasks does not change the order of process steps, though it can change the nature of operator tasks (e.g. a manual component attach task becomes equipment loading and monitoring).

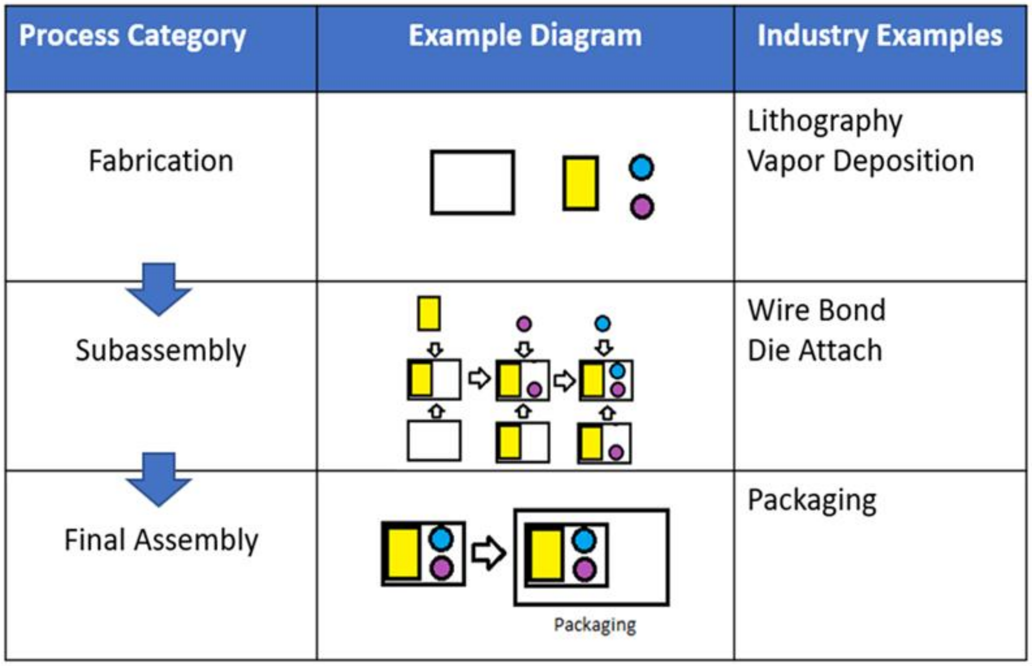


Figure 1 Process Flow Categories

5. Data Collection

5.1 Firm Sample

Our sample comprises four firms in total. These firms are leaders by volume in the production of the device we study, with operations across North America, Europe, Japan, China and Southeast Asia and include two of the broader industry's largest companies by revenue as well as by volume.[4] We capture positions across the industry technical domain by studying firms on the technical frontier of the industry in terms of the level and timing of parts consolidation and automation, as well as firms with relatively low levels of automation and/or parts consolidation. We also capture the industry's range of organizational models: both globally distributed firms and those with primarily U.S.-based production, as well as both vertically integrated (fabrication and assembly) and fabless firms. The firm product designs included in our study account for between 42% and 44% of the total annual output on the global market (see Table 2). This domain includes the production of two designs that match our low consolidation scenario and three that match our medium consolidation. There are no designs currently on the market that match our high consolidation scenario; however such designs are technically feasible and produced

[4]All participant firms requested deidentification before agreeing to involvement in this study.

in small-scale research contexts. Our sample also includes different levels of automation and equipment scale for many production steps, including industry state-of-the-art in automation of production steps as well as manual or small-batch configurations.

Table 2 Normalized Annual Production Volume (APV) and Share of Industry Production by Product Design

Product Designs	Industry Share (High Estimate)	Industry Share (Low Estimate)
Design 1	9%	9%
Design 2	16%	15%
Design 3	8%	7%
Design 4	4%	4%
Design 5	8%	7%
Total	44%	42%

Low share estimates are based on upper bound estimates of industry production and lower bound estimates of firm production volume. High share estimates are based on lower bound estimates of industry production and upper bound estimates of firm production volume.

5.2 Model Inputs

PBCMs considered in the literature (e.g., Johnson and Kirchain 2009, Fuchs et al. 2011) require collecting data on more than 20 inputs for each step of the production process. We contacted 12 firms and collected extensive process data from four firms on five different processes. For each of 481 production steps, we collect standard operational inputs to a process-based cost model, such as yield rate[5], cycle time[6], and wages[7] (see Appendix 2.2). We collect mean values as well as weekly maximum and minimum values for these inputs. Further, we collect data on the required experience, education, training time, and skill levels of physical and cognitive skills to complete the tasks associated with each production step (see Table 3).

The Department of Labor's "Occupational Information Network" (O*NET) Database offers one data source for capturing skill in detail. The database offers hundreds of occupational definitions and a variety of survey-based occupation-specific ratings of the difficulty and importance of skills and abilities required. O*NET's common survey instrument facilitates the development of a taxonomic approach to both tasks and occupations (Peterson et al. 2001, NAS 2010) by allowing us to measure their skill

[5] Defined in our model as the number of pieces passing through a production step for processing at the next step.
[6] Defined in our model as the time to process a full batch (including any rejected parts) through a production step. Batch size is a per-step characteristic, often dependent on equipment type.
[7] Wages do not include the cost of employee benefits (e.g. health insurance). An estimated increase of 20% in the cost of labor to approximate these costs did not significantly alter results.

content in detail. It also provides a framework for collecting industry-specific data where O*NET data may be missing or out of date (Eposto 2008). Several personnel studies draw on O*NET, for instance to study employment matching (Jeanneret and Strong 2003, Converse et al. 2004) and to forecast key competencies for the future of work (Burrus et al. 2013). Past studies in SBTC have used O*NET's predecessor, the Dictionary of Occupational Titles (DOT) to measure changing job task and occupational requirements (Autor, Levy and Murnane 2003, Lewis and Mahony 2006) and employment polarization (Goos et al. 2009), but these studies use skill ratings for highly aggregated job descriptions (e.g. a machine operator) without capturing detailed skill heterogeneity at the level of specific production tasks (e.g. running an automated wire bond machine). These measures cannot capture technological changes that affected the tasks performed by workers within the same aggregate job description, which our production task level approach allows.

We measure skill requirement levels using the O*NET survey instrument, which rates them using a 1-7 scale; the scale includes example anchors provided at each even-valued number, shown to result in reliable and consistent ratings.[8] For example, a dexterity level of 2 indicates the task requires a similar difficulty of dexterity as placing coins in a parking meter, while a dexterity level of 6 indicates a similar level of difficulty as assembling the inner workings of a wristwatch. We chose to collect data on operations and control, near vision, and dexterity based on our initial observations and interviews[9] (O*NET). Although we employ a 1-7 scale based on the O*NET survey, no tasks in our study exceeded a difficulty rating of 5. This is unsurprising, as ratings of 6 or 7 reflect very high skill requirements (e.g. air traffic control).

[8] The O*NET taxonomy was devised based on taxonomic methods common in the literature (Meehl and Golden 1982, Carrol 1993) and reflects a continuation of interest and capability typologies used in past skill tests (Dvorak 1947) and occupational databases (e.g. Dictionary of Occupational Titles). The O*NET content model and survey instrument draws on an extensive literature for measuring and categorizing skills (Peterson et al. 1999) and abilities (Dvorak 1947, Meehl and Golden 1982, Carrol 1993, Geisinger et al. 2007); taxonomies of ability have been used in labor and psychology contexts to characterize individuals (Fleishman and Reilly 1992), and a literature has emerged specifically around developing taxonomies of ability, skill and tasks for O*NET and similar databases (Borman et al. 1999). Hence, the categorization of skill and ability and the calibration of skill or ability descriptions (e.g. level of precision) are well supported by examples and methods from past literature.

[9] Within the O*NET survey instrument, finger dexterity and near vision are physical abilities, while operations and control is a cognitive skill: "an ability is an enduring talent that can help a person do a job" and a "skill is the ability to perform a task well." With reference to minimum capabilities and in connection to the task literature, however, we refer to all three dimensions as "skill requirements."

Table 3 New Labor-Related PBCM Inputs Collected

Input Name	Range/Typical Values
Training and Experience	
Years of Education, Experience	Education: Operator 8-12 years, Technician 14 years, Engineer 16-18 years Experience: 0 – 2 years
Training Time	3 to 30 days Training
Annual Turnover Rate	10% to 33%
Skill Requirements	
Operations and Control Controlling operations of equipment or systems	2 = Adjust copy machine settings 4 = Adjust speed of assembly line based on product 6 = Control aircraft approach and landing at large airport
Near Vision The ability to see details at close range (within a few feet of the observer)	2 = Read dials on car dashboard 5 = Read fine print 6 = Detect minor defects in a diamond
Dexterity The ability to make precisely coordinated movements of the fingers of one or both hands to grasp, manipulate, or assemble very small objects	2 = Put coins in a parking meter 4 = Attach small knobs to stereo equipment on assembly line 6 = Put together the inner workings of a small wristwatch

In addition to our process inputs and skill data for each of our 481 process steps, we have even more detailed worker task descriptions for 78 of our assembly process steps.[10] For these process steps, we collect the level of automation for every task that makes up the step (e.g., within the same process step, an adhesive application task may be automated but a part inspection task may be manual).

5.3 Model Scope and Boundaries

We scope our analysis to focus on the production line in each firm associated with the case optoelectronic device, and the immediate inputs associated therewith. Empirically, the process flows for the devices are from firm settings that dedicate one single line to produce the device. There is wide variation in the range of other products produced by the firms, and thus, significant variation in indirect inputs and overhead across firms derived from other products than the device of interest. Therefore, for this study, we do no collect overhead and indirect labor costs, but focus instead only on direct inputs for the production line of the device. We also do not collect data on energy usage, as prior data suggests that energy costs are negligible (Fuchs et al. 2011).

[10]These detailed task descriptions are drawn from the assembly processes of low as well as medium consolidation designs with process steps corresponding to both low and high automation in our scenario design.

Another notable assumption of our model is that it does not include scale diseconomies. None of the firms in our study (including industry leaders by production volume) operate at a scale requiring duplicate facilities dedicated to the same production tasks, and in observing the production line there were no obvious cases of diseconomies, such as traffic and queuing for common equipment or long transit times within large facilities: across our empirical production scales, we did not observe significant differences in line organization and equipment dedication choices to suggest adjustment for scale diseconomies.

6. Research Design

6.1 Generating Counterfactuals

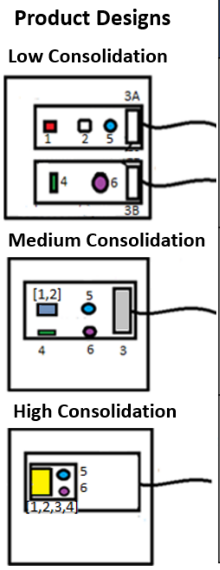
Using the engineering process model, we are able to separately examine the effects of simultaneous technological changes (here, parts consolidation and automation) by generating counterfactual scenarios that represent variations in the level of implementation of a single technological change *ceteris paribus*. To control for parts consolidation across our counterfactuals, we use consistent process flows (i.e. the same steps in the same order) but allow the level of automation of the steps to vary; conversely, to control for automation, we generate counterfactuals with different process flows (i.e. to produce different designs) but with consistent levels of automation for all steps. Combinations of parts consolidation and automation levels within the data allow us to generate four counterfactual scenarios (A, B1, B2, C). These counterfactuals reflect three levels of parts consolidation (A is low parts consolidation, B1 and B2 are medium parts consolidation, and C is high parts consolidation) and two levels of automation (A and B1 at a lower level of automation than B2 and C). The separation of automation and parts consolidation in our research design is illustrated in Figure 2.

	Lowest Consolidation	Medium Consolidation	High Consolidation
Low Automation	**Scenario A**	**Scenario B1**	
High Automation		**Scenario B2**	**Scenario C**

Figure 2 Research Design: Parts Consolidation without Automation and Automation without Parts Consolidation

Figure 3 shows diagrams of the three levels of parts consolidation represented in our scenarios and indicates for each level of parts consolidation which components are consolidated; components consolidated with each other are fabricated as a single component with no assembly required. Scenarios

B1 and B2 consolidate the same components, but they differ in the level of automation of their specific process steps.



Scenario	Component 1	Component 2	Component 3A	Component 3B	Component 4	Component 5	Component 6
A	Not Consolidated	Not Consolidated	Not Consolidated	Not Consolidated	Not Consolidated	Not Consolidated	Not Consolidated
B1, B2	Consolidated into [1,2]		Consolidated into 3		Not Consolidated	Not Consolidated	Not Consolidated
C	Consolidated into [1,2,3,4]					Not Consolidated	Not Consolidated

Figure 3 Optoelectronic Products and Components by Level of Parts Consolidation

Our high-parts consolidation case is not yet in commercial production. Data collection for the production of this design is based on detailed engineering design, process flow, and production plans for future large-scale production in the industry. For the assembly of the high-consolidated case, we use the process flow from Fuchs et al. (2011) to define each production step. We then populate this process flow with updated per-step inputs collected as part of our study. For the fabrication of the high-parts consolidation case, we collect data from two firms to update the process flows as well as the per-step data from Fuchs et al. (2011)[11]

We use Frohm et al.'s (2008) taxonomy of level of automation to characterize the equipment used by each firm in each process step (see Appendix 2.1). This taxonomy allows us to compare level of automation across process steps and across firms: process flows in the same automation scenario use inputs with the same level of automation. Fabrication is already highly automated across the industry (NAS 2013) and therefore does not vary across our automation scenarios.

[11] See online supplement for discussion of the updated data and comparison between fabrication in our medium parts consolidation scenario and high parts consolidation scenario (not yet in production).

6.2 Baseline Analyses and Sensitivity to Inter-firm Variation

For each design, we create a baseline production function, and then multiple reconfigurations of the production functions based on observed inter-firm variation in inputs. For our baseline production function, we use the mean input values reported by each firm. For each design, we prioritize data from what our comparison of the per-process step data suggest is the most efficient configuration for each step in processing a particular design. Notably, a firm may have the most efficient overall production of a design compared to other firms without having the most efficient configuration for each step required for producing that design. Leveraging per-step differences across firms, we generate cost best case and worst case (i.e. minimizing and maximizing given the per-step inputs available across firms) and labor minimizing and maximizing configurations (see Appendix 1.2). The inclusion of interfirm efficiency variation in our estimates allows us to independently characterize the labor demand effects of parts consolidation and automation even under conditions of firm-specific heterogeneity (driven, e.g., by differences in equipment quality within the same level of automation).

6.3 Model Validation

We validate our model by comparing our aggregate required inputs to produce each firm's device against in-house aggregate input quantity and cost estimates. We validate our models of each firm's facilities by comparing the quantity of operators and equipment required at annual production volumes found in our participant firms to the actual quantity of labor and equipment in each facility. Modeling the firms' production lines using weekly maximum and minimum performance estimates generated ranges that fully overlapped with the firms' in-house capital, material and labor cost accounting. Our baseline configurations for all scenarios produced aggregate results that were within 10% of in-house estimates for four of the five empirical production lines and within 20% of in-house estimates for the fifth production process. (see Appendix 2.3)

6.4. Identification

Our use of a process-based cost model allows us to directly identify empirical process parameters. Firms non-randomly select their level of automation and parts consolidation, based on their capabilities and input characteristics (e.g. labor cost).[12] As a consequence, one threat to identification is that apparent shifts in labor demand partially reflect firm rather than technological characteristics. To

[12] This statement is based on our conversations with executives at each firm.

help address this issue, we collect a technologically and organizationally representative sample of the industry (see data section 5.1). We expect that our sample is representative of the range of firm efficiency levels: Given duplication of tasks across the firms, our data includes between 1 and 5 examples (on average 1.6 in assembly, 1.2 in fabrication) of each of the 362 unique production tasks, including at each level of automation and parts consolidation. In addition, to avoid confounding technological variation with interfirm variation, our results focus only on instances where labor demand differences across scenarios exceed our interfirm variation bands.

Within our sample, more tasks are automated in production facilities sited in the United States, Japan and Europe than in developing East Asia. Thus, another threat to identification is that the apparent effect of automation may be biased by relatively higher (lower) labor productivity in certain countries. However, we do not believe this is a concern: while level of automation and geography may be correlated, the skill demand effects of automation appear consistent across countries. While U.S. facilities tend to be more highly automated, our sample also includes U.S. production that is not highly automated. We find that these low automation tasks are comparable in their labor productivity (i.e. labor time per part) to tasks performed in East Asian facilities at the same level of automation. Moreover, more highly automated tasks in facilities across countries do not appear to be consistently more or less efficient with geography.

7. Empirical Results

7.1 Unit Production Cost Estimates by Scenario

As can be seen in Figure 4, a low-cost leader does not currently exist across different levels of parts consolidation and automation, thus allowing heterogeneous designs to persist in the industry. As discussed in section 6.2, the dotted lines reflect our baseline configurations while the bands represent the best and worst case configuration of each technology scenario (with normalized axes to protect firm confidentiality).[13] All cost configurations correspond to fabrication sited in the United States, assembly sited in Developing East Asia for low automation scenarios and assembly site in the United States for high automation scenarios. Both parts consolidation and automation increase the production cost share of capital while decreasing the cost share of operator wages (see online supplement 5).

[13]The values are normalized such that the highest empirical cost is set equal to $100 and all other costs are adjusted proportionally, and the highest production volume in the range presented is set to 100 units with all others volumes adjusted proportionally.

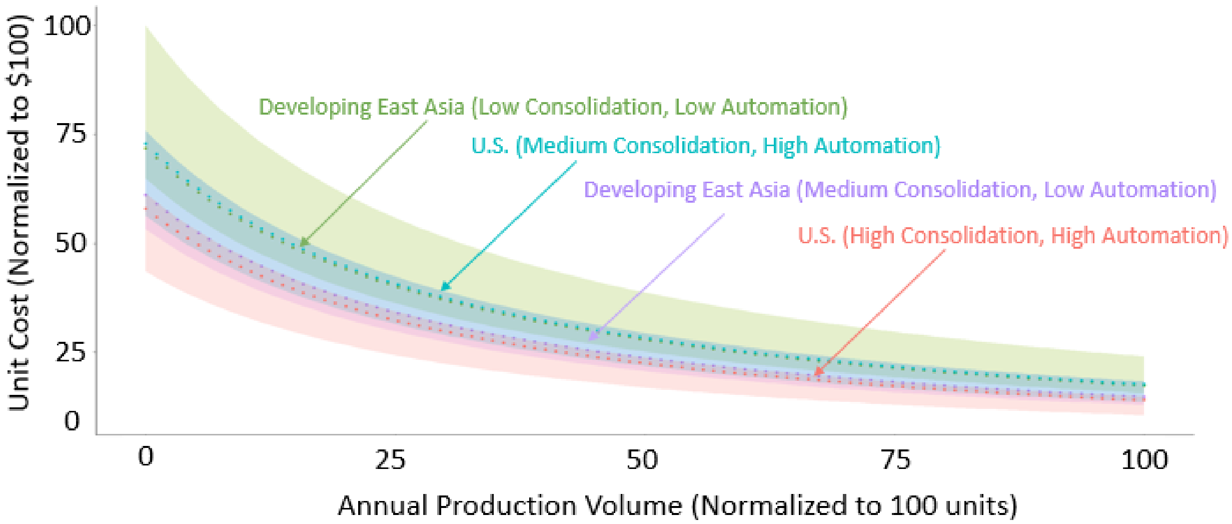


Figure 4 Unit Costs by Annual Production Volume, Level of Automation and Parts Consolidation

7.2 Process Flow Breakdowns and Operators by Process Category

As discussed in section 6.2, the error bars in the following figures reflect labor minimizing and maximizing configurations using per-step differences across firms. The figures that characterize labor demand are calculated at the median of the annual production volumes described by our industry participants.[14] At this volume, the production lines in our scenarios mostly have fully utilized equipment, with a few exceptions particularly in the most highly automated scenarios.

Figure 5 shows that the number of fabrication and testing steps increases with more parts consolidation, while the number of assembly steps decreases. These results are intuitive because parts consolidation fabricates components previously sub-assembled, shifting tasks between these two categories of production. The increase in fabrication testing steps from medium to high parts consolidation may reflect process engineers expecting early challenges with process variability or quality for the high parts consolidation design, which is not yet produced commercially.

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[14] We find that our results are robust to an increase from the median APV of our empirical sample to our maximum sample APV (available upon request). Also, note that number of process steps, shown in Figure 5, is independent of APV.

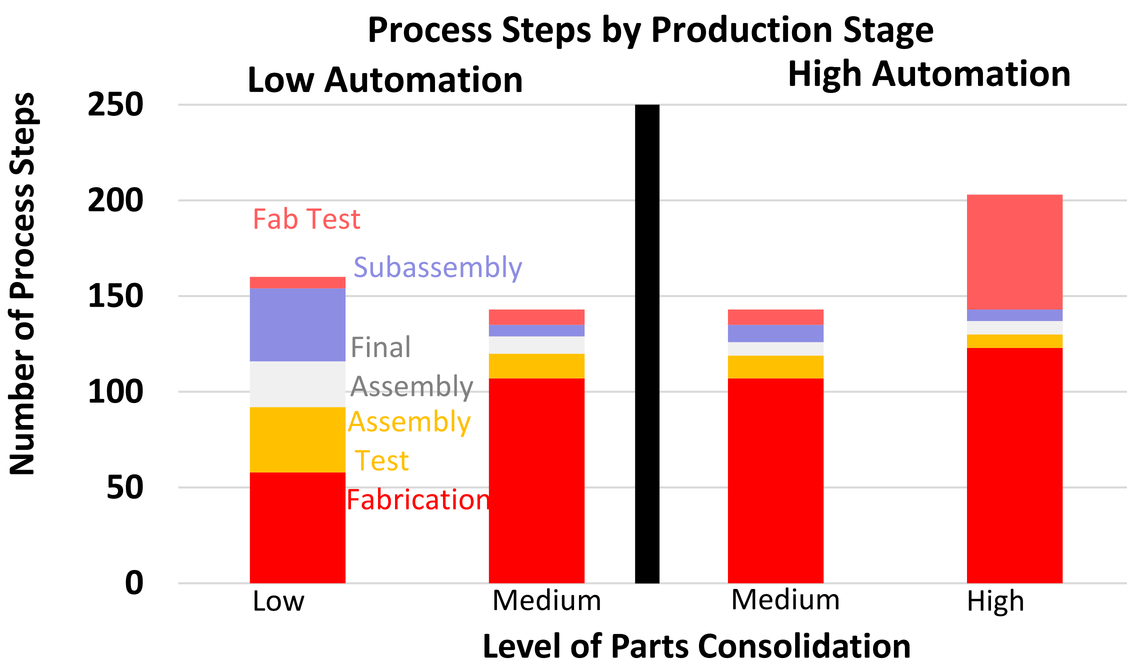

Figure 5 Process Breakdowns by Parts Consolidation and Automation Scenario

Figure 6 shows the number of operators required by process category within the model facility to meet the median of the annual production volumes of the facilities included in our data. Unpacking Figure 6 helps highlight the importance of the detailed manufacturing model. As can be seen in the figure, the number of operators in sub-assembly, final assembly, and testing decreases with parts consolidation.[15] Although additional testing steps are required for high parts consolidation (as seen in Figure 5), labor is shared across testing steps and fabrication testing is sufficiently labor-efficient such that there is no significant increase in the net quantity of test operators. The number of fabrication operators increases with parts consolidation but decreases with automation (the latter due to higher yields in assembly for the automated design and hence, fewer overall components needing to be processed through each step). Finally, though the number of operators per part fabricated increases with parts consolidation, this effect is offset by improvements in the cumulative yield of assembly. With fewer assembly steps in which to have part failures, parts consolidation increases cumulative yields in assembly (without increasing per step yields). Better cumulative assembly yields mean fewer fabricated parts and fabrication operators required for higher parts consolidation.

[15]Automation and consolidation both lead to a net decrease in labor demand per widget, but these technological changes may affect equilibrium price and output (hence, number of jobs) and possible or optimal geographic locations for production: see Appendix 3.3 for further discussion.

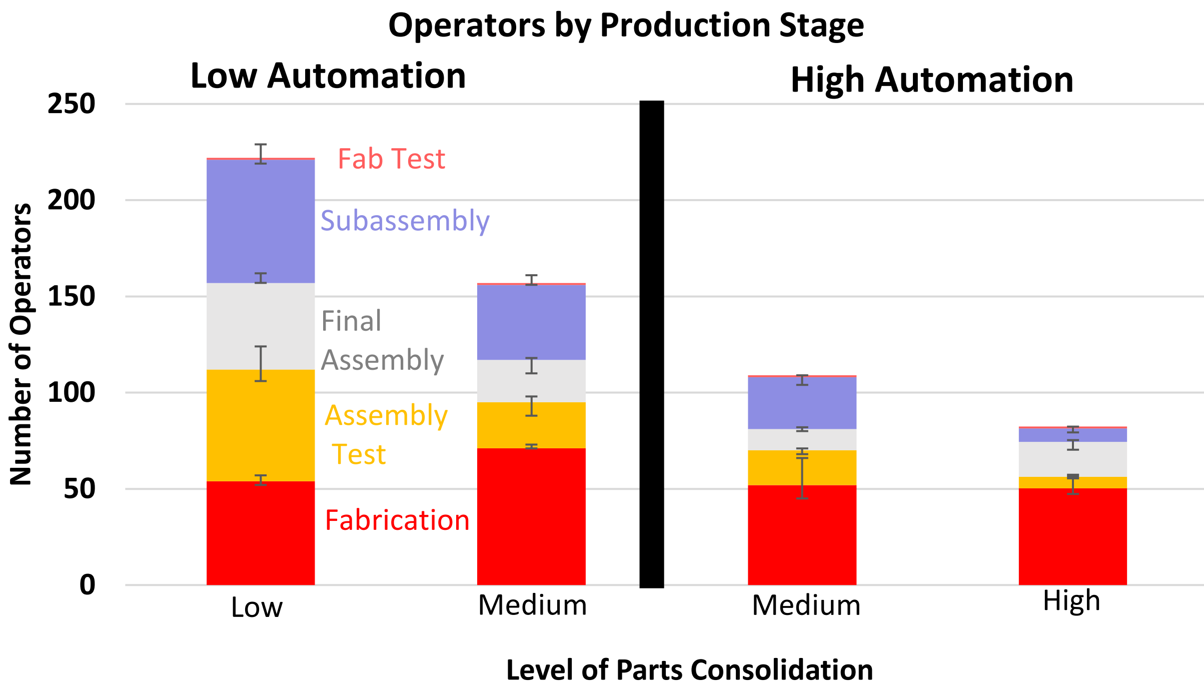

Figure 6 Number of Operators Required by Scenario and Production Category

7.3 Heterogeneous Skill Demand Shifts with Different Technological changes

We find the skill demand effects of automation and parts consolidation differ, both for cognitive skills such as operations and control as well as physical skills such as near vision and dexterity. Figure 7 shows how operations and control skill demand changes with automation and parts consolidation. (Appendix 3.1 shows the same for near vision and for dexterity). Automation drives an upward shift in operations and control skill requirements, with fewer operators at levels 1 through 3 and more at levels 4 and 5, and operators reduced the most at levels 2 and 3. In contrast, parts consolidation from low to medium drives convergence, with fewer operators proportionally and in absolute terms at the highest and lowest levels of skill, and more at the mid-levels (2-4). The shift in the number of operators under further parts consolidation from medium to high does not exceed the range of inter-firm variation.

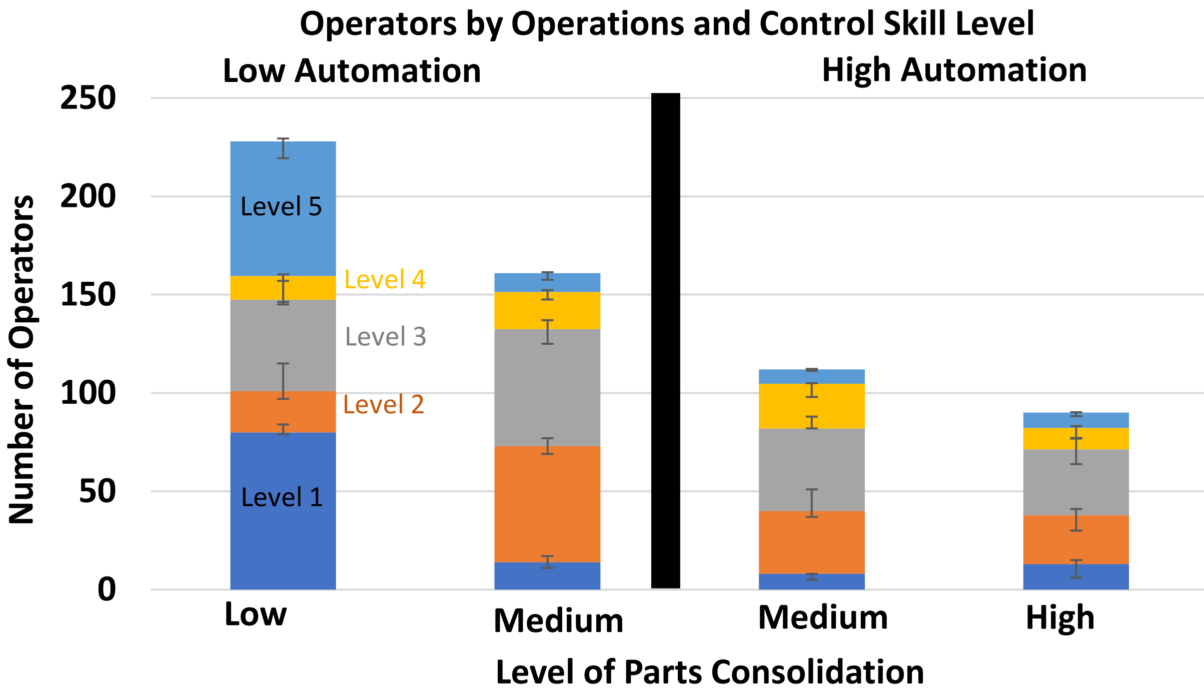

Figure 7 Number of Operators by Scenario and Operations and control Requirement

Figure 8 and Figure 9 show how aggregate measures of technological change can mask the opposing labor outcomes of automation and parts consolidation. In these figures, the error bars reflect the maximum and minimum differences across scenarios using the labor minimizing and maximizing configurations described in section 6.4. For operations and control, aggregate measures suggest a decrease in labor demand across skill levels 2-5 and no change for skill level 1. Once disaggregated, we see that automation decreases labor demand across all skill levels with the greatest losses in the middle (2-4), while parts consolidation increases labor demand across skill levels 2-4, and decreases demand at the extremes. For near vision, aggregate measures suggest a decrease in labor demand at the bottom and top (skill levels 1 and 5), a decrease skill level 2 but an increase at levels 3 and 4. Once disaggregated, we see that automation decreases labor demand in the middle (skill levels 2 and 3), while parts consolidation decreases demand at the bottom and top (skill levels 1 and 5), and increases demand in the middle (skill levels 2 and 3). Other plots of aggregated versus disaggregated outcomes can be seen in Appendix 3.1. In almost all cases, the aggregate measures mask opposing outcomes.

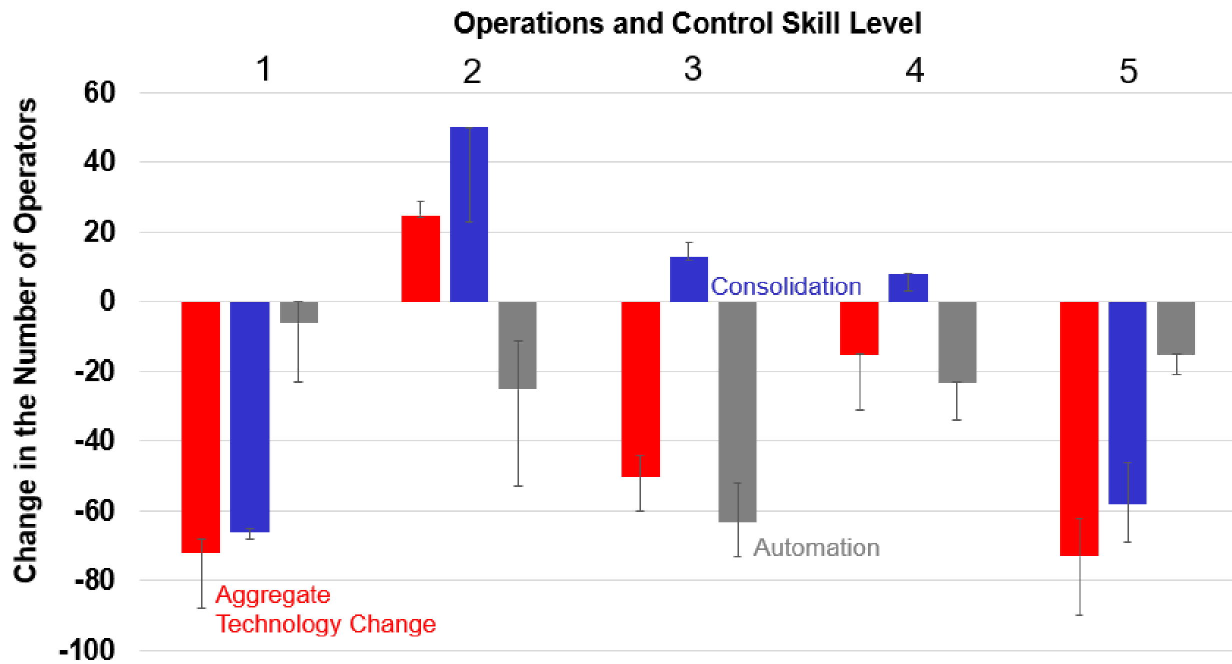

Figure 8 Operations and Control Skill Effects of Disaggregated Automation and Parts Consolidation: Shifting from Low Parts Consolidation, Low Automation to Medium Parts Consolidation, High Automation

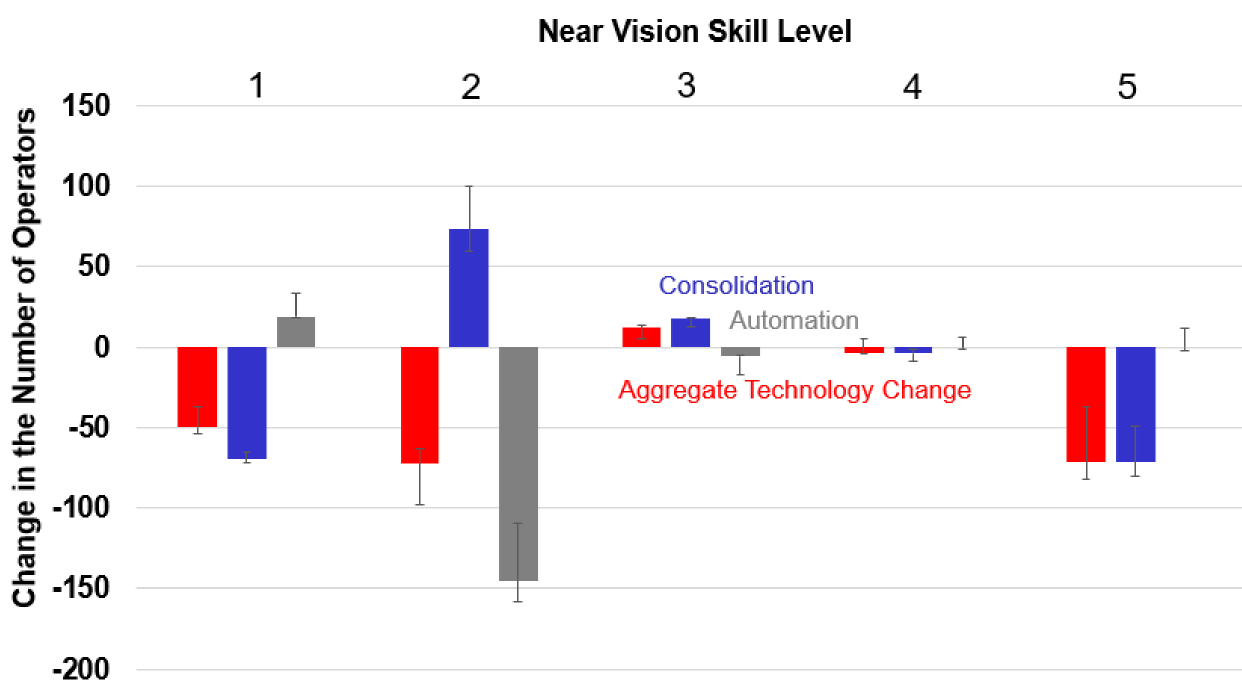

Figure 9 Near Vision Skill Effects of Disaggregated Automation and Parts Consolidation: Shifting from Low Parts Consolidation, Low Automation to Medium Parts Consolidation, High Automation

7.4 Multi-Dimensional Skill Shifts

Finally, changes in operator skill requirements may not be independent across skill dimensions. Figure 10 shows the joint distribution of demand for operator skills, represented by the number of operators of given skill levels required in our model facility to meet a desired annual production volume under one of our production scenarios. We measure operator skill simultaneously on two dimensions: operations and control, and near vision. We find that moving from low to medium parts consolidation (keeping low automation) shifts skill requirements from extremes (e.g. near vision, and operations and control ratings both of 1 or both of 5) toward more mid-level skill requirements (e.g. near vision and operations and control ratings of 2 or 3). Other plots of joint skill distributions are shown in section 3 of our online supplement and suggest that this convergence holds for other skill pairings and for parts consolidation from medium to high.

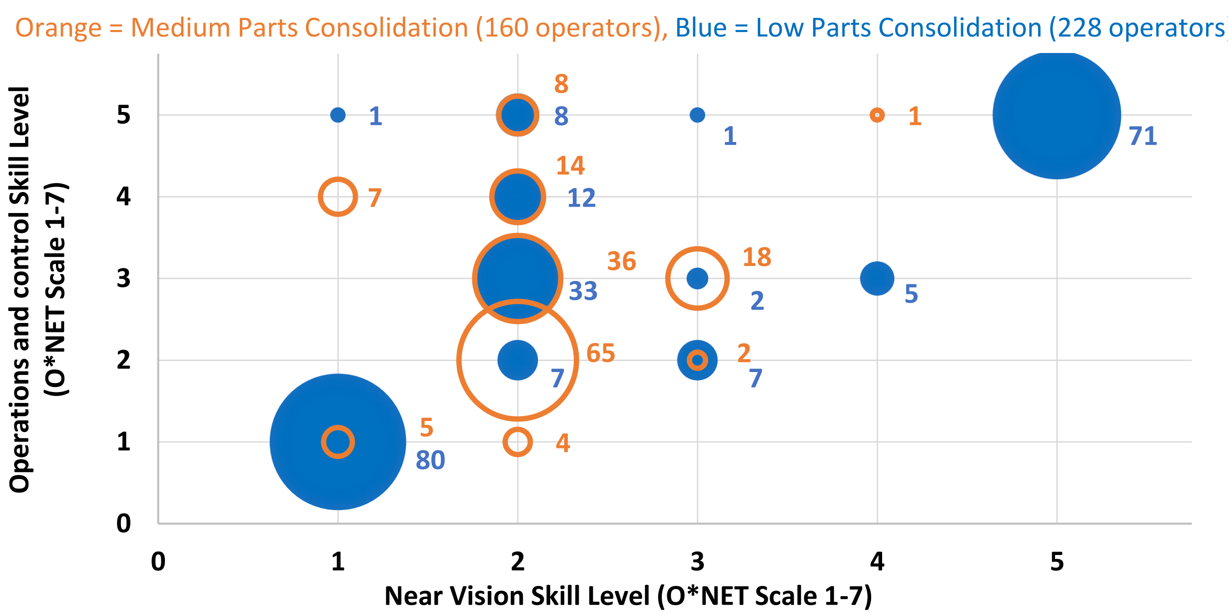

Figure 10 Parts Consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

8. Generalizability of Methods and Empirical Findings

8.1. Generalizability of Methods

This paper demonstrates that it is possible to use engineering process models and associated data to directly measure the implications of current and future technological changes on labor outcomes. In doing so, we are able to examine the effects of emerging technological changes on labor demand without needing to rely on historic factor substitutions, which are potentially implausible during periods of fundamental technological change (Chenery 1949, Lave 1966, Pearl and Enos 1975, Wibe 1984, Smith 1986). In addition, the specificity of our model and data as well as our ability to generate counterfactuals technology scenarios enables us to capture different forms of technological change invisible in aggregate statistical data.

The intensity and confidentiality of data required for such engineering process models makes large-scale economy-wide analysis comparable to current macroeconomic work impracticable without census intervention. That said, insights from a representative sample of firms in a few, carefully selected set of industries and technological contexts may uncover novel unexpected insights that can subsequently be incorporated into approaches to classical production functions. Indeed, in the longer term we hope models such as these may lead to improvements and alternatives to classical production functions, more representative of empirical mechanisms. In addition, better measurement of simultaneous technological changes, many such as parts consolidation not currently part of the economics discourse, may lead to a new taxonomy of how different technologies can be expected to have different labor outcomes, and that these distinctions could likewise eventually be formally characterized in production functions. To quote a 1986 Oxford Review of Economic Policy interview with Herbert Simon (The Failure of Armchair Economics), which is still relevant today, "We badly need better ideas of how to put together the stuff we find out at the micro-micro level and aggregate it. For that, economists need much more data." Simon continues, "…if you studied about a dozen firms, you have a pretty good feeling of the range of behavior you are likely to encounter in firms, … the idea that we must have huge samples in order to know how a system works is not necessarily so."

8.2. Generalizability of Labor Demand Implications to Semiconductors

There are important distinctions between different subsectors of the semiconductor industry, including photonics and electronics. At the same time, similarities between photonics and other subsectors suggest that much of our insights on the labor implications of automation and parts consolidation in optoelectronic semiconductors have relevance to the historic, current, and future semiconductor industry.

Design, manufacturing, and technological change in photonic, optoelectronic, and electronic semiconductors have many similarities. The vast majority of equipment used in optoelectronic semiconductors, including nearly all fabrication (e.g. metal oxide vapor deposition, lithography, etching) and much assembly and testing (e.g. pick-and-place, wirebonding, microscopes for visual inspection) have parallels in electronic device production (NAS 2013). Nonetheless, there are important temporal differences. Monolithic integration in electronic semiconductors faced 30-40 years ago many of the same challenges faced today in optoelectronic semiconductors (Cheyre et al 2015, Yang et al 2016.) Monolithic integration in optoelectronics raises materials and process challenges not present in electronic semiconductors, several of which remain unresolved (Fuchs and Kirchain 2010). In addition, lack of process control and understanding mean that CAD models enabling the separation of design and manufacturing, such as those available in electronics for VLSI, are also yet to be attained (Fuchs and Kirchain 2010). Optoelectronics has surely been able to benefit from the electronic semiconductor industry's wealth of knowledge—both in terms of automation as well as the stages of parts consolidation (discrete to hybrid to monolithic integration), which optoelectronics proceeds to mimic (Cheyre et al 2015, Yang et al 2016) As such optoelectronic semiconductor production is surely more advanced than electronic semiconductor production of 40 years ago, despite current technological challenges.

Given the historic parallels, we might expect labor shares for a low automation, low parts consolidation case of optoelectronics to resemble but not be exactly the same of those in electronics 30-40 years ago while labor shares for a high automation, high parts consolidation cases to more closely resemble but again not be exactly the same (due to lower levels of parts consolidation and automation) as those in electronics today. To explore these similarities, we compare the computed value of labor share of costs from our engineering process model to the labor share of costs (payroll over value added) derived from the aggregate historical data from the Semiconductor and Related Device Manufacturing (NAICS 334413) industry, as available in the NBER Center for Economic Studies (CES) Manufacturing Industry Database. Optoelectronic semiconductors would be a part of the NAICS category, but with annual optoelectronic production volumes in the millions compared to total semiconductor annual production volumes forecasts above 1 trillion units in 2018 (IC Insights), electronic semiconductor trends (and particularly electronic integrated circuit production) will easily dominate the aggregate data (Khan et al 2018).

Table 4 PBCM-Based Labor Share of Input Costs

Scenario	Labor Share
Low Parts Consolidation Low Automation	0.442
Medium Parts Consolidation Low Automation	0.308
Medium Parts Consolidation High Automation	0.232
High Parts Consolidation High Automation	0.184

As shown in Table 4, we can use our PBCM to determine how different technological developments affect the cost share of labor. As expected, an increase in the degree of automation and part consolidation reduces the overall share of labor costs in the production process. We next compare this value with aggregate US data. We find that the labor share in our low parts consolidation, low automation scenario compares with the industry labor share in the mid-80s (the average for the years 84-86 is equal to 0.435). The labor share in our high parts consolidation, high automation scenario (which is not yet on the market) compares with the overall industry labor share first achieved in the late 90s (the average for the years 97-99 is equal to 0.167). The labor share in the industry remained fairly flat with an average labor share of 0.182 for the period from 2000-2011. The placement of optoelectronics' labor shares within the overall semiconductor industry are within the bounds of what we might expect given technological change in both. These results are suggestive that understanding technological change and labor outcomes in optoelectronics may have relevance in thinking about technological change and labor outcomes in the broader industry historically as well as more recently. Further, the increasing substitution of photonics for electronics (NAS 2013) would suggest that findings from the optoelectronics subsector will increase in relevance.

8.3. Generalizability of Labor Demand Implications of Automation versus Parts Consolidation (Operators in Other Manufacturing Industries)

To better understand our findings and identify hypotheses for their generalizability, we aggregate our detailed O*NET findings to identify common trends and suggest mechanisms behind these trends. See Figure 11 and Figure 12.

We aggregate our detailed O*NET findings on the change in demand for skills in two ways: first, we group the O*NET skills we collect into one of two broader categories: cognitive or physical. The operations and control skill is the cognitive category; we group dexterity and near vision skills under the physical category. Second, we group the O*NET skill ratings into one of three broader categories: low, medium, and high. Here, we label a skill rating of 1 as "low," a rating of 2, 3, or 4 as "medium," and a rating of 5 as high. We then translate into these groupings our detailed findings on the change in skill demand—here, number of operator jobs requiring a given level of skill—with technological change. For example, to calculate the change in demand for low cognitive skill with automation, we calculate the difference in the number of jobs at operations and control skill level 1 between our low automation, medium parts consolidation and our high automation, medium parts consolidation scenarios (thus holding parts consolidation constant while changing automation). To calculate the change in demand for medium cognitive skill with automation, we calculate the difference in the total number of jobs at operations and control skill levels 2, 3 and 4 between our low automation, medium parts consolidation and our high automation, medium parts consolidation scenarios. For example, to calculate the change in demand for low physical skill with automation, we add the number of jobs with dexterity skill level 1 or near vision skill level 1, and then calculate the difference in number of jobs between our low automation, medium parts consolidation and our high automation, medium parts consolidation scenarios. Note that due to our aggregation of physical skills, a single job may appear in Figure 11 and Figure 12 in two different physical skill categories: for example, a job lost (gained) requiring low near vision skill and high dexterity skill would count toward changes in both low and high physical skill. To calculate the change in relative medium physical skill demand with automation, we calculate the number of jobs requiring dexterity skill levels 2, 3 and 4 or near vision skills 2, 3 and 4, and we then calculate the difference in this number of jobs between our low automation, medium parts consolidation and our high automation, medium parts consolidation scenarios. For parts consolidation, since we measure two shifts in parts consolidation (low-to-medium and medium-to-high), we plot the results for both beside each other and only propose a generalizable relationship between parts consolidation and physical or cognitive skills, if both changes in parts consolidation shift labor demand in the same direction for a given skill grouping (as for our empirical results in 7.3, the error bars in Figure 11 and Figure 12 reflect the maximum and minimum differences across scenarios using the labor minimizing and maximizing configurations described in 6.4). Thus, the effects of technological change on relative demand for cognitive skill are given by the change in operator jobs by skill level, while the effects of technological change on physical skill are expressed as the change in operator jobs by skill level in either near vision or dexterity. We show intermediate outputs in Appendix 3.2 and the full equations for our calculations in Appendix 1.3.

We find that the number of jobs with high cognitive skill requirements decreases under both low-to-medium and medium-to-high parts consolidation. While we find that the number of jobs with medium physical skill requirements increases under low-to-medium and medium-to-high parts consolidation, some individual skill levels within the medium category show decline or no change.

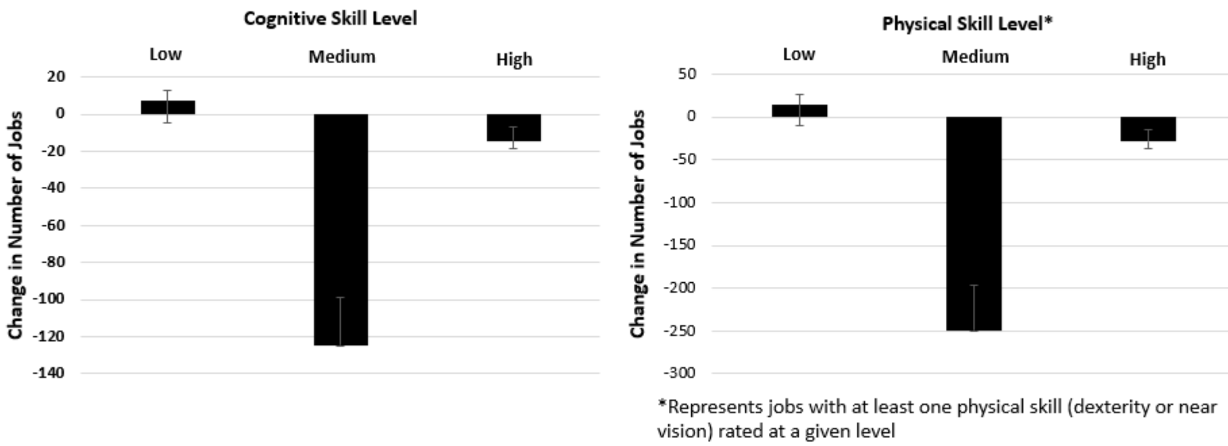

Figure 11 Aggregate Change in Number of Operator Jobs by Cognitive and Physical Skill Level Under Automation

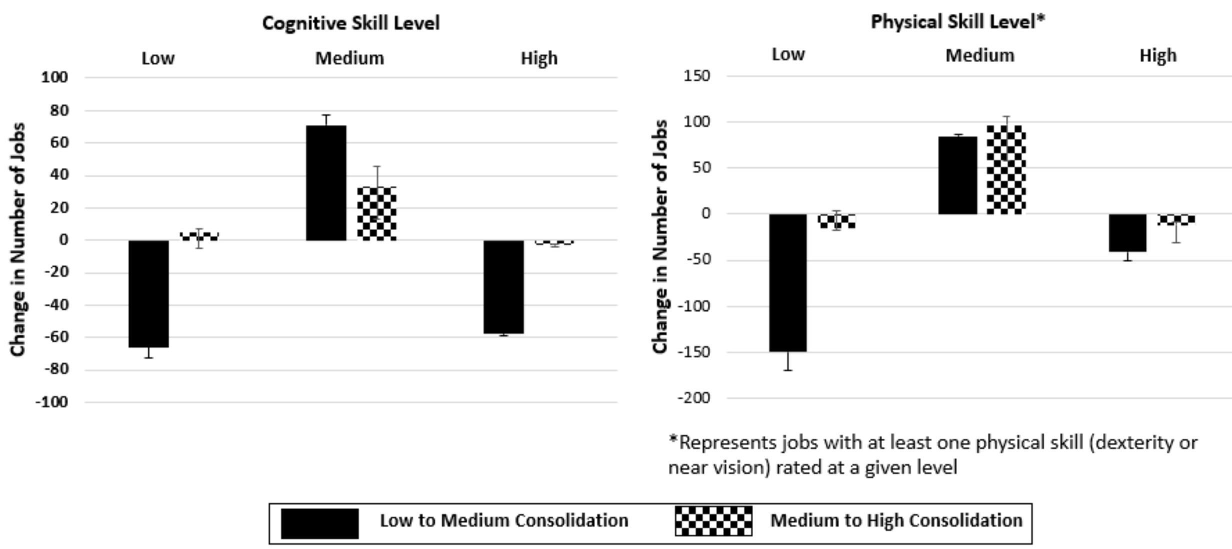

Figure 12 Aggregate Change in Number of Operator Jobs by Cognitive and Physical Skill Level Under Parts Consolidation

In the case of automation (Figure 11), we see demand for physical and cognitive skills shifting away from the middle, leading to skill polarization in operator jobs. We find that demand for high physical skills decreases with automation: fabrication is already highly automated throughout our dataset and manual assembly steps with higher physical skill requirements are replaced by machines. Automation does not change aggregate demand for low level physical skills: manual tasks with the lowest skill requirements tend to be automated, but the physical requirements of the operator production tasks created by automation tend to be at a lower skill level (e.g. pressing a button, loading and unloading a part, monitoring a machine lifting a piece). We find that automation reduces medium physical skill demand more than demand for high physical skill: assembly tasks with high physical skill requirements often involve complex part geometries that make them harder to automate than more straightforward medium physical skill assembly tasks. Automation reduces demand for high level cognitive skills: automation can affect process steps with high cognitive skill requirements (e.g. complex assembly steps), but it is offset partly in some cases by automated processes leading to the creation of new tasks (e.g. calibration or monitoring) with high operation and control skill requirements. Automation also reduces demand for low level cognitive skills: while the least complex assembly steps are often automated, some of the new tasks created by automation require a low level of cognitive skill (e.g. loading and unloading equipment). Automation most reduces demand for medium level cognitive skills: assembly steps of medium complexity, and hence requiring medium cognitive skill levels, are more often automated than high complexity, and new tasks created by automation do not tend to have medium level operation and control skill requirements.

We find that parts consolidation (Figure 12) does not have a singular effect on the demand for skills. In contrast to automation, parts consolidation in no cases polarizes skill demand. In aggregate, parts consolidation converges demand for both the physical and cognitive skills required of operators in the industry. As more parts are monolithically fabricated as a single unit and assembly steps (and associated tasks) eliminated, demand for the highest level of physical skills is often reduced as these higher level skills are predominantly required in assembly. Demand for the lowest level of physical skills is also often reduced, as tasks in fabrication and assembly formerly requiring low level skills are transformed to require more medium (or high) skill levels. For both fabrication and assembly, the increase in physical skills from low to medium (or high) may be associated with consolidated parts having a greater cost of production failure, and thus a demand by the firm for increased skill requirements to minimize failure.[16] As more parts are monolithically fabricated as a single unit and assembly steps (and associated tasks) eliminated, demand for high level cognitive skill consistently decreases. This decrease is frequently due to the elimination of more complex assembly tasks with higher cognitive requirements such as part orientation and the management during assembly of more complex geometries. In addition, with fewer total parts, there are fewer opportunities for testing, which also tends to require higher cognitive skills. Demand for the lowest level of cognitive skills is also often

[16] This increase in the cost of failure is greatest when parallel lines are merged, which is more pronounced in our transition from low to medium than from medium to high consolidation, the latter where the reduction in assembly steps dominates skill demand outcomes. This difference between the two transitions shows up in Figure 35 of Appendix 3.2 in that moving from low to medium consolidation shifts skill demand from low to high dexterity, while moving from medium to high consolidation shifts skill demand from high to medium dexterity.

reduced, as tasks in fabrication and assembly formerly requiring low level skills are transformed to require more medium skill levels. For example, in fabrication, certain deposition steps become longer and more complex, including requiring more monitoring and calibration.

We expect the common trends we identify – polarization of skill demand for automation and convergence of skill demand for parts consolidation – and their associated mechanisms to largely generalize beyond semiconductors to other manufacturing contexts and to have important parallels in non-manufacturing contexts. We expect the common trends to be especially relevant for those workers directly involved in production.

For automation, we hypothesize that the patterns of polarization of operator physical and cognitive skill demand to persist across manufacturing industries. Which process steps are automated will naturally influence which skills are affected: In many manufacturing contexts, automation of routine codifiable tasks shifts demand toward low physical skills. While not visible in the aggregate trends, there are also cases in our data in which high physical skill requirements are correlated with difficulties in automation, meaning that work with highest physical skill requirements may be preserved (at least in the short term). We expect this less dominant trend to also generalize other manufacturing contexts. We likewise expect the polarization of operator cognitive skill demand under automation to persist across manufacturing industries, and have important parallels in other contexts. In many manufacturing contexts, automation of routine, codifiable tasks is likely to reduce demand for medium and high cognitive skills, while sometimes simultaneously creating more cognitively demanding jobs in equipment monitoring, calibration and maintenance. Likewise, in many manufacturing contexts, jobs with the lowest cognitive requirements are both eliminated and at times created (such as button pushing) by automation.

For parts consolidation, we hypothesize that the patterns of convergence of operator physical and cognitive skill demand to persist across many if not most manufacturing contexts. One possible limitation in extending our findings on the physical skill demand implications of parts consolidation to outside industries is that parts consolidation of sufficiently large parts (e.g. many discrete auto body components into very large single pieces (e.g. Patrick and Sharp 1992)) may lead to parts too large for human workers to manage (e.g. too heavy to lift). This may force a shift under parts consolidation toward automation or collaborative robotics (e.g. a machine to lift formerly portable components), thus moving physical skill demand toward lower skill. However, we expect that parts consolidation, when coupled with miniaturization or focused on modestly sized components, will have effects on physical skill demand across manufacturing similar to our findings. Higher skilled work, especially the assembly of very small components, will be reduced in some cases, while lower skill work may be upskilled to account for the increased cost of production failure from de-parallelization of production: in some instances, this upward pressure will lead to an increase not only in mid-skill demand but also demand for high physical skill. We expect cognitive skill demand to increase for medium skill jobs in other manufacturing contexts. In industries with high cognitive skill tasks affected by parts consolidation, we expect such jobs to be reduced, while in all industries we expect lower skill jobs may be upskilled to account for the increased cost of production failure from de-parallelization of production.

Further work is required to explore the relevance of these findings in non-manufacturing contexts, such as software and design.

9. Discussion: Toward a Theory of Technological changes and their Effects on Tasks, Jobs, and Occupations

Our task-level manufacturing data enables us to operationalize and expand the task-based theory described by Acemoglu and Restrepo (2016). [17]

9.1. A Taxonomy for Technological change's Effects on Tasks

A task is characterized by a *performer* (here, human labor or a machine) and an *action* done by that performer to produce an intermediate good (e.g. partial assembly of a device) toward a final product in a production process. Given our data, rather than being forced to think about categories of tasks per O*NET, we are able to define the *task as an action whose performance would not naturally be divided into smaller units*. For example, in automotive body assembly, a single rivet to connect two parts is indivisible, each required rivet is a different task and might be performed by a different performer. Indeed, in automotive body assembly, with higher production volumes, more performers are brought in to each do fewer of the total required rivets.

Technological change may or may not change the performer and may or may not change the action. For example, if a component cleaning task is automated, the same action previously performed by a human may instead now be performed by a machine. In this case, the action associated with the task is unchanged. Alternatively, if in automating cleaning, the machine now performs a different, and more precise action, the action associated with the task is transformed.

[17] Mathematical formalization of the theory that follows is available upon request.

When performed by a human, a task has a set of skill requirements. If the action associated with a task is transformed, the skill requirements may also change. For example, if a task to join two parts changes from welding to adhesive joining, but both actions still require high skill levels, then the nature of the task is transformed but the skill requirements remain the same. In the context of this paper, we group skill requirements into physical and cognitive, each with bins of low, medium or high (Figure 13). The skill requirements of a human performer of a task can be thought of in terms of the O*NET categories, which are grouped by O*NET into two domains: cognitive versus physical. Simplifying O*NET (whose scale goes from 1-7), the required skill can be thought of as existing on a difficulty scale (which we represent below as ranging from low to medium to high). In the theoretical discussion and figures that follow, we represent cognitive skill requirements with an icon of a brain, and physical skill requirements with an icon of a flexing arm. We represent the skill level by changing the size of the image – with larger images indicating greater difficulty.

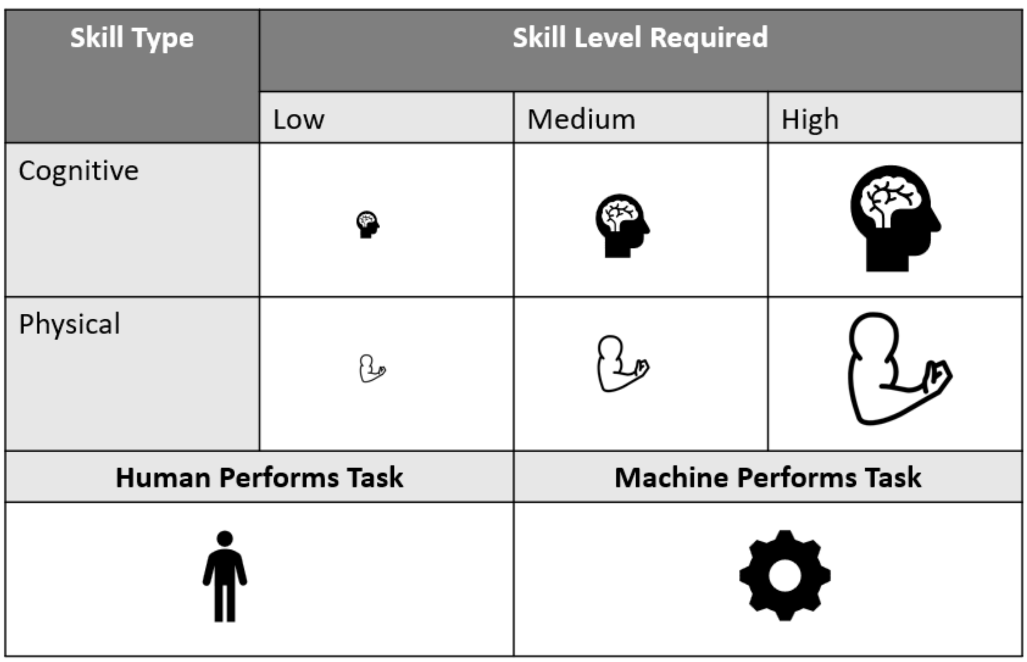

Figure 13 Icon Legend by Skill Type and Skill Level[18]

A job is held by a single human worker and, similarly to Autor, Levy and Murnane (2003) and Brynjolfsson, Mitchell and Rock (2018), we consider a job as a union of one or more tasks (Figure 14).

[18] Muscle icon source: Freepik. All other icons, Microsoft PowerPoint

We define the skill requirements for a job as the maximum of the skill requirements for the tasks that make up the job.

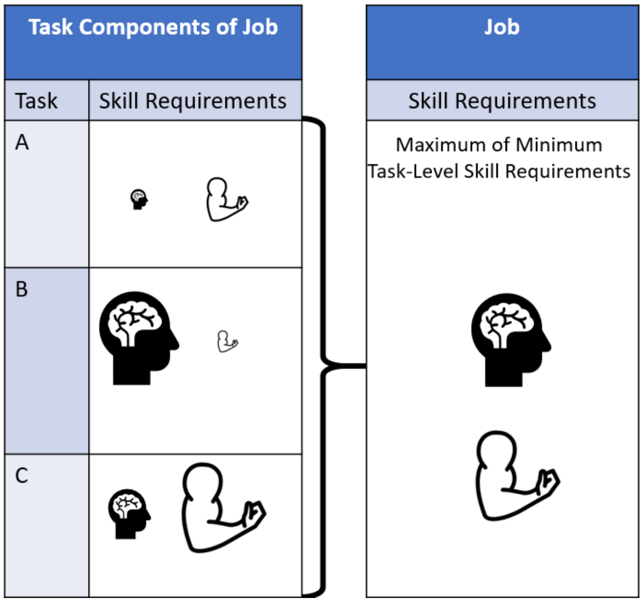

Figure 14 Aggregating Task Skill Requirements into Job Skill Requirements

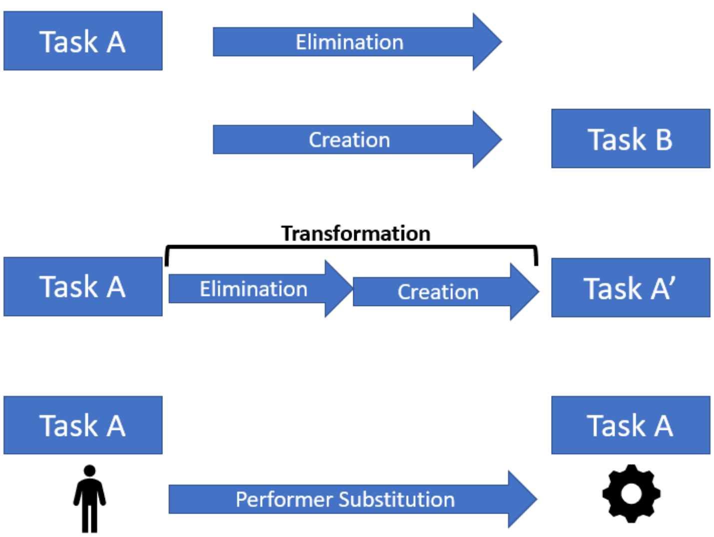

Figure 15 Mechanisms by which technological change affects tasks: Elimination, Creation, Transformation (Elimination and Creation) and Performer Substitution

Building on our empirical findings, Figure 15 presents the mechanisms by which technological change affects tasks: Technological change can *eliminate* existing tasks and can *create* new tasks. Technological change *transforms* the actions associated with tasks when it eliminates existing tasks and creates new ones to replace them with different actions but the same objective (i.e. same intermediate output). Finally, technological change can *substitute* who or what performs tasks.

Within the above taxonomy, automation by definition substitutes the task performer – specifically machines for humans (as shown in the performer substitution example in Figure 15). Parts consolidation by definition changes the design and thereby transforms the actions required to create that new design (as shown in the transformation example in Figure 15). These relationships are summarized by the solid arrows in Figure 16. Additional relationships that are possible by not required, are shown with dotted lines. As discussed earlier, automation may change the action associated with a task. Likewise, changing the action associated with a task may lead to different skill requirements.

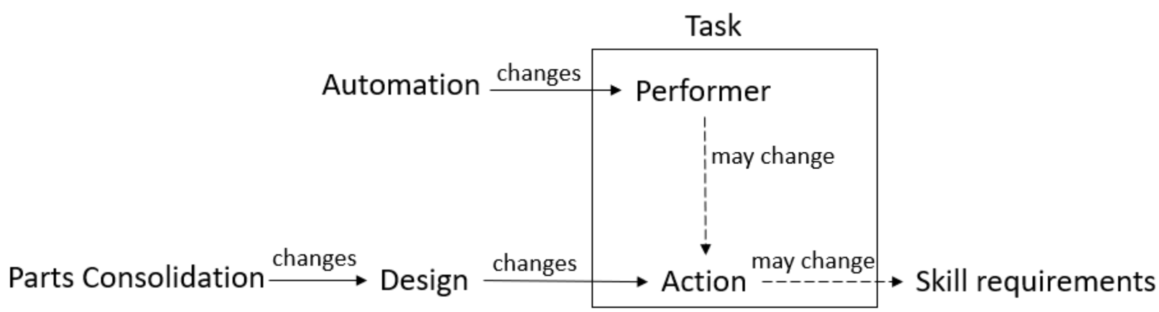

Figure 16 Mechansisms of Task Change through Parts Consolidation and Automation

Figure 17, Figure 18, and Figure 19 conceptualize key trends observed in our empirical findings for how automation and parts consolidation change task and job skill requirements. Figure 17 and Figure 18 conceptualize how automation polarizes skill demand as routine, codifiable tasks requiring low and medium skills are executed by machines instead of humans, while the remaining (Figure 17) and newly created (Figure 18) human tasks tend to require low and high skills. Figure 19 conceptualizes how parts consolidation converges skill demand as formerly divisible low and high skill tasks are transformed into a single indivisible task with medium skill requirements and higher cost of failure.

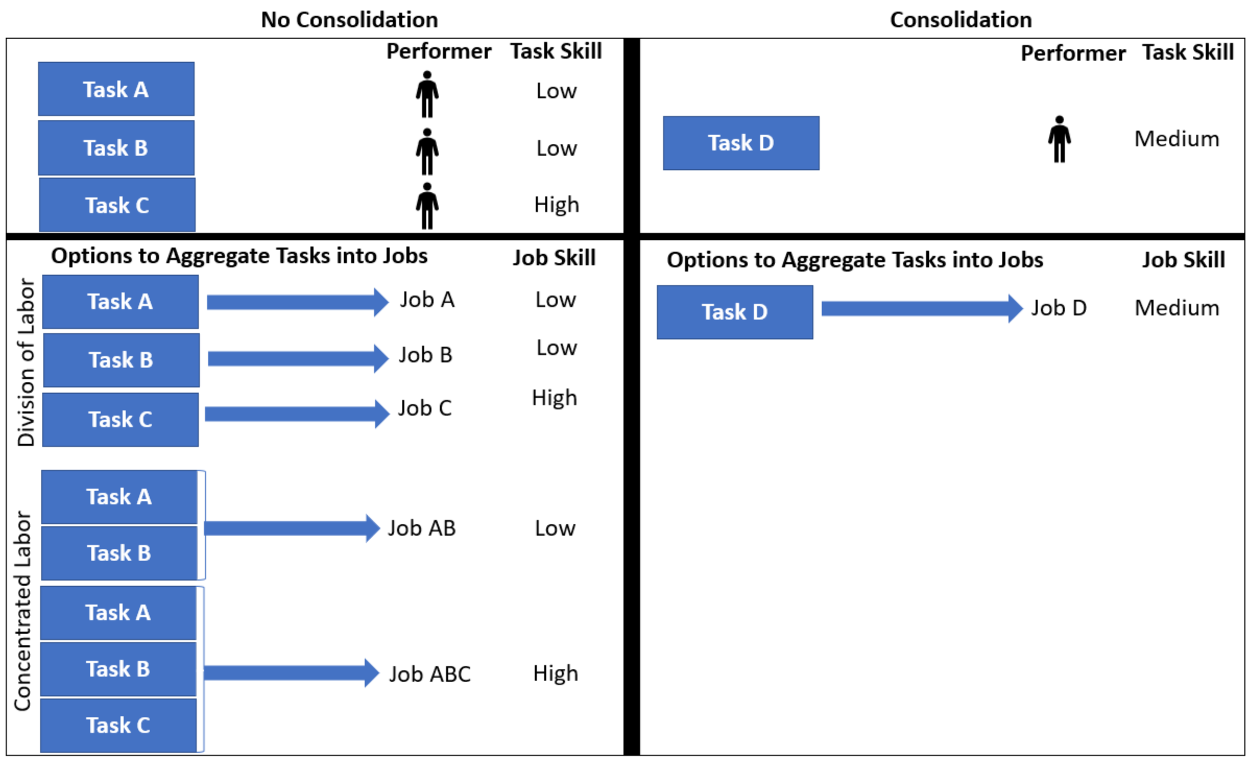

Figure 17 High Level Skill Effects of Parts Consolidation

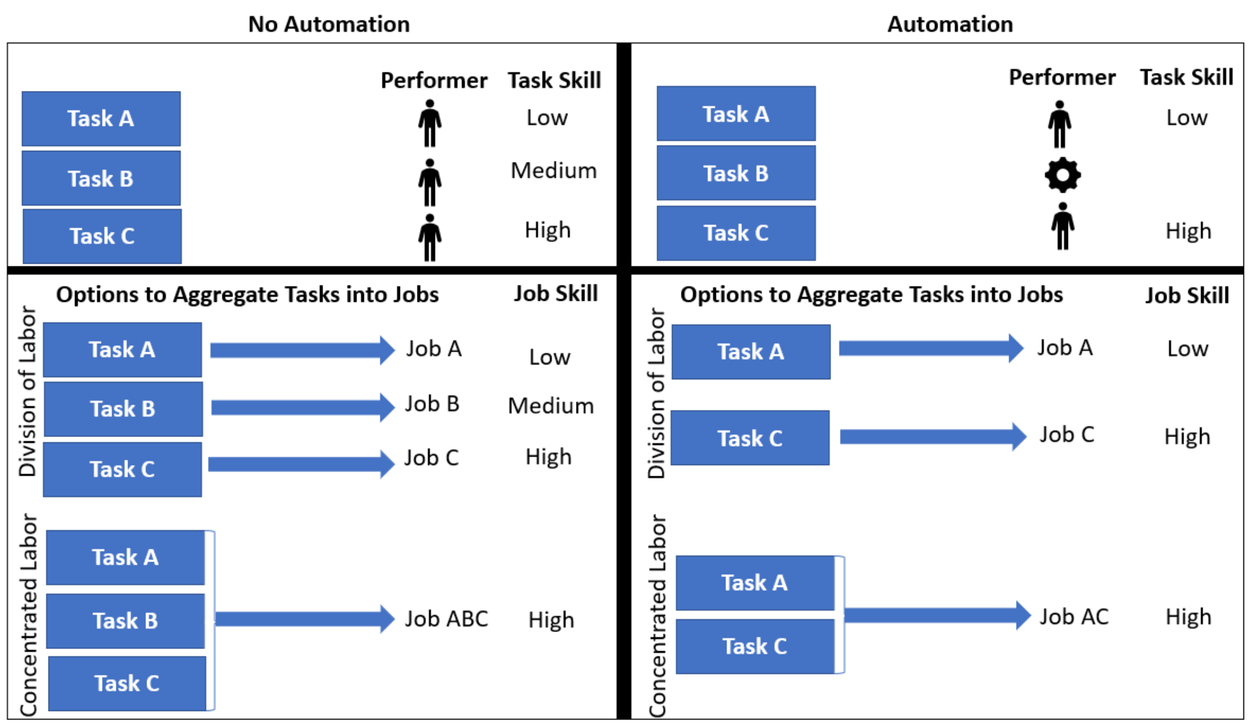

Figure 18 High Level Skill Effects of Automation

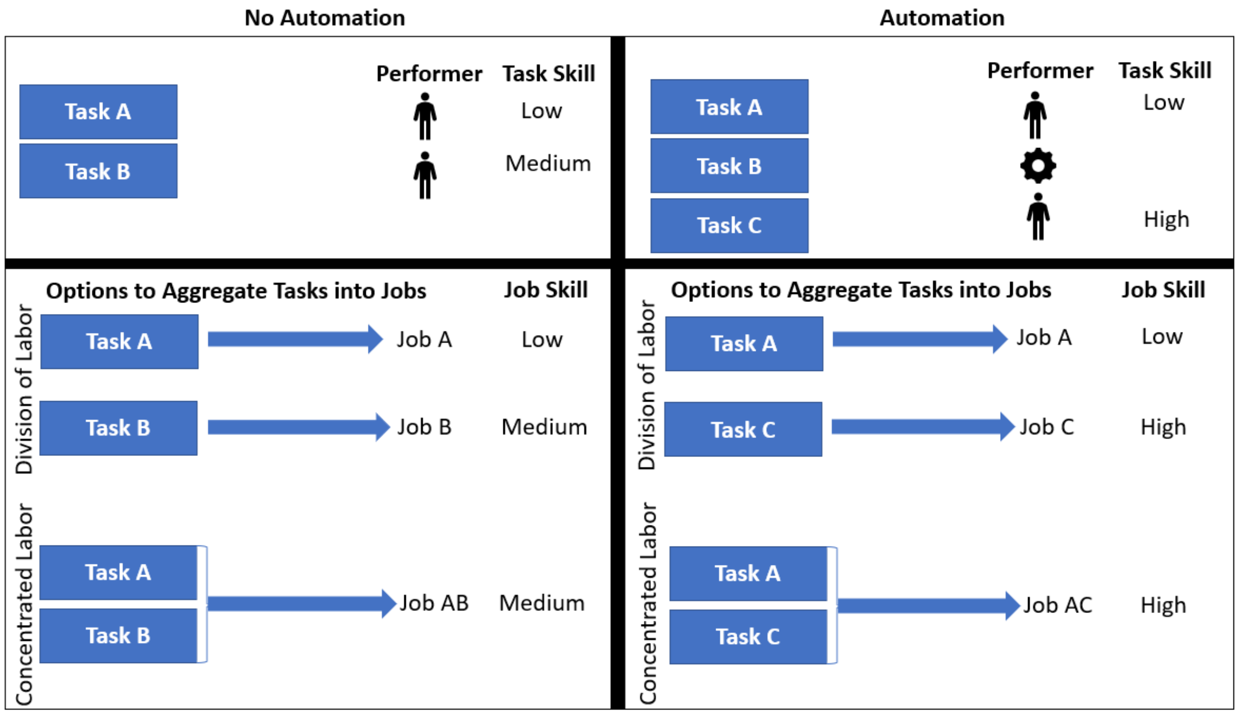

Figure 19 High Level Skill Effects of Automation with Task Creation

9.2 Categories of Tasks: Mediating the effect of technological change on job skill requirements

We now consider the impact of technology on skill requirements. Based on our manufacturing task data, we divide tasks into one of three categories – preparation, execution, and monitoring – where a process step could contain multiple tasks in a given category. We give examples of each of these types of tasks from our empirical setting in Table 5. We know from past PBCMs that these task categories generalize across manufacturing industries (Fuchs et al. 2008, Johnson and Kirchain 2009, Fuchs et al. 2011). We expect these task categories to also be informative in other production contexts, including software and services.

Table 5 Task Categories and Examples

<table>
<tr><th>Category of Tasks</th><th>Examples of Tasks</th><th>Example of Aggregation into Step</th></tr>
<tr><td>Preparation</td><td>Loading/Unloading a machine, Calibration, Laying out tools in a workstation</td><td rowspan="3">Wire bonding
<u>Preparation</u>
Clean Station
Load Station
<u>Execution</u>
Apply adhesive
Attach wire to die
Attach wire to substrate
<u>Monitoring</u>
Check wire hold</td></tr>
<tr><td>Execution</td><td>Hand wire bonding two parts, Activating a chemical vapor deposition machine</td></tr>
<tr><td>Monitoring</td><td>Is the operation running correctly? Does the part look of high quality?</td></tr>
</table>

We observe systematic differences in the rate at which technological change affects task categories. We find that different task categories are automated at different rates:[19] we find that a majority of automated tasks are execution, followed by monitoring (see Table 6). The large majority (91%) of production steps with automated tasks include an automated execution task (Table 7), with few cases of monitoring automated alone (9%) and no cases of preparation automated alone. Parts consolidation affects task categories differently than automation: whereas automation affects different task categories at different rates, consolidation in our data affects all task categories equally.

Table 6 Level and Share of Automation by Task Category

Task Category	Task Automation within Category	Share of all automated Tasks
Preparation	3%	3%
Execution	53%	64%
Monitoring	27%	33%

Table 7 Combinations of task categories automated within steps

Combinations of task categories automated within steps	Number of Steps Associated	Share of all automated tasks
Execution automated alone	22	49%
Execution automated, monitoring automated	17	38%
Monitoring automated alone	4	9%
Preparation automated, execution automated	2	4%
Preparation automated alone	0	0%
Preparation automated, monitoring automated	0	0%
All automated	0	0%

We believe that the propensity for execution steps to be automated is likely to generalize more broadly in manufacturing, as routine and codifiable execution tasks formerly conducted by humans are instead performed by machines. For example, in our data, one commonly automated execution step is die-attach: the task of picking up and placing a die onto an adhesive-prepared surface is repetitive and well characterized. As is the case in our data (Table 7), we suspect that within current technological constraints that automation of monitoring tasks often happens along with or after automation of execution tasks. The automation of monitoring requires codification of proper execution: for example, in our data, an automated monitoring process for fluid deposition on a wafer surface requires parameters for the thickness and distribution of fluid. Hence, if monitoring can be automated, execution usually has already been codified and had the potential for automation. Automating preparation tasks such as

[19] While our task data is limited to assembly, the highly automated fabrication at all firms would likely not have provided many examples of manual vs. automated tasks for detailed comparison.

equipment loading or part transfers between equipment may not be cost-effective at the production scales observed in our data.

In Figure 20, Figure 21, and Figure 22, we illustrate predominant mechanisms from our empirical data of automation and consolidation's effect on job skill requirements through task-level changes. In Figure 20, automation substitutes a machine for human labor in an execution task. Automation shifts job requirements from medium to low skill. By substituting a machine for a human in the most physically and cognitively intensive task of the process step (one requiring medium skills), automation shifts the minimum skills requirements for the job from medium to low. In Figure 21, the performer substitution of a machine for a human in the execution step is such that it requires also creating a new monitoring task which is more cognitively skill-intensive than the existing tasks. This shifts physical skill requirements for the job from medium to low but increases cognitive requirements from medium to high. In Figure 22 parts consolidation eliminates a task with high skill requirements and transforms the remaining tasks from requiring low skill to requiring medium skill. Tasks which may have been split among workers – one low-skilled and the other high skilled – *must* now constitute one medium skill job.

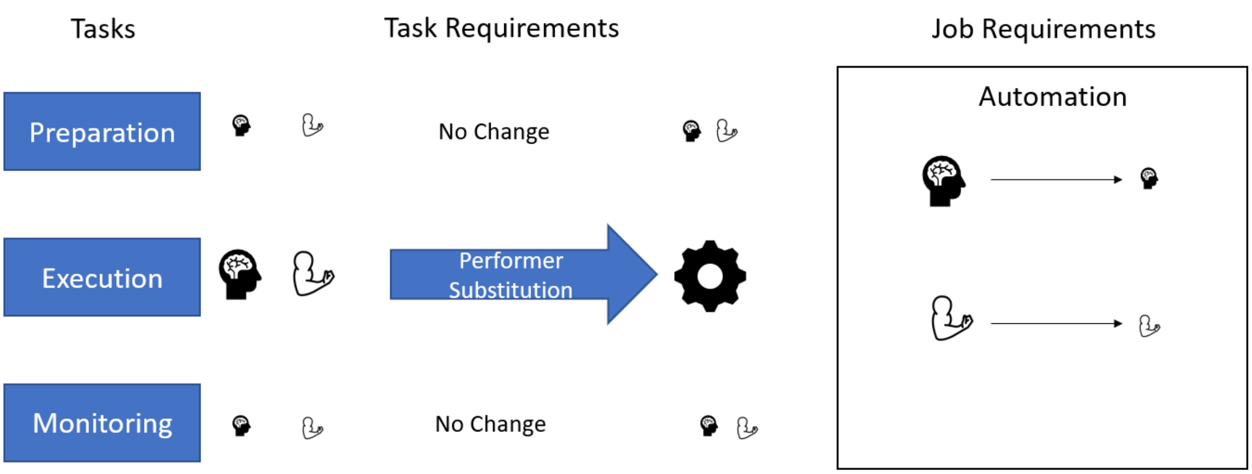

Figure 20 Example of Performer Substitution under Automation

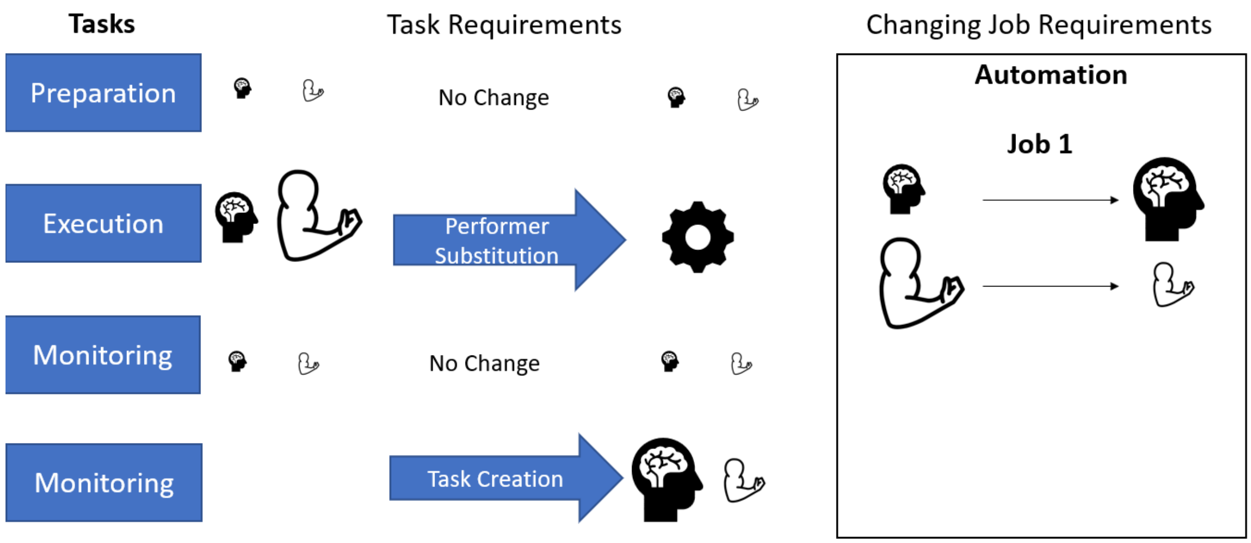

Figure 21 Example of Job Requirement Changes through Automation (Substitution, Creation)

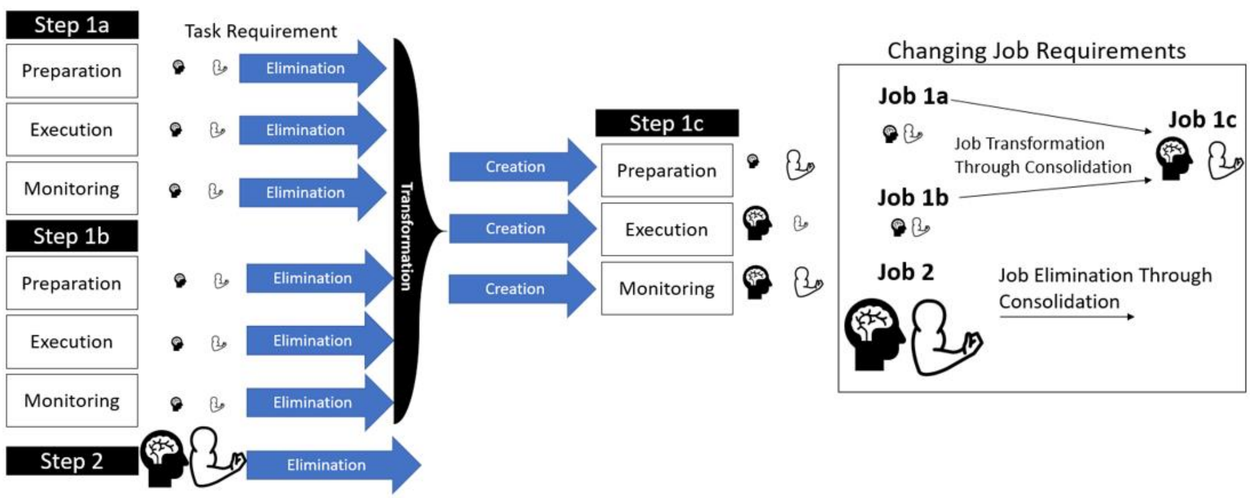

Figure 22 Example of Job Requirement Change through Consolidation

10. Conclusions

A significant literature identifies skill-biased technological change as a driver of the polarization of wages and employment in the economy (e.g. Card and DiNardo 2002, Autor and Dorn 2013). This literature faces the limitations of coarse and aggregate data such as having to use education or wage percentile as a measure of skill (e.g. Carneiro and Lee 2011, Autor and Dorn 2013), and having to use aggregate capital spending as a measure of technology adoption (e.g. Bresnahan et al. 2002, Michaels et al. 2014). In addition, future technological effects on labor outcomes may not necessarily correspond to past phenomena. A recent literature has emphasized the need to consider task-level implications of technological change (Acemoglu Autor 2011 and Acemoglu Restrepo 2016). Empirical evidence of the benefits of such task-based approaches includes surveying of managers on the facility-level (rather than process step and task) impact of information technology adoption on skill requirements (Bartel et al. 2004 and 2007) and crowd-sourcing of which O*NET skills and work tasks are likely to be automated (Brynjolfsson, Mitchell and Rock 2018). While these papers provide indirect indications by surveying of experts, managers and general respondents in the cloud (e.g. Amazon MTurk), to date direct measurement of technological effects on skill requirements has been lacking. This paper fills that gap.

Our paper demonstrates the benefits of directly measuring the effect of technological changes on skill demand, here, achieved by using an engineering process model and detailed, equipment-level production data. The specificity of our model and data as well as our ability to generate counterfactual scenarios enables us to simulate past, ongoing *and emerging* technological changes, thus going beyond the restrictive assumptions of classic production functions, of aggregate data, and of historic data being representative of the future. We are also able to disentangle simultaneous technological changes with differential labor effects invisible in aggregate data, and to characterize task-level mechanisms behind our findings regarding the effects of technological change on skill demand.

We make five contributions. First, we directly measure the effect of technological changes on skill demand, addressing the gap in the task-approach literature. In addition to automation's effect on labor demand, we measure the effect of parts consolidation, a product innovation that allows formerly discrete parts to be fabricated as a single component (Schwedes 2001). Second, we show that aggregate measures of technological change can mask the opposing skill demand shifts of multiple technological changes. Understanding these differential effects of technologies on labor outcomes is a key first step to analyzing the impact of emerging technological changes on labor demand, and eventually markets. Further, challenges with awareness, identification, and measurement of such simultaneous forms of technological change in aggregate data may complicate causal inference using traditional methods.

Third, whereas the majority of SBTC research has been economy-wide, our results are within an occupation, here operators. Our focus on jobs requiring a lower level of education helps unpack how technological change is affecting a population of workers known to have low workforce participation (BLS 2018) and particular vulnerability to technological displacement (Autor and Dorn 2013, Acemoglu and Restrepo 2017).

Fourth, we find that automation polarizes while parts consolidation converges skill demand within an occupation.[20] In the case of automation, we see demand for physical and cognitive skills shifted in opposing directions, leading to skill polarization among operators within the industry. One predominant mechanism underlying these results is machines replacing humans in more physically and cognitively intensive work, such as intricate assembly tasks, but also creating more cognitively intensive work, such as monitoring of automated processes. These findings build on Bartel et al.'s (2007) facility-level survey findings, in which managers report that that adoption of new IT-enhanced capital equipment coincides with increases in the skill requirements of machine operators. In contrast to automation, parts consolidation converges demand for the physical and cognitive skills required of operators in the industry. As more parts are monolithically fabricated as a single unit, assembly tasks requiring the highest physical and cognitive skills are eliminated, and fabrication and assembly tasks requiring the lowest physical and cognitive skills are transformed to tasks requiring more middle-level skills. Parts consolidation also reduces opportunities for divisions of labor between tasks of different skill levels, further shifting demand (in our data) from low to medium or (we hypothesize sometimes in other industrial contexts) to high. This shift from low to middle-level (or high) skills is in part associated with consolidated parts having a greater cost of production failure, and thus a demand by the firm to minimize such failures.

Fifth, we leverage our task- and step-level data to propose new theory for the mechanisms underlying the effect of technological change on skill demand: We propose that technological change leads to three outcomes for tasks and their associated skill requirements: task elimination, task creation, or performer substitution. Within our taxonomy, automation by definition leads to performer substitution, parts consolidation by definition to task transformation task (defined as elimination followed by creation).

The mapping of the differential effects of technologies on labor outcomes presented for the first time in this paper, along with its associated theoretical framework for thinking about such change, introduce new dimensions to the effect of technological change on labor demand, and open up new questions regarding the implications for labor markets and appropriate policy response.

[20] While beyond the scope of this paper, we hypothesize that consolidation will also converge skill demand across occupations. We further hypothesize that direct measurement will uphold the theory that automation polarizes skill demand across occupations.

Acknowledgements:

Our utmost thanks to Brian Kovak and David Hounshell for their extensive guidance and insights on this research. Any remaining errors are our own.

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Appendix 1: Equations

Appendix 1.1: Process-based Cost Model Architecture and Cost Calculations

We build on the model decision rules used in Fuchs and Kirchain (2010) and Fuchs, Kirchain, and Liu (2011), the full equations for which can be found in Fuchs and Kirchain (2010). Rather than using the notation from Fuchs and Kirchain (2010) we represent the same and our new equations using the notation from *Quantitative Entrepreneurship: Analysis for New Technology Commercialization* (Michalek and Fuchs 2018). This newer notation provides several advantages in the extensions we develop over Fuchs and Kirchain (2010).

Per Fuchs and Kirchain (2010), aggregate costs are calculated as follows:

$$C_{Tot} = C_{Material} + C_{Labor} + C_{Equipment} + C_{Tooling} + C_{Building}$$

$$C_{element} = \frac{AC_{element}}{PV}$$

Where C_{tot} is the unit production cost of the product, given an annual production volume *PV*. $C_{element}$ is the unit cost of an element (material, labor, equipment, tooling, building) and $AC_{element}$ is the annual cost of each element.

Compared with Fuchs and Kirchain (2010), we do not include energy costs as in Fuchs et al (2011), energy costs in the production of an optoelectronic device were less than one percent of unit production cost. We also, different from Fuchs and Kirchain (2010) do not include overhead costs, as our focus is on direct production and labor demand.

We do not calculate embedded yields, i.e. yields that happen during the process but are not caught until later testing steps (see Fuchs and Kirchain (2010) for an extended discussion), as we do not have that information (nor did Fuchs and Kirchain (2010), in their case the embedded yields were estimates by engineers as to where the revealed yields were coming from.) In our paper, all yields are simply accounted for at the step where they show up empirically.

Material Cost:

We treat material costs as in Fuchs and Kirchain (2010), except we do not include a material scrap rate (i.e. extra material needed due to excess material that does not end up on the final part). This difference is because we received material inputs as total material required to go through one processing cycle (widget or batch of widgets) at each step, rather than as an amount of material required for the actual part plus some amount of additional material required for the step that would be lost and not end up on the final part.

Labor Cost:

We consider only direct operator labor for this paper. Our labor cost equation has two differences from Fuchs and Kirchain (2010): first, matching our empirical observations, we treat operator labor as always dedicated to process steps (labor is not dedicated in Fuchs and Kirchain (2010)); in our empirical observations operators did not move between machines. Second, whereas all operators have the same wage in Fuchs and Kirchain (2010), in our model, we have different average operator wages for different process steps. Hence:

$$AC_{labor} = \sum_j W_j (t_j^{ALB}) u\left(EPV_j\right)^{LB}$$

W_j is average operator wage in step j (this may vary if some steps are performed in different locations); t_j^{ALB} is the annual hours worked by an operator employed in a production step (in our model, typically 40 hours a week, 50 weeks a year for 2000 hours a year, but allowed to vary). EPV_j is the effective production volume of step j: taking the annual production volume PV of the finished good as given, EPV_j is a function of both PV and the product of the yield rates y_n of subsequent steps in the set N (the production path to which step j belongs): $EPV_j = PV \prod_{n \geq j+1, n \in N} y_n$.

$u\left(EPV_j\right)^{LB}$ is the annual quantity of laborers demanded at a given process step:

$u\left(EPV_j\right)^{LB} = \left\lceil \frac{\mathrm{t}\left(EPV_j\right)^{LB}}{t_j^{ALB}} \right\rceil$, and $t\left(EPV_j\right)^{LB} = \frac{n\left(\mathrm{EPV_j}\right)^{LN} t_j^{AVL}}{\phi_j^{LB} \rho_j^{LB}}$

Where $\mathrm{t}\left(EPV_j\right)^{LB}$ is the annual labor time required in step j to satisfy effective production volume, $n\left(\mathrm{EPV_j}\right)^{LN}$ is the number of capital lines required in step j to satisfy its effective production volume, ϕ_j^{LB} is the fraction of equipment time requiring a human operator and ρ_j^{LB} is the number of pieces of equipment in step j that one operator can manage and t_j^{AVL} is the net available annual hours (after downtime) that capital in step j can operate.

Capital Cost: (equipment and tooling)

We annualize costs using the standard capital recovery factor formula, as in Fuchs and Kirchain (2010). As with Fuchs and Kirchain (2010), we use a discount rate of 10%.

We treat equipment and tooling costs and calculate capital lines required $n\left(\mathrm{EPV_j}\right)^{LN}$ as in Fuchs and Kirchain (2010) and denoted in Michalek and Fuchs (2018), but with expanded options for capital sharing: in addition to capital dedicated to a process or shared across other products outside our model scope, we allow cases of capital sharing across multiple specific steps within the same production process but *not* across products. If capital is dedicated to the overall production process but shared across process steps in the set G of cardinality R, we define $n\left(\mathrm{EPV_j}\right)^{LN}$ the lines required in step j:

$$n\left(\mathrm{EPV_j}\right)^{LN} = \frac{reqLT_j}{availLT_j} + \left[\left\lceil \sum_{g \in G} \frac{reqLT_g}{availLT_g} \right\rceil - \sum_{g \in G} \frac{reqLT_g}{availLT_g}\right] / R$$

Where $reqLT_j$ is the line time required in step j to meet effective production volume (as in Fuchs and Kirchain (2010)) and $availLT_j$ is the available annual time per line.

Building Cost:

In Fuchs and Kirchain (2010), building costs are linear with equipment, but they are described as a more general function of building capacity and required line time. We explicitly relate building costs linearly with equipment requirements, as in Michalek and Fuchs (2018):

$$AC_{Building} = \sum_j n\left(\mathrm{EPV_j}\right)^{LN} A_j p_q^{BL}$$

Where $A_{j,q}$ is the square footage of type q (e.g. a cleanroom) required of capital in step j and p_q^{BL} is the annualized cost per square foot of facility space type q, annualized using the standard capital recovery factor.

Appendix 1.2: Calculating Skill Demand and Interfirm Variation Ranges

Skill Demand:

In order to calculate operator skill demand from our model, we first multiply the number of operators required at a given process step by a 5x3 index matrix of the skills S_j required for that step:

$$S_j u\left(EPV_j\right)^{LB} = \begin{bmatrix} Dexterity_{1,j} & \cdots & Ops\&Control_{1,j} \\ \vdots & \ddots & \vdots \\ Dexterity_{5,j} & \cdots & Ops\&Control_{5,j} \end{bmatrix} u\left(EPV_j\right)^{LB} = D_j$$

Where $u\left(EPV_j\right)^{LB}$ is the annual labor demanded at process step j for an annual output PV_j from step j, and where $Skill_{j,m}$ indicates for a given skill in step j the level m of difficulty required [1-5]. $Skill_{j,m}$takes the value 0 if skill level m is not required and 1 if required, and $\sum_{m=1}^{5} Skill_{j,m} = 0$ (meaning that two levels of the same skill cannot be required for the same step:[21] within our theory, the higher of the two levels would be the required skill level). Thus, D_j is a matrix of process-step level demand for skill. The sum across the entire production process thus gives us the process-level demand matrix for skill:

$$D = \sum_{j=1}^{N} D_j$$

Process Configurations that Minimize and Maximize Unit Production Cost or Labor

In order to account for interfirm variation (see section 6.3-6.4), we select sequences of inputs (from the available empirical alternatives for each production step in the process) that will maximize or minimize unit production cost and labor quantity required and use these to construct ranges of production cost and labor demand.

Each step j in a production process has a set of alternative equipment inputs $\{I_j\}$ drawn from the empirical examples in our data of different firms performing the same production task. For a given scenario we refine the set $\{I_j\}$ to elements whose level of automation corresponds to the scenario (i.e. high or low): $\{I_j\} \cap \{Scenario\ Automation\}$: the mechanisms for interfirm variation hold with or without this refinement.

[21]It may be possible for different tasks within a process step to require different levels of the same skill level, but in our empirical context operator jobs are at the process step level.

All elements $i_j \in \{I_j\}$ have corresponding Leontief production functions relating capital, material and labor inputs to y_j, the annual output of the step j: because of our Leontief construction, the selection of capital alternatives includes labor and material requirements. Because we collect our skill requirement data at the process-step level, each i_j also has a corresponding skill requirement matrix, $S_{j,i}$.

Given y_j, we can select $i_j \in \{I_j\}$ such that the cost or labor requirements of step j are minimized or maximized:

The range of labor required in a given production step is given by:

$$[\min_{i_j \in \{I_j\}} u(i_j, EPV_j)^{LB}, \max_{i_j \in \{I_j\}} L(i_j, EPV_j)^{LB}]$$

Thus, the range of labor skill demand for a production process is given by:

$$[\sum_{j=1}^{N} S_{j,i} \min_{i_j \in \{I_j\}} L(i_j, EPV_j)^{LB}, \sum_{j=1}^{N} S_{j,i} \max_{i_j \in \{I_j\}} L(i_j, EPV_j)^{LB}]$$

Where $u(i_j, EPV_j)^{LB}$ is the quantity of labor demanded in step j given the input alternative i_j and the effective production volume of step j.

The range of annual production costs for step j is a function of input requirements as a function of i_j and y_j multiplied by the vector of input prices. Input prices are collected for each possible input in our data and are expressed as a function of i_j (i.e. while material and labor prices are invariant in choice of i_j i_j determines which type of capital is used and hence, the price of a unit of capital).

$$[\min_{i_j \in \{I_j\}} \left(\left(u(i_j, EPV_j)^{EQ}, u(i_j, EPV_j)^{T}, u(i_j, EPV_j)_b^{BL}, u(i_j, EPV_j)^{LB}, u(i_j, EPV_j)_k^{M} \right) p(i_j)^{\mathrm{T}} \right),$$

$$\max_{i_j \in \{I_j\}} \left(\left(u(i_j, EPV_j)^{EQ}, u(i_j, EPV_j)^{T}, u(i_j, EPV_j)^{BL}, u(i_j, EPV_j)^{LB}, u(i_j, EPV_j)_k^{M} \right) p(i_j)^{\mathrm{T}} \right)]$$

Where $u(i_j, EPV_j)^{EQ}, u(i_j, EPV_j)^{T}$ are the quantity of capital, building area of type b and tooling (respectively) required per step given the input alternative i_j and the effective production volume of step j, $u(i_j, EPV_j)_k^{M}$ is the quantity of material k required given the input alternative i_j and the effective production volume of step j of step j. $p(i_j)^{\mathrm{T}}$ is the transpose of the vector of (annualized) prices of capital, labor and material (with capital and labor costs possibly a function of i_j).

These terms correspond to the annual step level production cost given input alternative i_j:

$$\left(u(i_j, EPV_j)^{EQ}, u(i_j, EPV_j)^{T}, u(i_j, EPV_j)^{BL}, u(i_j, EPV_j)^{LB}, u(i_j, EPV_j)_k^{M}\right) p(i_j)^{\mathrm{T}} = AC(i_j, EPV_j)_j$$

Thus the range of overall production costs is given by:

$$[\sum_{j=1}^{N} \min_{i_j \in \{I_j\}} \left(AC(i_j, EPV_j)_j\right), \sum_{j=1}^{N} \max_{i_j \in \{I_j\}} \left(AC(i_j, EPV_j)_j\right)]$$

As in 1.1, our process-based engineering model takes the annual production volume PV of the finished good as given, but EPV_j is a function of both PV and the product of the yield rates y_n: Thus, for each production step in our process and the above optimizations, we set $EPV_j = PV \prod_{n=j+1}^{N} y_n$ independently of i_j using the yield rates of *baseline inputs* (see section 6) to subsequent steps.

By definition, the inputs that give us our interfirm variation in labor demand also produce a range of production costs that is a subset of our interfirm cost range: we illustrate from our empirical data that the range of production costs (at the median annual production volume of our industry sample) associated with our sequence of labor variation inputs is equal to or within the range associated with our sequence of cost variation inputs:

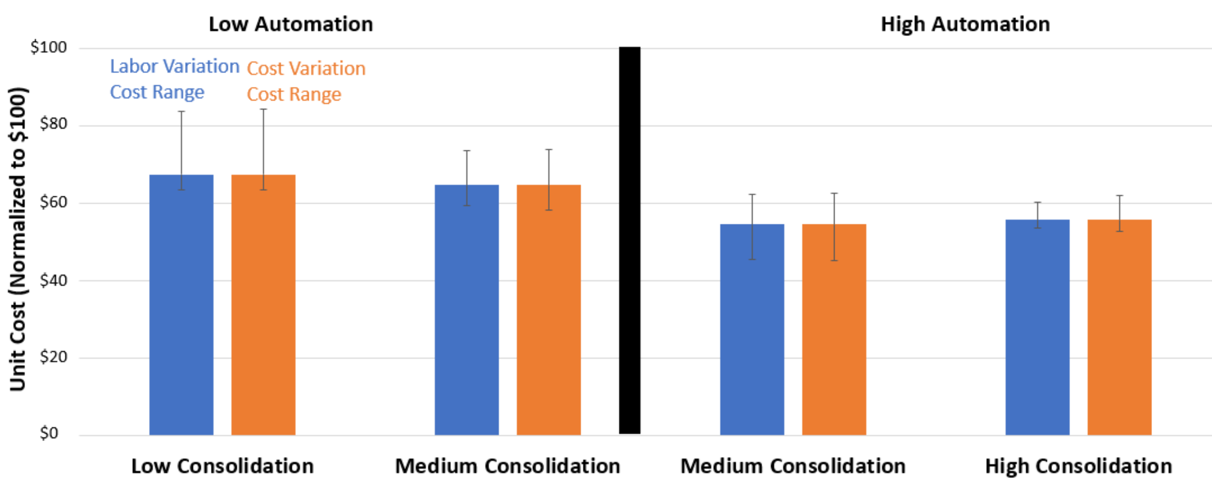

Figure 23 Cost Range Comparisons of Interfirm Labor and Cost Variation Inputs

Appendix 1.3: Equations for Aggregation of Shifts in Skill Demand

We calculate the change in jobs of a given skill level within a given skill type using the following equation:

$$\Delta J_{t,s}(X, Y) = J_{t,s}(Y) - J_{t,s}(X)$$

Where $J_{t,s}(X)$ is the number of operator jobs requiring level s (e.g. skill level 1) of skill type t (e.g. operations in control) in scenario X. We define $\Delta J_{T,s}(X,Y)$ as the change in operator jobs requiring skill level s when moving between scenario X and scenario Y. Following the scenario codes in section 4, the change in demand for low skill (skill level 1) cognitive (i.e. operations and control) operators under automation is thus the change in demand for low cognitive skill between low automation (scenario B1) and high automation (scenario B2):

$$\Delta Low\ Cognitive\ Skill\ Jobs\text{: } \Delta J_{Ops\,\&\,Control,1}(B1,B2) = J_{Ops\,\&\,Control,1}(B2) - J_{Ops\,\&\,Control,1}(B1)$$

$$\Delta High\ Cognitive\ Skill\ Jobs\text{: } \Delta J_{Ops\,\&\,Control,5}(B1,B2) = J_{Ops\,\&\,Control,5}(B2) - J_{Ops\,\&\,Control,5}(B1)$$

To calculate the change in demand for medium skill of a given type, we refer to the following equation where $\Delta J_m(X,Y)$ is the change in number of operator jobs with medium skill requirements (skill level 2 through skill level 4):

$$\Delta J_{t,m}(X,Y) = \sum_{s=2}^{s=4} J_{t,s}(Y) - J_{t,s}(X)$$

For example, the change in medium cognitive skill jobs under automation is given by:

$$\Delta J_{Ops\,\&\,Control,m}(B1,B2) = \sum_{s=2}^{s=4} J_{Ops\,\&\,Control,s}(B2) - J_{Ops\,\&\,Control,s}(B1)$$

To calculate changes in jobs within skill categories that contain multiple skill types, we refer to:

$$\Delta J_{t,s}(X,Y) = \sum J_{t,s}(X,Y) \mid t \in C$$

Where $\Delta J_{C,s}(X,Y)$ is the change in jobs at skill level s within a skill category C. The equation above is the change in jobs with skill level s in at least one of the skill types t in the category C (e.g. dexterity and near vision in physical skill). For example, the change in demand for low and high physical skills under automation is given by:

$$\Delta Low\ Physical\ Skill\ Jobs\text{: } \Delta J_{Physical,1}(B1,B2) = \Delta J_{Near\ Vision,1}(B1,B2) + \Delta J_{Dexterity,1}(B1,B2)$$

$$\Delta High\ Physical\ Skill\ Jobs\text{: } \Delta J_{Physical,5}(B1,B2) = \Delta J_{Near\ Vision,1}(B1,B2) + \Delta J_{Dexterity,1}(B1,B2)$$

To calculate the change in medium skill jobs within a skill category C, we refer to:

$$\Delta J_{C,m}(X,Y) = \sum J_{t,m}(X,Y) \mid t \in C$$

Where $\Delta J_{C,m}(X,Y)$ is the change in jobs at skill level m within skill category C. The equation above is the change in medium skill jobs across all skill types t in the category C (e.g. dexterity and near vision in physical skill). For example, the change in demand for medium physical skills under automation is given by:

$$\Delta J_{Physical,m}(B1,B2) = \Delta J_{Near\ Vision,m}(B1,B2) + \Delta J_{Dexterity,m}(B1,B2)$$

Appendix 2: Data and Validation

Appendix 2.1: Automation Level by Process Category and Automation Scenario

Table 8 Taxonomy of Mechanical and Equipment Level of Automation (Frohm et al. 2008)

Level of Automation	Machinery and Equipment
1	Totally physical – totally physical work, no tools are used, only the operators' own muscle power.
2	Static hand tool – physical work with support of static tool. (e.g. screwdriver)
3	Flexible hand tool – physical work with support of flexible tool. (e.g. microscope)
4	Automated hand tool – physical work with support of automated tool. (e.g. power screwdriver)
5	Static machine/workstation – automatic work by machine that is designed for a specific task (e.g. curing oven)
6	Flexible machine/workstation – automatic work by machine that can be reconfigured for different tasks (e.g. die attach machine)
7	Totally automatic – totally automatic work; the machine solves all deviations or problems that occur by itself; autonomous systems.

None of our process steps are "totally physical" or "totally automatic." Most equipment in our study is in the 3 to 6 range, though some static hand tools exist (e.g. screwdrivers for packaging). Our per-step data includes detailed equipment descriptions (e.g. hand microscopes for visual inspection vs. automated testing tools or hand vs. power screwdrivers for physical assembly. In presenting results of the influence of technological change on physical and non-physical tasks, we aggregate levels 1-4 in the taxonomy as "physical", and levels 5-7 as non-physical. We control for automation by matching input steps according to task, physical status and equipment description (e.g. Step 1 requires a microscope to physically inspect a part (level of adjustment 3) and must be matched with other inspection steps performed physically, using a microscope).

Appendix 2.2: Process Based Cost Model Inputs and Sample of Per Step Inputs

Table 9 Other PBCM Inputs Collected

Input Type	Industry Sample
Equipment and Tooling Inputs: Across 318 unique pieces of equipment and 108 unique tools	
Equipment Price	0 to $8,000,00
Tooling Price	$0 to $30,000
Batch Size	1 to 34,000
Yield Rate	85% to 100%
Operation Time	0 to 44 hours
Load/Unload Time	0 to 8.75 minutes
Annual Downtime	5 days to 20 days
Equipment Dedicated?	True or False
Labor Inputs: Across three categories of labor	
Supervisor to Operator Ratio	N/A or 1:25 to 1:50
Technician to Equipment Ratio	N/A or 1:11 to 1:1
Labor Dedicated?	True or False
Equipment to Operator Ratio	1:10 to 1.9 : 1
Operator Wage	$2.50 to $20.00 (varies by country)
Supervisor Wage	$6.00 to $30.00 (varies by country)
Technician Wage	$5.40 to $25.00 (varies by country)
Material Inputs: Across 114 unique materials	
Material Price	$0.00 to $31.00 per unit
Facility Wide Inputs: Across 9 unique facilities	
Shift duration	8 to 12 hours
Shifts per Day	1 to 3
Facility-Wide Annual Downtime	0 to 2 weeks

Values of 0 for an input indicate that there is no input of that type for a specific process step (e.g. $0.00 material price means no material input) or facility (e.g. 0 weeks Facility-Wide Annual Downtime).

Appendix 2.3: Education, Training

We find that operators with different levels of education (8-12 years) performed tasks with comparable equipment and process inputs (yields, cycle time, skill requirements). As our descriptive tables below illustrate, educational requirements and level of parts consolidation varied by region but were typically fixed at 8 or 12 years for all operators; operators in the United States, Europe and North America all required a high school education.

Table 10 Minimum Educational Requirements for Fabrication Operators

	Low Parts consolidation	Medium Parts consolidation	High Parts consolidation
Operator Share by Education	Japan	North America	Controlled Scenario Only
8 Years	0%	0%	
12 Years	100%	100%	

Table 11 Minimum Educational Requirements for Assembly Operators

	Low Parts consolidation		Medium Parts consolidation			High Parts consolidation
Operator Share by Education	China	Developing East Asia	North America And Europe		China[22]	Controlled Scenario Only
8 Years	13%-16%	100%			10-15%	
12 Years	84%-87%		100%	100%	85-90%	

Appendix 2.4 Validation:

In the following tables, we provide deidentified examples of empirical quantities of equipment and labor in our sample facilities for comparison with estimates produced by our models of those facilities. The models of individual production steps that underlie these facility-level estimates were then used to construct our counterfactuals. In Table 12 and Table 13, variation in our estimates of equipment and labor quantity was driven by differences in utilization assumptions, with the upper bound assuming that inputs dedicated to specific production steps and the lower bound assuming that equipment was shared across all production steps in which it was utilized, as well as within-firm variation in operational inputs (e.g. load and unload time); the baseline assumption was that inputs were shared across steps. We discussed cases of apparent over or under capacity in our estimates with firms both as a means of checking operational parameters (e.g. cycle time) and calibrating our utilization assumptions, including varying whether our baseline estimate reflected shared or dedicated capital.

Table 12 Sample of Empirical Validations of Equipment Quantity Estimates

Process Category	Equipment Type	Equipment Quantity in Sample Facility	Estimated Equipment Required in Sample Facility
Testing	Burn-In	10	10
Subassembly	Wire Bond	4	3 to 4 (baseline 4)
Subassembly	Die Bond	8	6 to 9 (baseline 7)

[22] Using low parts consolidation educational data to populate medium parts consolidation scenario.

Table 13 Sample of Empirical Validations of Labor Quantity Estimates

Process Category	Operator Quantity in Sample Facility	Estimated Operators Required in Sample Facility
All Assembly	220	190 to 235 (baseline: 212)
Fabrication	50	48 to 64 (baseline: 48)

To further validate our counterfactual scenarios, we also compared counterfactual unit cost estimates to our unit cost estimates of production within empirical facilities (we did not use firms' estimate of unit cost as they did not necessarily include the same factors as our model). We find that unit productions costs in our counterfactuals overlap with our estimates of unit costs at empirical facilities for the range of annual production volumes shared by firms.

Appendix 3: Results Not Shown in Main Body

Appendix 3.1: Demand Distributions by Skill and Scenario

3.1.1 Dexterity Requirements for Operators

We observe that dexterity requirements skew upward from low to medium parts consolidation, reducing the lowest difficulty factor and increasing the absolute number (Figure 24) and share (Figure 25) of operators at the highest skill factor (5), even as the total number of operators decreases. Further parts consolidation (under high automation) reduces both lower (level 2) and high skill requirements (level 5), driving a shift toward the center, as mid-level skill (i.e. level 3) operators increase in absolute terms (Figure 24) as well as proportionally (Figure 25). Automating the medium parts consolidation scenario, conversely, shifts operators toward lower skill requirements. The quantity of level 5 operators decreases in absolute and proportional terms, while levels 1, 3 and 4 are stable and level 2 operators increases in absolute and proportional terms. Not only do dexterity-intensive final assembly tasks persist from low to medium parts consolidation, greater failure and yield considerations appear to drive an upward skewing in skill requirements. Unlike under low to medium parts consolidation, parallel process flows are not merged (i.e. process steps eliminated by parts consolidation were already sequential) from medium to high parts consolidation. This suggests that yield considerations driving dexterity requirements in medium parts consolidation are unchanged, and the effect of high dexterity task elimination is dominant, driving down dexterity requirements overall.

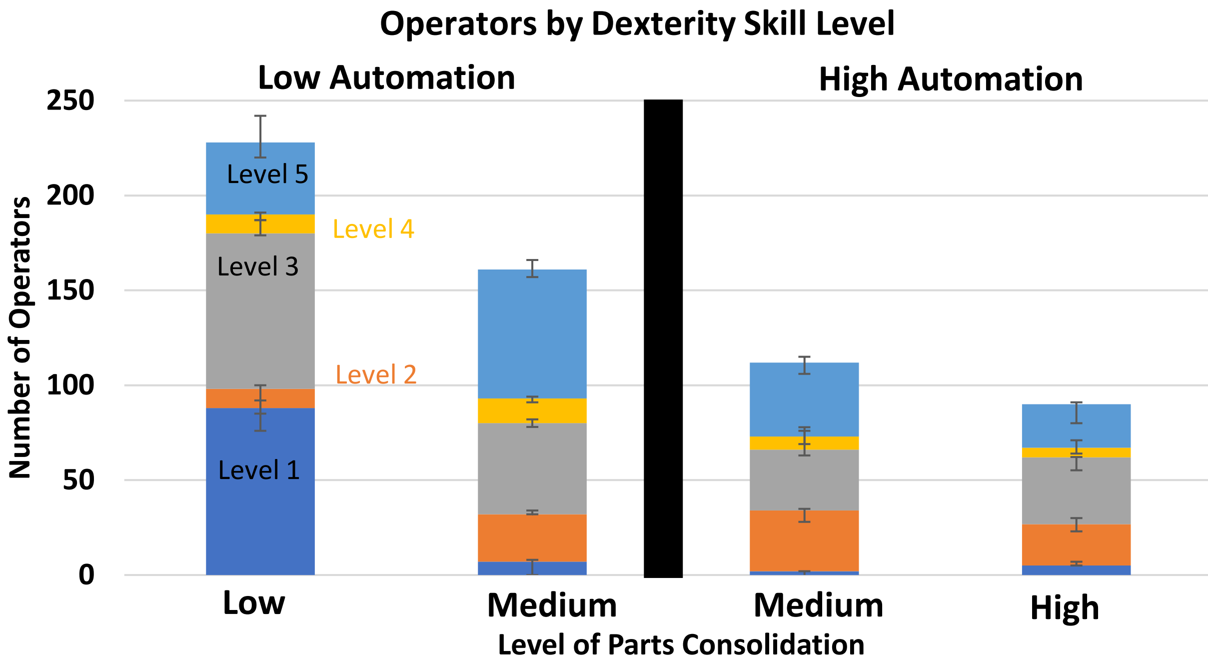

Figure 24 Number of Operators by Scenario and Dexterity Requirement (Median APV)

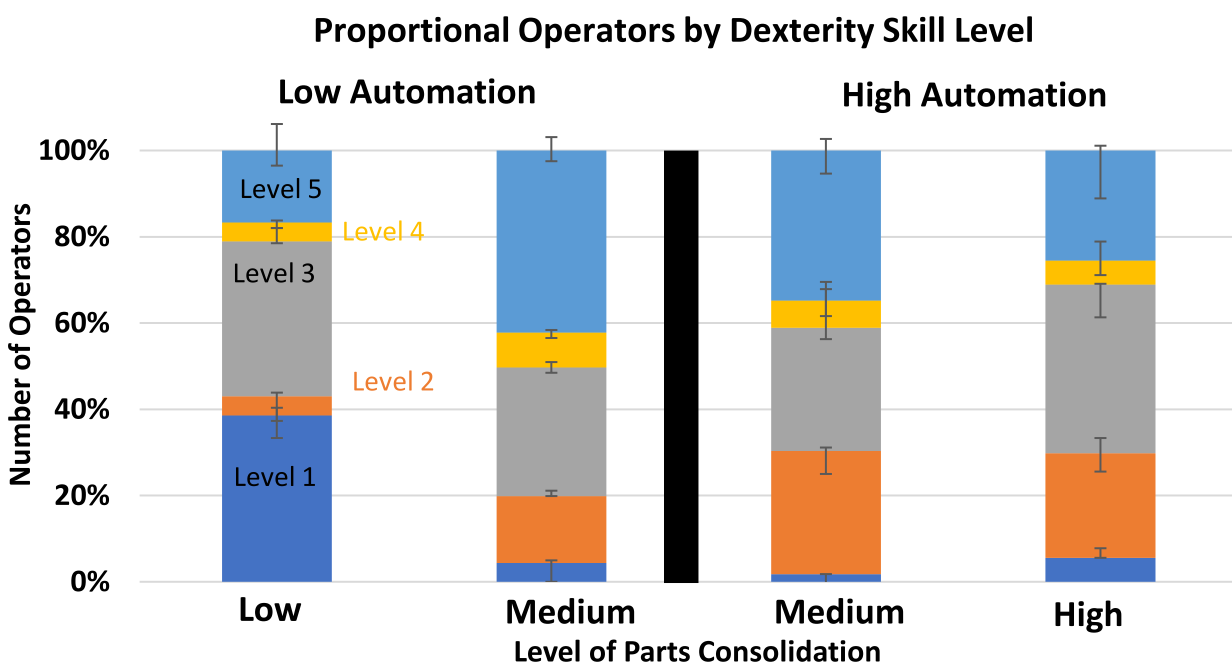

Figure 25 Share of Operators by Scenario and Dexterity Requirement (Median APV)

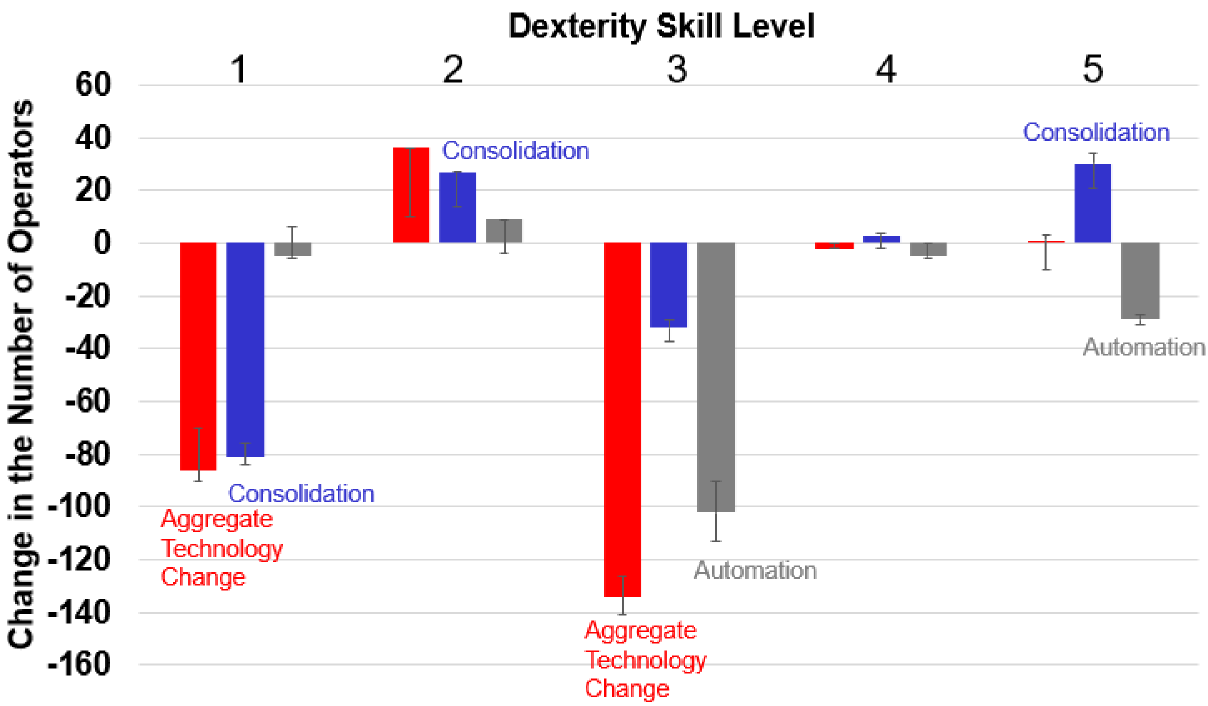

Figure 26 Aggregate Dexterity Skill Effects of Disaggregated Automation and Parts Consolidation: Shifting from Low Parts Consolidation, Low Automation to Medium Parts Consolidation, High Automation

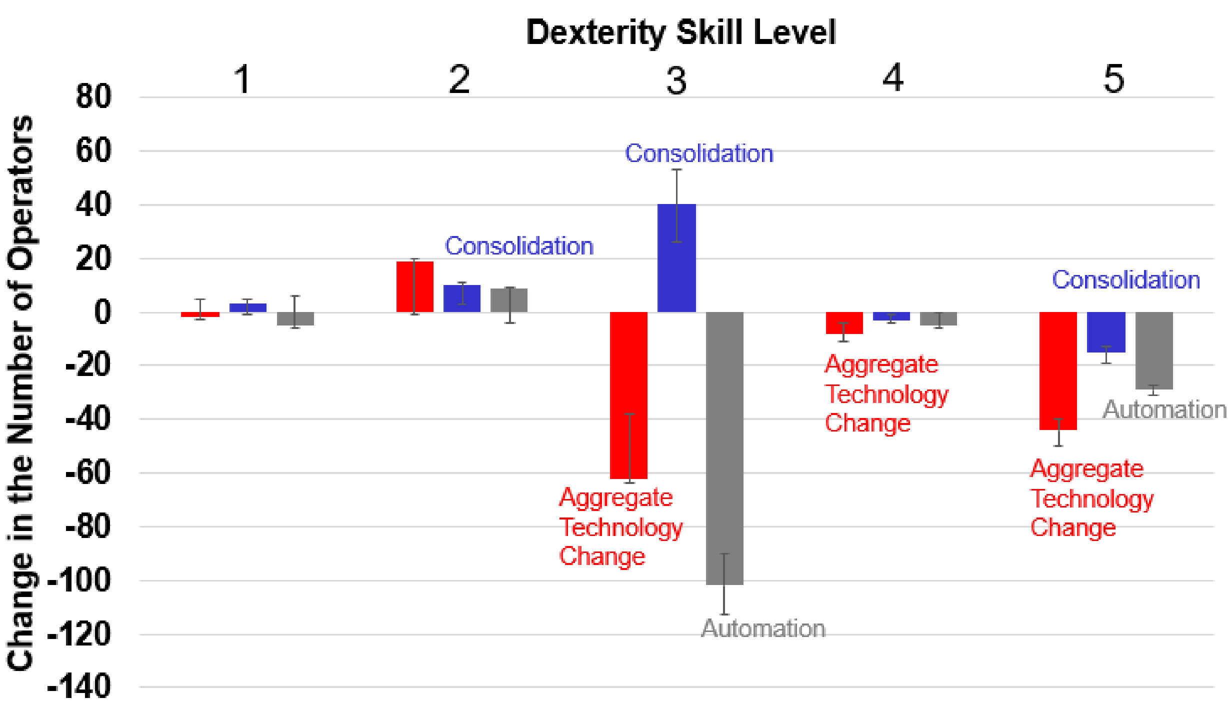

Figure 27 Aggregate Dexterity Skill Effects of Disaggregated Automation and Parts Consolidation: Shifting from Medium Parts Consolidation, Low Automation to High Parts Consolidation, High Automation

3.1.2. Near Vision Requirements for Operators

The distribution of near vision requirements does not exhibit the same upward skewing with parts consolidation under low automation as dexterity. Both extremes of our observed difficulty distribution (levels 1 and 5) under low parts consolidation are reduced in absolute terms (Figure 28) and proportionally (Figure 29) moving from low to medium parts consolidation. Parts consolidation (medium to high) under the high automation scenario does not displace the proportion of operators by near vision skill beyond the range of interfirm efficiency variation. Meanwhile, the number of operators with more moderate skill requirements increases, even as total operators decrease. Automation under medium parts consolidation appears to drive down the near vision requirements for operators. The number (Figure 28) and share (Figure 29) of operators at skill level 1 increases even as we see decline in the proportion and number of operators at skill levels 2 and 3.

Medium to high parts consolidation does not change the per-step skill requirements of production beyond the range of interfirm efficiency variation; while testing and subassembly labor decreases relative to final assembly, the combined near vision distributions of testing and subassembly resemble final assembly, offsetting these skill effects.

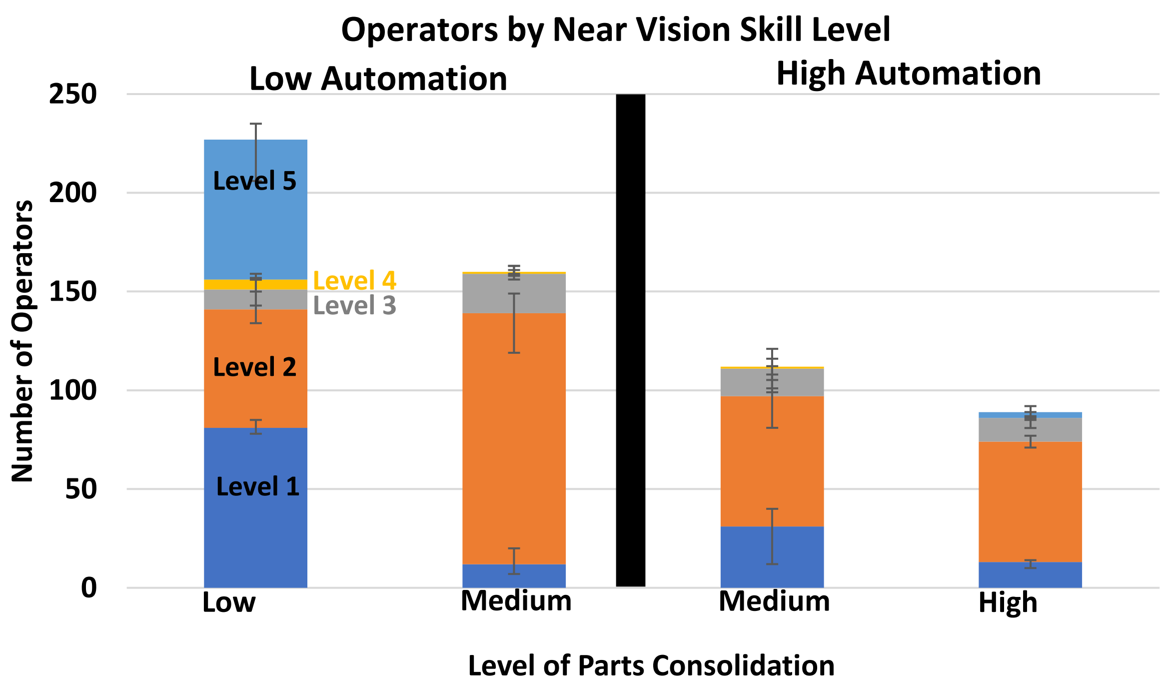

Figure 28 Number of Operators by Scenario and Near Vision Requirement (Median APV)

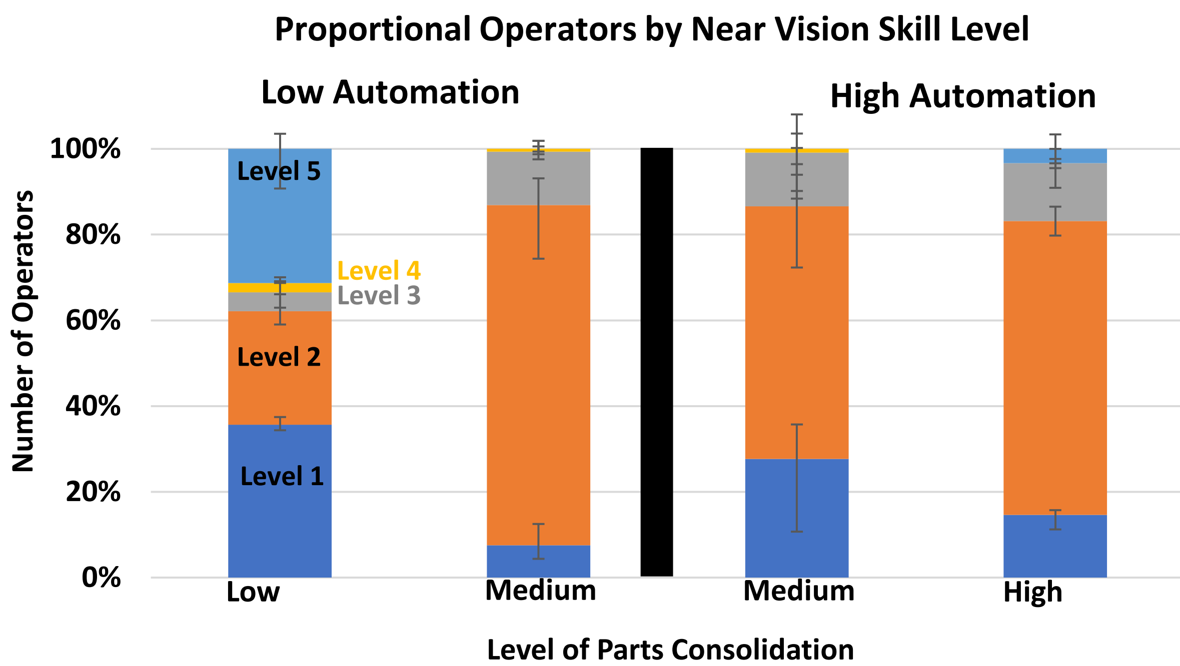

Figure 29 Share of Operators by Scenario and Near Vision Requirement (Median APV)

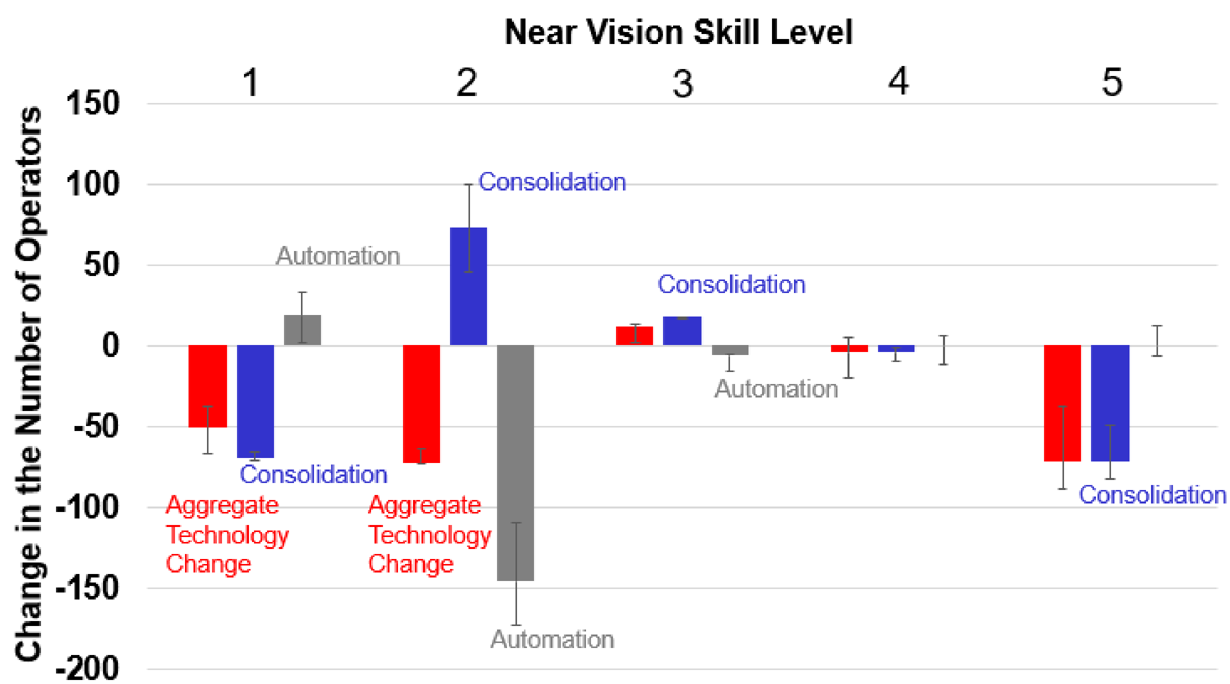

Figure 30 Aggregate Near Vision Skill Effects of Disaggregated Automation and Parts Consolidation: Shifting from Medium Parts Consolidation, Low Automation to High Parts Consolidation, High Automation

3.1.3. Operations and Control Requirements for Operators

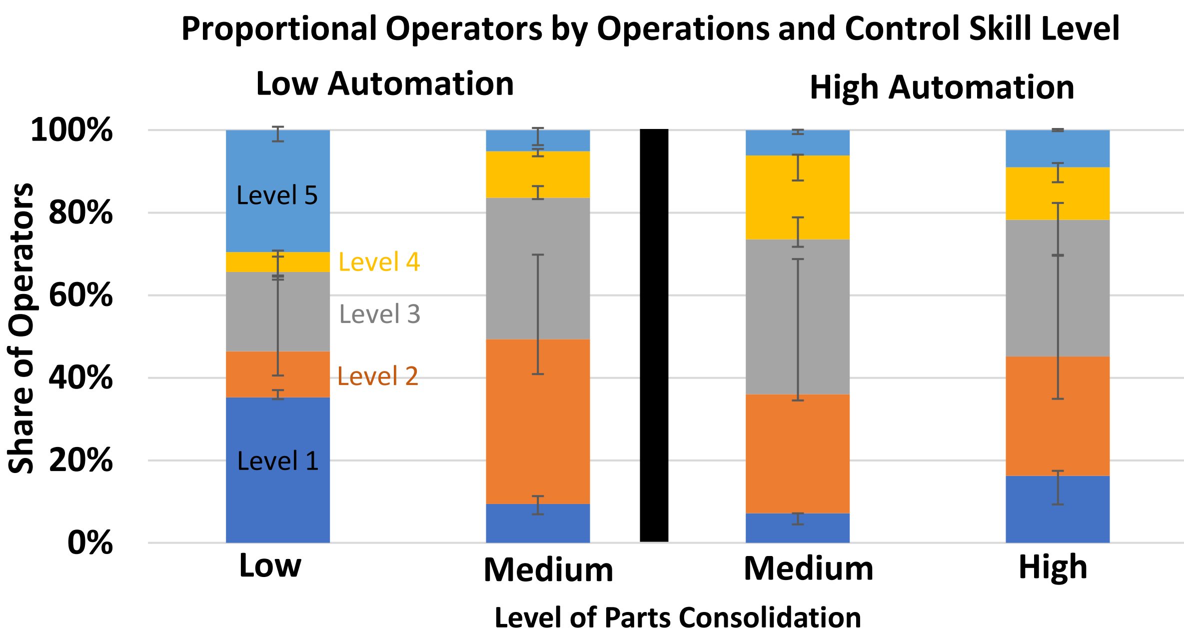

Figure 31 Share of Operators by Scenario and Operations and Control Requirement (Median APV)

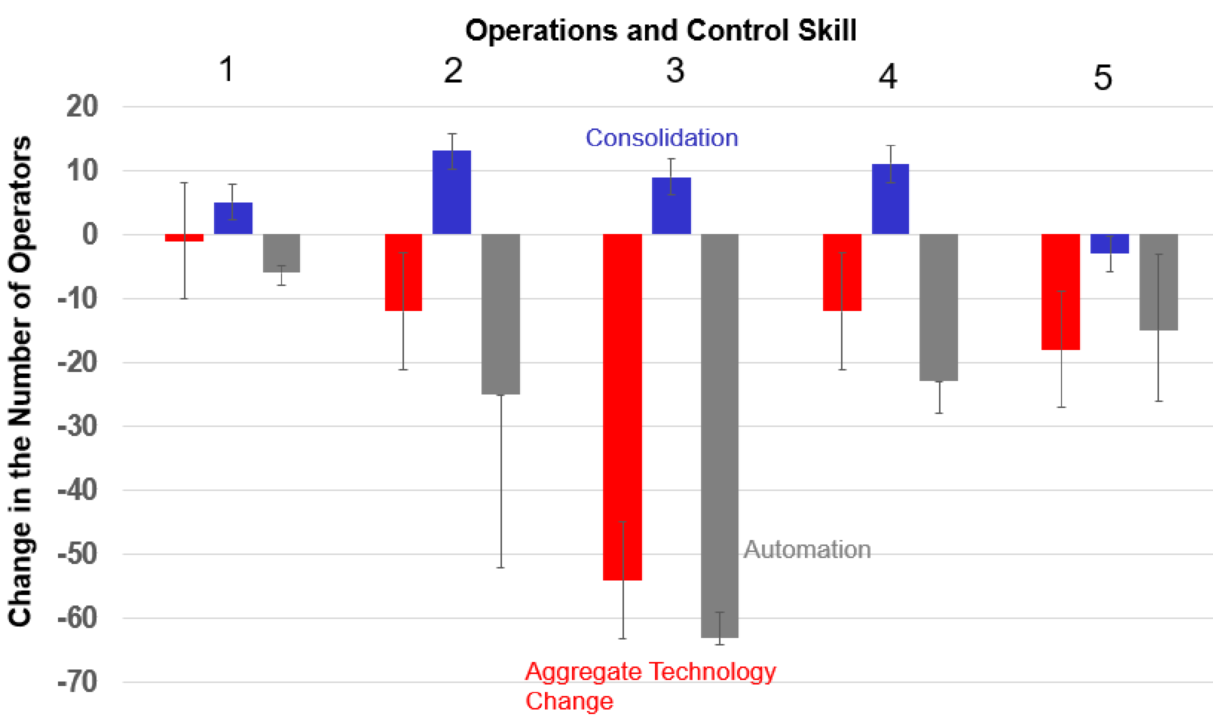

Figure 32 Operations and Control Skill Effects of Disaggregated Automation and Parts Consolidation: Shifting from Medium Parts Consolidation, Low Automation to High Parts Consolidation, High Automation

3.1.4: Distribution of Physical Labor: Physical Tasks Preserved under Parts consolidation

The following figure displays the number of operators required for three operator categories at our median sample APV: those involved in nonphysical or partially physical assembly tasks, those involved in fully physical assembly tasks and those involved in fabrication tasks. While we perform equipment matching on both the fabrication and assembly side, we find “fully physical steps” (Level of Automation 1-4) only in assembly.

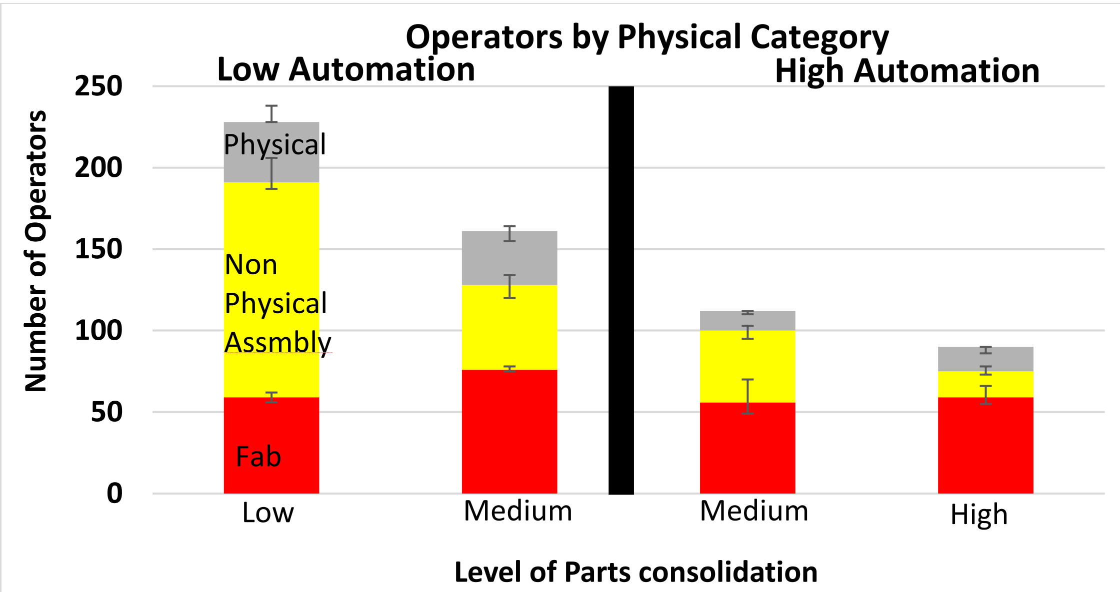

Figure 33 Physical, Nonphysical Assembly Operators, Total Fabrication Operators

This suggests a different relationship between parts consolidation and the elimination or substitution of labor requirements than automation; in this context, physical assembly tasks are typically associated with packaging and other elements of final assembly, which we note previously as being less susceptible to elimination through parts consolidation than subassembly, which tends to be more automated.

Appendix 3.2: Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level

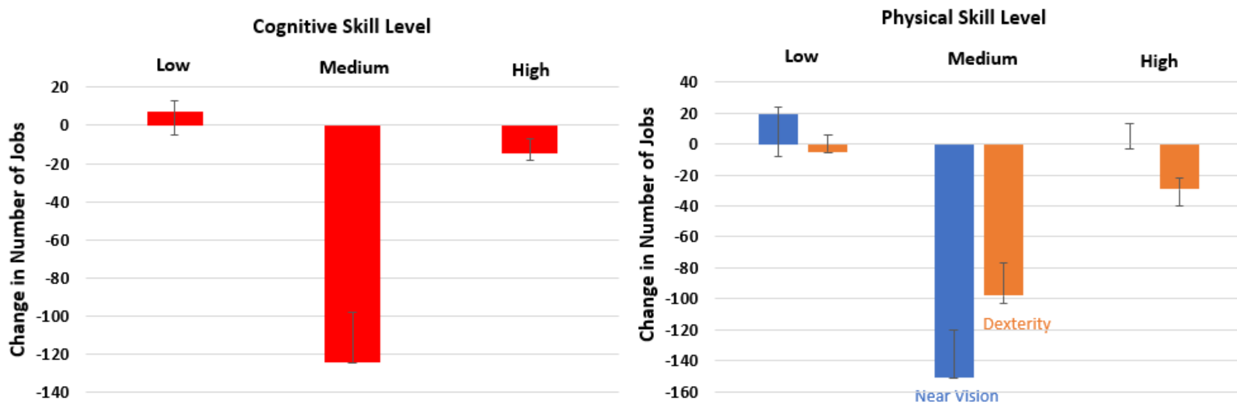

Figure 34 Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level under Automation

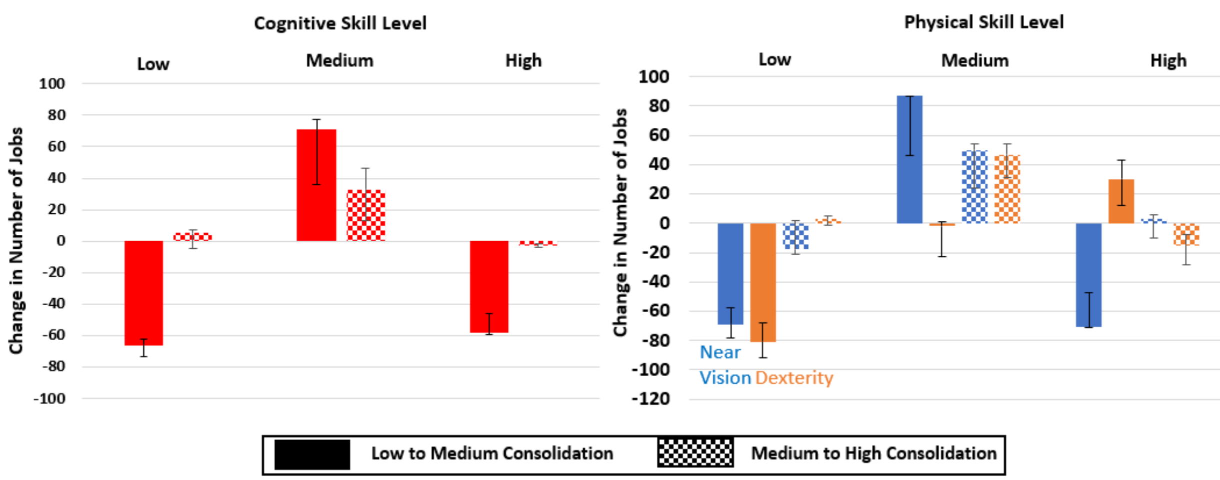

Figure 35 Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level under Parts Consolidation

Appendix 3.3: Global Location of Jobs by Scenario

In our empirical context, both automation and parts consolidation induce a net decrease in jobs per widget; however, the potential effect of automation and parts consolidation on product price and (in the future) performance may lead to equilibrium labor outcomes that do not necessarily reduce total jobs. The implications for jobs in market equilibrium are beyond the scope of this paper. Similarly, technological change such as increasing automation or parts consolidation could also change the geographic distribution of jobs. As shown in Fuchs and Kirchain 2010, Fuchs et al 2011, and Fuchs 2014; which design technologies are most profitable for firms can change with manufacturing location, and particularly between developed and developing nations. In terms of the location of operator jobs, empirically, while we find low and high automated production lines in both developed and developing world, the highest levels of automation occur in the developed world. In our data, we only observe low parts consolidation production lines in the developing world, while we observe medium parts consolidation in both the developed and developing world. High parts consolidation—while not yet on the market—is likely only possible in the developed world in the near term (Vogelesang and Vlot 2000, Fuchs and Kirchain 2010, Fuchs, Kirchain and Liu 2011). Figure 36 maps the geographic location of the facilities in our empirical data to the geographic locations thus also represented in the production cost estimates of our design scenarios.

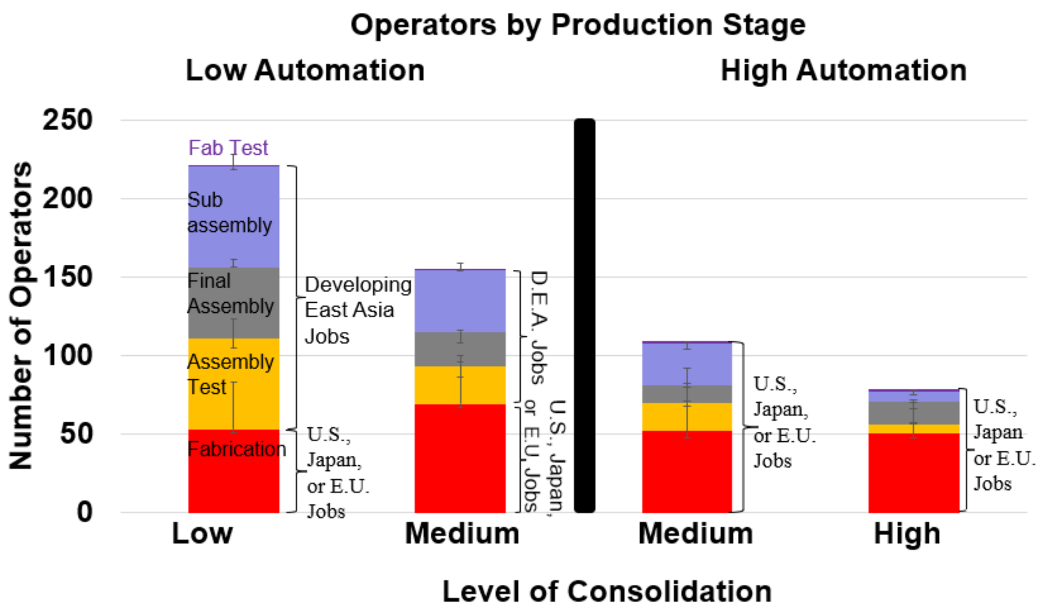

Figure 36 Probable Global Location of Jobs by Production Stage and Scenario

We expect the correlation between high parts consolidation and manufacturing in developed country locations as well as the correlation between parts consolidation and potential for higher performance to also apply to other manufacturing contexts. Parts consolidation is pursued for both its production cost and performance advantages in multiple industries, including aerospace, and automotive (Carle et al 1999). Parts consolidation removes labor-intensive assembly steps, the cost advantages of which are higher in developed nations. Furthermore, parts consolidation often involves advanced materials and process developments that require continual interaction between technical experts and the production line (Bohn 1995, Pisano 1997, Bohn 2005, Lecuyer 2006, Fuchs and Kirchain 2010, Bonnin-Roca et al 2017), and these experts are currently primarily located in developed countries (Fuchs and Kirchain 2010, NAS 2013). Past work has shown in both optoelectronic semiconductor (Fuchs and Kirchain 2010) and automobile body (Fuchs et al 2011) contexts that the most parts consolidated designs, while having short to medium term performance advantages, are only profitable when manufactured in developed countries.

We likewise expect highly automated manufacturing to be more attractive in developed contexts and to open up opportunities for higher product performance. With higher wages, the higher capital costs and lower labor implications of automation will have greater cost savings in developed country contexts. Automation can also open up opportunities for higher product performance, through higher precision and increased opportunities for subsequent innovation (Utterback and Abernathy 1975).

Online Supplement:

An online supplement to this paper is available upon request.

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