Not all Technological Change is Equal: How the Separability of Tasks Mediates the Effect of Technological Change on Skill Demand

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Abstract

We measure the labor-demand effects of two simultaneous forms of technological change—automation of production processes and consolidation of parts. We collect detailed shop-floor data from four semiconductor firms with different levels of automation and consolidation. Using the O*NET survey instrument, we collect novel task data for operator laborers that contains process-step level skill requirements, including operations and control, near vision, and dexterity requirements. 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. 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 conclude by developing a new theory for how the separability of tasks mediates the effect of technology change on skill demand by changing the divisibility of labor.

1. Introduction

A sizable literature seeks to understand 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).[1] Many of these studies hypothesize that computation and automation technology increases demand for high skills relative to “middle skills”, and that these technologies may explain wage inequality among skill groups (Autor, Katz and Kearny 2008; Acemoglu and Autor 2011; Autor and Dorn 2013). Scholars recognize that multiple forms of technological change can occur concurrently (Pauling 1964; Stoneman and Kwon 1994; Colombo and Mosconi 1995; Goldin and Katz 1998; Bartel et al 2007).[2] However, the existing literature does not

[1] Studies in the literature have highlighted skill-biased technological change (SBTC) as a source of unequal labor demand outcomes across skill. SBTC heterogeneously affects relative productivity or capital substitution of different types of labor, thereby changing demand (Brynjolfsson and Hitt 1995; Dewan and Min 1997; Bresnahan et al. 2002).

[2] 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 include the simultaneous adoption of broadband technology and automation across industries (Gramlich 1994; Koutroumpis 2009), simultaneous consolidation (Lecuyer 1999) and automation (Pillai et al. 1999) in semiconductors, and 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)

separately measure simultaneous technological changes, in part because of difficulty distinguishing the effects given available data. Aggregate observations capture the joint effect of all simultaneous changes but not the effects of individual technological changes which may oppose (and thus mask) each other.

We focus on disentangling the skill demand effects of two examples of technological change: automation and consolidation. Our focus industry is optoelectronics, a subset of the semiconductor industry. In optoelectronics, consolidation is a product innovation that allows multiple formerly discrete components to instead be produced as a single component (Schwedes 2001). In optoelectronics there exist competing designs that are perfect substitutes in the market, but with different levels of part consolidation and automation of their production. We collect data from four leading firms pertaining to five different product designs for functionally homogeneous devices. Our data includes information such as cycle times, yields, material usage and machine prices for 481 production process steps, as well as labor usage and skills requirements for those same steps. These data are used to populate a Process Based Cost Model (PBCM), an engineering process model which unpacks a firm's production function into individual process steps and uses empirical data and technical information to calibrate each step. This method allows us to construct diverse technological scenarios which separate out different technological effects. We extend the PBCM literature by using this model to determine how different technological change affects the demand for different levels of worker skill.

We make three main contributions. First, we show that technological change can affect skill demand within an occupation: our direct measurements show that automation polarizes skill demands for operators by decreasing demand for middle skills. Second, we find that other forms of technological change (here, consolidation) can have opposing effects to automation, causing aggregate measures that do not disentangle the two to be misleading. Third, we show through direct measurement of process step level parameters and skills, that technological change can be tasked-biased as well as skill-biased, and that task composition mediates the effect of technology change on skill demand.

We develop a new theory for how the separability of tasks mediates the effect of technological change on skill demand by changing the divisibility of labor. Specifically, we seek to explain how, as in our results, there can be both one-way skill biases and multimodal shifts in skill demand (i.e., convergence or polarization). Here, the separability of tasks is the cost (and in some cases feasibility) of having tasks completed separately from each other. While multiple tasks can be grouped into a "job" held by a single worker, tasks must be separable from one another for the division of labor. The skill requirements of a job are the maximum of the skill requirements across tasks. By these definitions, as the separability of tasks declines, tasks are combined into jobs held by individual workers, and skill demand converges or increases. Further, the more tasks that are inseparable, the more difficult it is to automate those tasks.

Our theory for how task separability mediates the effect of technology change on skill demand is relevant for labor economics, management, and policy. Our direct measurement of simultaneous technological changes allows us to uncover mechanisms by which different technologies can be expected to have different labor outcomes. For policymakers and firms, understanding how task separability mediates the effect of different technology changes on skill demand is important for technology-specific policy. Our findings and theory are especially important for policymakers concerned with job outcomes for high-school level workers: while these workers are historically vulnerable to

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), contributing to differential labor outcomes.

technological displacement in aggregate (Autor and Dorn 2013; Acemoglu and Restrepo 2017), not all technology change has the same effect on skill demand, and a granular understanding of labor outcomes is necessary to avoid overly blunt assessments of technological risks for labor.

2. Literature Review

We review three aspects of the SBTC literature: commonly discussed patterns and heterogeneity in SBTC; the measurement of skills; and the focus of the literature on historic factor substitutions. We then introduce the literature on the capability based theory of the firm, specifically nuances in that literature with respect to technological heterogeneity and factor substitutability. We then review the literature on engineering process models and their applications in engineering and management to understand the effects of technological decision-making.

With respect to heterogeneous SBTC, while skill biased technological change could potentially affect the relative marginal product of labor skill levels in many different combinations, the SBTC literature has typically measured aggregated outcomes that show increased productivity returns to skill. Examples of SBTC increasing the returns to higher skill include automation (Autor et al. 2003 Autor and Dorn 2013) as well as 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). The literature has recognized that organizational change, process, and management innovations could lead to heterogeneous worker productivity effects (Goldin and Katz 1998; Caroli and van Reenen 2001; Ichniowski and Shaw 2009). Goldin and Katz, for example, suggest that changes in process technology such as the assembly line can increase the relative demand for low skill, while their work shows that more recent innovations such as continuous processing shifts skill demand upward, consistent with other work on SBTC. However, despite the recognition of heterogeneous SBTC, the literature has not been able to separate the potentially different labor effects of simultaneous technological changes.

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). More recent task-focused work on automatability through machine learning suggests that within automation broadly, different occupational tasks are more substitutable with different automation methods (Brynjolfsson, Mitchell and Rock 2018). Though automation is a strong focus of the literature on technological change and labor outcomes, there is also evidence of non-automated changes in process technology and of consolidation affecting the composition of production. Process changes such as the assembly line and continuous processing may both have shifted relative demand for skill (Goldin and Katz 1998). Consolidation is an inherent feature of modularization (or demodularization) in product architecture, making it relevant to the composition of industry and the internal organization of firms and their production activity (Ulrich and Eppinger 1995; Baldwin and Clark 2003) and hence the organization of processes and the division of labor.

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. Emerging implementations of technologies such as machine learning, (Brynjolfsson, Rock and Syverson 2017; Brynjolfsson, Mitchell and Rock 2018) may affect the marginal product of different labor skill levels in distinctive ways from other historical technological changes.

With respect to measurement of the effect of SBTC, the literature draws heavily (but not solely) on education and wages as proxies of skill (Autor, Levy and Murnane 2003; Acemoglu and Autor 2011; Carneiro and Lee 2011; Autor and Dorn 2013), although different technological changes may have important, heterogeneous effects on skill requirements within the same aggregate category (e.g.

manufacturing jobs with all the same low educational requirements). Measures such as past wages can offer more detail than education (Autor, Levy and Murnane 2003; Autor and Dorn 2013) but have the potential to mask important worker reallocations and other shifts in demand, such as inversions in the relative demand for different types of skills (whose levels are not necessarily correlated) which are simplified onto an axis of past wages (Lane 2005). 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) and allowing jobs to be re-bundled around tasks which remain non-automated (Brynjolfsson, Mitchell and Rock 2018). 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.

Studies that collect detailed technical and operation skill and training information on operators describe the direction but not the magnitude or distribution of skill demand changes under technological change (Bartel et al. 2004; Bartel et al. 2007). Bartel et al. measure whether specific skills became more or less important to operators (as determined qualitatively by managers) after an establishment adopted information technology. This work suggests skill bias in technological change among manufacturing operators but lacks measures for differences in the level of skill required and the share of operators affected. Such measures less easily describe the magnitude of shifts in skill demand, as well as possibly overlooking multidirectional effects of technological change within the same skill (i.e. rather than a bidirectional skewing of skill requirements).

Distinct from SBTC, the capability-based theory of the firm views technological change as the path-dependent result of local conditions and firm capabilities (Wernerfelt 1984), with the implication that factor substitution is not unconstrained in the manner assumed by traditional production functions (Dosi and Grazzi 2006). Firms face technologically feasible procedures to produce certain outputs: the capabilities of firms influence which procedures are available to them and at what level of efficacy they can be performed (Barney 1986; Teece 1993). Using a given procedure requires certain input ratios to actually produce the desired output, regardless of factor prices. These constraints on substitution underlie the "recipe" perspective in the literature, which views technology as a sequence of procedures (a recipe) which the firm must perform to produce a good (Dosi and Grazzi 2010). This restriction is important for potentially separating technologically driven changes in the feasible space of factor input ratios from narrower substitutions by firms within a certain technological regime.

In our study, technological restrictions on substitution offer a useful analytical lens to extend approaches such as those used in the SBTC literature. While substitution is restricted for a given technology, technology adoption provides a channel for long-run factor substitution: this view makes it possible to identify technological effects on skill demand directly from engineering-level technological parameters. Even under the strictest constraints of a Leontief view of production, however, heterogeneous production functions (such as suggested by the capability based theory of the firm) can generate aggregate factor substitution (Johansen 1972) of the form typically seen in the SBTC literature, preserving the analytical benefits of such approaches. Thus, technological restrictions on substitution do not require the suspension of factor substitution.

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, operations and hence factor demand at scale (Pearl and Enos 1975; Fuchs and Kirchain 2010). PBCMs have been used in engineering and management to understand the effects of technological decisions on factor demands and costs prior to large-scale investments (Bloch and Ranganthan 1991; Field, Roth, Kirchain 2007; Fuchs et al. 2008). These models have informed engineering and production decisions in multiple industries (Field, Roth, Kirchain 2007; Ulu et al. 2018; Laureijs et al. 2018). Previous work (Fuchs and Kirchain 2010; Fuchs et al. 2011; Fuchs 2014) used 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.

Engineering process models relax typical assumptions of classical production functions (e.g. time-constant factor share and degree of factor substitution) to capture novel factor substitutions and production relationships that may be important to the effects of technological change on factor demand and other economic behavior (Chenery 1949; Lave 1966; Pearl and Enos 1975; Wibe 1984; Smith 1986). Thus, engineering process models accommodate heterogeneity in equipment, labor and material input. Prior models have been used to simulate production, estimate cost, and simulate technology decision-making, but ours is the first to use a PBCM to study the implications of technological change on labor outcomes or to disentangle the implications of different forms of technological change.[3]

3. Technology, Firm and Industrial Context

Consolidation occurs when multiple formerly discrete parts are designed as one component (Schwedes 2001; Johnson and Kirchain 2009). Consolidation is a product innovation with many process implications. Consolidation is enabled by technological advances in design (e.g. topology optimization), materials (e.g. composites or strained silicon), and processes (e.g. additive manufacturing or e-beam lithography). Consolidation can help reduce fabrication and assembly costs in manufacturing, (Smith 1999; Selvaraj et al 2009; Atzeni and Salmi 2012) and improve performance in software design (Barrett et al 1996; Sanner 1999) and healthcare services (Doherty and Bresinger 2004; Pitroda and Desai 2017).[4] Table 1 provides examples of consolidation across several high value manufacturing industries.

Table 1 Examples of 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

[3] Not only is this application novel, developing it required changes to existing process models, to build skill requirements into each process step (described in detail in Appendix 1.1).

[4] A keyword search of global patents (Google Patents) shows that either "consolidation" or "integration" are mentioned in approximately 5 million patents from 1878 to the present (and 567,344 patents since January 1, 2009), including 2.37 million patents that also have the keyword "manufacturing" and 3.78 million patents that include keywords "software." Other sectors include electronics (668,740 results), automotive/automobile (208,322 results), aerospace (20,934 results) and healthcare service (8,463 results).

Automation changes the performer of a task from human workers to machines (Frohm et al. 2008). Automation is a process-based (rather than product design, as in consolidation) technological change (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 optoelectronic devices on which we focus in this study combine electronics and photonics (light) to send and receive information. Optoelectronic device production can be broken into four main categories: (1) fabrication, (2) subassembly, and (3) final assembly (see Figure 1), with (4) testing throughout the other three categories. In fabrication, materials are deposited and etched in specific sequences to control the behavior of electrons and photons (NAS 2014). In subassembly, components are connected to one another according to the device architecture. In final assembly, optical fibers are attached to the device substrate, and the device is put into a standardized metal casing, or package. Testing throughout the process consists of visual inspection and machine-based tests of various device functions. See Appendix 5 for further detail on the process steps.

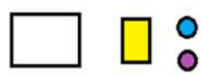
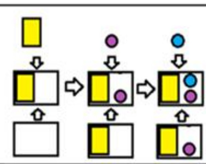
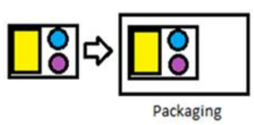
Process Category	Example Diagram	Industry Examples
Fabrication		Lithography Vapor Deposition
Subassembly		Wire Bond Die Attach
Final Assembly		Packaging

Figure 1 Process Flow Categories

In the optoelectronics industry, functionally homogeneous designs have different levels of consolidation: low consolidation designs with individual discrete components mounted onto a semiconductor wafer; medium consolidation (called “hybrid” integration by the industry) with some discrete parts fabricated together as single components; and high consolidation (called monolithic integration), with multiple components fabricated as one rather than assembling them together (NAS 2013; Yang et al. 2016).

The optoelectronics industry is globally distributed. Optoelectronics fabrication is concentrated in the U.S. and Japan, although capabilities also exist in China and Taiwan: optoelectronics fabrication is highly automated regardless of location. Assembly activities are spread throughout Europe, North America and East and Southeast Asia, with generally greater automation in North America, Japan and South Korea (NAS 2014). While fabrication and assembly of various designs is performed worldwide, the most consolidated designs tend to have production more often located in the U.S. and Japan.

Optoelectronics is a particularly conducive case for heterogeneous technology regimes because even standardized optoelectronic devices permit significant internal variation in design. Competition in the specific optoelectronic devices we study is driven primarily by price (Fuchs and Kirchain 2010; Personal Interviews with Industry Leaders).[5] Prior research (Fuchs et al. 2011) suggests that a low-cost leader did not exist among products with different levels of consolidation as far back as the mid-to-late 2000s. There are also widespread barriers to the adoption or replication of capabilities outside a firm, including specialized workforce requirements and technological uncertainty, which can provide the conditions for technological heterogeneity (Wernerfelt 1984; Peteraf 1993). Even production scale-up within the same firm can mean shifting to new and uncertain production methods.

4. Methods and Research Design

4.1 Constructing the Production Function Using Engineering Process-Based Cost Models

We use engineering process-based cost models (PBCMs) to construct counterfactuals of technological changes at each production process step, which then allow us to map their consequences for skill demand. These models are constructed based on firm production plans across different contexts, basic scientific principles, and observations of production activities before and after a technological change (Bloch and Ranganthan 1991; Fuchs, Ram, Bruce and Kirchain 2006). For our purposes, the PBCM has the following advantages: (1) it allows us to recover production functions without relying on structural assumptions that may not be well supported by the nature of a technology or production process, (2) it makes use of process step-level inputs rather than aggregate data, allowing us to map technological 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 technological changes by constructing counterfactual technological configurations that are technologically feasible but not observed in historical firm operations.[6]

A PBCM unpacks the aggregate production function of a single product into individual process steps by mapping the product design (e.g. geometry) and process design (e.g. level of automation) decisions to actual technical parameters in each process step (e.g. cycle time, labor usage, equipment type, yields) and relationships among process steps (described in detail in Appendix 1). Our empirical values for model parameters allow us to implicitly represent the optimized production possibility frontier (e.g., resolving bottlenecks, minimizing worker downtime, etc.) conditional on technology choices, within the PBCM. These parameters come from product design, process, and factor input information collected from firms, such as the number of workers per machine. Each value represents locally efficient choices by the firm with respect to a production function given by a specific process and product technology.

The process model takes as inputs the sequence of process steps (the “process recipe”) needed to produce the specified product design, and the choice of possible equipment alternatives required to

[5]Industry interviews also suggest some competition around serving client-firm needs, but customization is typically around form factor and hence independent of internal component consolidation.

[6]An alternative approach to capturing the production process is an Agent Based Model (ABM), which is a class of computational model that has been used to characterize transport and supply chains and other sequences of input-output relationships, including in manufacturing (Madureira and Santos 2005; Datta 2007; Holmgren et al 2012). The nature of the data captured for this study does not include the necessary statistical or scheduling information (e.g. shipping schedule) to model dynamics within the plant using an ABM. An advantage of the PBCM is that model’s assumptions about production relationships are embedded statically rather than stochastically, making it easier to follow how input parameters propagate through the model and, in turn, to develop mechanisms for how changes in inputs or model structure (e.g. technological changes to process flow) generate to outputs such as skill demand. Moreover, the PBCM allows us to characterize the efficient production possibility frontier for different technologies, whereas an ABM does not necessarily guarantee this outcome.

complete each step. The production of a final good can be thought of as a set of steps $\Phi = \{1, \dots, \mathrm{n}\} \subset \mathbb{N}$. Process steps may be thought of as collections of tasks that are performed with or on common equipment, toward a common intermediate output, by labor of the same type, without any intervening tasks that deviate from these three criteria.

We label product technology, $r \in \mathbb{N}$: for each r, there is a set of steps Φ_r to achieve the final product. Each step s has a set $P_{s,r} \subset \Phi_\mathrm{r}$ of steps that precede it (i.e. which must be completed before step s can be completed),[7] giving the total production process a "recipe" consisting of a set of steps Φ_r and a corresponding collection of preceding steps $\boldsymbol{P}(r) = \{P_{s,r}\}|_{s=1}^{n}$. Product technology affects the set of steps and the sequence (i.e. the precedents of steps) required to achieve the final product.

Product technology also determines which *process technologies*, given by $\mathrm{T_{s,r}} \subset \mathbb{N}$ are available to perform each step (hence $\mathrm{T_{s,r}}$ corresponds to step s and product technology r). Each step is performed using a technology labeled by $t_{s,r} \in T_{s,r}$.

PBCMs take labor, capital, and material as inputs to production. Each step s has its own Leontief relationship, determined by process technology t_s, to generate output q_s:

$$(1)\quad q_s = q(K_s, L_s, M_s, t_s, P_{s,r}) = \min\left\{f_{s,t_{s,r}}(K_s), g_{s,t_{s,r}}(L_s), h_{s,t_{s,r}}(M_s), \left\{\sigma_{s,j,t_{s,r}}(q_j) \middle| j \epsilon P_{s,r}\right\}\right\}$$

where $f_{s,t_{s,r}}(K_s)$ is a function of the capital inputs K_s to step s, $g_{s,t_s}(L_s)$ a function of the labor input(s) L_s and $h_{s,t_{s,r}}(M_s)$ a function of the material input(s) M_s to step s. Each input term is possibly a vector of heterogeneous inputs (e.g. different types of machine under capital). $\sigma_{s,j,t_{s,r}}(q_j)$ is a function relating the output of other steps j as inputs of step s, provided that these steps precede s.

The Leontief functional form is used in PBCMs in many industrial contexts (Ngueyn, Tommelein and Ballard 2008; Fuchs et al 2008; Fuchs et al 2011; Ciez and Whitacre 2017; Laureijs et al 2019). Firms face a series of technologically feasible procedures with restrictions on the ratios of inputs to achieve a desired outcome. These restrictions do not prevent factor substitutability, however; aggregation across technologically heterogeneous production plants generates factor substitution (Houthakker 1955), and the choice of process technology by firms can change the optimal ratio of factors, providing factor substitutability through technology. In addition to being common in PBCMs, our interviews with plant managers and engineers highlighted both fixed input ratios to production under given technological parameters and the possible motivation of changing technology to alter these ratios of inputs (i.e. to perform factor substitution across technology choice).[8]

We use the "final step" of production to capture the production function of the entire process. By construction, a production process has one and only "final step," n, such that for $i \in P_{n,r}$, $\forall i \in \Phi_r, i \neq n$ and (indicating an exclusive final step) $\nexists j \neq n$ s.t. $i \in P_{j,r}$, $\forall i \in \Phi_\mathrm{r}$. Thus, the production structure given by $P_{n,r}$ builds in all preceding steps. The inputs from prior steps into a step can also be

[7] This set may be empty in the scope of the model, including but not limited to the first step in a process. Steps may precede s directly, in the sense of s requiring an input produced in step i, or indirectly in terms of step s requiring a direct input from a step that itself depends on the preceding steps.

[8] This construction also aligns with the recipe view of technology in the capability-based theory of the firm (Dosi and Nelson 2010), in which it is not necessarily possible for a firm to trade off between any two inputs (e.g. butter and eggs in making a cake) without changing the final product or at least following a different recipe (Dosi and Grazzi 2006). Indeed, changing the recipe to allow a different ratio of inputs would amount in our model to changing the production technology, and some factor ratios are simply (currently) infeasible in the domain of available production technologies.

incorporated. For a final product output volume of y units, the production function embedded in a PBCM is analogous to the output of the final step: [9]

(2) $y = q_n$

Based on this relationship, one output of the PBCM is the minimum operator labor required per process step to satisfy a given production volume for given technological parameters:

(3) $q_s(q_x) = \sum_{x|s\in P_x(r)} \sigma^{-1}_{s,j,t_{s,r}}(q_x)$

(4) $L_s^{\min}(q_n, r, t_i | i \in \Phi_r) = g^{-1}_{s,t_{s,r}}(q_s(q_n))$

where $\sigma^{-1}_{s,j,t_s,r}$ is the output of step s encoded as material inputs to satisfy q_x.

From process inputs per step, we map the inputs required to meet operations at scale.[10] Given input prices, the PBCM can then map from operations at scale to production cost (for a deeper engineering characterization of our PBCM, including cost functions, see Appendix 1).

We now incorporate skill requirements for each step into our model. There are multiple skill types, indexed by $v \in \mathbb{N}$ (e.g. dexterity). A step with product technology r and using process technology $t_{s,r}$ has skill requirements for each skill type: $D_s(r, t_{s,r}) = \{d_s^1(r, t_{s,r}), \dots, d_s^v(r, t_{s,r})\}$, where $d_s^v(r, t_{s,r})$ indicates the level of skill required $d \in \mathbb{N}$ for skill type v.[11]

Workers are indexed by their skill level across each skill type: a worker type indexed by $j \in \mathbb{N}$ has a unique set of skill levels across skill types given by $A_j = \{a_j^1, \dots, a_j^v\}$, where a_j^v is the level of skill of worker type j in skill type v. Note that $a_j^v > a_i^v$ implies that worker j is more skilled on that dimension than worker i.

Labor inputs to step s, previously given as L_s, now also include the subscript j for a complete notation of $L_{s,j}$, indicating which type of worker is used in the step. The labor term in the production function now takes the expanded formulation:

$$\varepsilon_{s,t_{s,r}}(L_{s,j}) = g_{s,t_{s,r}}(L_{s,j})\theta_{s,t_{s,r}}(A_j).$$

This formulation builds in the skill requirements of the step and the output effect of the labor type used failing to meet skill requirements. If the worker has a lower skill level on any dimension than the skill requirements of step s, then the output of the step will always be 0:

$$\theta_{s,t_{s,r}}\left(A(L_{s,j})\right) \coloneqq \begin{cases} 1 \text{ if } \nexists i\ s.t.\ a_j^i \in A_j\ < a_s^i \in D_s(r, t_{s,r}) \\ 0 \text{ if } \exists i\ s.t.\ a_j^i \in A_j\ < a_s^i \in D_s(r, t_{s,r}) \end{cases}.$$

Thus, the production function building in worker skill now takes the form:

(5) $q_s^{skill} = \min\left\{f_{s,t_{s,r}}(K_s), \varepsilon_{s,t_{s,r}}(L_{s,j}), h_{s,t_{s,r}}(M_s), \{\sigma_{s,j,t_{s,r}}(q_j) | j\epsilon P_{s,r}\}\right\}.$

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[9] Equation (2) is analytically equivalent to $y = \min\{f_{s,t_{s,r}}(K_s), g_{s,t_{s,r}}(L_s), h_{s,t_{s,r}}(M_s), \{\sigma_{s,j,t_{s,r}}(q_j)|j\epsilon P_{s,r}\}\}|_1^n$ where the production process consists of process steps indexed 1 to n and final output is simplified from the minimum of the output q_i of each process step. The choice of product technology, by changing the steps and relations among steps in a production process represents a form of factor substitution in addition to the previously mentioned substitutability by production technology.

[10] The firms that we studied did not exhibit scale diseconomies or operate at volumes or under conditions suggesting scale diseconomies, and so we exclude any such relations from our model.

[11] In our empirical context, our skill level data take values in the set $\{1, \dots, 7\}$ for each skill type.

We assume wages are strictly increasing in labor skill level for any skill type without any additional output from higher labor skill, so that firms will choose labor inputs j in step s so that $A_j = D_s(r, t_{s,r})$.

We use our PBCM to estimate the quantity of labor demanded (i.e. changes in a_s^m leading to different required inputs for operations at scale) at differing levels of rated skill difficulty. We use the sum of labor required across process steps with a given skill level (1-5) and type to estimate the total quantity of labor required at that skill level. This information is used to generate quantitative (i.e. production process level) estimates of the direction(s) and magnitude of technological change effects on relative demand for different labor skills.[12]

4.2. Research Design

Using a PBCM allows us to use well-documented, empirically founded structural rules (Appendix 1) to strip out possible covariation in automation and consolidation (or indeed firm heterogeneity) and recover causal, process step-level mechanisms relating each technological change to skill demand. To provide the necessary variation for our analysis, our sample covers positions across the industry technological domain, including firms at the technological frontier of the industry in terms of the level and timing of consolidation and automation, as well as firms with relatively low levels of automation and/or consolidation. The five 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). Using this coverage of the industry, we construct four scenarios (A, B1, B2, C) to separate the implications of automation and consolidation on skill demand.[13]

Table 2 Normalized Annual Production Volume and Share of Industry Production by Product Design[14]

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%

The separation of automation and consolidation in our research design across four scenarios is illustrated in Table 3: it shows the positioning of each scenario in terms of its level of consolidation and automation. Note that scenarios B1 and B2 have the same level of consolidation but differ in their level of automation. Our research design consists of comparing skill demand generated across these four

[12]We also use our model to capture changes in relative demand to show changes in labor demand per unit output. That is, for constant volume, we show that the number of workers would decrease (or increase) given a technological change, and more precisely how the number of workers will change by skill level. However, our analysis does not include any prediction on changes in volume: thus, because technology change might also lead to a change in volume, we cannot predict whether the total number of employees in an industry will change.

[13]Automation and consolidation were chosen because they were identified as significant sources of technological heterogeneity across firms based on our line observations and interviews with industry leaders. Other types of technologies, such as digitization or process standardization had little or no variation in our industry sample. For example, technologies supporting digitization and interconnection, logistics software, shop-floor statistical data collection and part-tracking capabilities had already been uniformly adopted in the firms that we studied.

[14] Low share estimates are based on upper bound estimates of industry production (Yole 2016) 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.

scenarios: changing consolidation changes the process flow, while changing automation changes which inputs are used in each step (e.g. a machine vs. a human).

Table 3 Research Design: Consolidation without Automation and Automation without Consolidation

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

The production sequences that make up each scenario in our research design are drawn directly from firm production flows: that is, a step (e.g. die-attach) occurs in the same order as in a real process, but our scenario analysis may rely on multiple feasible ways to perform that step based on our real-world observations.[15] For each scenario, we create a baseline production function, and then multiple reconfigurations of the production functions based on observed inter-firm variation in inputs,[16] in order to 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).[17] To control for 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 following Frohm et al.'s (2008) taxonomy of level of automation.[18] We validate our model and scenarios by comparing our aggregate required input estimates to produce each firm's device against in-house aggregate input quantity and cost estimates (see Appendix 2.3).

Figure 2 shows a diagrams of the three levels of consolidation represented in our scenarios and indicates for each level of consolidation which components are consolidated; components consolidated with each other are fabricated as a single component with no assembly required.[19] In the low consolidation case, each function of the device is performed by a different component, which must be fabricated individually and assembled into the whole. In medium consolidation, some functions are consolidated into a single component, requiring more complex fabrication but less assembly. The move from low to medium consolidation also involves collapsing some parallel production tasks into a single sequence. In high consolidation, further functions are consolidated into a single component, further reducing assembly.

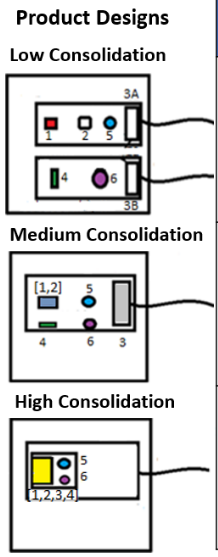
[15] Fabrication is already highly automated across the industry (NAS 2013) and therefore does not vary across our automation scenarios.

[16] 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.

[17] The development and implementation of an estimation process for interfirm variation in production cost and labor demand represents a methodological innovation of this paper over prior engineering process models.

[18] Our sorting of tasks by level of automation is robust to the use of a widely cited taxonomy of level of automation other than Frohm et al: Kaber and Endsley (1997) (see Appendix 2.2).

[19] Our firm domain includes the production of two designs that match our low consolidation case and three that match our medium consolidation case. There are no designs currently on the market that match our high consolidation case: we use process flows from Fuchs et al. (2011) for the high consolidation design and update their structure and inputs (including novel skills data) with data from across our sample firms (See Appendix 4).



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 2 Optoelectronic Products and Components by Level of Consolidation

Our model specification and data allow us to identify technological parameters using only a subset of the equilibrium conditions: firm-level feasibility and firm-level optimality.[20] We address two threats to econometric identification in Appendix 2.6: 1) changes in labor demand may be driven by firm characteristics as well as technological change and 2) technological change is not geographically uniform. In brief, we address 1) by varying process steps used in our scenarios across multiple firms with distinct organizational characteristics and we are unconcerned by 2) because we find that changes in skill demand with technology are consistent across the multiple countries in our sample.

5. Data Collection and Model Inputs

We collect data on the required experience, education, training time, and skill levels of physical and cognitive skills to complete the tasks associated with every single process step (see Table 4). Our sample comprises four firms in total. These firms have 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.

Of the six empirical process flows and attendant step-level parameters in our dataset, five were freshly collected from our four sample firms and populated for this paper, and the sixth process flow (taken from the data used in Fuchs 2011) was reverse-populated with novel skills data. Empirically, the process flows for the devices are from firm settings that dedicate one single line to produce the device.

We contacted 12 firms and collected novel, extensive process data from four firms on five different processes. PBCMs used 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 scope our analysis to focus on the production line in each firm associated with the case optoelectronic device, and the immediate inputs associated therewith. For each of 481 process steps, we collected standard

[20] The identification relies on our (empirically grounded) assumption that for each step of production the underlying relationship between factor inputs is Leontief so that for all factor prices, firm optimality implies a fixed ratio of inputs.

operational inputs to a process-based cost model, such as yield rate[21], cycle time[22], and wages[23] (see Appendix 2.2). We collected mean values as well as weekly maximum and minimum values for these inputs.[24]

We measure skill requirement levels using the Department of Labor's "Occupational Information Network" (O*NET) survey instrument, which rates skills using a 1-7 scale. The scale includes example anchors, shown to result in reliable and consistent ratings.[25] 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[26] (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).[27]

Table 4 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

[21] Defined in our model as the number of pieces passing through a process step for processing at the next step.
[22] Defined in our model as the time to process a full batch (including any rejected parts) through a process step. Batch size is a per-step characteristic, often dependent on equipment type.
[23] 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.
[24] We do not collect overhead and indirect labor costs: 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. We also do not collect data on energy usage, as prior data suggests that energy costs are negligible (Fuchs et al. 2011).
[25] The O*NET taxonomy was devised for use by the U.S. Bureau of Labor Statistics based on taxonomic methods common in the literature (c.f.e. 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.
[26] 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."
[27] The existing O*NET database does not include the industry or establishment level detail to assess technological mechanisms at the process step level. 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).

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*
Operations Monitoring *Watching gauges, dials, or other indicators to make sure a machine is working properly.* *(collected but not reported in results due to close correlation with Operations and Control)*	*2 = Monitor completion times while running a computer program* *4 = monitor machine functions on an automated production line* *6 = monitor and integrate control feedback in a petrochemical processing facility to maintain production flow*
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.[28] 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).

6. Empirical Results

6.1 Cost Curves and Coexistence of Competing Technologies

As can be seen in Figure 3, we find that a low-cost leader does not currently exist across different levels of consolidation and automation in the optoelectronics industry: the range of possible costs of production for optoelectronics firms are overlapping in any of the technological regimes that make up the dominant share of the industry by volume or revenue. This result holds strongly as annual production volumes increase, suggesting that even as firm or industry size grows, a dominant regime still does not necessarily emerge. All cost configurations correspond to fabrication sited in the United States, assembly sited in Developing East Asia for low automation scenarios and assembly sited in the United States for high automation scenario, though even in the same geographic context it may be possible for technological regimes to coexist, depending on firm capabilities. The dotted lines in the figure 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): these show how different capabilities and strategies could map to cost.[29]

[28]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.
[29] 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 other volumes adjusted proportionally.

As can be seen in Appendix 3.5, the production cost implications from automation and consolidation differ with geographical context. Underlying our findings is a greater diffusion of some forms of consolidation (specifically, medium consolidation) worldwide than of automation. Lower wages in the developing world reduce the production cost savings from automation. In the developed world, automation has the greatest comparative value (versus the developing world) in labor-intensive steps like assembly. As consolidation increases fabrication and reduces assembly steps, the production cost savings are greater in the developed world due to more expensive labor. However, at the lower edge of the cost distributions (i.e. the possible technical frontier), the returns to consolidation are more equal between developed and developing country firm locations. Consequently, consolidation offers savings across geographic context, which can encourage wider diffusion.

Consistently across geographic contexts, however, automation permits more incremental capital investment than consolidation: where a single production step may be automated independently of the others (as indicated by the diversity of automation in our data), consolidation requires changes across multiple production steps from fabrication to design, meaning that capital outlays must be made simultaneously.

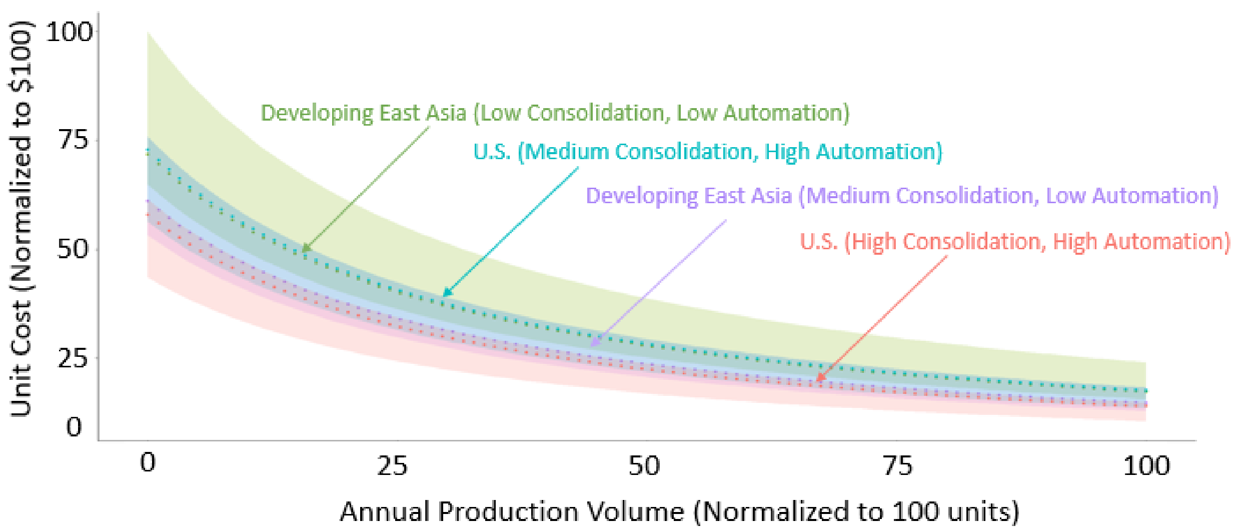


Figure 3 Unit Costs by Annual Production Volume, Level of Automation and Consolidation

6.2 Process Step and Task-Level Implications of Automation and Consolidation

In this section we show how the type and number of production steps changes with technology, and how technological change affects labor demand for specific types of steps and tasks. We find that *different* technologies have *different* task-biases. We find that consolidation converges skill demands—increasing relative demand for medium skill levels—whereas automation polarizes skill demand—decreasing relative demand for medium skills. Additionally, both automation and consolidation affect different task categories at different rates.

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.[30] 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 4 shows that the number of fabrication and testing steps increases with more consolidation, while the number of assembly steps decreases. These results are intuitive because under consolidation, components which were previously sub-assembled are fabricated jointly, thereby shifting tasks between these two categories of production. The increase in fabrication testing steps from medium to high consolidation may reflect process engineers expecting early challenges with process variability or quality for the high consolidation design, which is not yet produced commercially.

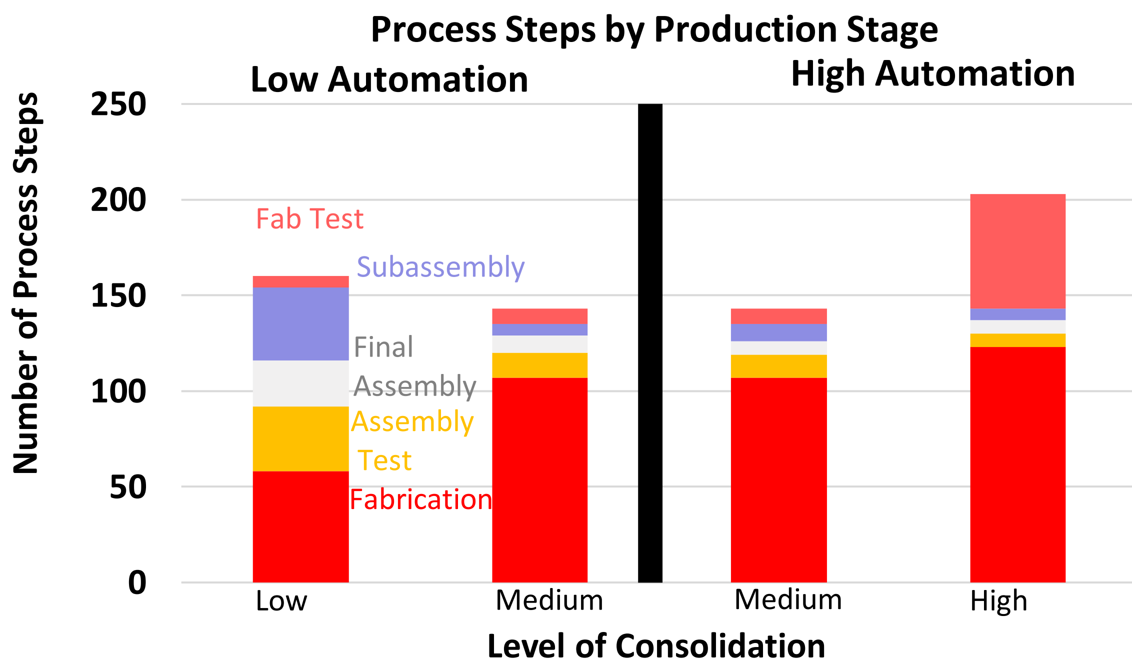


Figure 4 Process Breakdowns by Consolidation and Automation Scenario

Figure 5 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 5 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 consolidation.[31] Although additional testing steps are required for high consolidation (as seen in Figure 4), 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.

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[30] 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 4, is independent of APV.

[31] Automation and consolidation both lead to a net decrease in labor demand per unit output, but as we note in section 3 our model does not account for how technological changes may affect equilibrium price and output and hence, the absolute number of jobs or optimal geographic sites for production. See Appendix 3.3 for further discussion.

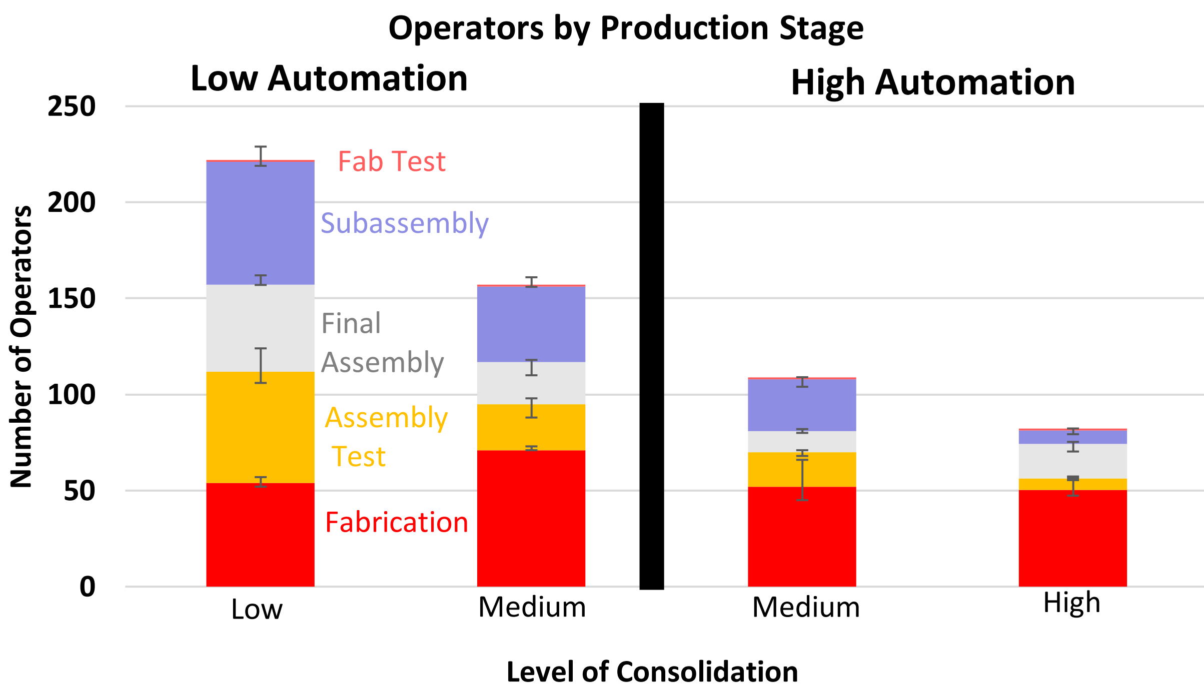

Figure 5 Number of Operators Required by Scenario and Production Category

Our findings above clearly show that automation and consolidation differentially affect the number of and labor demand for different categories of production step. We now examine in more detail the breakdown of production steps into categories of tasks. We discuss in turn which of these tasks are disproportionately affected by automation, and then those that are disproportionately affected by consolidation.

Variation in the level of automation occurs most in assembly process steps, partly because fabrication is already highly automated (that is, fabrication was perhaps *more* susceptible to automation than assembly). Automation in assembly disproportionately affects certain testing and geometrically simpler assembly steps: picking up and placing components has been widely automated in different segments of our sample (though still performed manually at some firms), while the more challenging angle of attack, grip and force management of fiber attach have not been as readily automated.

We find that different task categories, as with process categories (such as assembly), are automated at different rates: we describe apparent biases in which tasks within process steps are automated in Appendix 7.[32]

6.3 Heterogeneous Skill Demand Shifts with Different Technological Changes

We find that *different technologies have different skill demand effects*. Automation polarizes relative demand away from medium skill and toward low and high skill labor, while consolidation converges demand toward the middle of the skill distribution. Figure 6 shows how operations and control skill demand changes with automation and 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

[32] 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.

reduced the most at levels 2 and 3. 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 consolidation from medium to high does not exceed the range of inter-firm variation.

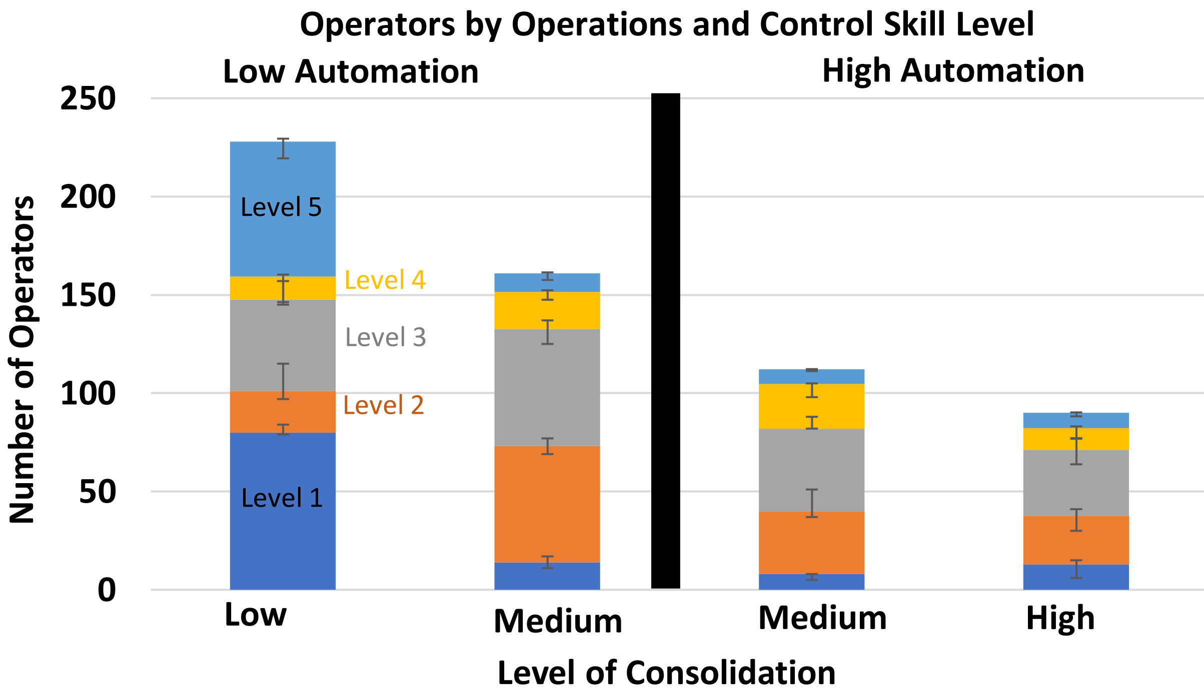

Figure 6 Number of Operators by Scenario and Operations and control Requirement

Figure 7 and Figure 8 show how aggregate measures of technological change can mask the opposing labor outcomes of automation and 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 5. 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 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 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 the cases we developed, the aggregate measures mask opposing outcomes.

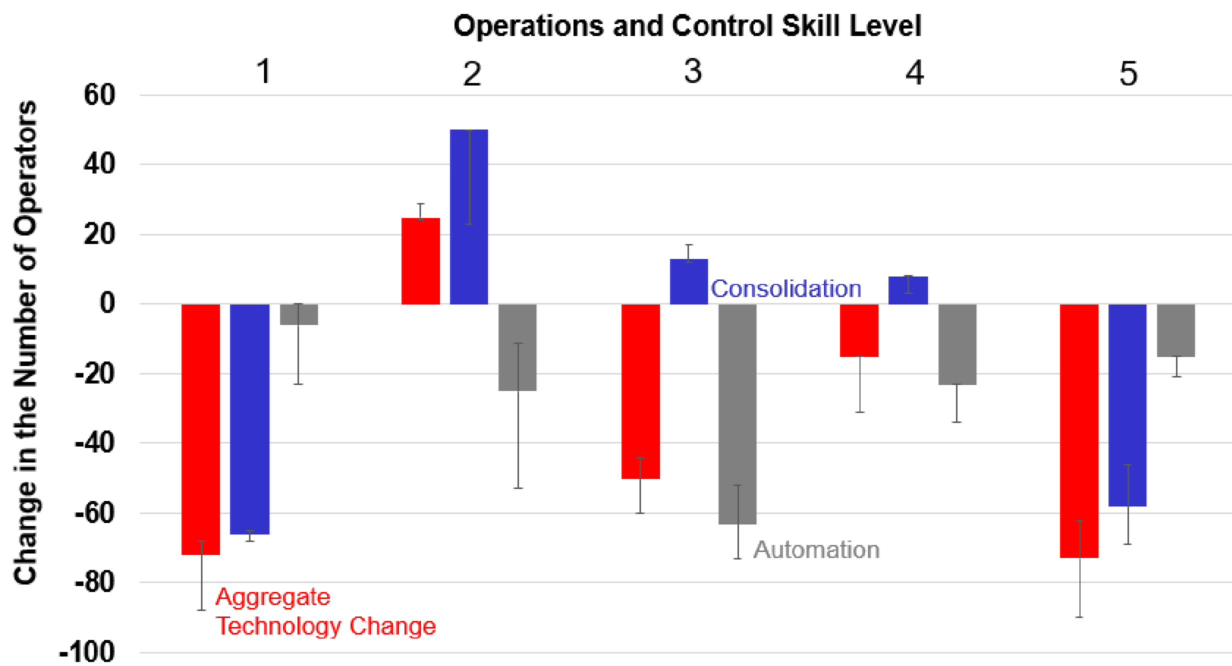

Figure 7 Operations and Control Skill Effects of Disaggregated Automation and Consolidation: Shifting from Low Consolidation, Low Automation to Medium Consolidation, High Automation

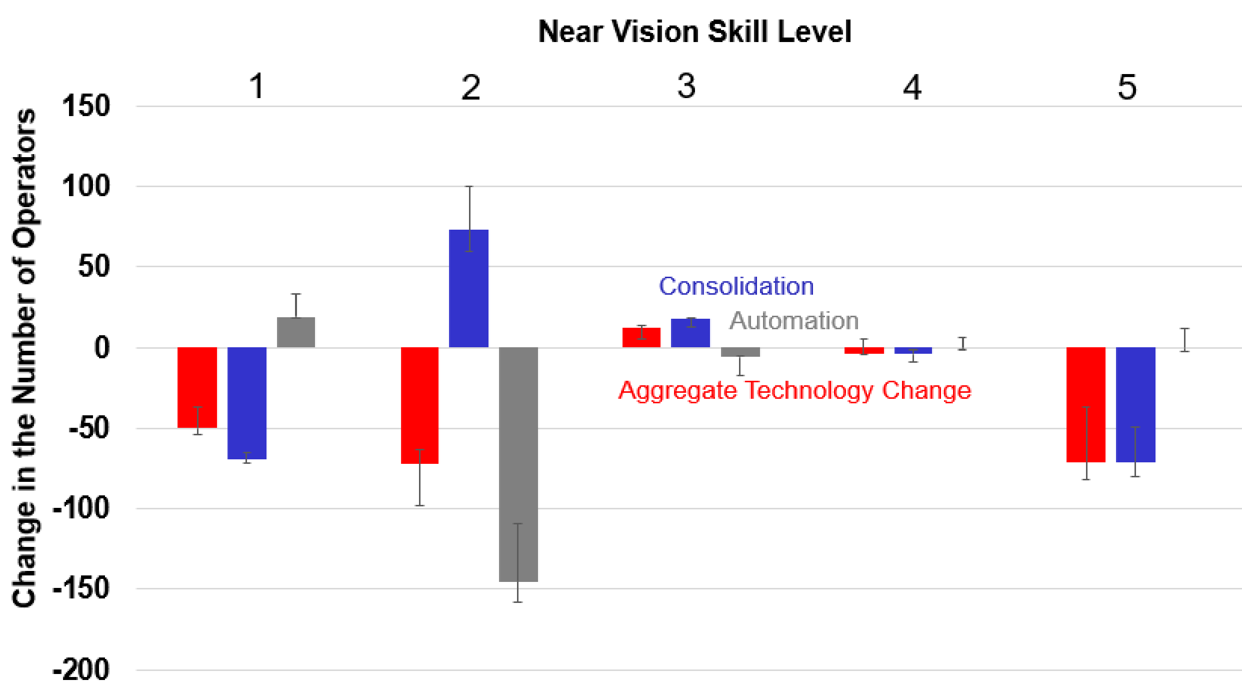

Figure 8 Near Vision Skill Effects of Disaggregated Automation and Consolidation: Shifting from Low Consolidation, Low Automation to Medium Consolidation, High Automation

Changes in operator skill requirements may not be independent across skill dimensions. Figure 9 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 find that consolidation not only converges demand along one skill dimension but shifts demand from high and low skill sets toward medium skill sets. We measure operator skill simultaneously on two dimensions to create a two dimensional skillset requirement: operations and control, and near vision. We find that moving from low to medium 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 Appendix 3 and suggest that this convergence holds for other skill pairings and for consolidation from medium to high.

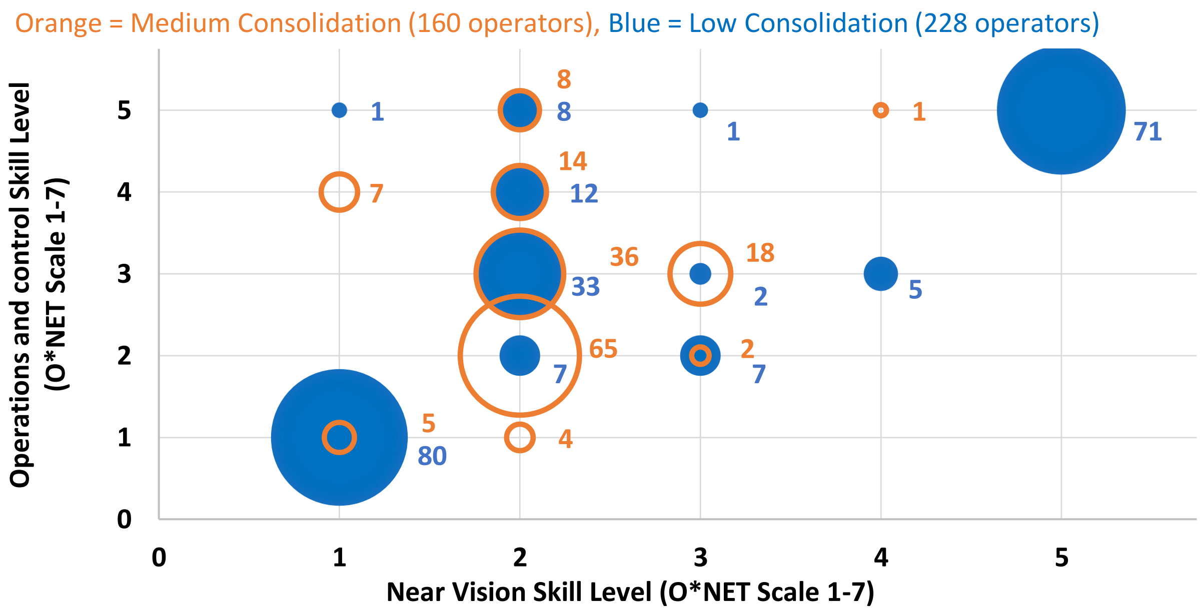

Figure 9 Consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

6.4 Aggregating Changes in Skill Demand

We aggregate our detailed O*NET findings to identify common trends and suggest mechanisms behind these trends (see Figure 10 and Figure 11). We first aggregate our detailed O*NET findings on the change in demand for skills (at consistent production volumes) 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 our detailed findings on the change in skill demand with technological change into these groupings. Here, demand is the number of operator jobs requiring a given level of skill and, so, change in relative demand with technological change is given by the number of operator jobs by skill level under different technological scenarios.

To obtain 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 consolidation and our high automation, medium consolidation scenarios (thus holding 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 consolidation and our high automation, medium consolidation scenarios. 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 consolidation and our high automation, medium consolidation scenarios.

For consolidation, since we measure two shifts in consolidation (low-to-medium and medium-to-high), we plot the results for both beside each other. We only suggest a generalizable relationship between consolidation and physical or cognitive skills if both changes in consolidation shift labor demand in the same direction for a given skill grouping. As with our empirical results in section 6, the error bars in Figure 10 and Figure 11 reflect the maximum and minimum differences in labor demand between technological scenarios.[33]

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

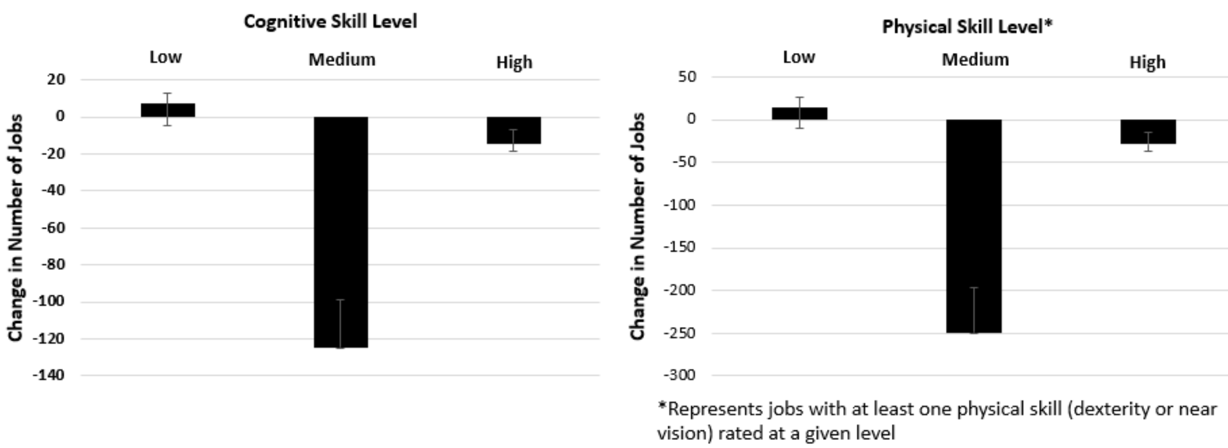

Figure 10 Aggregate Change in Number of Operator Jobs by Cognitive and Physical Skill Level Under Automation

[33] We show the full equations for this analysis in Appendix 1.3 and report intermediate outputs in Appendix 3.2. Note that due to our aggregation of physical skills, a single job may appear 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.

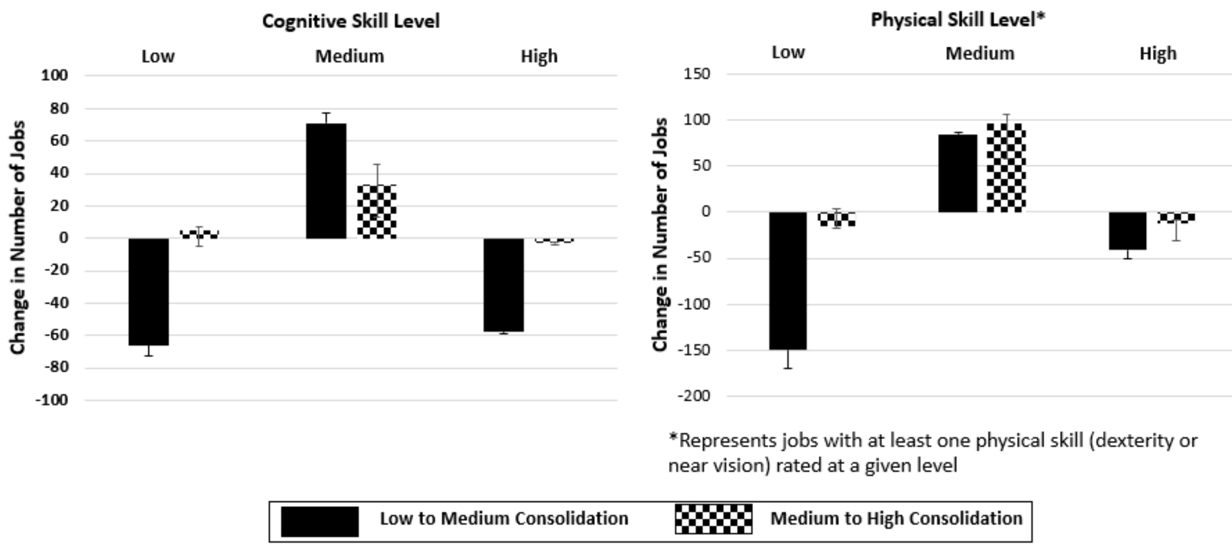

Figure 11 Aggregate Change in Number of Operator Jobs by Cognitive and Physical Skill Level Under Consolidation

In the case of automation (Figure 10), we see demand for physical and cognitive skills shifting away from the middle, leading to skill polarization in operator jobs, as in the detailed case described in Section 6. Automation does not change aggregate demand for low level physical or cognitive skills. Jobs with high skill requirements decrease slightly, but far less than the change in medium skill. We find that in contrast to automation, consolidation (Figure 11) converges rather than polarizes overall demand for both the physical and cognitive skills required of operators in the industry.

7. Generalizability of Empirical Findings

7.1. Matching Optoelectronic Labor Demand Implications to Semiconductors

Similarities between optoelectronics and other subsectors within the semiconductor industry[34] suggest that matching the labor implications of automation and consolidation in optoelectronics to semiconductors more broadly offers a useful possible validation and comparative basis for drawing broader sectoral implications.

We match the different levels of consolidation and automation examined in the optoelectronics context to historic parallels in electronic semiconductors. The design and production of our low automation, low consolidation scenario most closely resembles the state of electronic semiconductor production 30-40 years ago (NBER CES 2018). We would expect the high automation, high consolidation case to best resemble electronic semiconductor production today or in recent years.

Comparing our technological scenarios to the broader semiconductor sector, however, requires a few important caveats. First, optoelectronics has been able to benefit from the electronic semiconductor industry's historical knowledge. As such optoelectronic semiconductor production is more advanced than electronic semiconductor production of 40 years ago, despite current technological challenges (Cheyre et al 2015; Yang et al 2016). Second, the shift toward technologies that reduce labor share in semiconductors may also have accelerated the decline of labor share in optoelectronics,

[34] 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).

distorting the historical analogy between technology and labor share. Third, our model does not account for possible differences in the level of firm competition between optoelectronics and semiconductors, which could result in different technological strategies between historic semiconductors and the current optoelectronics industry.

Table 5 compares the labor share of production costs across scenarios in our model to the trajectory of the semiconductor industry more broadly. We compare our PBCM outputs to aggregate data from Semiconductor and Related Device Manufacturing (NAICS 334413) industry, as available in the NBER Center for Economic Studies (CES) Manufacturing Industry Database.[35]

Table 5 PBCM-Based Labor Share of Input Costs

Scenario	Labor Share	Latest Matched Semiconductor Period*
Low Consolidation Low Automation	0.442	1986-1987
Medium Consolidation Low Automation	0.308	1991-1992
Medium Consolidation High Automation	0.232	1999-2001
High Consolidation High Automation	0.184	2006-2009

**Based on the latest periods in NBER CES Time Series Data whose labor shares cover the labor share for each optoelectronics scenario in our study*

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 industries. These results suggest that technological change and labor outcomes in optoelectronics have followed a trajectory similar to that of electronic semiconductor devices through their technological history. This finding is an important piece of validation for the outputs of the PBCM. Further, the increasing substitution of photonic components for electronic components (NAS 2013) would suggest that such findings from the optoelectronics subsector will increase in relevance for the wider electronics industry.

7.2 From Firm Capabilities to Skill Demand

Our findings on the coexistence of multiple cost-competitive technological regimes in a commoditized market (section 6.1) confirm that it is possible to disentangle the labor demand effects of automation and parts consolidation in our analysis of the optoelectronic industry. The coexistence of heterogeneous technological regimes is relevant to many other industries and contexts. Piore and Sable (1981; 1984), for instance, highlight the coexistence of flexible manufacturing versus mass production, and both approaches have now coexisted on an international scale for decades (Rungtusanatham and Salvador 2008, Eckel and Neary 2010). In their case they propose that society may choose flexible production over mass production, with more fulfilling outcomes for workers (and perhaps consumers as well). Notably, however, while flexible production may offer greater product customization, it does not offer the scale of production output possible with mass production (Womak, Jones, and Roos 1990).

We add the implications for labor and skill demand to the discussion and evidence around coexisting, heterogeneous technology regimes. Specifically, different technologies can be used to produce perfect substitutes with comparable production costs, but substantially different skill demands.

[35] Optoelectronic semiconductors are part of the same 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 and starker differences historically, electronic semiconductor trends will easily dominate the aggregate data (Khan et al 2018).

Combined with Fuchs and Kirchain (2010), our work shows that the production cost functions for heterogeneous technologies can overlap for an extended period (at least 10 years in optoelectronics).

In showing that different technologies can be used to produce perfect substitutes with comparable production costs, but substantially different skill profiles, our findings open up the possibility that labor and skill outcomes can be chosen by firms without adversely affecting competitiveness or product outcomes. With comparable production costs under automation or consolidation, differences in the separability of capital investment (piece-meal automation by step or simultaneous consolidation across steps) may be important to such choices by capital-constrained firms. Since certain geographic locations such as the U.S. and Europe may have a comparative advantage for producing consolidated designs, and because the most advanced consolidated designs may have technological advantages for accessing other new markets in the longer term (Fuchs and Kirchain 2010, Yang Nugent and Fuchs 2016), policy-makers in the U.S. and Europe may wish to evaluate the implications of firms' access to capital for technology adoption on national competitiveness and skill demands for their workforce.

8. Theory and Discussion: Mechanisms for the Effect of Technological Change on Tasks and Jobs

Our research design and step-level manufacturing data enable us to propose new theory for the relationship between technology change and skill demand. While the focus of our paper is automation and consolidation, the underlying mechanisms for their different effects on skill demand could be shared by other technological changes. Unpacking the mechanisms driving the different implications for skill demand seen in our study requires defining five terms (see Table 6).

Table 6 Theoretical Definitions

Concept	Definition	Example
Task[36]	An action that is not divisible into smaller units with a separate performer.	Swinging a hammer onto a nail cannot be divided into completing half the arc of the hammer swing and then giving it to another worker.
Performer	The entity (human, machine, animal) which autonomously completes the task.	The human swinging the hammer is the performer.
Task Separability	The feasibility (e.g. cost) of having two tasks assigned to different performers.	Consolidation can make it infeasible for tasks to be performed in parallel.
Job[37]	A union of one or more tasks which are performed by a single worker.	Loading Machine A, letting it run autonomously to manage Machine B, then returning to unload Machine A.

[36] A process step (as in our empirics) is a continuous sequence of one or more tasks. Our focus in this theory on mapping tasks into jobs is analogous to steps which have a consistent performer (e.g. Loading, monitoring and then unloading a wire-bonding machine).

[37] Our definition is similar to Autor, Levy and Murnane (2003) and Brynjolfsson, Mitchell and Rock (2018), though we are able to directly analyze the production elements of a job in developing our mechanisms.

Task Skill	The minimum level of skill (along one dimension, e.g. dexterity) for a performer to successfully complete a task to given specifications.	Manually attaching a die to a substrate within a certain tolerance and with a success rate of at least 95% requires a Dexterity Skill Level of at least 4.
Job Skill[38]	The maximum of skill requirements for tasks that make up a job.[39]	A job consists of two tasks: A and B. A requires low physical skill and high cognitive skill. B requires high physical skill and low cognitive skill. The job thus requires both high physical and high cognitive skill.

*In our production context, all workers were dedicated to a specific step, such that jobs and steps were identical. However, we break out these two concepts in our definition so that our technology mechanisms can generalize beyond a specific organizational model in optoelectronics.

Our definition of job skill is particularly important to understanding our results and to our theory: any task whose skill requirements are greater than those of other tasks in a step or job increases the skill requirement of the entire job, while any task whose skill requirements are lower than the rest of the job has no effect on skill demand. Hence, the more separable tasks are from each other, the fewer tasks will be bundled into the same jobs and the lower the demand for skill within those jobs.

We begin by identifying technology-specific mechanisms for the effect of each technology on skill demand. We then move to generalize these relationships by explaining the skill demand mechanism in terms of task separability.

We identify two forces that drive the mechanism for the effect of automation on skill demand. The first explains why highly skilled labor may be less affected by automation than middle skill: highly physically and cognitively skilled steps often involve complex part geometries that make them harder to automate than more straightforward medium skill assembly tasks. An industry expert offers a practical example: “Machines are limited in what they can do. Most of the [epoxy] dispensing systems, for example, the needle is perpendicular to the thing you’re squeezing epoxy on. In optics, you use the third dimension; a lot happens vertically... it’s easier to use an operator. There’s a lot of factors that have to apply to make it worthwhile to spend the time and money to automate. You’re better off using skilled operators.”

The second force driving the effect of automation explains why low skilled labor is less affected by automation than middle skill. Many of the requirements of the operator production tasks created by automation are at a lower skill level (e.g. loading and unloading a part, monitoring a machine), while not

[38] The same definition holds for the skill demand of a process step (i.e. the upper envelope of task skill requirements): in our context, steps and jobs are the same, but they are important to separate in cases where workers are responsible for disconnected tasks (hence, multiple production steps).

[39] The skills required for a job are determined not by the job profile (e.g. “machine operator”) but by the actions associated with each task making up a job (e.g. “load and unload the machine” and “monitor for process defects”) and the particular skill requirements to perform each action in that context (e.g. monitoring one machine may require greater skill than another).[39] For instance, essential tasks (such as unloading a machine) may require lower skill compared with tasks that are important but not strictly required (such as monitoring a machine at every instant).

requiring sufficient volume of activity to justify a dedicated machine. Such work offers less scope for operator intervention (and thus, all else equal, demands less skill) than manual tasks.[40]

The next step is to relate the two forces above to task separability. Automation represents a case of technology change which consists of substituting new performers for existing ones. We propose that the separability of tasks influences the likelihood of existing performers to be substituted by new performers. If tasks are highly inseparable, they tend to be grouped into jobs with correspondingly high skill requirements. Any technology that offers substitutes for existing performers needs to outperform incumbent performers on more dimensions the less separable tasks are. Conversely, if tasks are highly separable, it is easier to break them into pieces that are best suited to the capabilities of new performers. Thus, collections of tasks with high skill requirements see less substitution than lower skill, and affected jobs are likely to have their tasks separated from each other into yet lower skilled activities.

In the case of automation, jobs whose tasks are separable can more easily be broken into operations for machines to perform. For example, fiber attachment in our context requires multiple simultaneous alignments and applications of force by a manual worker: these cannot be readily separated, and the job as a whole becomes difficult to automate. Because jobs with more tasks tend to be more difficult, separability-bias in automation leads to skill-bias by preserving higher skill activities. Meanwhile, automation of jobs with highly separable tasks generates new low-skilled jobs: activities such as transferring parts between workstations are examples of tasks with low-skill requirements which can be broken out from automated steps and assigned to workers. Automation thus interacts with task separability to generate skill demand polarization.

Current theory proposes that the task composition of jobs can determine their degree of automatability (Brynjolfsson, Mitchell and Rock 2018), and that automation most affects routine tasks (Autor, Katz and Kearney 2008). However, the existing theory does not use task composition to explain multidirectional skill demand effects from automation. As we show, routine tasks— such as part orientations in assembly—can remain manual, showing that routineness is insufficient to understand the automatability of jobs.

We identify three additional forces to understand the implications of consolidation for skill demand, one putting downward demand pressure on high skill demand, and two reducing low skill demand relative to middle skill.

The first force, task elimination, accounts for a downward pressure on high skill demand. In our case, more parts are consolidated into a single unit, and a disproportionate share of assembly steps (and associated testing) is eliminated. Demand for the highest level skills is often reduced because these higher-level skills (such as complex part orientation) are predominantly required in operator assembly tasks, which are eliminated with consolidation. With fewer components, there are fewer opportunities for testing, which also requires higher cognitive skill. Though the specific mapping of tasks to process categories (assembly, testing) may be industry-specific, the most cost-effective tasks to eliminate are (all else equal) those with the greatest skill demand, suggesting that adoption of consolidation could be more likely when this downward pressure on skill demand is realized.

Task combination and increased cost of failure, our second and third forces, put downward pressure against the demand for low skill. Tasks throughout the production process are merged into the

[40] Though some machine operation is highly skilled, multiple industry experts explained that the role of a machine operator is often performing the rote (low physical and cognitive skill) motions of setting up and transferring parts: “The first thing you do is learn how to simply change out reels of parts that run out. The next is to set up a new job… The machines are pretty automatic, and what you do is train them [operators] how to set up the machine.”

same step during consolidation, increasing the number of tasks per step: steps take on the highest requirements of their component tasks, thus driving up overall skill requirements. For example, in fabrication, certain deposition steps become longer and more complex in order to produce components with multiple functions. The cost of failure increases because consolidated parts mean that production failure with one part can now damage other parts as well. One of the experts we interviewed offered an instructive quote: "You've got to understand that quality is what this is all about. If you make a mistake it's quite expensive."

The next step is to relate the three above forces to task separability. Consolidation represents a case of technology change that changes task separability, and thus, skill demand in jobs. If a technology reduces the separability of tasks, all else equal, jobs will consist of more tasks. Since the skill requirement of a job is the maximum of the skill requirements of its constituent tasks, such technologies will increase the demand for skill. That said, there may be a greater shift from low to medium skill demand than from medium to high, because any given task being added to a high-skill job is less likely to exceed the current skill content of the job than if the job is low-skilled. If so, and in combination with the elimination of some tasks by consolidation (e.g. bundles of assembly tasks no longer necessary), both low and high skill jobs can be lost while the greatest shift in demand is toward the middle.

Change in the cumulative value of tasks due to consolidation also follows from the change in task separability. When tasks are inseparable, so are their outputs, such that failure in one task may compromise the work done in other tasks. Moreover, the cumulative value of a bundle of tasks increases with more tasks. The result is a shift toward higher skill demand, especially for previously low-skilled work, to reduce costly failures.

The existing literature has not connected technology change to skill demand through shifts in task separability as in our theory.[41] While the technology-specific forces we describe can apply in other contexts (especially semiconductors but also other industries), we expect the relationships between changes in task separability and skill demand outcomes to be the most general of our findings, as these do not rely on any particular mapping between skill and specific tasks.

9. Conclusions

This paper fills a gap in the skill biased technology change literature around the direct measurement of technological change and the mapping of technological change to skill demand through the characteristics of production.

We demonstrate the benefits of directly mapping the effect of technological changes on skill demand using an engineering process model. We collect unprecedented data on the skill, training, education, and experience requirements of every step in a manufacturing process. The specificity of our model and data allows us to use counterfactual scenarios to simulate past, ongoing and emerging technological changes.[42] We are thus able to disentangle simultaneous technological changes with differential labor effects invisible in aggregate data, and to characterize task-level mechanisms behind the skill demand effects of technological change.

[41] Baldwin and Venables (2013) suggest that reducing the divisibility of processes (task separability) would increase the cost of division of labor. They show that reducing frictions (costs) in the division of labor can increase polarization of factor intensity across nations (or firms): this result parallels our findings on skill demand outcomes.

[42] These counterfactuals enable us to move beyond restrictive assumptions of classic production functions, of aggregate data, and of historic data being representative of the future.

While our deep level of data detail on specific technologies and contexts may not be feasible at an economy-wide level, we believe that such parameters should be collected more broadly by government and academic data collection efforts, such as through census instruments like the Annual Survey of Manufacturers. To quote a still-relevant 1986 interview with Herbert Simon (The Failure of Armchair Economics), "We badly need better ideas of how to put together the stuff we find out at the micro-micro level and aggregate it." Simon continues, "…if you studied about a dozen firms, you have a pretty good feeling of the range of behavior … the idea that we must have huge samples in order to know how a system works is not necessarily so."

We make three main contributions. First, we directly measure the effect of technological changes on skill demand, addressing the gap in the task-approach literature. In concert with literature on the polarization of skill demand, our findings suggest that automation not only polarizes skill demands across occupations, but within occupations.

Second, we show that aggregate measures of technological change can mask the opposing skill demand shifts of multiple technological changes. We find that, in contrast to automation (described above) consolidation converges skill demand toward middle skill. Our results thus provide empirical evidence for the coexistence of technological regimes with very different implications for skill demand.[43] 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.

Third, we leverage our task- and step-level data to develop new theory for how the separability of tasks mediates the effect of technology change on skill demand by changing the divisibility of labor. Our theory explains how technological change can generate complex, multi-modal skill demand shifts. Technologies that decrease task separability lead to jobs with more tasks. Because job skill demand is the maximum of task skill requirements, more tasks can drive skill increases or convergence toward middle skill (as the skill demand of lower-skill jobs is more likely to be increased by new tasks). The situation is reversed with technologies that increase task separability, driving skill demand decreases or polarization. Technologies such as automation that substitute performers can also be described in terms of task separability: the least separable tasks are the least likely to be divided and their performers substituted (preserving high skill demand), while the most separable tasks are the most likely to split into new low skill jobs due to technological change (generating low skill demand), resulting in polarization of demand away from middle skill.

The direct mapping of different technological changes onto labor outcomes, presented for the first time in this paper, enables us to uncover the mechanisms of skill demand effects at the level of tasks (task separability) and their aggregation into jobs. Our work introduces the relationships among tasks as a guide to understanding skill demand impacts of technological change, and it opens up new questions regarding the implications of technological change for labor markets and technology-specific policy responses.

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[43]These findings suggest a natural extension of the capability-based theory of the firm: we connect differences in capabilities and local conditions with differences in incentives for technological development or adoption, and thus differences in skill demand.

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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:

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

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

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 $\alpha_{element}$ 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 (single unit or batch output) 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:

$$AC_{labor} = \sum_{s} \omega_s h_s u(v_s)$$

$\omega_s \in \mathbb{R}^+$ is average operator wage in step $s \in \mathbb{N}$ (this may vary if some steps are performed in different locations); $h_s \in \mathbb{R}^+$ is the annual hours worked by an operator employed in a process step (in our model, typically 40 hours a week, 50 weeks a year for 2000 hours a year, but allowed to vary). $v_s \in \mathbb{R}^+$ is the effective production volume of step s: taking the annual production volume γ of the finished good as given, v_s is a function of both γ and the product of the yield rates $y_n = [0,1]$ of all steps $i\ s.t. s \in P_i$, where P_i is the set (see section 3 of the main body):

$$v_s = \gamma \prod_{i\ s.t. s \in P_i} y_n$$

$u(v_s)$ is the annual quantity of laborers demanded at a given process step:

$$u(v_s) = \left\lceil \frac{\eta_s}{h_s} \right\rceil$$

$$\eta_s = \frac{n(v_s)\kappa_s}{\psi_s \rho_s}$$

Where η_s is the annual labor time required in step s to satisfy effective production volume $u(v_s)$, $n(v_s)$ is the number of capital lines required in step s to satisfy its effective production volume, ψ_s is the fraction of equipment time requiring a human operator and ρ_s is the number of pieces of equipment in step j that one operator can manage and κ_s is the net available annual hours (after downtime) that capital in step s 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 $n(v_s)$ 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 $s \in R \subseteq \Phi$ (see section 3 for discussion of the step set Φ) we define $n(v_s)$ the lines required in step s:

$$n(v_s) = \frac{l_s}{a_s} + \frac{\left\lceil \left\lceil \sum_{g \in \Phi} \frac{l_g}{a_g} \right\rceil - \sum_{g \in \Phi} \frac{l_g}{a_g} \right\rceil}{|R|}$$

Where l_s is the line time required in step j to meet effective production volume (as in Fuchs and Kirchain (2010)) and a_s 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):

$$\alpha_{Building} = \sum_{s} n(v_S)\, b_{j,s} p_q^{BL}$$

Where $b_{j,s}$ is the square footage of type $j \in \mathbb{N}$ (e.g. a cleanroom) required for a capital line in step s 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

Where prior work generates broad ranges of possible costs based on individual variation of high and low parameters of production (sometimes treating the parameters of a piece of equipment as independent from each other), the model used in this paper for the first time builds in a step-level (taking technology as fixed) optimization process to generate a set of empirical equipment and labor options that minimize (maximize) production cost or labor demand. By constructing these sets from individual equipment options, we allow parameters that are technologically and physically related to each other (e.g. batch size and cycle time) to remain related in the generation of bounds of possible variation from our empirical "baseline" estimates. We believe that minimum and maximum values of cost or labor demand obtained in this manner are more representative of current or near term technological constraints on production parameters and thus more likely to capture the true possibility for interfirm variation in cost and labor demand under differing technological scenarios – hence, our methodological innovation allows us to more precisely distinguish changes in factor demand (including labor skill demand) from interfirm variations.

This skill bundling is a helpful approach for aggregation of skill requirements across process steps. It does not necessarily occur at the level of the entire production process, but rather it happens across a subset of process steps. One type of worker does not perform the entire production process: there might be (at most) N types of workers on N steps, but even some workers with responsibility across process steps (as in our model) would still lead to differentiation in skills demanded throughout the process. The logic for this bundling approach is that, empirically, some jobs involve responsibility for multiple process steps and performing all steps successfully will require meeting the maximum skill requirements across all steps.

Skill Demand:

In order to calculate the matrix D_s of demand for operators of each skill type in step s from our model, we first multiply the number of operators required at a given process step by an index matrix of the skills required for that step:

$$D_s(u(v_s)) = \begin{bmatrix} \theta_s(\sigma_0, w_0) & \cdots & \theta_s(\sigma_0, w_0) \\ \vdots & \ddots & \vdots \\ \theta_s(\sigma_0, w_0) & \cdots & \theta_s(\sigma_0, w_0) \end{bmatrix} u\left(EPV_j\right)^{LB}$$

Where $u(v_s)$ is the annual labor demanded at process step s for an annual output v_s, and where $\theta_s(\sigma_\xi, w_j)$ is an indicator function of whether s requires labor of type and level $\sigma_\xi, w_j \in \mathbb{N}$

t$\theta_s(\sigma_\xi, w_j)$takes the value 0 if skill level w is not required and 1 if required, and $\sum_j \sum_\xi \theta_s(\sigma_\xi, w_j) = 0$ (meaning that two levels of the same skill cannot be required for the same step:[44] within our theory, the higher of the two levels would be the required skill level). Thus, D_s 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:

$$D = \sum_{s=1}^{n} D_s$$

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 process 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 s in a production process has a set of alternative equipment inputs $I_s \subset \mathbb{N}$ 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_s to elements $i_s \in I_s$ whose level of automation corresponds to the given scenario z (indexed $\lambda_{z,s}(i) \in \{0,1\}$): $\{ i_s | i_s \in I_s, \lambda_{z,s}(i_s) = 1\}$. The mechanisms for interfirm variation hold with or without this refinement.

All elements $i_s \in I_s$ have corresponding Leontief production functions relating capital, material and labor inputs to y_s, the annual output of the step s: 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_s also has a corresponding skill demand given y_s.

The range of labor required in a given process step is given by: $[\min_{i_s \in I_s} u(i_s, v_s), \max_{i_s \in I_s} u(i_s, v_s)]$

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

$$[\sum_{s=1}^{n} \min_{i_s \in I_s} D_s(I_s), \sum_{s=1}^{n} D_s(I_s)]$$

The range of annual production costs for step s is a function of input requirements as a function of i_s and y_s multiplied by the vector of input prices $\overrightarrow{p(\iota_s)} \in \mathbb{R}^n$. A demand for input factors $\overrightarrow{D(\iota_s)} \in \mathbb{R}^n$ expresses the demand for labor, materials and capital dependent on choice of i_s, in which the parameters of the cost and input functions described prior, but not their structure, are determined by input alternatives. Input prices are collected for each possible input in our data and are expressed as a function of i_s.

$$[\min_{i_s \in I_s}(\overrightarrow{p(\iota_s)}\, \overrightarrow{D(\iota_s)}), \max_{i_s \in I_s}(\overrightarrow{p(\iota_s)}\, \overrightarrow{D(\iota_s)})]$$

Thus the range of overall production costs is given by:

$$[\sum_{s=1}^{n} \min_{i_s \in I_s}(\overrightarrow{p(\iota_s)}\, \overrightarrow{D(\iota_s)}), \sum_{s=1}^{n} \max_{i_s \in I_s}(\overrightarrow{p(\iota_s)}\, \overrightarrow{D(\iota_s)})]$$

[44]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.

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.

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:

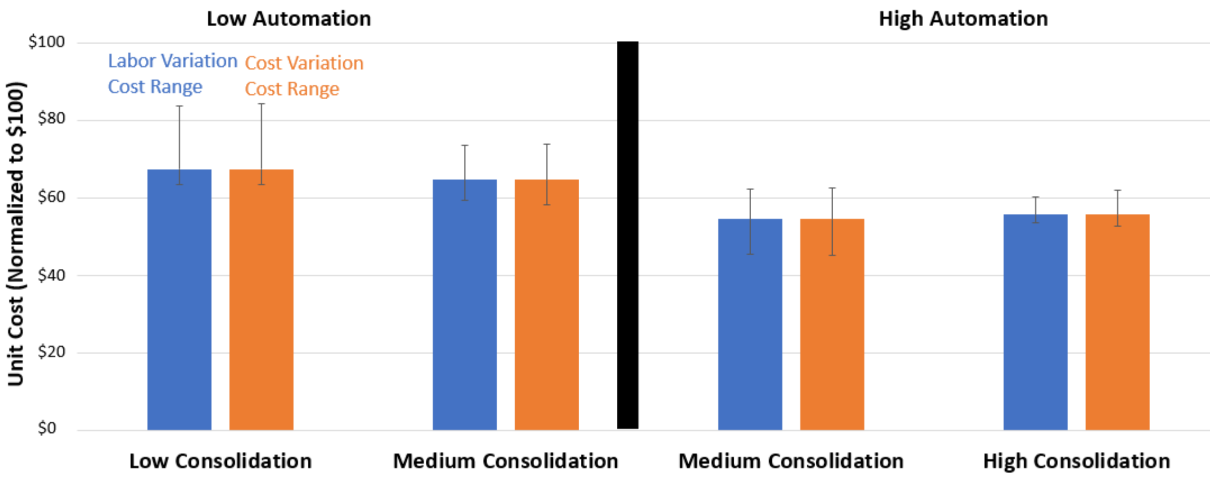

Figure 12 Cost Range Comparisons of Interfirm Labor and Cost Variation Inputs

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:

$$\Delta J_{w,\sigma}(X,Y) = J_{w,\sigma}(Y) - J_{w,\sigma}(X)$$

Where $J_{w,\sigma}(X)$ is the number of operator jobs requiring level $w \in \mathbb{N}$ (e.g. skill level 1) of skill type $\sigma \in \mathbb{N}$ (indexing, e.g. near vision or operations and control) in scenario X. We define $\Delta J_{w,\sigma}(X,Y)$ as the change in operator jobs requiring skill level w 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):

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

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

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; $w \in M = \{2,3,4\}$):

$$\Delta J_M(X,Y) = \sum_{\sigma} \sum_{w \in M} J_{w,\sigma}(Y) - J_{w,\sigma}(X)$$

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

$$\Delta J_{Ops\,\&\,Control,M}(B1,B2)=\sum_{\sigma}\sum_{w\in M} J_{w,Ops\,\&\,Control}(B2)-J_{w,Ops\,\&\,Control}(B1)$$

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

$$\Delta J_{w,C}(X,Y)=\sum_{\sigma\in C}\Delta J_{w,\sigma}(X,Y)$$

Where $\Delta J_{w,C}(X,Y)$ is the change in jobs at skill level *w* within a skill set $C\subset\mathbb{N}$. The equation above is the change in jobs with skill level s in at least one of the skill types $\sigma\in C$ (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:

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

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

Combining our notation to calculate the change in medium skill jobs within C, we refer to:

$$\Delta J_{M,C}(X,Y)=\sum_{\sigma\in C}\sum_{w\in M}\Delta_{w,\sigma}(X,Y)$$

Where $\Delta J_{m,C}(X,Y)$ 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).

Appendix 2: Data and Validation

Appendix 2.1: Automation Level by Process Category and Automation Scenario

Table 7 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).

While appropriate for our focus on the automation of a manufacturing production process, Frohm et al do not offer the only taxonomy of level of automation: alternate taxonomies include widely cited examples from Kaber and Endsley (1997) and Parasuraman, Sheridan and Wickens (2000).

Kaber and Endsley focus on process control and Parasuraman et al focus on the level of automation of decision and action selection (i.e. interactions between humans and automation): our interest in performance of actions by humans or machines (rather than decision-making only) takes us beyond the scope of Parasuraman, and Kaber and Endsley’s taxonomy, while detailed, is prescriptive about the order (1-10) in which functional categories (monitoring, generating, selecting, implementing) are automated (see below).

Table 8 Endsley and Kaber’s LOA Taxonomy (1997)

Level of Automation	Functions			
	Monitoring	Generating	Selecting	Implementing
1	Human	Human	Human	Human
2	Human/Computer	Human	Human	Human/Computer
3	Human/Computer	Human	Human	Computer
4	Human/Computer	Human/Computer	Human	Human/Computer
5	Human/Computer	Human/Computer	Human	Computer
6	Human/Computer	Human/Computer	Human/Computer	Computer
7	Human/Computer	Computer	Human	Computer
8	Human/Computer	Human/Computer	Computer	Computer
9	Human/Computer	Computer	Computer	Computer
10. Full Automation	Computer	Computer	Computer	Computer

The taxonomy of Frohm et al. was chosen for its focus on manufacturing systems and its less prescriptive approach to the order of mechanization/automation of functions (allowing mechanical and equipment automation vs. information and control automation to occur at different rates). However, in our data, selecting functions (deciding on a particular option or strategy) are performed by humans and generating (formulating options to achieve system goals) functions are performed by machines only if the machine also performs monitoring and implementing functions. Thus variation in level of automation reduces to the monitoring and implementing functions identified by Endsley and Kaber. The four levels of automation from Endsley and Kaber taxonomy in our data are “manual control,” “action support” and “batch processing” and “shared control,” each strictly more automated than the last (unlike later levels of automation in the taxonomy, e.g. level 6 to level 7): taken to our data, the automation of different inputs to the same process steps using this taxonomy maps 1:1 with the relative automation across inputs based on Frohm et al, which we used to demarcate our low and high automation scenarios.

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 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 Consolidation	Medium Consolidation	High 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 Consolidation		Medium Consolidation			High Consolidation
Operator Share by Education	China	Developing East Asia	North America And Europe		China[45]	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 process 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 process steps and the lower bound assuming that equipment was shared across all process 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)

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

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

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 2.5: Robustness of Findings to Choice of Skills Measured

While the O*NET survey instrument includes a wide variety of skills and abilities, we measure a subset of four. The omission of other skills in the O*NET database was partly a feasibility measure: firms supplied data on skill requirements for each process step, requiring an engineer or manager to fill out data for each skill and step, and asking these individuals to fill out all of the O*NET skill/ability requirements (35 skills, 52 abilities) for every single process step (481 across our dataset) would have been infeasible for participants. The current methodology for populating the O*NET database involves relatively small sample sizes for each occupation: task descriptions average 59 responses per occupation, abilities and skills average 8 responses per occupation and skill. We collected data at the job level within the same occupation, capturing 481 process steps, task descriptions and their requirements in four skills/abilities.

With this limitation in mind, the skills we chose to measure (near vision, finger dexterity, operation and control) were based on preliminary discussions with industry experts that suggested relevant areas of variation and past examples of specific skills used in the labor economics literature, such as manual dexterity and eye-hand-foot coordination from the *Dictionary of Occupational Titles* in Autor, Levy and Murnane (2003).[46] We selected skills to demarcate physical or manual skill from cognitive skills relevant on the shop floor, including a fourth item (operations monitoring) which mapped very closely with "operation and control" in our data and thus was not included in our results. Our selections were further refined by characteristics of the industry and product we studied (e.g. physical strength is not relevant in the production of small optoelectronic products) and the nature of the occupation of shop floor operators (e.g. operators in the context we studied did not engage in instruction or coordination with peers as part of their daily job operations but rather completed job tasks individually).

Appendix 2.6: Addressing Threats to Identification

One threat to identification is that apparent shifts in labor demand partially reflect firm rather than technological characteristics. Firms non-randomly select their level of automation and consolidation, based on their capabilities and input characteristics (e.g. labor cost).[47] To help address this identification issue, we collect not only technologically but organizationally representative sample of the industry: our sample covers both globally distributed firms and those with primarily U.S.-based production, as well as both vertically integrated (firms that perform design, fabrication and assembly) and "fabless" firms.[48] Thus, 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 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.

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[46] Based on task descriptions from firms and skill data collected, high levels of near vision and dexterity requirements jointly would approximate a high level of eye-hand-foot coordination

[47] This statement is based on our conversations with executives at each firm in our sample.

[48] Fabless firms do not possess fabrication capabilities but design devices and at least partially assemble them . Such firms make use of contract manufacturers, including foundries, which are large high-capacity fabrication facilities serving both optoelectronic and traditional semiconductor manufacturing (Hochberg and Baehr-Jones 2010).

Another threat to identification is that the apparent effect of automation may be biased by relatively higher (lower) labor productivity in certain countries. Within our sample, more tasks are automated in production facilities sited in the United States, Japan and Europe than in developing East Asia. We believe that this threat to identification is not a concern, because 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.

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 consolidation, reducing the lowest difficulty factor and increasing the absolute number (Figure 13) and share (Figure 14) of operators at the highest skill factor (5), even as the total number of operators decreases. Further 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 13) as well as proportionally (Figure 14). Automating the medium 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 consolidation, greater failure and yield considerations appear to drive an upward skewing in skill requirements. Unlike under low to medium consolidation, parallel process flows are not merged (i.e. process steps eliminated by consolidation were already sequential) from medium to high consolidation. This suggests that yield considerations driving dexterity requirements in medium consolidation are unchanged, and the effect of high dexterity task elimination is dominant, driving down dexterity requirements overall.

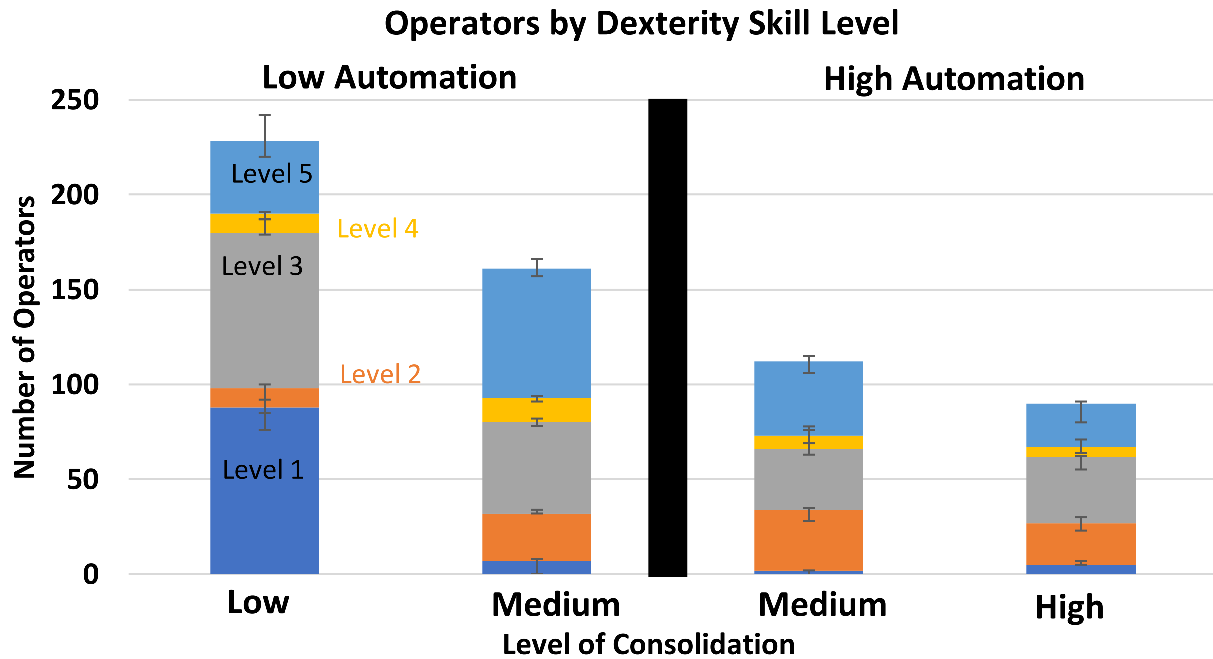

Figure 13 Number of Operators by Scenario and Dexterity Requirement (Median APV)

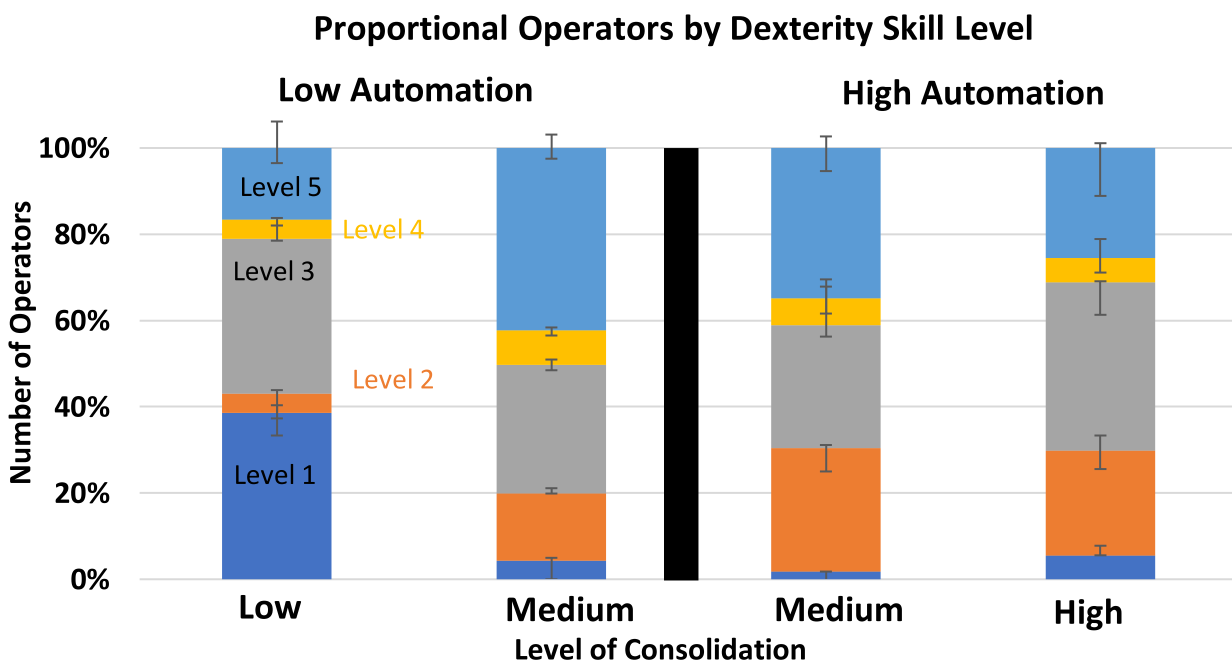

Figure 14 Share of Operators by Scenario and Dexterity Requirement (Median APV)

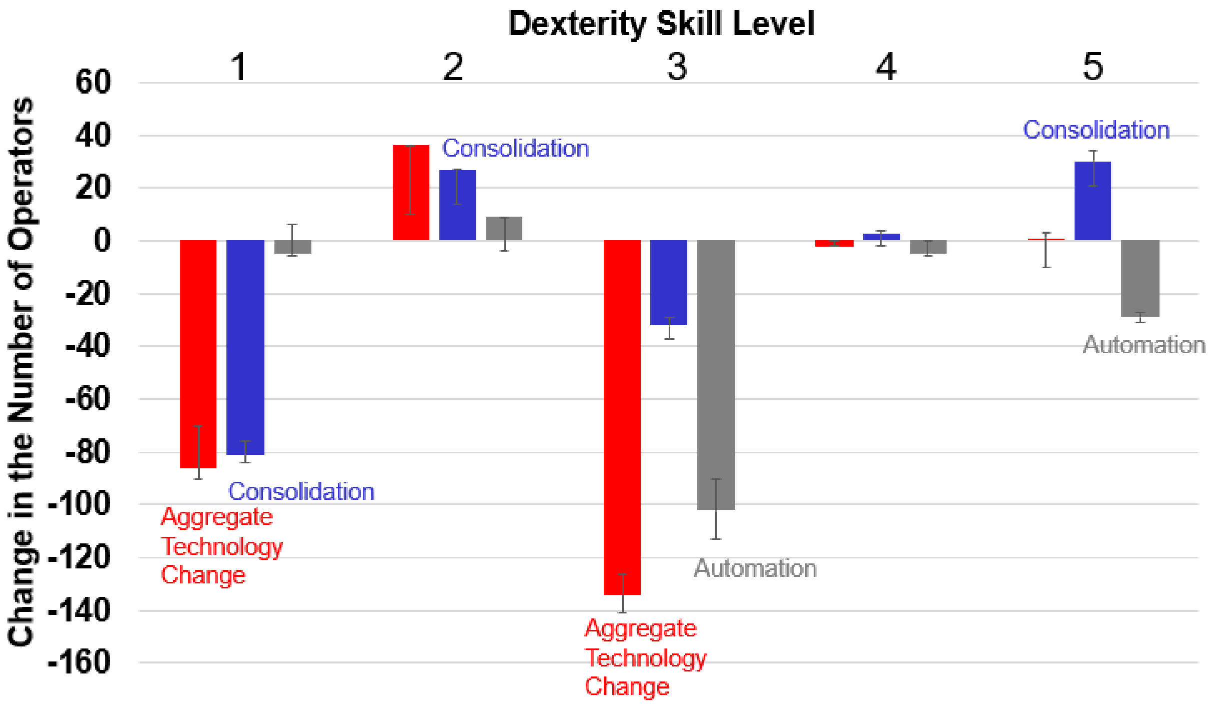

Figure 15 Aggregate Dexterity Skill Effects of Disaggregated Automation and Consolidation: Shifting from Low Consolidation, Low Automation to Medium Consolidation, High Automation

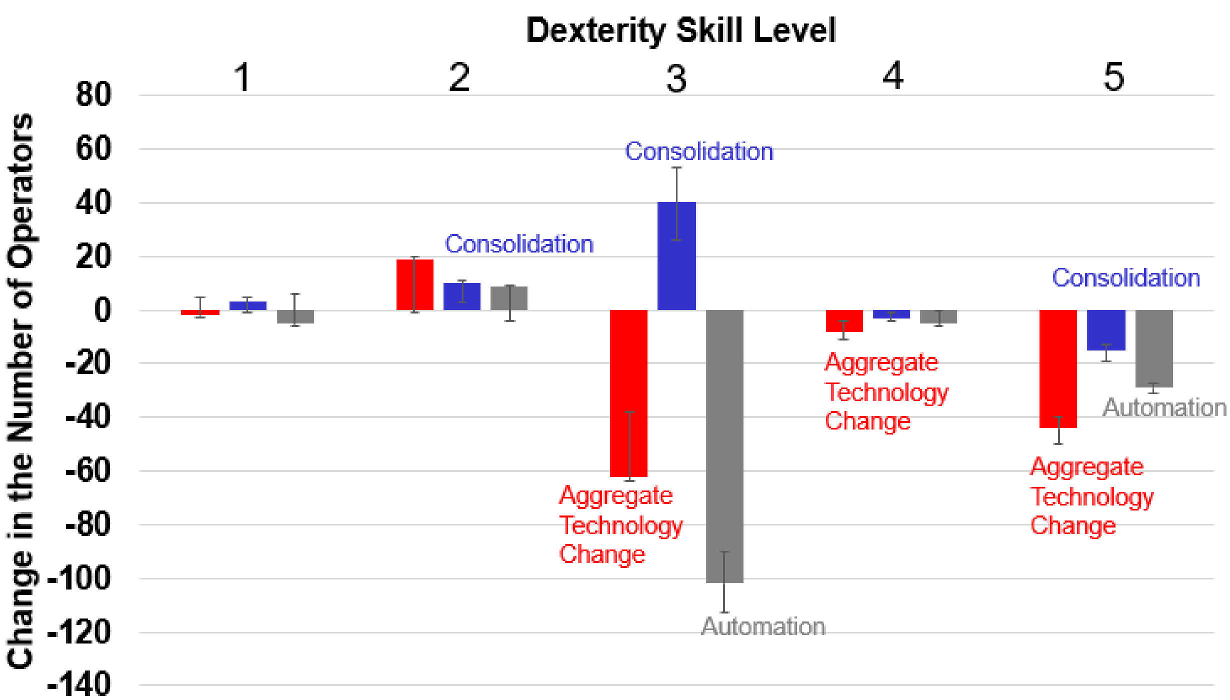

Figure 16 Aggregate Dexterity Skill Effects of Disaggregated Automation and Consolidation: Shifting from Medium Consolidation, Low Automation to High Consolidation, High Automation

3.1.2. Near Vision Requirements for Operators

The distribution of near vision requirements does not exhibit the same upward skewing with consolidation under low automation as dexterity. Both extremes of our observed difficulty distribution (levels 1 and 5) under low consolidation are reduced in absolute terms (Figure 17) and proportionally (Figure 18) moving from low to medium consolidation. 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 consolidation appears to drive down the near vision requirements for operators. The number (Figure 17) and share (Figure 18) 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 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.

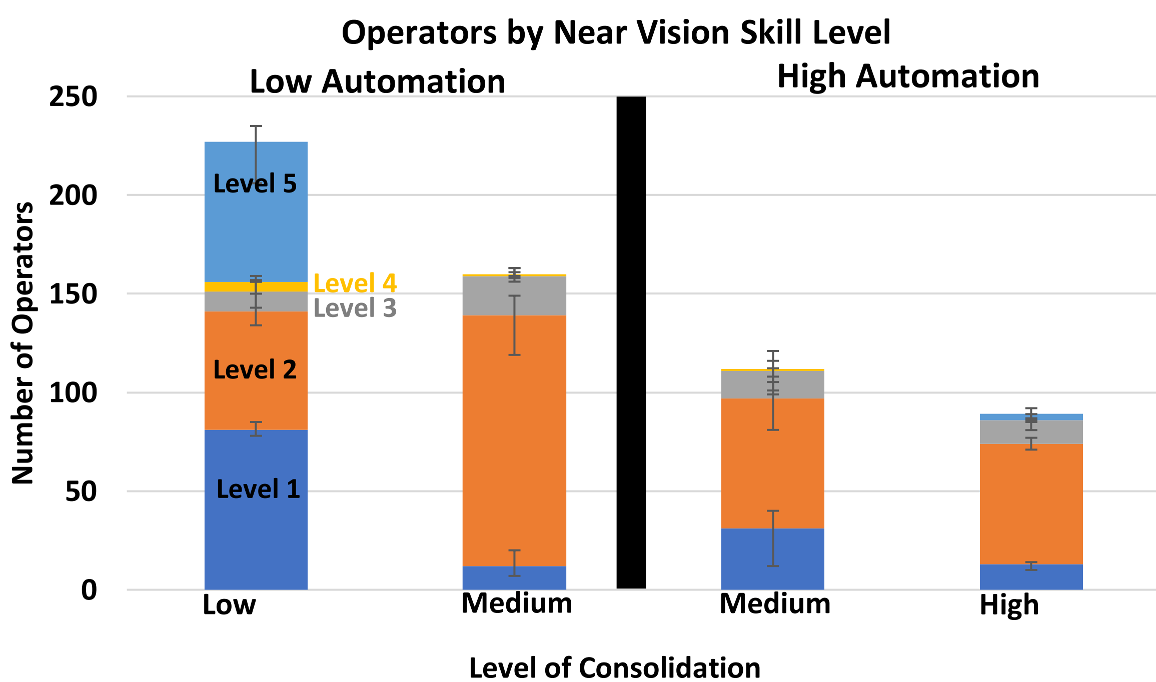

Figure 17 Number of Operators by Scenario and Near Vision Requirement (Median APV)

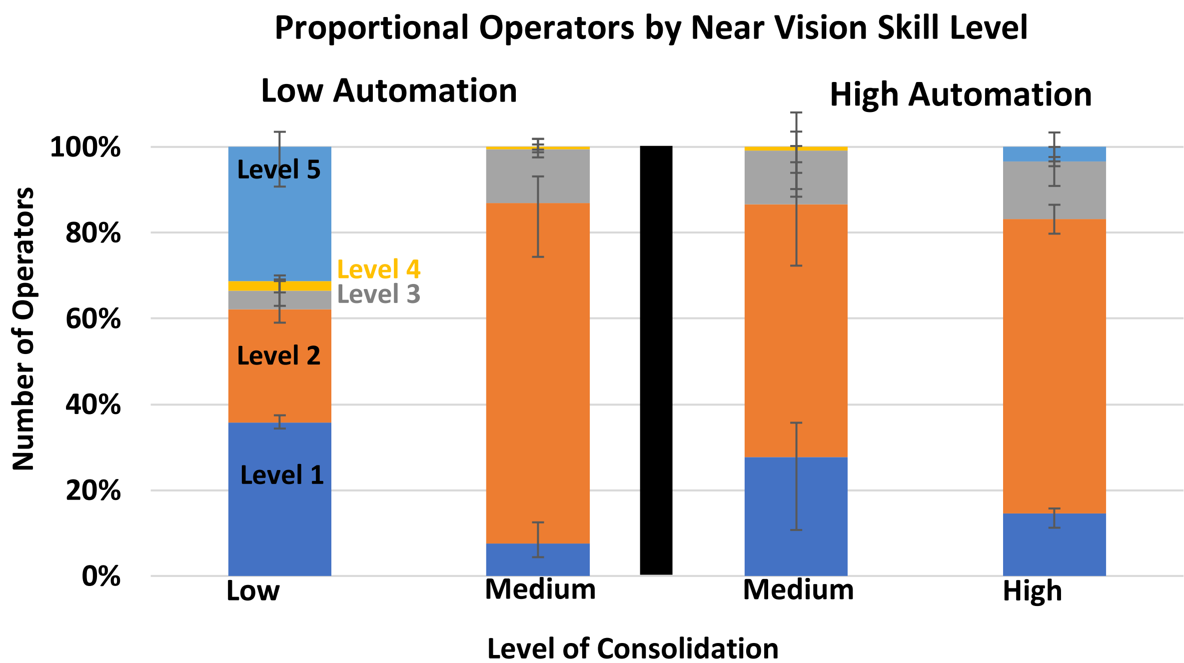

Figure 18 Share of Operators by Scenario and Near Vision Requirement (Median APV)

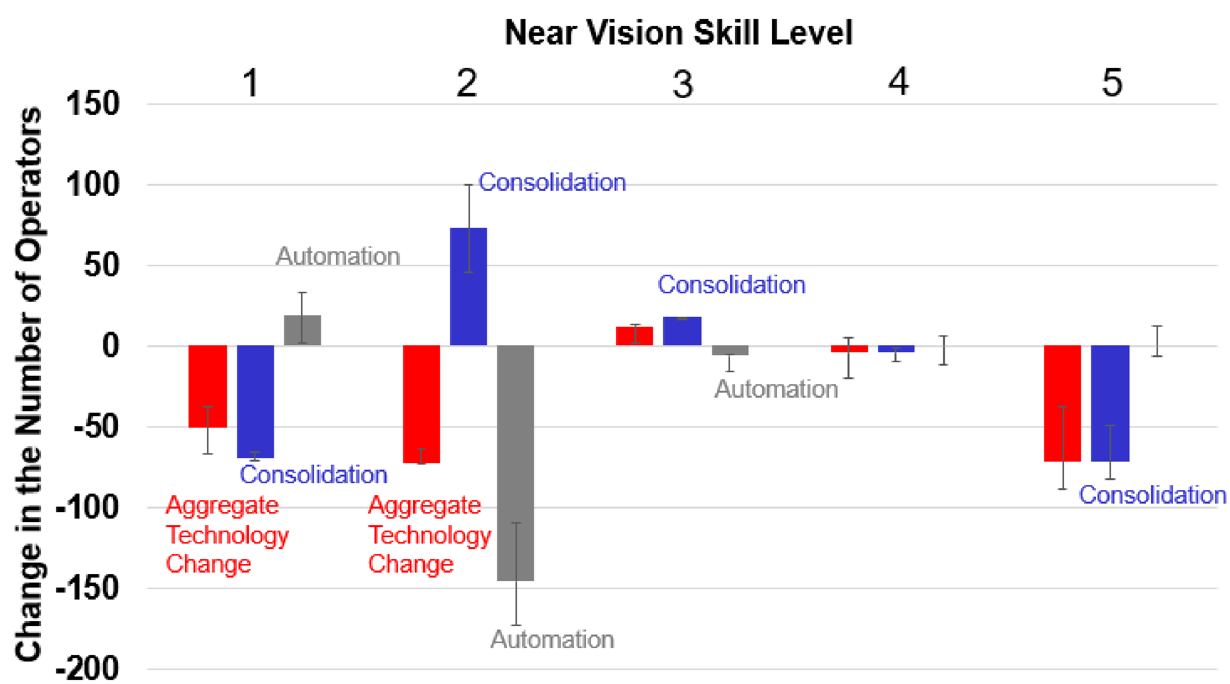

Figure 19 Aggregate Near Vision Skill Effects of Disaggregated Automation and Consolidation: Shifting from Medium Consolidation, Low Automation to High Consolidation, High Automation

3.1.3. Operations and Control Requirements for Operators

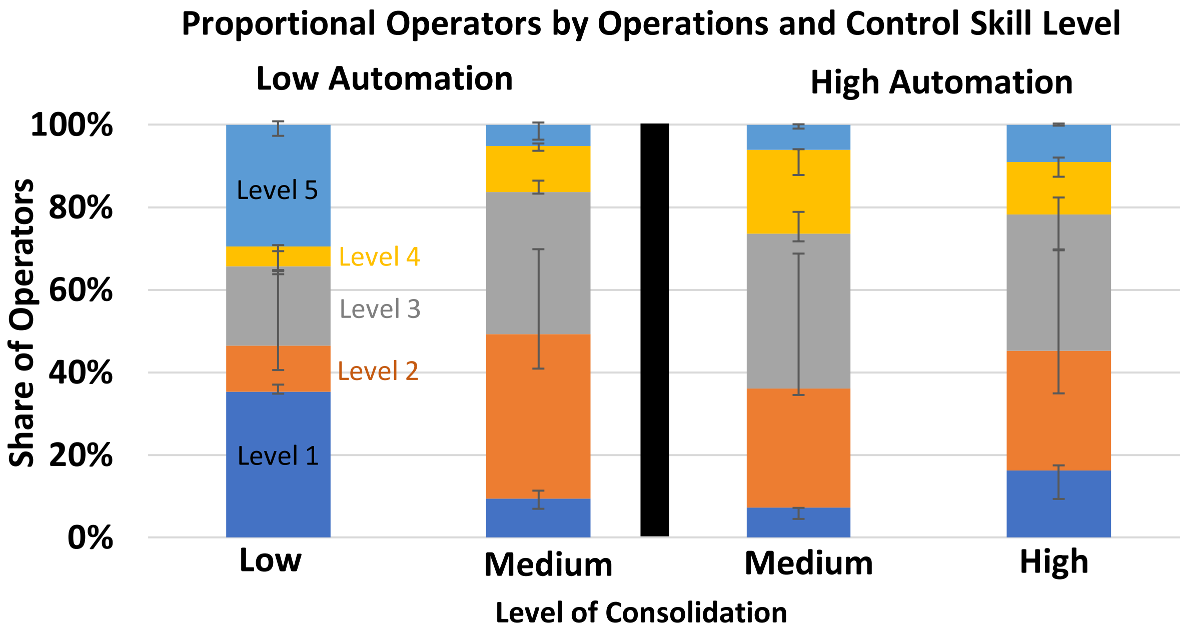

Figure 20 Share of Operators by Scenario and Operations and Control Requirement (Median APV)

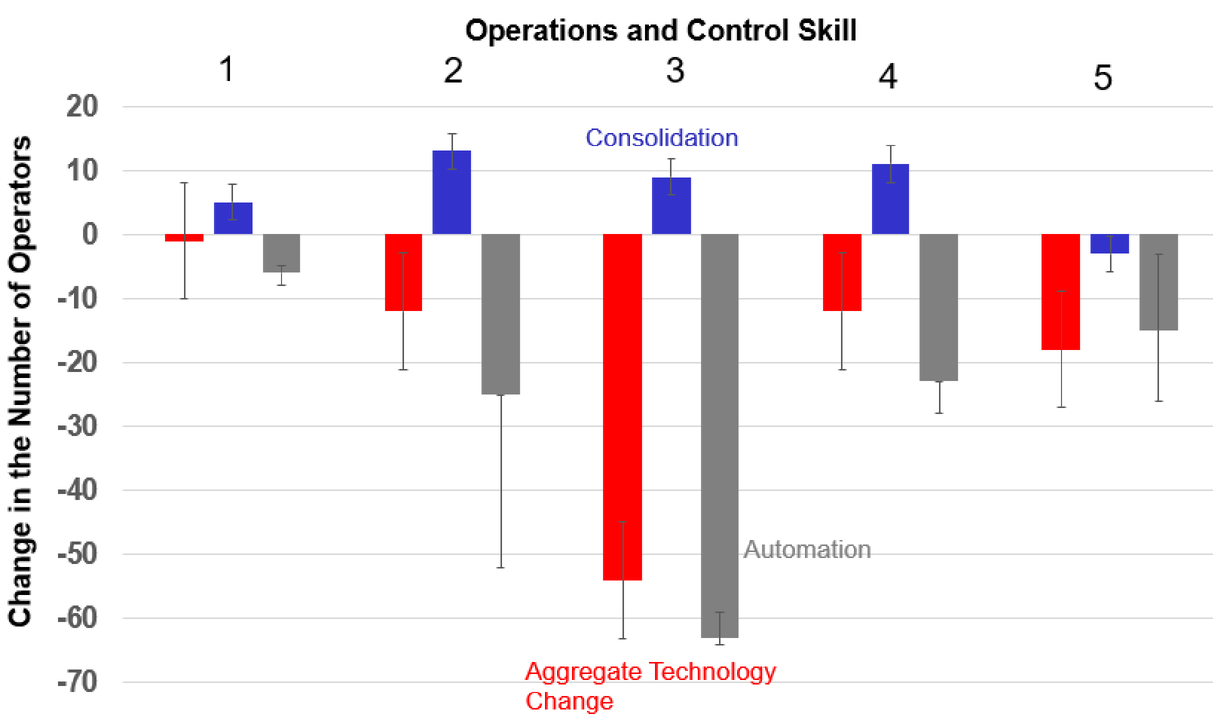

Figure 21 Operations and Control Skill Effects of Disaggregated Automation and Consolidation: Shifting from Medium Consolidation, Low Automation to High Consolidation, High Automation

3.2.4: Distribution of Physical Labor: Physical Tasks Preserved under 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.

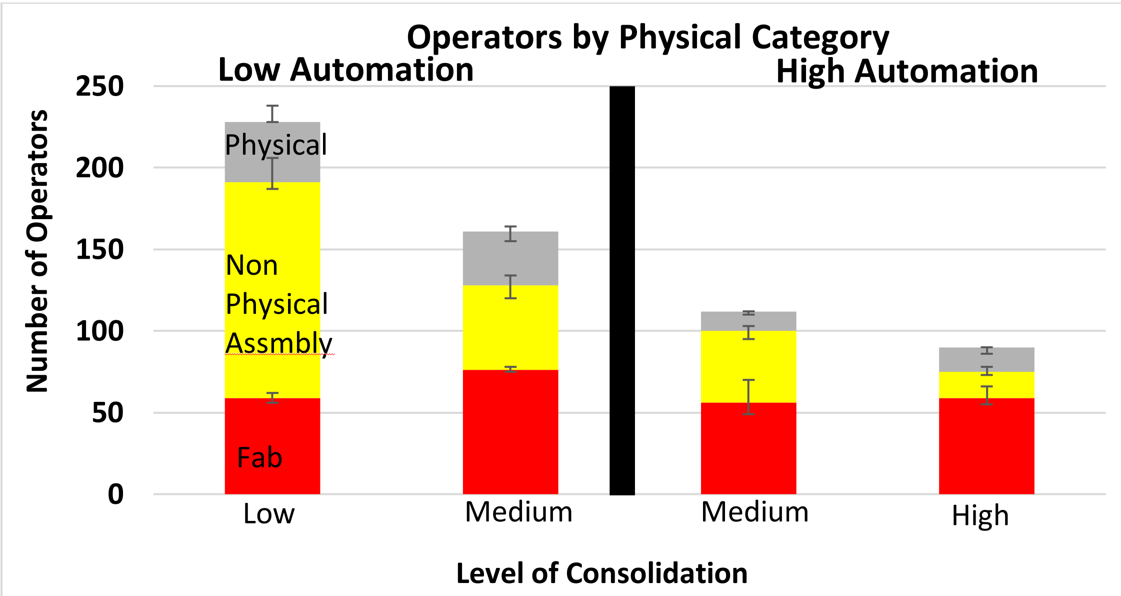

Figure 22 Physical, Nonphysical Assembly Operators, Total Fabrication Operators

This suggests a different relationship between 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 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

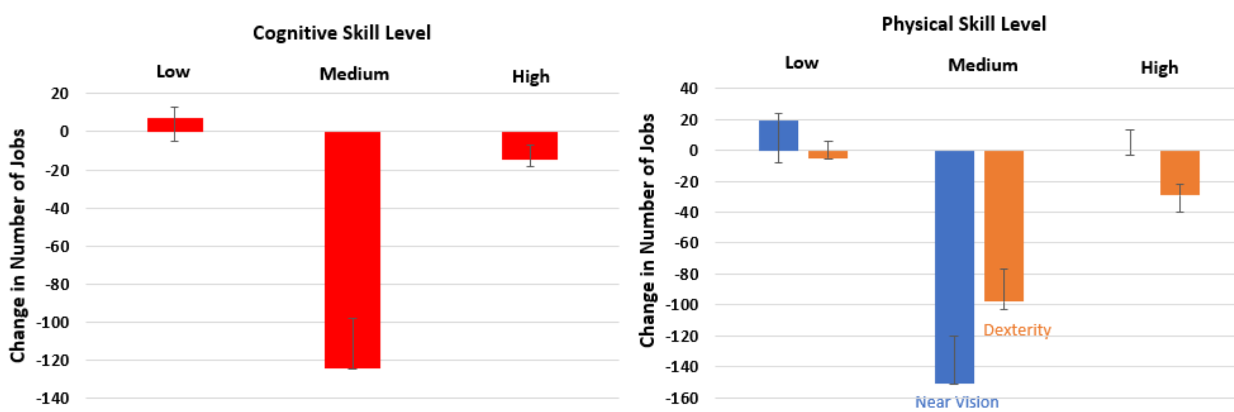

Figure 23 Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level under Automation

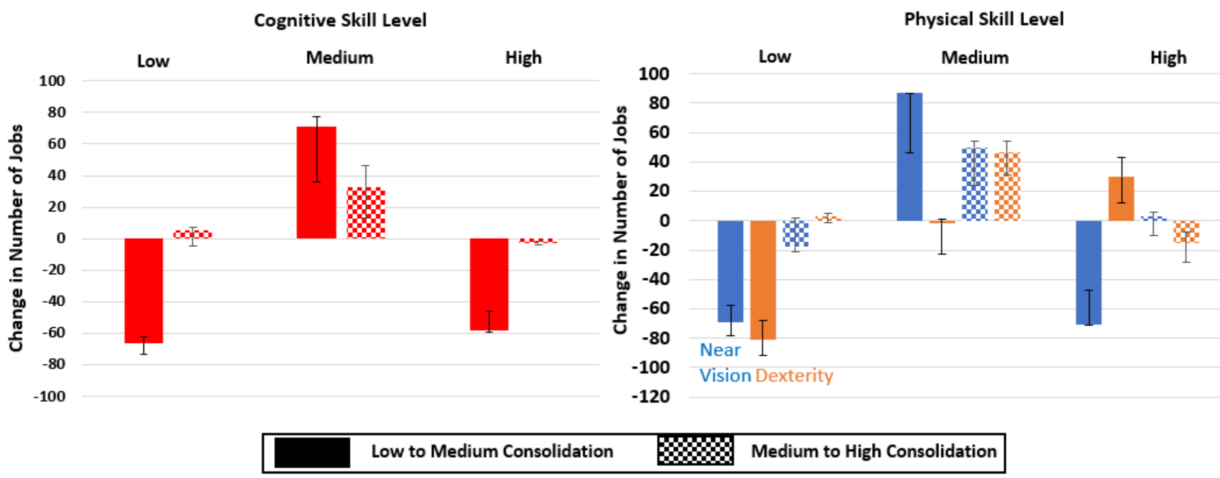

Figure 24 Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level under Consolidation

Appendix 3.3: Global Location of Jobs by Scenario

In our empirical context, both automation and consolidation induce a net decrease in jobs per unit output; however, the potential effect of automation and 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 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 consolidation production lines in the developing world, while we observe medium consolidation in both the developed and developing world. High 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 25 maps the geographic location of the facilities in our empirical data to the geographic locations represented in the production cost estimates of our design scenarios.

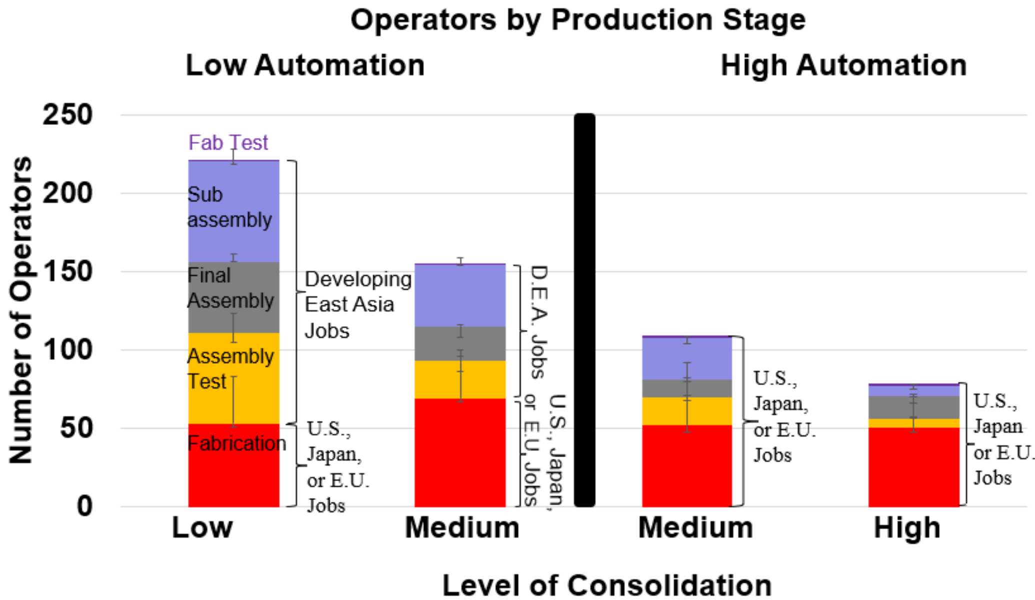

Figure 25 Probable Global Location of Jobs by Production Stage and Scenario

We expect the correlation between high consolidation and manufacturing in developed country locations as well as the correlation between consolidation and potential for higher performance to also apply to other manufacturing contexts. Consolidation is pursued for both its production cost and performance advantages in multiple industries, including aerospace, and automotive (Carle et al 1999). Consolidation removes labor-intensive assembly steps, the cost advantages of which are higher in developed nations. Furthermore, 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).

While technological capacity for consolidation and cutting edge automation are stronger (in optoelectronics) in the developed world, and the incentives for labor-cost savings are greater, we find that a developed-developing difference does not alone account for the coexistence of technologies. Assuming a developing world context for all processes, our consolidation and automation scenarios remain largely overlapping in their possible cost ranges, as show in Figure 26 (note that while low consolidation and automation appears dominant, its cost range overlaps slightly with all others at any volume, and overlaps more closely as volume increases). Indeed, as we observe in our firm sample and support in this figure, it is possible for different technological regimes to coexist in a developing context.

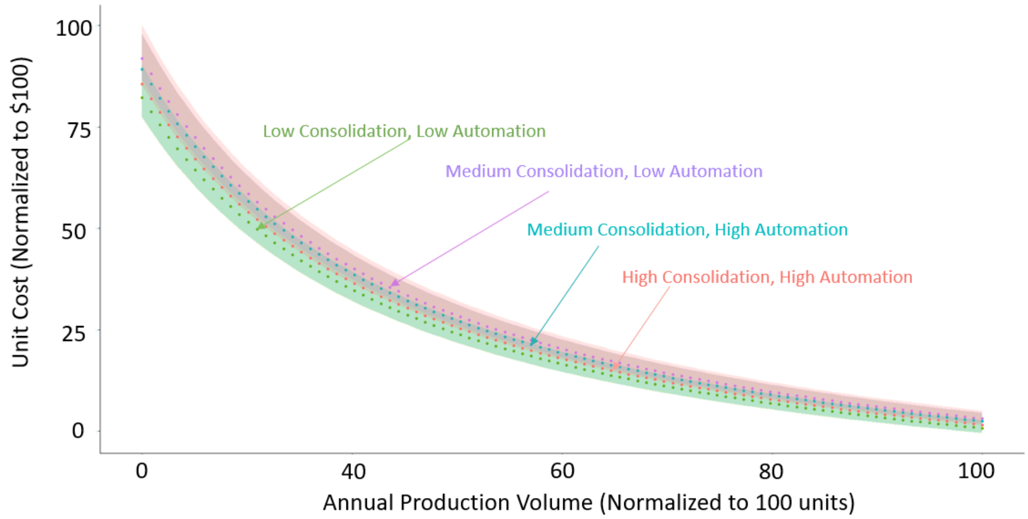

Figure 26 Cost Ranges for Automation and Consolidation Scenarios in Developing World

Appendix 3.4: Joint Skill Distribution Shifts

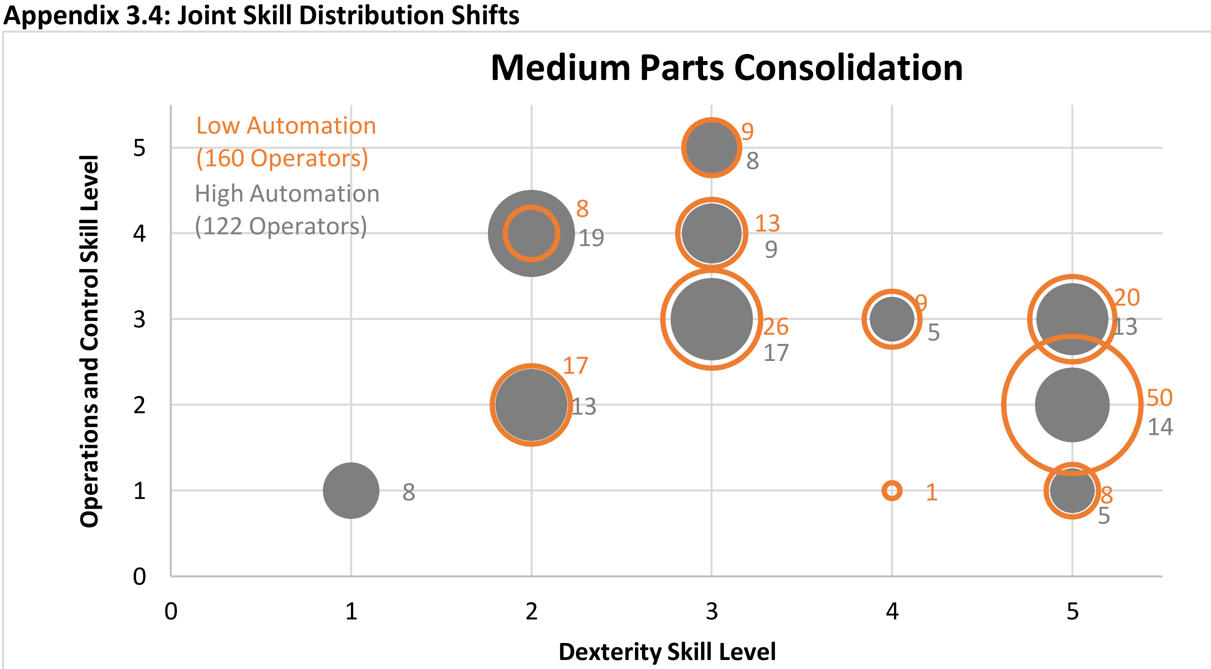

Figure 27 Automation from Low to High, Under Medium Parts Consolidation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

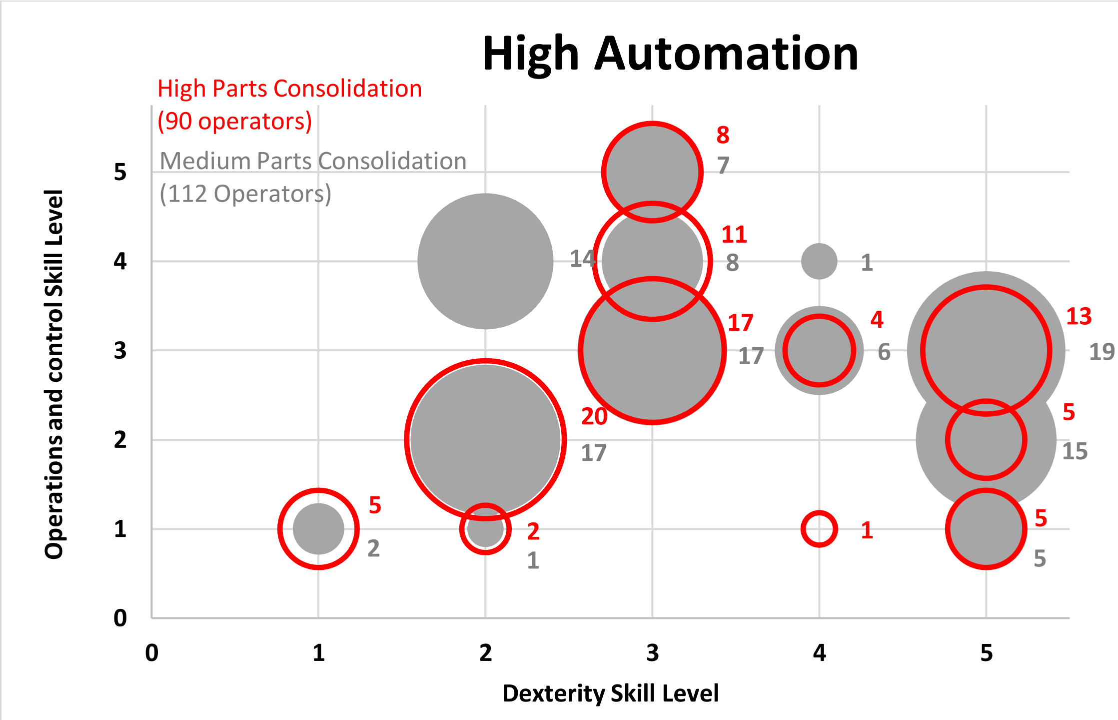

Figure 28 Parts consolidation from Medium to High, Under High Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

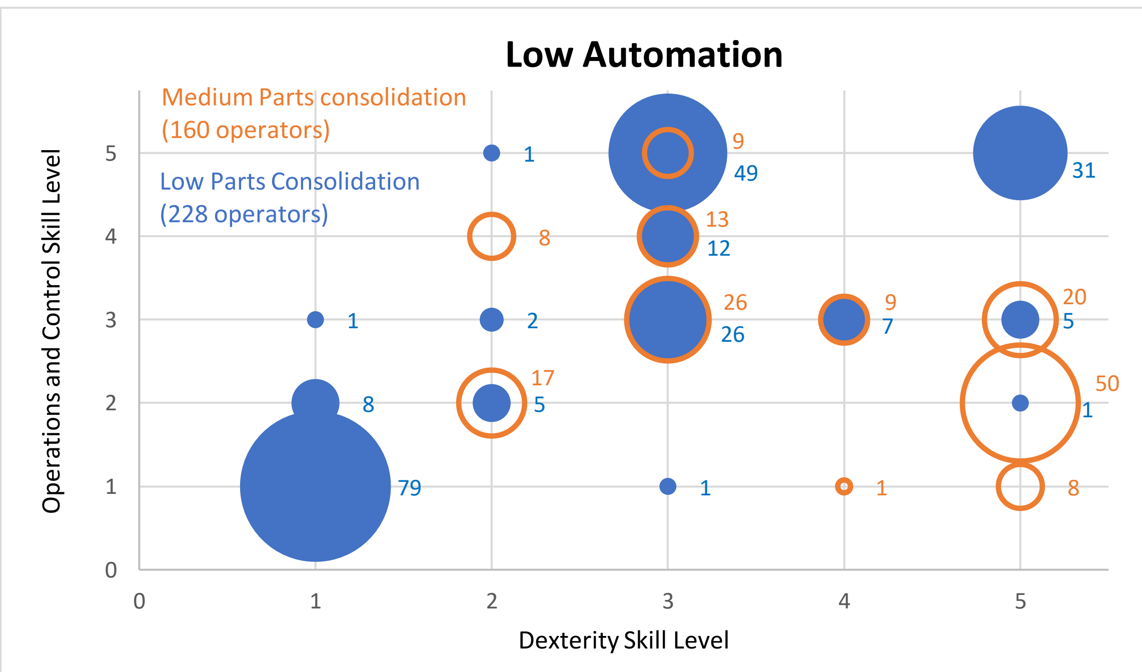

Figure 29 Parts Consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Dexterity Skill

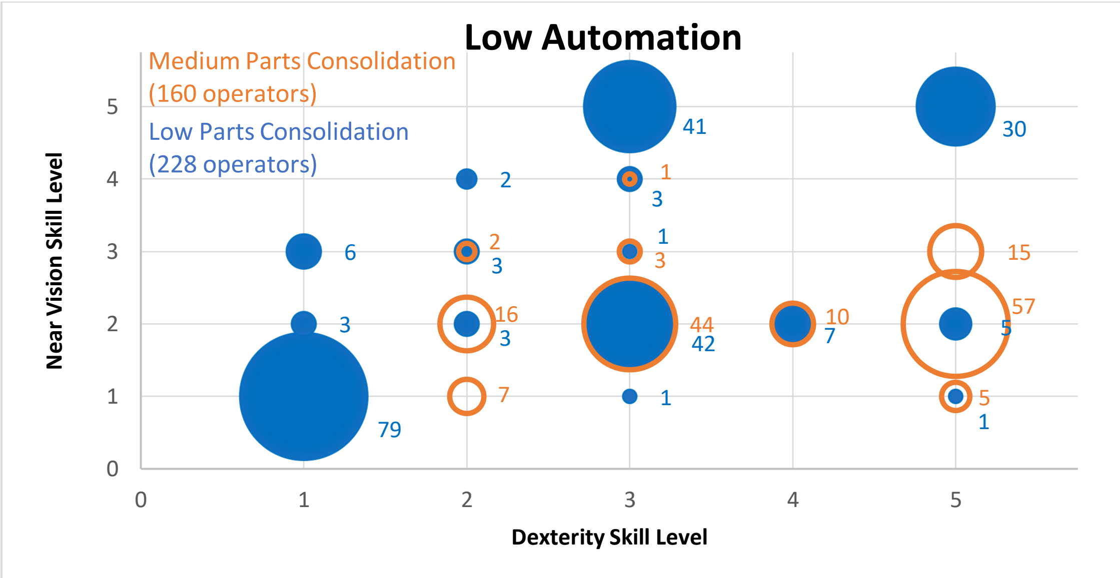

Figure 30 Parts consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Near Vision and Dexterity Skill

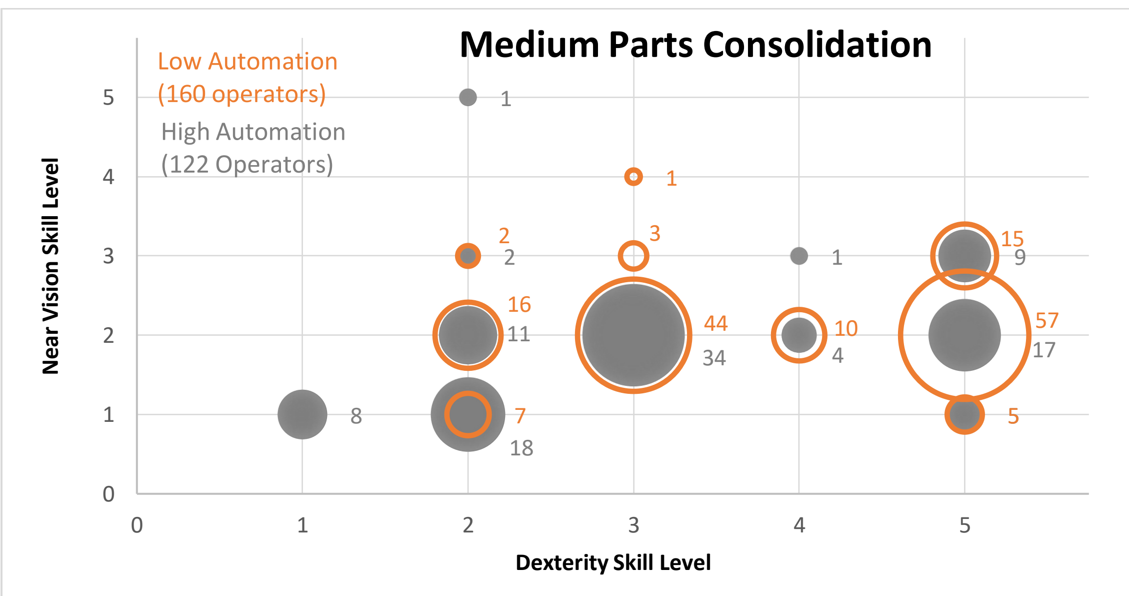

Figure 31 Automation from Low to High, Under Medium Parts consolidation: Shifts in the Joint Distribution of Near Vision and Dexterity Skill

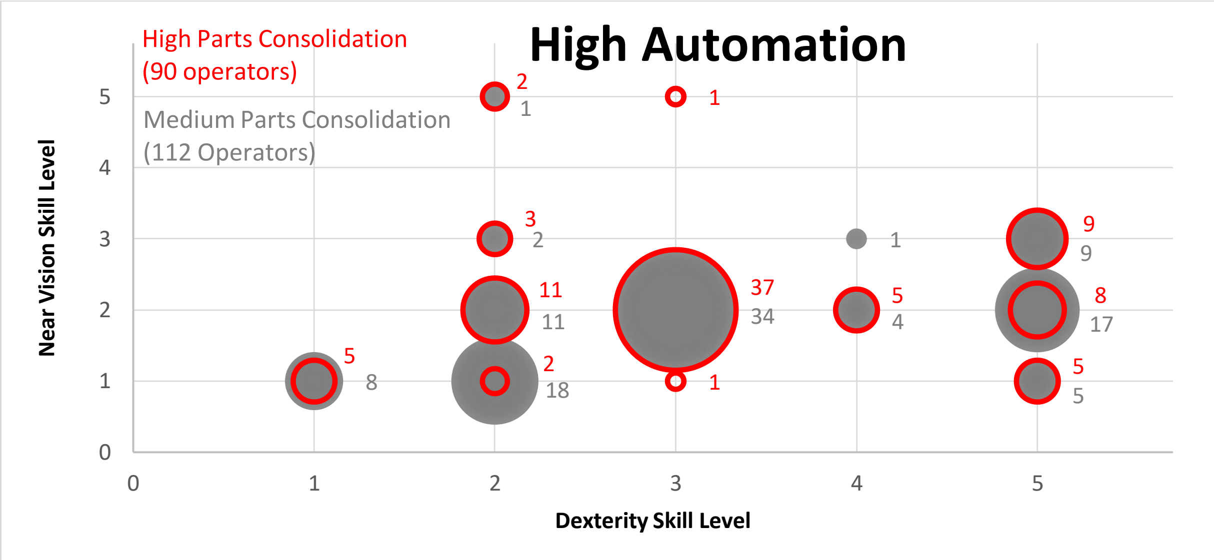

Figure 32 Parts Consolidation from Medium to High, Under Low Automation: Shifts in the Joint Distribution of Near Vision and Dexterity Skill

Operations and Control vs. Near Vision:

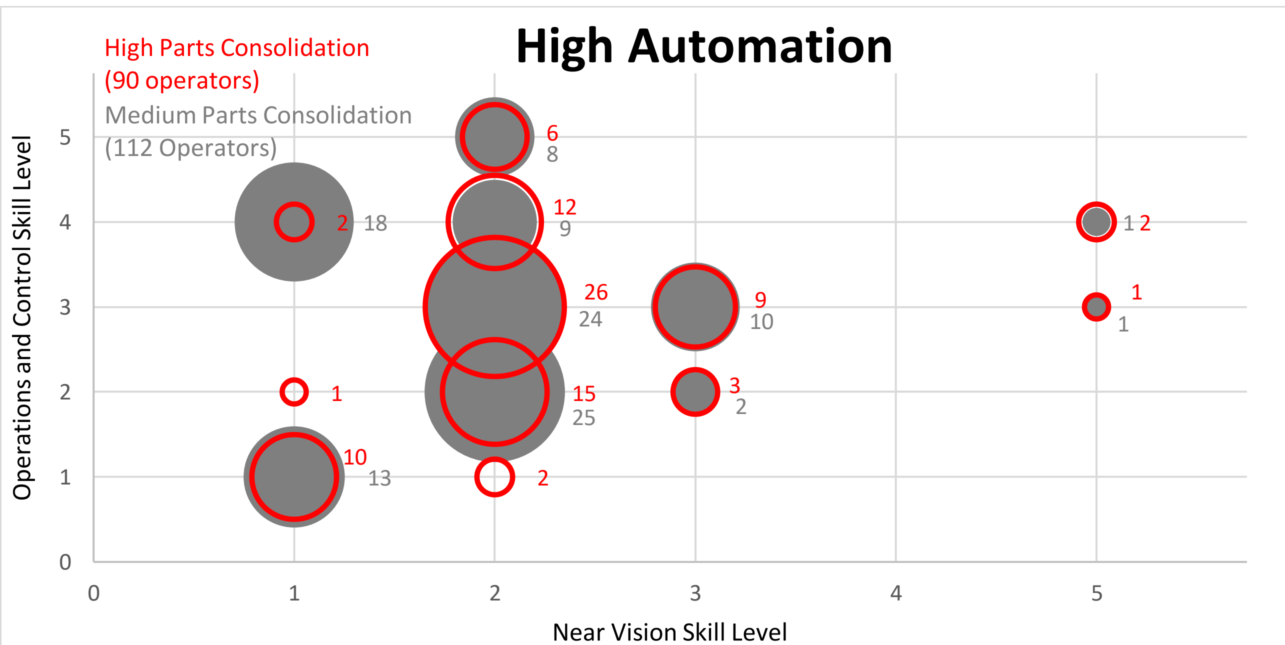

Figure 33 Parts Consolidation from Medium to High, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

Appendix 3.5: Unit Cost Breakdowns at median annual production volume

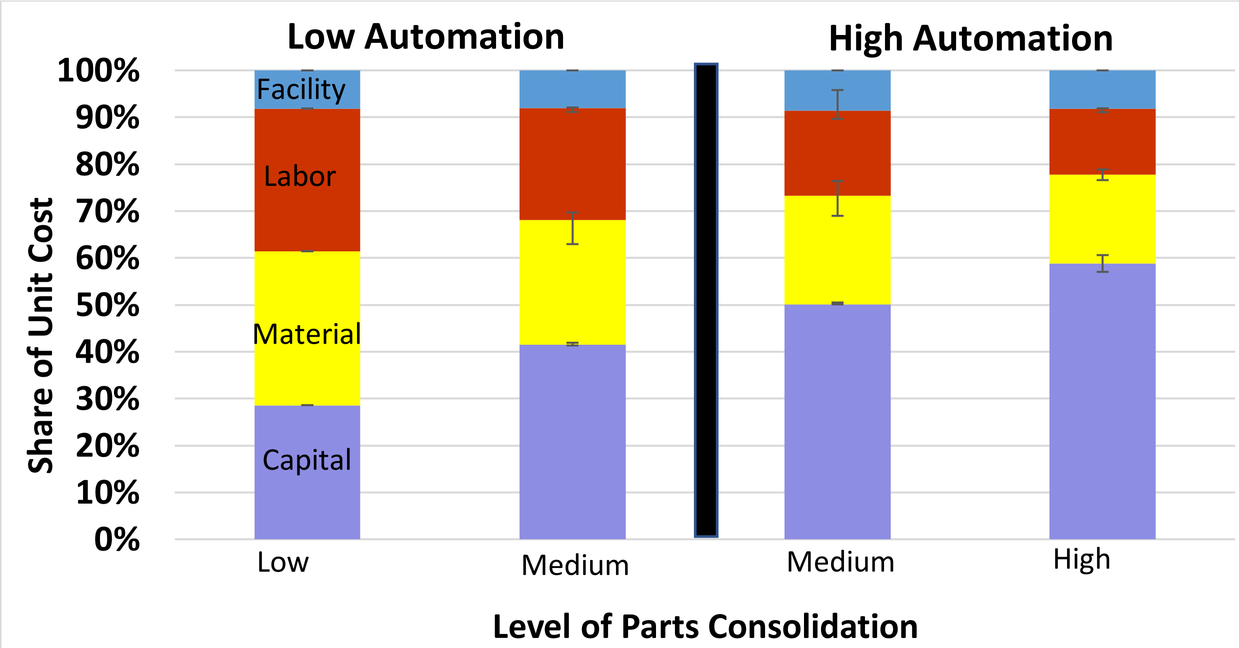

Figure 34 Unit Cost proportions by Cost Category

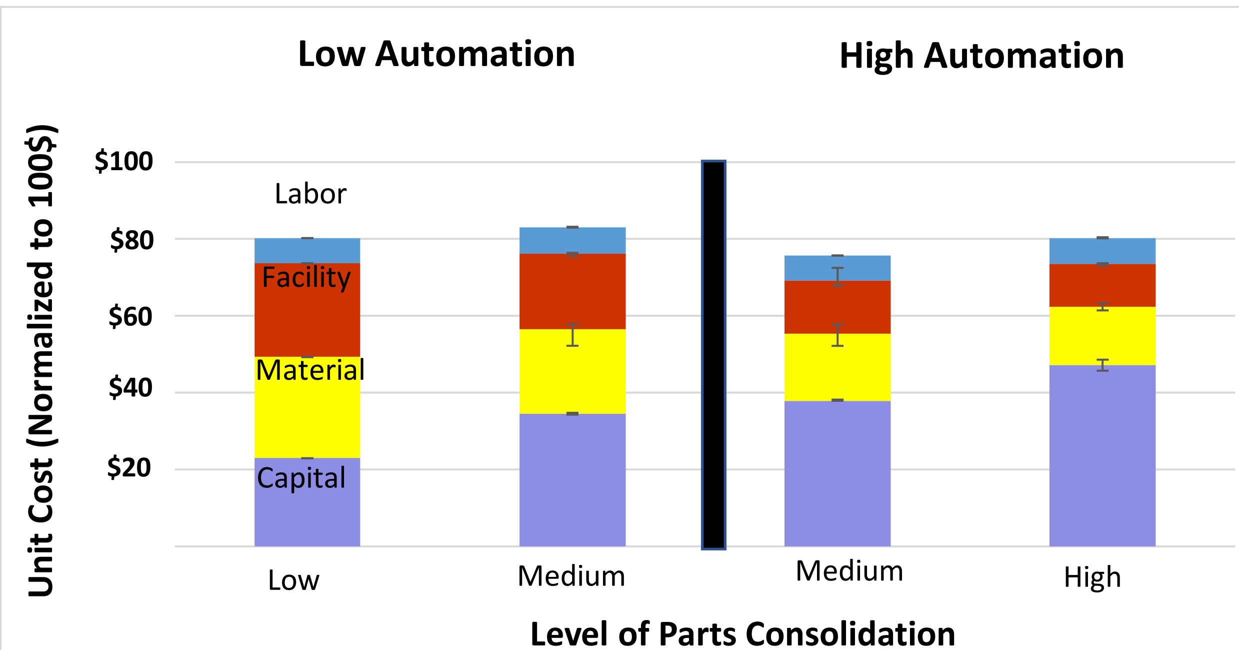

Figure 35 Unit Costs by Cost Category

Appendix 4: Fabrication Analysis and Comparison of Medium and High Parts consolidation

In using our new fabrication data (i.e. data collected beyond Fuchs 2011), we make two assumptions. First, our new fabrication data pertain only to laser production (albeit from multiple industry sources). We assume the per-step characteristics (e.g. employee skill) relevant for laser fabrication are relevant to the fabrication of other components consolidated in our study, such as waveguides. This assumption is unlikely to significantly affect our main conclusions because of similarities in the equipment (e.g. plasma etching machines) and operator production tasks (e.g.

equipment monitoring during material deposition) across component types. Second, we assume that the process flows specified by current engineering production plans are an accurate representation of what they would be at full production. This assumption is most pronounced in the quantity of fabrication testing throughout the process flow for our high parts consolidation case, which may be overstated due to technological uncertainty (i.e. there may more testing at the immature stage of the technology if the process is less stable than we might expect at full production). This assumption is also unlikely to significant affect our main labor and cost because the input costs and labor associated with these uncertain testing steps represent a very small proportion of overall operators and costs, within the range of interfirm variation (even under what may be an overestimate of testing activity).

In our fabrication data, the high parts consolidation fabrication process flow consists of 118 total steps, compared with 57 process steps associated with the fabrication of the medium parts consolidation design. This increase is not uniform across process categories, however; certain deposition, etching and treatment stages see in reduced step count from medium to high parts consolidation. Process steps whose functional category is unique to high parts consolidation represent 28 of the 118 steps, while 33 of the 61 additional process steps under high parts consolidation consist of functional categories that are also present under medium parts consolidation. Hence, while a substantial share (23%) of the high parts consolidation process consists of functions unique to that process, more steps (77%) share a function with steps from the fabrication process for the medium parts consolidation design. Additionally, these unique functions represent 2 of 16 total function categories in the high parts consolidation scenario.

Measurement and testing steps represent 54 of the 118 steps involved in fabrication of the high parts consolidation design, compared with 3 of 58 steps in the fabrication of the medium parts consolidation design. This disproportionate share of testing may have been driven by uncertainty around an immature technology (high parts consolidation designs do not yet appear on the market) and will likely be reduced as high parts consolidation designs enter production and mature; for instance, the high parts consolidation flow features photolithography testing, whereas medium parts consolidation involves no testing during photolithography. If fully reduced to the testing steps associated with medium parts consolidation, the high parts consolidation fabrication process would consist of 67 steps, or 9 more than under medium parts consolidation (of which one would have a function unique to the high parts consolidation process). Even the increased testing steps under current technological uncertainty represent a relatively small commitment of capital and labor within our model, suggesting that our labor requirement and unit cost estimates are unlikely to be dramatically biased by relative technological uncertainty in the high parts consolidation case.

Table 14 Functional Categories and Number of Steps by Level of Parts Consolidation

Function Category High Parts consolidation	# Steps Medium Consolidation	# Steps High Consolidation	Difference in Step # from Medium Parts consolidation
Incoming Inspection	1	1	0
Thermal	4	2	-2
CMP	1	1	0
Epi	2	1	-1
Anneal	1	1	0
H-ion Implant	0	3	3
Sputter	2	1	-1
PECVD	7	6	-1
Photolith	14	9	-5

Plasma Etch	16	10	-6
Wet Etch	3	0	-3
Clean	2	11	9
Resist Strip	1	19	18
PL Test	0	25	25
Measure	2	27	25
Scribe Wafer Cleave	1	1	0
Die Test	1	1	0
Total	58	119	61

Appendix 5: Sources of Process Step Level Production Data

In the following table, we break down the names and numbers of process steps by process category (see section 3.2) and subcategory, for each level of consolidation in our study (low, medium, high). We also list the designs (identified by a number to preserve firm confidentiality) that provided the data for each process category at each level of consolidation.

Table 15 Sources of Process Step Level Production Data

Consolidation Level	Process Category	Process Subcategory	Processes	Data Sourced from Process Flow of Design #
Low	Fabrication	Surface Treatment	Spin Dry (20) Wafer Cleave (2) Die Cleave (3) Chip Cleave (1) Clean and Strip (14) Planarization and Polish (4)	3,5
		Growth Deposition	Metal Organic Chemical Vapor Deposition (MOCVD) (19) Plasma-enhanced Chemical Vapor Deposition (PECVD) (2) E-Beam Deposition (2) Cap Layer Removing (1)	
		Etch	Dry Etch (32) Ion Milling (2) Wet Etch (4)	
		Lithography	Resist Coat (11) Stepper (10) Photo-Lithography (11) Developer (13) Resist Remove (18)	
		Thermal	Anneal (1) Hot Plate (7) Bake (16) Alloy (3)	
		Test	Measure Film Thickness (2) Chip and Die Test (2) Visual Inspect (2)	

		Other	Other (11)	
	Subassembly	Component Attach	Epoxy and Thermal Curing (12) Lens (1) Mounting (9) Die Bond (4) Discharge (1)	3,4,5
		Wirebond	Wire bond (6)	
		Test	Screening and Inspection (6) Characteristic Check (6) Data Check (3) Continuity Check (2) Other Tests (12)	
	Final Assembly	Packaging	Weld (2) Vacuum Bake (2) Fiber Cut and Attach (4) Aging and other Treatments (2) Housing, Plating and Pads (7) Epoxy (1) Molding (5)	3,4,5
		Test	Inspection (10) Thermal Cycle Test (2) Final Tests and Quality Control (7)	
		Other		
Medium	Fabrication	Surface Treatment	Spin Dry (24) Wafer Cleave (2) Die Cleave (4) Chip Cleave (1) Clean and Strip (15) Planarization and Polish (4)	4,5
		Growth Deposition	Metal Organic Chemical Vapor Deposition (MOCVD) (23) Plasma-enhanced Chemical Vapor Deposition (PECVD) (6) E-Beam Deposition (5) Cap Layer Removing (1)	
		Etch	Dry Etch (33) Ion Milling (2) Wet Etch (10)	
		Lithography	Resist Coat (15) Stepper (10) Photo-Lithography (12) Developer (13) Resist Remove (21)	
		Thermal	Anneal (1) Hot Plate (7) Bake (16) Alloy (2)	
		Test	Measure Film Thickness (2) Chip and Die Test (2) Visual Inspect (2)	
		Other	Other (12)	

	Subassembly	Component Attach	Mounting (2) Lens (1) Epoxy (4) Module Installation (5)	1,2,4,5
		Wirebond	Wirebond (1)	
		Test	Measurement (2) Visual Inspect (1)	
	Final Assembly	Packaging	Fiber Attach (2) Cleaning (1) Housing, Plating and Pads (5)	1,2,4,5
		Test	Module Test (5) Visual Inspect (1)	
High	Fabrication	Surface Treatment	Spin Dry (24) Wafer Cleave (1) Die Cleave (2) Chip Cleave (1) Clean and Strip (15) Planarization and Polish (4)	4,5
		Growth Deposition	Metal Organic Chemical Vapor Deposition (MOCVD) (16) E-Beam Deposition (5) Cap Layer Removing (1)	
		Etch	Dry Etch (26) Ion Milling (2) Wet Etch (8)	
		Lithography	Resist Coat (15) Stepper (10) Photo-Lithography (12) Developer (13) Resist Remove (29)	
		Thermal	Anneal (1) Hot Plate (7) Bake (16) Alloy (2)	
		Test	Measure Film, CD (27) Chip and Die Test (2) Defect Inspect (18) Optical Inspect (7) Visual Inspect (2)	
		Other	Other (39)	
	Subassembly	Component Attach	Chip Bond (2) Epoxy (4) Bake (1) Mounting (2) Lens (1)	1,2,4,5
		Wirebond	Wirebond (1)	
		Test	Visual Inspect (1) Measurement (2)	
	Final Assembly	Packaging	Fiber Attach (2) Cleaning (1) Housing, Plating and Pads (5)	1,2,4,5
		Test	Module Test (5)	

			Visual Inspect (1)	

We now provide some additional detail on the content of each production category, and how differences in consolidation (as in the preceding table) affect each category technologically.

In fabrication, the depositions of material and patterns of etching give each fabrication component a geometry which must be accommodated in assembly. The production of consolidated designs must include architectures that can accommodate multiple functionalities (more with greater consolidation) (NAS 2014). During the fabrication process, operators may transfer work in progress between machines and calibrate or monitor equipment.

In subassembly, each component must be fitted into the device architecture directly by being attached to a substrate or by being attached to a different component. Wirebonding allows the components in the device to interact with each other. The more consolidated a device, the fewer components must be fitted and linked together. Operators working in subassembly may manually perform attachment and bonding activities, transfer work in progress between machines and calibrate or monitor equipment.

The device package in final assembly is a standardized “form factor” that allows it to interface with the rest of the communications or computing system. In this step, operators may take on manual roles such as attaching optical fibers or screwing together packaging cases, or they may perform transfer, calibration and monitoring roles as above.

While some material inspection is performed during fabrication, many testing steps check whether a component (or the entire device) can perform its function. Testing can consist of visual inspection by performers (especially for defects in subassembly), of simple functionality tests such as shining light through a material or of more complex data transmission tests. The more consolidated a device, the more functions overlap and the more they must be tested simultaneously.

Appendix 7: Task Biases in Automation

Across the subset of our process steps for which we have detailed task-specific data, we observe that different types of tasks in our data are automated at different rates.

An industry expert described how automation differentially affects tasks: “The machines are very automatic, and basically what the operators are doing is putting in parts and taking them out. In most of this optical stuff, it’s not so true that you have this automatic transfer... they [operators] replenish reels or trays or sources of parts, and make sure that when things come off the end of the line, they’re properly packaged.” Based on our manufacturing task data, we divide tasks within process steps 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 16. In examining past PBCMs, these task categories appear to 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 industry contexts, including software and services.

Table 17 and Table 18 report the breakdown in level of automation across 45 production steps as observed in our firm data using detailed information on the level of automation at each task in the step. We find that a majority of the tasks for which automated alternatives exist are execution, followed by monitoring (see Table 17) The large majority (91%) of process steps with automated tasks include an automated execution task (Table 18), with few cases of monitoring automated alone (9%) and no cases of preparation automated alone.

Table 16 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>

Table 17 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 18 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%

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