Essays on the Implications of Technology Change for Skill Demand and the Nature of Work

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Dissertation Abstract

Technological change leads employers to transform their demand for workforce skills, with dramatic consequences for the distribution of economic prosperity and the future of work. However, different technologies can place different and even opposing pressures on skill demand and organizational structure: they may drive increased or decreased division of labor or make workers of different skill levels more or less competitive with machines. To understand and respond to these changes, the objective of the research in this dissertation is to develop and explore frameworks for thinking about technological change in relation to labor and organizations. This dissertation seeks to address four questions of interest (in each of four corresponding chapters) for our understanding of technology change, labor outcomes and opportunities for policy and strategy. 1) What are the implications of two simultaneous technological changes (automation, parts consolidation) for labor skill demand within an occupation? 2) Why and how do technological changes differ in their effects on skill demand? 3) How are the effects of technology change modified when applied to tasks of different types? 4) How might organizational structure and technical uncertainty provide different opportunities for worker participation in new technology development and implementation?

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Introduction

Technological change can lead employers to transform their demand for workforce skills, with dramatic consequences for the distribution of economic prosperity and the future of work. This dissertation focuses on the intersection of technological change, production process structure, and skill demand in order to identify and understand differences in the labor implications of different technologies. The dissertation is organized into four major chapters, each based on a different stream of academic work.

Chapter 1 is derived from work published in Industrial and Corporate Change (Combemale, Whitefoot, Ales and Fuchs 2021). 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, whereas 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.

Chapter 2 is based on my academic job market paper (Combemale, Ales, Fuchs and Whitefoot 2022). This paper develops a general theory relating technology change and skill demand that is capable of rationalizing the labor impacts of various technology changes since the 19th century. Performers (human or machine) face stochastic issues that must be solved in a given time to complete tasks. Firms choose how production tasks are divided into steps, the rate at which steps need to be completed, and the type of performer assigned to a step. Performers differ in the breadth of issues they can solve (generality) and in their tolerance for working at higher rates. Human performers tend to be generalists with low rate-tolerance. Machine performers tend to be specialists less sensitive to rate. Central to the theory are the cost of fragmenting tasks into smaller steps, the cost of allocating performers to multiple steps, and the negative relationship between step complexity and the rate of completing that step. We derive the cost-minimizing division of tasks, the level of automation of production, and the demand for workers of different skills that those conditions create. Our theory predicts that the division of tasks under increased complexity is skill polarizing; automation is skill polarizing at lower production volumes and upskilling at higher volumes; and that parts consolidation increases the demand for mid-level skills. We find counterparts to the theory across a range of industrial contexts and time periods, including the Hand-Machine Labor Study covering mechanization and process improvement at the end of the 19th century, contemporary automotive body assembly, and emerging technological changes in optoelectronic semiconductors used for communications.

Chapter 3 is based on my work extending the model of Chapter 2 to encompass how technology change interacts with tasks of different types in affecting the problem of the firm. By introducing different types of tasks, this extension of the previous model investigates implications of tasks with high and low-variance of production issues for automation. A key result of the expanded theory is that, due to greater human competitiveness with machines under high variance conditions, polarization of skill demand due to automation is more pronounced at sufficiently low volumes when tasks are of low variance. However, we also show in the model that the upskilling effect of automation (rather than polarization) occurs at *lower volumes* for low-variance tasks than for high variance. This work is part of a broader and continuing expansion of the model to encompass implications of technology change for managerial scope and structure and the division among workers or machines of solving different types of issues that emerge from production (Combemale and Whitefoot 2022).

Chapter 4 is based on qualitative work drawing on my extensive observations of optoelectronics production and firms and interviews (Combemale and Fuchs 2022). In this stream of work, we draw on qualitative evidence from leading-edge firms and organizations in the optoelectronics industry to identify organizational characteristics associated with manufacturing worker participation in innovation, which may present an alternative to the passive or adversarial experience of many workers with respect to technological change. We identify possible firm-level mechanisms for generating greater worker scope of influence in the innovation process and discuss potential policy implications and further work. We find that firms in our sample which are more vertically integrated (outsource less) from design to production exhibit a greater tendency to interface between technology developers and production workers, and in turn we propose that this may give workers a greater influence over how their work will evolve. We find also in our sample that firms on the experimental leading-edge of process innovation, with limited theoretical foundations, emphasized a reliance on experiential knowledge (for production and technology design workers) to support development. We observed in such contexts that production workers were able to serve as local experts on the highly sensitive “black-box” characteristics of specific equipment or processes. These observations suggest that firm structure and technical certainty could influence the role and influence of workers as participants in technological change.

Chapter 1: Not all technological change is equal: how the separability of tasks mediates the effect of technology change on skill demand

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 et al., 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 et al., 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 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, 2002). 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

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[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) 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.

for functionally homogeneous devices. Our data include 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. Although 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 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 ▯., 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 et al., 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 et al. 2018). Though automation is a strong focus of the literature on technological change and labor outcomes, there is also evidence of nonautomated 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 et al., 2017, 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 et al., 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 et al., 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 rebundled around tasks which remain nonautomated (Brynjolfsson et al., 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, 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. Although 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 et al., 2007; Fuchs et al., 2008). These models have informed engineering and production decisions in multiple industries (Field et al., 2007; Ulu et al., 2017; Laureijs et al., 2018). Previous work (Fuchs and Kirchain, 2010; Fuchs et al., 2011b; 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; Pearl and Enos, 1975; Wibe, 1984; Smith, 1986; Lave, 1996). 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, 2002; 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 Brensinger, 2004; Pitroda and Desai, 2017).[4] Table 1 provides examples of consolidation across several high value manufacturing industries.

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[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

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

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: (i) fabrication, (ii) subassembly, and (iii) final assembly (see Figure 1), with (iv) 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.

sectors include electronics (668,740 results), automotive/automobile (208,322 results), aerospace (20,934 results) and healthcare service (8,463 results).

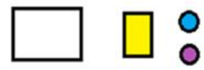
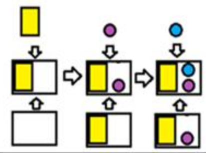
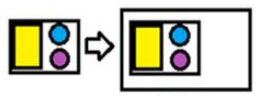
Process Category	Example Diagram	Industry Examples
Fabrication		Lithography Vapor Deposition
Subassembly		Wire Bond Die Attach
Final Assembly	 Packaging	Packaging

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 USA 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). Although fabrication and assembly of various designs is performed worldwide, the most consolidated designs tend to have production more often located in the USA 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., 2011b) 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

[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.

heterogeneity (Wernerfelt, 1984; Peteraf, 2003). 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 PBCMs

We use engineering 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 et al., 2006). For our purposes, the PBCM has the following advantages: (i) 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, (ii) 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 (iii) 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

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[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.

alternatives required to 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:

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

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). $\sigma_{s,j,t_{s,r}}\left(q_j\right)$ 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]

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[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

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

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

where $\sigma_{s,j,t_s,r}^{-1}$ 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

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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.

[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.

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:

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

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

[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.

the global market (see Table 2). Using this coverage of the industry, we construct four scenarios (A, B1, B2, and 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 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, 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

[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.

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.

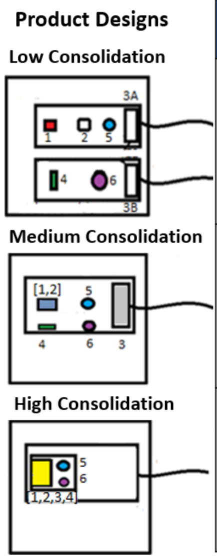
[15] Fabrication is already highly automated across the industry (NAS 2013) and therefore does not vary across our automation scenarios.

[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: (i) changes in labor demand may be driven by firm characteristics as well as technological change and (ii) technological change is not geographically uniform. In brief, we address (i) by varying process steps used in our scenarios across multiple firms with distinct organizational characteristics and we are unconcerned by (ii) 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 article, 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., 2011a,b) require collecting data on more than 20 inputs for each step of the production

[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.

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 operational inputs to a PBCM, 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

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[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."

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
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*

[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).

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 USA, 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]

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 (vs. 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

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[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.

data), consolidation requires changes across multiple production steps from fabrication to design, meaning that capital outlays must be made simultaneously.

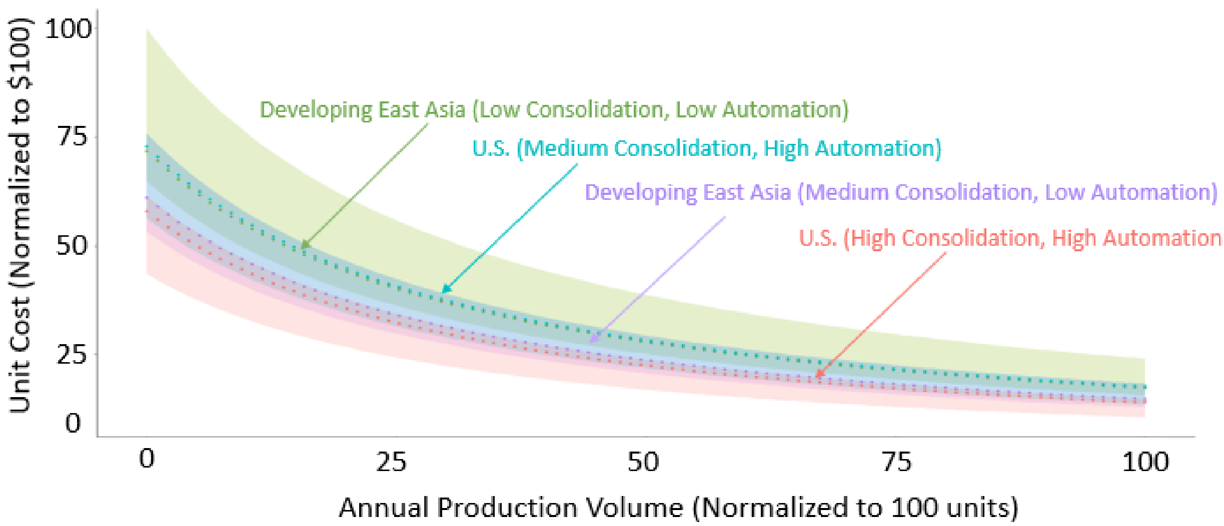

Figure 3 Unit Costs by Annual Production Volume, Level of Automation and Consolidation

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, whereas 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.

[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.

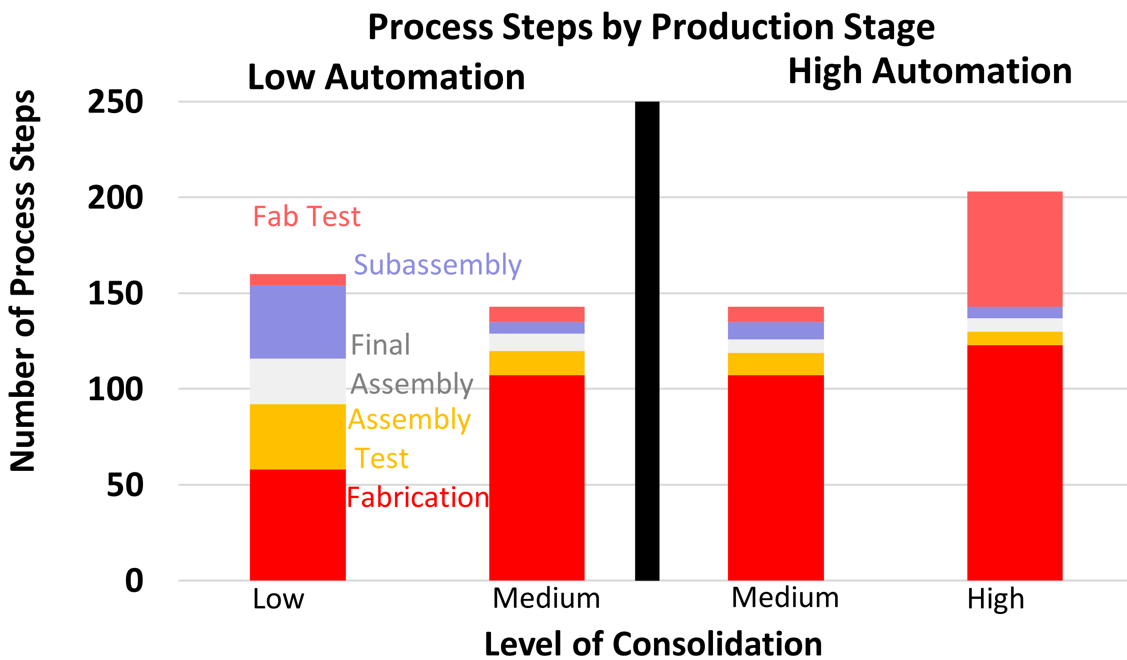

Figure 4 Process Breakdowns by Consolidation and Automation Scenario

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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[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.

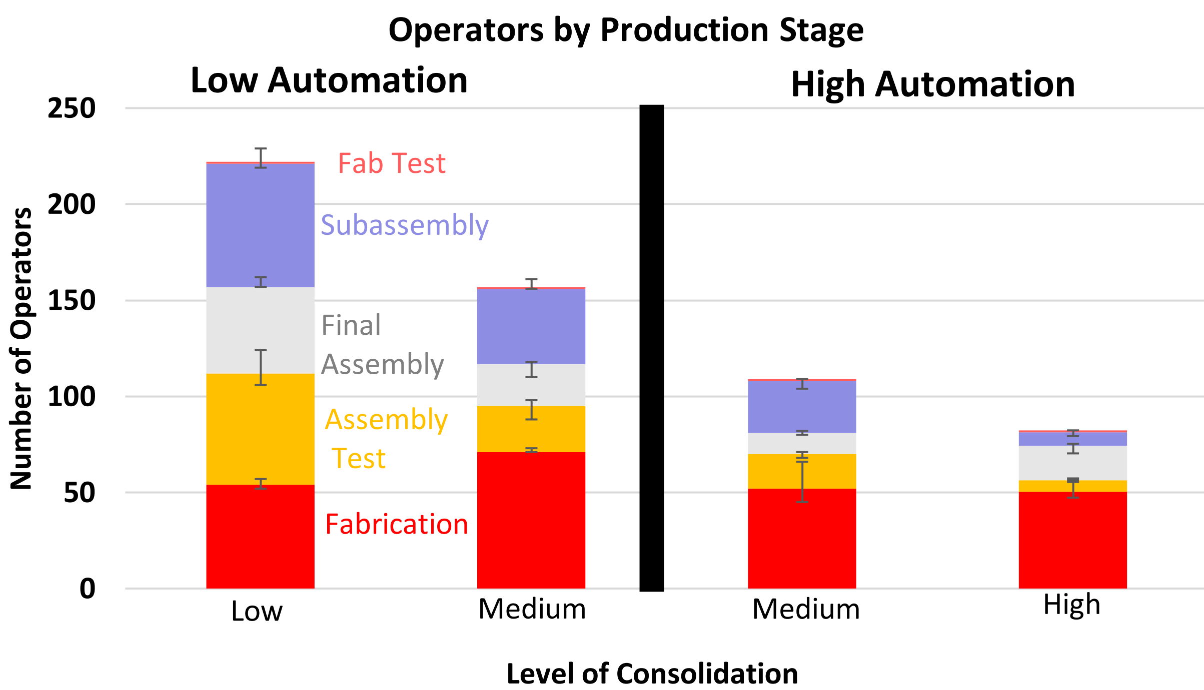

Figure 5 Number of Operators Required by Scenario and Production Category

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

[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.

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 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 interfirm variation.

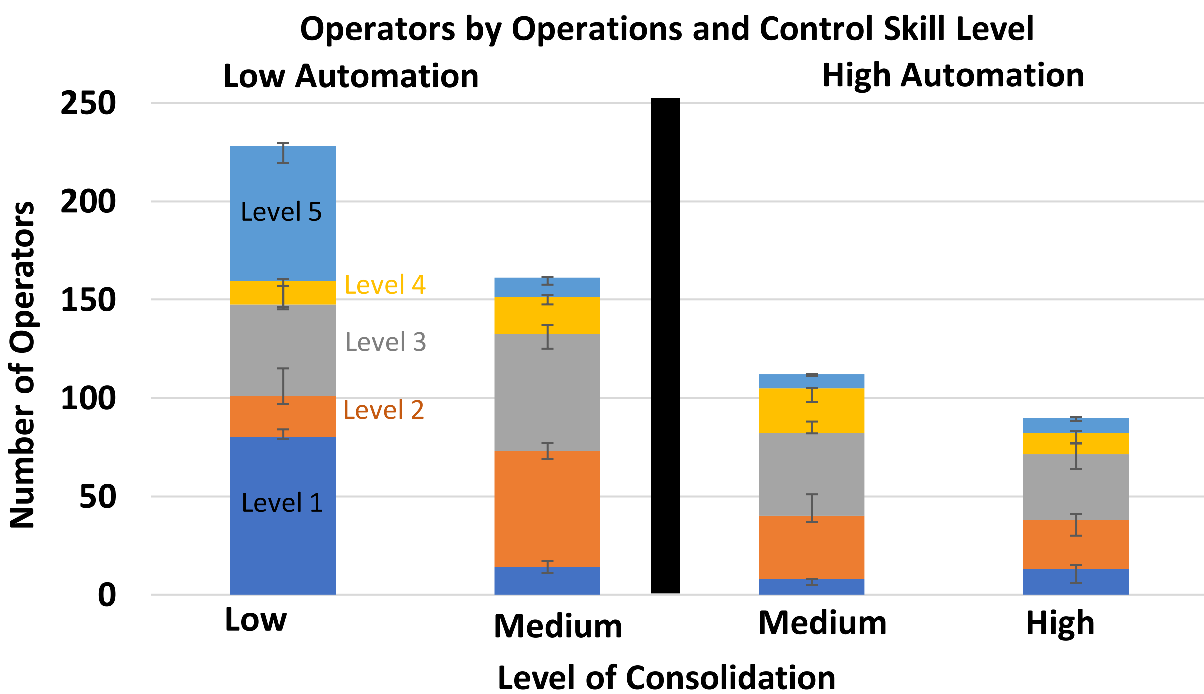

Figure 6 Number of Operators by Scenario and Operations and control Requirement

Figures 7 and 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), whereas 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), whereas 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.

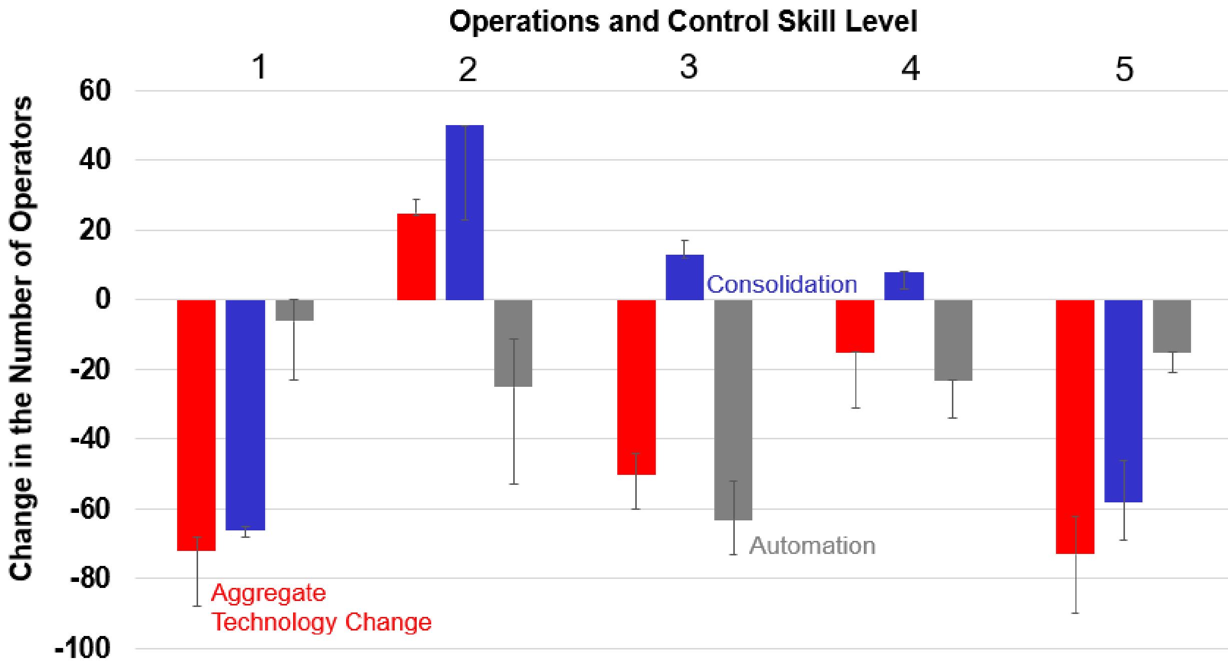

Figure 7 Operations and Control Skill Effects of Disaggregated Automation and Consolidation: Shifting from Low Consolidation, Low Automation to Medium Consolidation, High Automation

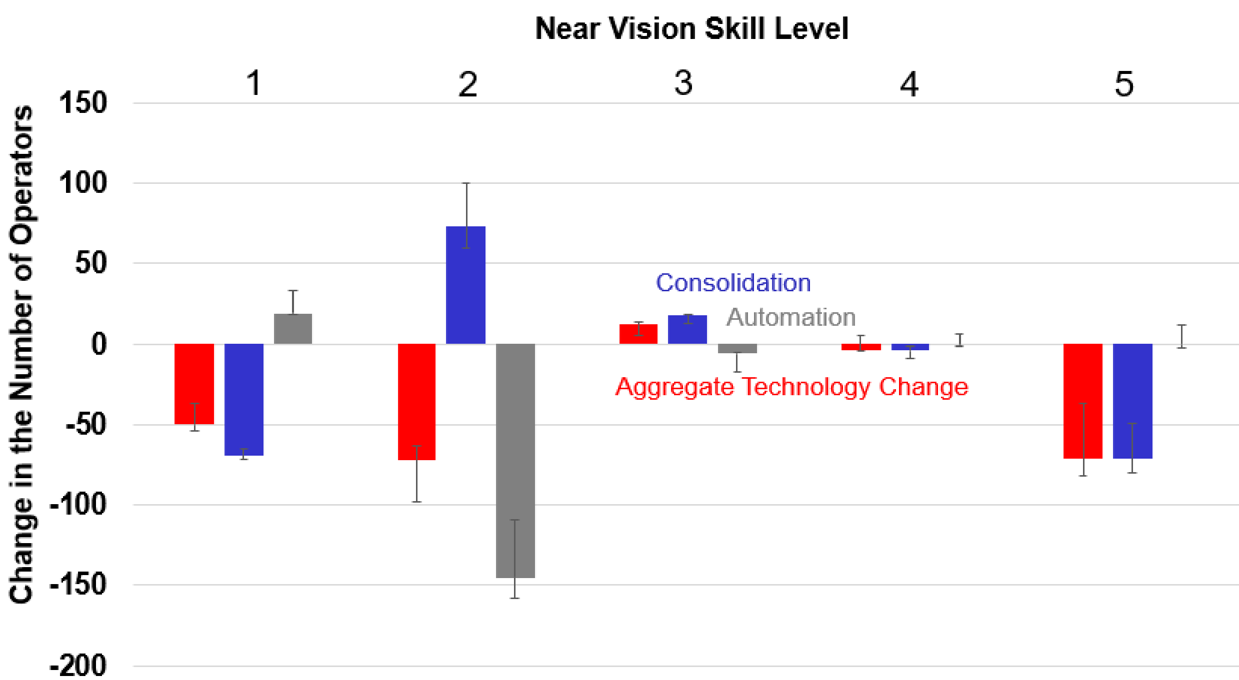

Figure 8 Near Vision Skill Effects of Disaggregated Automation and Consolidation: Shifting from Low Consolidation, Low Automation to Medium Consolidation, High Automation

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.

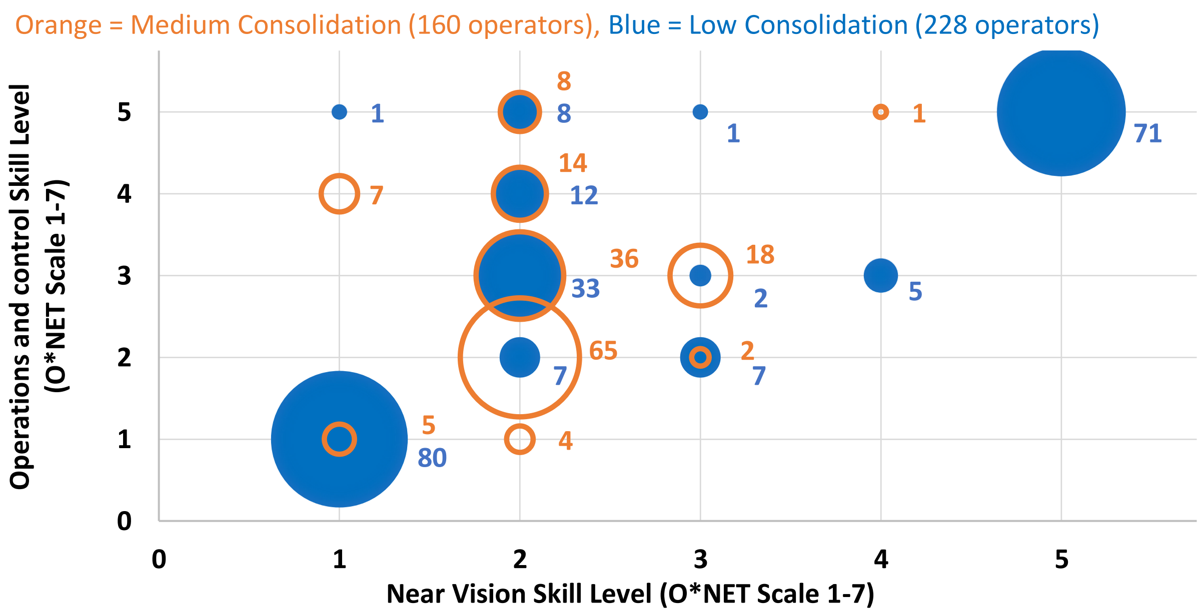

Figure 9 Consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

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 Figures 10 and 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 Figures 10 and 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.

[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.

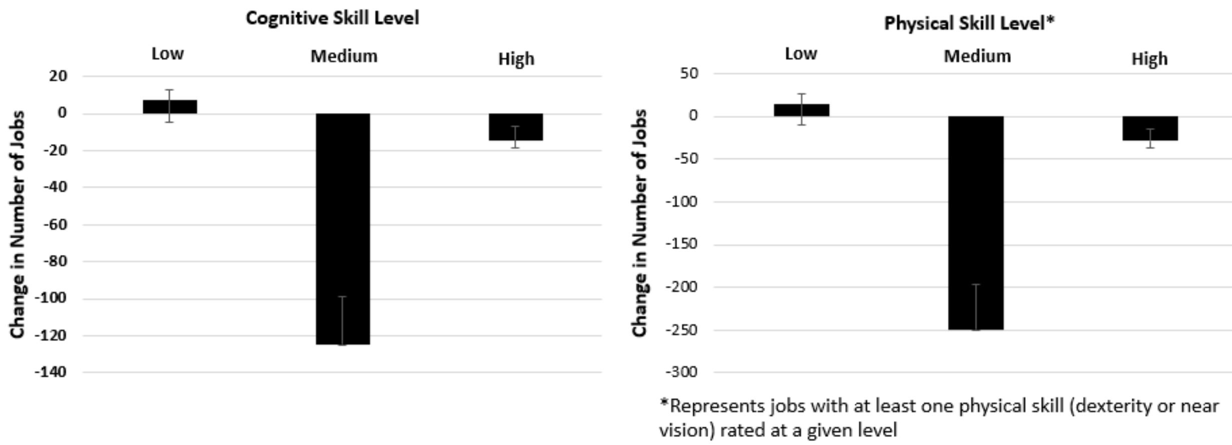

Figure 10 Aggregate Change in Number of Operator Jobs by Cognitive and Physical Skill Level Under Automation

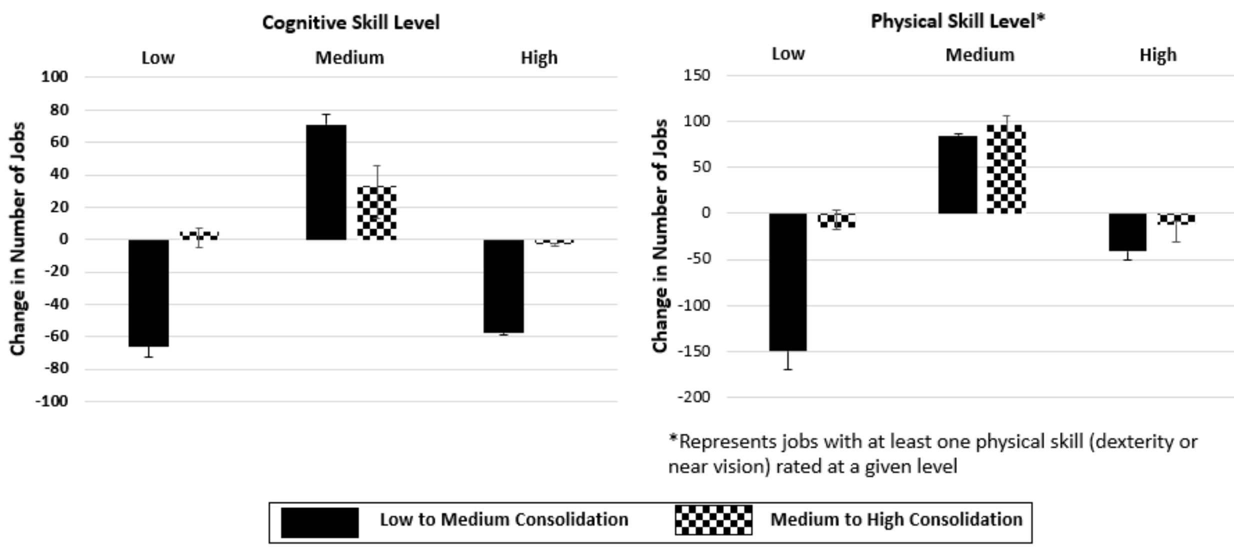

Figure 11 Aggregate Change in Number of Operator Jobs by Cognitive and Physical Skill Level Under Consolidation

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, 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*

[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).

[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).

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, 2009). 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 et al., 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. 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 USA 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 et al., 2016), policy-makers in the USA 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 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. Although 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.
Task Skill	The minimum level of skill (along one dimension, e.g. dexterity) for a	Manually attaching a die to a substrate within a certain tolerance

[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.

	performer to successfully complete a task to given specifications.	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

[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).

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 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 et al., 2018b), and that automation most affects routine tasks (Autor et al., 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.

[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."

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 require 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 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] Although 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 article 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.

Although 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 Simon (1986; 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.

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[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.

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. 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.

Chapter 2: How It's Made: A General Theory of the Labor Implications of Technology Change

1. Introduction

It has long been recognized that technology change plays an important role in labor markets, impacting inequality and the wage returns to skill. At the same time, technology has impacted workers in different manners over time. For example, the adoption of the factory system and machinery during the nineteenth century led to de-skilling (Goldin and Katz, 1998, 34) while the automation of routine tasks during the 1970s-1990s led to up-skilling (Autor, Levy and Murnane 2003).[43] While the literature has provided compelling evidence and explanation of these patterns in terms of substitutability between the capital that embodies a technology and worker skill, it does not explain why these differences in substitutability exist.

In this paper, we develop a general theory with the goal of understanding *why* different technologies impact workers differently. The theory is constructed by describing how the demand for workers' skill level is endogenously determined and deriving five dimensions on which technological change can affect this process. We formalize the theory in a structural model capable of analyzing operations-level production data, and we provide empirical counterparts to the theory showing how different technological changes can differentially affect skill demand. The model we develop is rich enough to incorporate insights from information theory, computer science, and industrial engineering concerning the production of goods and services and yet tractable enough to derive implications of technology change for the division of production tasks, automation, and skill demand.

The starting point of the model is the set of tasks that must be completed to make a product or a service. To minimize the cost of producing at a given volume, a firm must choose how to divide this set of tasks into production steps. The firm also chooses the performer type for each step (human or machine), and the rate of production for each step. A basic feature of the model is that the difficulty of a step is increasing in the number of tasks (the length of step) and in the rate at which the step needs to be completed. The degree to which the difficulty of a step is impacted by the number of tasks or the rate of completion is specific to the type of performer: humans are less sensitive to the number of tasks than machines (more general than machines), but more sensitive to rate. In deciding the division of production, the firm faces a trade-off. More difficult steps require a more able, and thus more costly, performer. This mechanism provides an incentive for smaller steps. On the other hand, division of two sequential tasks incurs fragmentation costs, providing an incentive for longer steps. The firm must also take into account excess performer capacity, either by allowing a performer to be idle or by reallocating the performer to a different step. Reallocation incurs a performer-specific divisibility cost. This cost is higher for machines than humans. Within the context of our model, technological change can be described in terms of how it alters five dimensions: 1) the overall

[43] The literature studying the impact of technology on workers and specifically the way in which different technologies differ is vast. As a starting point refer to: Caselli (1999), Bresnahan, Brynjolfsson, and Hitt (2002), Acemoglu and Autor (2011) Autor and Dorn (2013), Dinlersoz and Wolf (2018), Eden and Gaggl (2019), Acemoglu and Restrepo (2020).

complexity of a process, 2) the cost of dividing tasks in a process, 3) the sensitivity of performers to the rate of production, 4) the sensitivity of performers to the number of tasks in a step, 5) the cost of dividing performers among multiple steps.

We use the theory to characterize the impact of key technological changes on production and workers with three main results. First, we identify conditions under which it is optimal for firms to divide production into smaller steps. We show that heterogeneous costs of dividing different tasks are necessary for heterogeneity in performer ability demand within a firm (or skill demand in workers). We find that for division to occur, performer costs must be convex in the length of steps. This convexity occurs with sufficiently convex wages with increasing skill or with a sufficiently high production volume. From a historical perspective, the optimality of division of labor under high volume helps to explain the fact that the adoption of the factory system and later assembly line did not lead to significant variation in wages in certain production contexts.

Second, we provide conditions under which it is optimal to automate a step. We find that two dimensions determine the choices of automation: the volume of production and the step length. Within these two dimensions, our theoretical results identify a region we call a *cone of automation*. Specifically, we find that at sufficiently low production volumes, no automation is optimal because the higher divisibility costs of machines lead firms to leave them idle, thus raising costs. At middle production volumes, it is optimal to automate middle-length steps. This causes machines to substitute for middle skill workers, generating skill polarization. Short steps are not automated because they have high rates of work and hence low machine utilization, leading to high idling costs. Long steps are also not automated at middle production volumes. As steps increase in length, the cost of a machine performer increases faster than a human performer, because machine performers are less general than human performers. At high volumes, machine utilization is high even at high rates of work, and so only the longest steps are not economical to automate (substituting for low and middle skill workers). The cone of automation is a useful result for understanding the root causes of historical variation in the effects of automation (Goldin and Katz, 1998) and the more recent polarization of occupational demand (Goos, Manning and Salmonons 2009).

For our third main result, we explore how changes in the division of tasks can affect skill demand and hence wages. We show that declining costs of dividing tasks (occurring during the initial phases of the industrial revolution) reduces the lower bound of skill demand. We also consider technologies that reduce fragmentation costs but increase process complexity (such as modularization). We find that such technologies increase inequality between the highest and lowest wages by polarizing the upper and lower bounds of skill demand. This result also shows that technologies that reduce process complexity by eliminating opportunities to divide tasks (such as parts consolidation) can reduce inequality between the highest and lowest wages.

We take our model to the data and provide empirical counterparts to key results of the theory. The model presented in the paper is rich enough to provide a tight linkage with production operations data. Up until recently, this type of data has rarely been used in the economic analysis of technology change. We use three sources of detailed operations data. The first dataset is the Hand and Machine Labor Study (Wright, 1898), covering mechanization and process innovations at the time of the Second Industrial Revolution (1870s to 1910s). This dataset covers 15,700 process steps for 671 products spanning mining, agricultural, manufacturing and transportation service products. The other two data sets are contemporary and novel (collected by some of the authors in the present paper), capturing in great detail the optoelectronic semiconductor component production and assembly contexts (Combemale, Whitefoot, Ales and Fuchs, 2021) and the automotive body assembly context (Fuchs, Field, Roth and Kirchain, 2008). The optoelectronic semiconductor data involves hand-collected shop-floor-level production data on five different design and production alternatives for a single data communications product. The data comes from extensive line observations, technical interviews (including skill assessments for each production step using the O*NET survey instrument) and operations data capturing the entirety of production at firms representing 42 percent of the industry's production volume. The automotive body assembly data contains detailed data on process flow from multiple major U.S. vehicle manufacturers and key inputs such as machine type and price as well as quantifiable engineering measures of process complexity (e.g. number of joins per step).

The detailed production data we use supports multiple empirical connections to our theory. We start by connecting fundamental assumptions of the model to empirical evidence from our contemporary datasets. We find evidence (using the automotive and optoelectronic semiconductor data) of the trade-offs between the number of tasks in steps and the rate of operations, consistent with the developed model. We also find evidence (using the optoelectronic semiconductor data) that the level of ability demand is indeed increasing in the number of tasks in production steps.

We find that the theory can rationalize patterns of substitution of machines for human workers during the second industrial revolution: we recover an empirical analog to the cone of automation directly from the production data in the Hand and Machine Labor study. We also show polarization of ability demand under automation in the optoelectronics context, consistent with the automation implications of our theory at middle production volumes.

We also show that our theory can explain historical and contemporary changes in the distribution of worker ability demand under different technological regimes affecting the cost of dividing tasks. We show in the Hand and Machine Labor context that an increase in the division of tasks leads to polarization toward the highest and lowest wages, consistent with what the theory would predict for technology changes at the time such as interchangeable parts. The theory is also consistent with our observations in optoelectronics that technologies that reduce the divisibility of tasks but also process complexity (such as parts consolidation) lead to a convergence of ability demand, with less demand for the highest and lowest ability and higher demand for middle-level ability.

The idea that the division of labor is an important feature driving the demand for labor and productivity goes back at least to Adam Smith, with the famous pin-factory example (Smith, 1776). A small body of literature has analyzed when division of tasks should occur and what are the limits to the division of tasks. Smith himself argues that the degree of specialization is limited by market size, as small market sizes do not generate enough demand to support specialized firms. This insight is also supported by Stigler (1951). Other work has characterized the productivity returns of and limits to the division of labor. For example, in Becker and Murphy (1992) and Yang and Ng (1998), a task is split across workers and the upper bound on the division of labor is given by coordination costs across teams. In our model this mechanism is captured by the costs of breaking up the sequence of production tasks into multiple steps and assigning them to different workers.

This paper is related to three bodies of literature. First, it relates to literature modeling the task content of production (Autor, 2013; Acemoglu and Restrepo, 2018a,b). Similar to this literature, we consider a job as a bundle of steps and model the optimal assignment of a step to either a human or a machine. The emphasis of this literature (differently than ours) is in considering the long run effects of displacement of workers by capital. We take a broader approach to technology (going beyond automation) and emphasize the circumstances under which workers of different ability levels are displaced by other workers of different ability levels or by machines.

Second, the paper relates to the literature on polarization of occupational demand (Goos, Manning, and Salomons, 2009; Acemoglu and Autor, 2011; Goos, Rademakers, Salomons, and Vandeweyer, 2019). This literature has identified aggregate changes in the occupational structure of advanced economies in the last few decades. Polarization refers to the fact that middle-wage occupations exhibit lower (or negative) growth relative to low and high paying occupations. This has been put forward as evidence of ICT-capital adoption replacing mid-level skills. With respect to this literature, our theory provides a micro-founded mechanism for these occupational changes. We show the condition in which automation is more likely to occur for mid-level skills, and also are able to examine when automation occurs for low-level skills. In addition, the data presented in this paper provides additional evidence of the polarization phenomenon being present when looking at workers within a plant.

Third, the paper also connects to the literature on the labor consequences of different forms of automation, from traditional mechanization (Goldin and Katz, 1998) to robotics (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020) to machine learning (Brynjolfsson et al., 2018). We do so by explaining how these and other technological changes affect task divisibility and may generate differential labor outcomes. For example, in our theory, robotics offers more general performers than traditional mechanization, leading to more automation of high skill steps, while machine learning offers both greater generality and greater divisibility, which leads to more automation of high and low skill steps.

Our modeling strategy is related to the approach in (Garu), in which firms organize themselves into hierarchies. In their model problems of varying complexity are divided and assigned to different workers. As in our paper this approach creates an endogenous relationship between earnings and talent. Similarly to (Garicano and Rossi-Hansberg, 2006), we model production as generating a series of issues that need to be resolved. Differently from their paper, our theory allows for tasks to be arbitrarily divided, for different types of performers (human and machines), and for the production rate to be endogenously determined.

Our work is also related to the task-assignment literature.[44] The literature studies the optimal assignment of heterogeneous workers to jobs of varying complexity or composition. The bulk of the task-assignment literature is fairly general in the set of jobs and skills analyzed. This is expected as the scope of the analysis encompasses the entirety of the labor market. Most of the work in this area studies properties of the indirect production function over occupations inherited from the assignment problem. To make progress in this direction, strong assumptions on the primitives of the production function are needed. Our approach is closer to the original motivation of (Rosen, 1978): we characterize the endogenous bundling and assignment of work activities.[45] In our model, not only the assignment is endogenous but so also is the complexity of the job, which is determined by the set of tasks and the rate of production.

This paper aslo builds on the literature relating technology change to process and firm structure. The idea of fragmentation costs in this paper connects to past work on modularity and integration in product and process design (Baldwin and Clark 2003; Baldwin 2008). We extend these costs to motivate heterogeneity in production steps and introduce performer characteristics. Prior work connects organizational changes with technological change and skill demand (Caroli and Van Reenen 2001; Bresnahan, Brynjolfsson and Hitt 2002). Our model allows skill demand effects of new technology to originate from substitution of performers within existing steps (a non-organizational change) as well as from the reorganization of tasks (organizational change).

The paper proceeds as follows. Section 2 motivates and describes the key ingredients in the model. Section 3 formalizes the model. In Section 4 we analyze the implications of the model. We establish conditions for the optimality of division of tasks; give the relationship between step complexity and optimal rate and ability demand; describe different patterns of automation and their conditions and describe implication of changes in fragmentation costs. Section 5 provides empirical counterparts on the main findings of this paper. Section 6 concludes.

2. Empirical Motivation

The starting point of the theory is the set of tasks that the firm must complete to produce a good, and the ability of a firm to divide production in multiple steps and assign these steps to either a human or machine performer. This feature is key as it will generate an endogenous demand for performers with a different ability level. Before formalizing the model, this subsection describes key features of technological change that have been analyzed in the economic and industrial engineering literature. These features will determine the key ingredients of the model.

The historical literature provides extensive examples of the importance of the division of tasks for early US manufacturing. For example, Hounshell (1985) and Womak, Jones and Roos

[44] See for example, Rosen (1978); Costinot and Vogel (2010); Ales, Kurnaz and Sleet (2015); Lindenlaub (2017); Ocampo (2018); Haanwinckel (2020).

[45] We also study the effects of performer indivisibilities on differential returns to scale, a feature whose importance Rosen emphasized but did not include in the model.

(1990) provide specific measurement for Ford automotive assembly plants.[46] They report that with the introduction of the moving assembly line around 1913, the average cycle time of a worker decreased from 2.3 to 1.2 minutes (the cycle time was 514 minutes before a fine division of tasks was introduced). At the same time the total amount of worker time per vehicle declined by 88 percent. Hounshell (1985) and Womak, Jones and Roos (1990) also report that the demand for the skill of workers also changed during the move from craft production to factories to the adoption of the assembly line. In the time of craft production a worker was trained via lengthy apprenticeships on many aspects of automobile fabrication and assembly; however, by the time the assembly line was in full usage, the average training time for a worker was measured in minutes. This is an important ingredient of our theory: the fewer the tasks to perform, the easier the job for a worker.[47]

The difficulty of completing a job is also driven by the overall time a worker or a machine has available to complete a task. The trade-off between measures of complexity and speed of execution has been extensively documented for both humans and machines.[48] The common denominator of these empirical regularities resides in the fact that any task requires information to be completed, and any operator has a limited bandwidth for such information (Shannon 1948). Our own measurements confirm these regularities. In Figure 12 we display machine-level data from the automotive industry taken from (Fuchs, Field, Roth and Kirchain 2008). In this case, it can be clearly seen how more complex part production (involving multiple joins per each step) is associated with an overall decrease in the number of completed steps per unit of time.[49]

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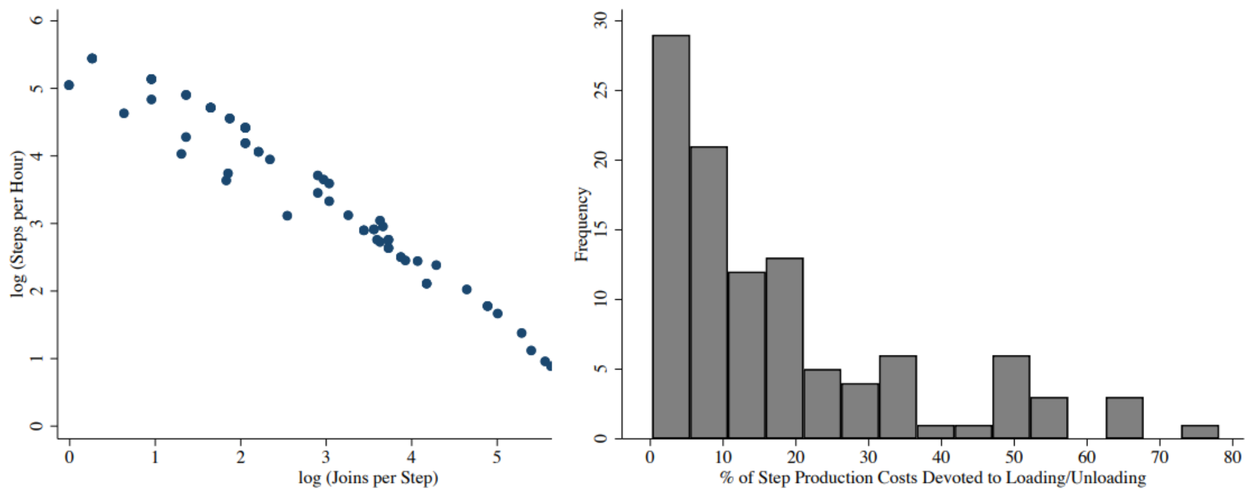
[46] For modern examples of the benefits of division of tasks outside of manufacturing refer to Staats and Gino (2012).

[47] For an example of this pattern for services refer to Autor, Levy and Murnane (2002), considering the division of tasks in a check-processing department before and after the introduction of computerized equipment.

[48] See the work of Fitts (1954), Welford (1981) and MacKay (1982) for the case of human motor movements; For application to robotic systems refer to Lin and Lee (2013).

[49] The time-per-join varies across steps (steps with more joins tend to require less time per-join), so that the relationship between complexity and the rate of steps completed is not merely a linear function of the number of joins.



(a) Speed Complexity Tradeoffs (b) Fragmentation Costs

Figure 12 Motivation for model ingredients. Production data exhibits (a) tradeoffs between rate and step complexity, and (b) heterogeneous costs of fragmenting steps into less-complex bundles of tasks[50]

Dividing production into ever smaller steps can introduce several benefits as described above. However, the division of production is not costless. When production is divided, one task in a sequence is handled by a different performer from the next task. Transferring a work-in-progress from one performer to another takes time for both parties and creates errors. This phenomenon has been extensively studied, see for example Becker and Murphy (1992) and Baldwin (2008). Our own measurements illustrate the importance of these costs. In Figure 12b, we look at machine-level data from the optoelectronic semiconductor manufacturing industry taken from Combemale, Whitefoot, Ales and Fuchs (2021). A lower bound on the step fragmentation costs is the time devoted by the operator to loading and unloading a machine. For a large number of steps, this time-cost alone amounts to more than 10 percent of all step-wise production costs. Introducing fragmentation cost is also essential to understand the impact of a large number of technological developments. For example, a key development behind the growth of mass production is the introduction of exchangeable parts, which lowered the cost of splitting production across multiple workers and greatly increased productivity Hounshell (1985). Technological progress does not always lead to decreases in costs of splitting production. For example, parts integration in electronics reduces divisibility due to monolithic part integration (Combemale, Whitefoot, Ales and Fuchs 2021).

The previous costs are embodied in the technology used in production. An additional source of costs in dividing production, and a final ingredient of the model, is incorporated in the cost of splitting performers across steps. Very short steps do not demand the full capacity of a performer, which introduces the possibility of a worker or a machine being under-utilized in

[50] For information on the data used for (a) refer to Fuchs, Field, Roth and Kirchain (2008). For information on the data used for (b) refer to Combemale, Whitefoot, Ales and Fuchs (2021).

production. Reallocating underutilized performers to other steps is not costless, for instance incurring time to reconfigure machines or for workers to change tooling or position. Differently from the previous costs, these opportunity costs now depend on the total level of production (see Hopp and Spearman (2011) and Laureijs, Fuchs and Whitefoot (2019) for an extensive analysis). Hence, a common outcome of high reallocation costs is lower utilization of performers.

Differences in utilization also appear to be associated in the aggregate with differences in occupational demand: Autor and Dorn (2013) explain the recent polarization of US employment by the substitution of routine tasks with information technologies, and recent theory (Acemoglu and Restrepo 2020) also tells us that automation drives up demand for the highest skills, substituting for humans in a domain of lower skill tasks that extends over time. However, as we show in the following figure, dis-aggregating from economy-wide data to changes in industry-level occupational demand within U.S. manufacturing suggest important industry variations that are not as readily explicable by current theory and that may be related to the costs described in this section.

Following the example of Autor and Dorn, this figure is constructed by using Census IPUMS and American Community Survey (ACS) data to determine the change in the share of employment in occupations of different skill percentiles between 2000 and 2019, with the additional feature of dis-aggregating industries by their level of utilization based on Federal Reserve Data for manufacturing industries (requiring us to focus on manufacturing due to limitations of utilization data: see Appendix 11 for details). Industries with low utilization over this period (such as aerospace manufacturing) show a strong polarization of occupational demand, while high utilization (such as automotive manufacturing) industries show a change more consistent with upskilling, seeing the largest relative growth in the highest-wage occupations.

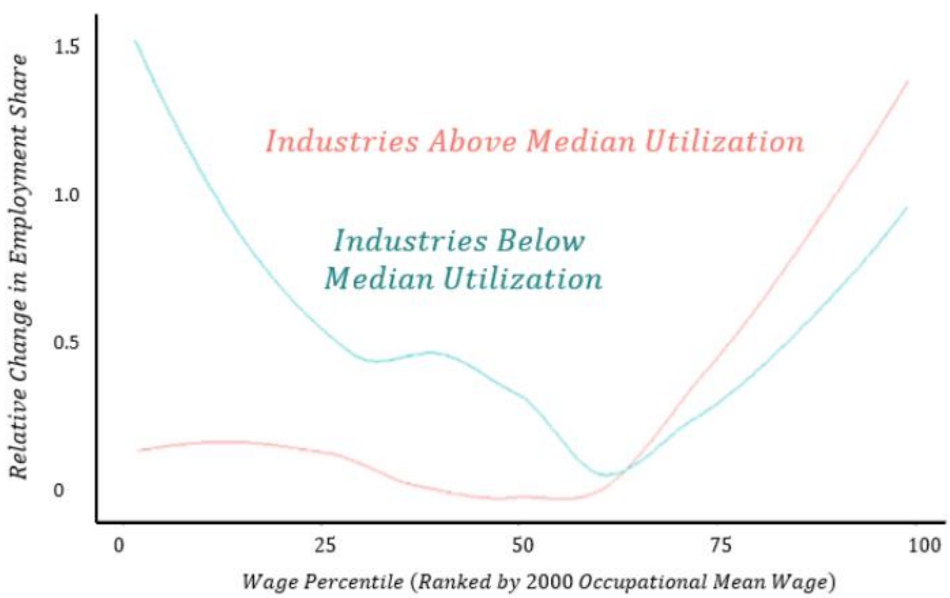


Figure 13 Relative Change in Occupational Demand Share by Industry Utilization (2000 - 2019)

The costs described in this section give intuitive dimensions to the problem of the firm in dividing production tasks: the firm must trade off between the cost of complex steps and the cost of dividing tasks and performers. We formalize these dimensions in the following section.

3. Model

The description of the model proceeds in several steps. First we describe the nature of production in terms of tasks and steps. Then we introduce the difficulty associated with each step. The description of how human or machine performers differ follows and the problem of the firm concludes this section.

3.1 Tasks and Steps

A good or service is produced by executing a set of tasks. The set of tasks that need to be completed is described by the interval $\mathcal{V} = [0, \overline{v}]$ with $\overline{v}$ finite.[51] Tasks are indexed by $v \in \mathcal{V}$. A task can be performed by a human or a machine. We codify this information with the indicator function:$o(\cdot): \mathcal{V} \to \{m, h\}$. When $o(v) = h$, a human (or when $o(v) = m$, a machine) is performing task v. A consecutive group of tasks $\mathcal{S}_t \subseteq \mathcal{V}$ performed by either a single human or a machine is referred to as a step.[52] To define a step, we introduce a series of $T \geq 1$ thresholds $\{s_t\}_{t=1}^{T}$ that split the set of tasks into steps. For all t we have $s_t \in \mathcal{V}$ and $s_T = \overline{v}$. T thresholds define T steps as follows: where $\mathcal{S}_t = (s_{t-1}, s_t]$ for $t = 2, \ldots, T$ and $\mathcal{S}_1 = [0, s_1]$. The type of performer in step t is defined with the indicator $o_t \in \{m, h\}$. For every step, we associate a length $l_t = s_t - s_{t-1}$ for all $t = 2, \ldots, T$ and $l_1 = s_1$.

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[51] This definition of a set of tasks is quite flexible to different forms of organizing production. Note that the interval of tasks does not necessarily indicate that tasks must be carried out sequentially in time. The model is capable of representing production processes where tasks assigned to different performers can occur simultaneously, as occurs with parallel production of subsystems that are later assembled together.

[52] It is possible for multiple performers of the same type to be involved in the completion of a step, through parallelization or coordination. For instance in automobile assembly, a firm might employ multiple welders in parallel to meet a given production volume, with each welder independently performing the same tasks. Alternatively, the firm might require multiple performers to work simultaneously, such as when two workers lift a car door to place it into a vehicle frame Fuchs, Field, Roth and Kirchain (2011). These cases are treated equivalently in the model, provided that the performer type and ability is the same. It is also common for performers of different types to work simultaneously on a specific unit (e.g. a human and a collaborative robot). In this case, each performer is generally performing a different task: a human might be responsible for visual and cognitive tasks, while a robot may be responsible for strength-based tasks (Vicentini, 2021). In our model this case is described as separate steps (with fragmentation costs potentially incurred from the robot-human interaction). Because steps are defined by a performer, they do not distinguish between a human and a tool (and tooling may be part of the price of a performer); a tool makes a task easier for a human (or machine), while a machine performs a task (Frohm et al., 2008).

Remark 1 Each task completed contributes to the final value of the good or service. Let Y be that value. Then denote with $y(\cdot): \mathcal{V} \rightarrow \mathbb{R}_+$ the individual contribution of tasks to the value of the good or service. We then have:

$$Y = \int_0^{\overline{v}} y(v)dv.$$

The indexing of the tasks and their relationship with value added is quite flexible. In general, our interpretation is that steps that include a larger measure of tasks than other steps, are also more complex. If $y(v)$ is a constant for all v, these more complex steps also contribute more to the value added of the good.

Associated with every consecutive pair of tasks there exists a fragmentation cost. This cost is paid by the firm whenever production is split into multiple steps, which are conducted by different performers. Fragmentation costs are characterized by the exact point at which a step ends, and by the type of performer executing the step. The costs are described by the function $f(\cdot,\cdot): \mathcal{V} \times \{0,1\} \rightarrow \mathbb{R}_+$. For a given production process split over T steps and executed by performers according to o_i, total fragmentation costs are then by: $\sum_{i=1}^{T} f(s_i, o_i)$. [53]

3.2 Jobs and Difficulty

Firms define each job, assigned to either a human or machine, by assigning the performer to a step of a particular length and by determining the rate at which the step needs to be completed. These two dimensions define the different margins on which humans and machines have an advantage. As shown below, human performers (in general) have an advantage in the difficulty associated with step-length complexity, and machine performers (in general) have an advantage in the difficulty associated with the rate of completion of a step. The overall difficulty of a job for a human or machine performer is determined by these two dimensions as we explain next.

Complexity

During the execution of a step, a performer needs to solve a number of issues that arise in production to complete the step. The complexity of each issue is modeled according to an i.i.d. random variable $X \in \mathcal{X} \subseteq \mathbb{R}_+$. We assume that all moments of X exist and are bounded. A key difference between a human and machine performer is the ability to solve closely related issues. For a typical machine, the ability to solve any issue is independent of the ability to solve other issues. For a human performer, the ability to solve an issue implies the ability to solve all

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[53] As an extension to the model we develop above, fragmentation costs can be thought of as deriving from the costs of transitional steps that allow a performer to hand-off the output of their task to another performer. Formally, the cost of these additional steps is:

$$f(s_i, o_i) = E\left[\left(\sum_{j=1}^{N} (X_j)^{\rho_{o_i}}\right)^{\frac{1}{\rho_{o_i}}}\right]; \quad N = \lfloor f(s_i)/\lambda_f \rfloor; \quad o_i = h, m.$$

This formulation introduces the arrival of fragmentation issues λ_f as a primitive parameter. It also generates a higher fragmentation cost for machine performers than human performers whenever $\rho_m < \rho_h$.

easier issues. We formalize this distinction as follows. Given n issues X_i with $i = 1, \dots, n$ the aggregate step-wide complexity is given by $\mathbf{X}(0|\rho) = 0$ and:

$$\mathbf{X}(n|\rho) = E\left[\left(\sum_{j=1}^{n} (X_j)^{\rho}\right)^{\frac{1}{\rho}}\right], \qquad n \geq 1.$$

The above equation is reminiscent of a CES production function with degree of substitutability ρ (and elasticity of substitution equal to $1/(1-\rho)$). In our formulation, $\rho \in [1, \infty)$ represents a key property of a performer; we will refer to ρ as the *degree of generality*. Below we assume a human performer has a higher ρ than a machine.

Assumption 1 *Let ρ_h (ρ_m) be the degree of generality of a human (machine) performer. Then $\rho_h > \rho_m$.*

To understand the role of ρ, it is convenient to consider two extreme cases:

1. **Perfect Generalist** A perfect generalist is a performer with $\rho = \infty$. In this case: $\mathbf{X}^g(n) \equiv \lim_{\rho \to \infty} \mathbf{X}(n|\rho) = \max_{i=1,\dots,n} X_i$, Let $X_{k:n}$ the k-th order statistic out of a sample of n draws of X. In this case the step-wide complexity for the perfect generalist is captured by $\mathbf{X}^g(n) = X_{n:n}$. This scenario captures the case in which only the most complex issues drive step-complexity for the performer, because solving an issue of given complexity implies the performer can solve all issues of lesser complexity.

2. **Perfect Specialist** At the opposite end, a perfect specialist is a performer with $\rho = 1$. This scenario captures the case in which each issue affects the step-wide complexity separately regardless of complexity. In this case $\mathbf{X}^s(n) \equiv \sum_{i=1}^{n} X_i$, so that the complexity of all issues contribute to the overall step-wide complexity.

To formally show the relationship between ρ and complexity, it is helpful to relate the definition of $\mathbf{X}(n|\rho)$ to an L^p norm. The result below follows from using Hermite-Hadamard inequalities for convex functions.

Lemma 1 For all $n > 1$, if $\rho_h > \rho_m$ then $\boldsymbol{X}(n|\rho_h) < \boldsymbol{X}(n|\rho_m)$.

Proof. In Appendix 8.

We next look at the role of n in the definition of complexity. For all n and for $\rho \geq 1$ we have:

$$n^{1/\rho}(E[X^{\rho}])^{1/\rho} = \left(E\left[\sum_{j=1}^{n} (X_j)^{\rho}\right]\right)^{\frac{1}{\rho}} \geq E\left[\left(\sum_{j=1}^{n} (X_j)^{\rho}\right)^{\frac{1}{\rho}}\right] = \mathbf{X}(n|\rho),$$

with equality holding when $\rho = 1$ or $n \leq 1$. As the number of issues increases, the complexity of a step for human and machine performers increases at a different rate. To see this, consider the case for large n. Let $\mathbf{S}_n(\{X_i\}_{i=1}^{n}) = \sum_{i=1}^{n} (X_i)^{\rho}$ and $\overline{\mathbf{S}}_n = E[S_n] = nE[X^{\rho}]$. We then have from Proposition 2 in (Biau and Mason 2015) that:

$$\lim_{n \to \infty} \mathbf{X}(n|\rho) \approx E\left[\overline{\mathbf{S}}_n^{-1/\rho} + \frac{1}{2}\frac{1-\rho}{\rho^2}\overline{\mathbf{S}}_n^{-1/\rho-2}\left(\mathbf{S}_n - \overline{\mathbf{S}}_n\right)^2 + \cdots\right] \approx n^{1/\rho}(E[X^{\rho}])^{1/\rho}. \qquad (1)$$

From (1) we see that $\mathbf{X}(n|\rho)$ increases more quickly with n for lower values of ρ. Finally, $\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho)$ is decreasing in n. This last observation is the basis for a concave relationship between step length and step complexity defined below.

Remark 2 *The difficulty of work originates from an interaction between tasks and the type of performer (e.g. task and different humans in (Campbell 1988)). Research highlights how, in general, humans are better able to solve a wide variety of issues than machines (see for example Wickens et al 2015) and experience a smaller increase in errors as complexity increases. When it is possible to divide complex work into many less complex parts, this human advantage is reduced, and machines can compete with humans in terms of low error rates. Humans experience sharp increases in their rate of failure as they are made to perform the same work faster; while machines are not immune to this effect, they typically outperform humans in terms of the error-effect of repeating simple tasks faster. As an example of this trade-off, an industrial robot that can reliably perform its tasks can do so at much higher rates than a human, but would need to be reprogrammed and refitted to perform a different set of tasks, while a human could complete either set (Korsah et al 2013).*

Issue Arrival

Just as the magnitude of issues is uncertain, so is the number of issues that need to be solved in order to complete the step. To capture this feature, we model issues as a compound Poisson process.[54] Issues arise according to a Poisson process with intensity λ so that the probability of n issues arising in a step of length l is given by:

$$P_n(l) = \frac{(\lambda l)^n}{n!} e^{-\lambda l}.$$

The parameter λ governs the relationship between step length (l) and the expected number of issues denoted by $N(l) = \lambda l$. The performer-specific expected complexity (or simply complexity henceforth) of solving the step is given by:

$$c(l|\rho) = \sum_{n=0}^{\infty} P_n(l)\mathbf{X}(n|\rho). \tag{2}$$

The complexity of a step inherits properties of $\mathbf{X}(n|\rho)$. The following lemma summarizes key properties of complexity used later in this paper.

Lemma 2 *The function $c(l|\rho)$ is: (i) strictly increasing and (ii) strictly concave in step length l.*

Proof. In Appendix 8.

To fix intuition, it is helpful to go back to the case of performers being either perfect generalists or perfect specialists and see how different performer characteristics impact step complexity.

Example 1 (A Solved Case) *This example derives a closed form equation for the complexity level of a step for the case of a perfect generalist and a perfect specialist. Assume that each X_i is uniformly distributed in $[0,1]$. We then have that the expected value for $X_{n:n}$ is given by:*

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[54] The modeling of difficulty with $\rho = 1$ becomes a version of the Cramer-Lundberg model. See also, Cai (2014).

$$E[X_{n:n}] = \frac{n}{n+1}.$$

Since the number of issues and their complexity are assumed independent of each other, we have that the expected total difficulty to complete steps of length l_i by a perfect generalist is given by:

$$c(l_i|\infty) = \sum_{n=0}^{\infty} \frac{n}{n+1} \frac{(\lambda l_i)^n}{n!} e^{-\lambda l_i} = \frac{1}{e^{\lambda l_i} \lambda l_i} + \frac{\lambda l_i - 1}{\lambda l_i}.$$

From the above (and as proved previously), it is easy to see directly that $D(l_i|\infty)$ is increasing and strictly concave in l_i for all λ. For a pure specialist, we have:

$$c(l_i|1) = \sum_{n=0}^{\infty} \frac{n}{2} \frac{(\lambda l_i)^n}{n!} e^{-\lambda l_i} = \frac{\lambda l_i}{2}.$$

In contrast to $c(l_i|\infty)$, $c(l_i|1)$ is linear in step length.

Rate & Difficulty

We now consider the second key characteristic of a job: the rate at which it is performed. A firm may choose the rate at which a performer must complete the tasks in a step. A higher production rate increases performer output per unit time but also raises the overall difficulty of a step. To proceed, we need to determine the unit of time. For simplicity, we will normalize time so that a unit of time corresponds to a work shift, which is exogenous to the model. Next consider the rate in terms of the number of repetitions of a step per unit time denoted by $r \geq \underline{r} = 1$. Having determined the complexity of a step (c) and the rate at which the performer executes the step (r), we can now determine the overall difficulty of a step with these characteristics. Step difficulty is generated by an aggregator function $D: \mathbb{R}^2 \to \mathbb{R}$. A step with complexity $c(l|\rho)$ performed by a performer of type $o = h, m$ with rate r is associated with a difficulty $D(c(l|\rho), r|o)$. We assume the following for the difficulty function D.

Assumption 2 *The function D is increasing in both arguments, linear and unbounded with respect to the first argument (complexity), and strictly convex with respect to the second argument (rate). The function D is differentiable in both arguments. Denote with D'_r the derivative of D with respect to r. We assume:*

$$D'_r(c, r, |h) > D'_r(c, r, |m); \qquad D''_r(c, r, |h) > D''_r(c, r, |m), \qquad \forall\ c > 0, r \geq \underline{r}; \quad (3)$$

$$D(c(l|\rho_h), \underline{r}|h) < D(c(l|\rho_m), \underline{r}|m), \qquad \forall\ l > 0. \quad (4)$$

Equations (3) and (4) formalize the differences between a human and machine performer with respect to sensitivity to rate. A step assigned to a human performer requires lower difficulty at low rate with respect to a machine performer. As the rate of the step grows, eventually the difficulty for a human performer overtakes that of a machine performer. The functional form D allows a trade-off between length and rate for a constant difficulty level. Totally differentiating $D(c(l|\rho), r|h)$ and keeping a constant difficulty level we get:

$$\frac{dr}{dl} = -c'_l(l|\rho) \cdot D'_l / D'_r. \quad (5)$$

An important property of the D function is the sensitivity with respect to rate r, which we define as:

$$\sigma = 1 + r\frac{D''_r}{D'_r}. \tag{6}$$

The value of σ controls the sensitivity of difficulty to the rate. An example of a functional form that satisfies Assumption 2 is:

$$D(c(l|\rho), r|o) = c(l|\rho) \cdot (\underline{c} + r^{\varsigma}), \tag{7}$$

with $\underline{c} > 0$ and $\varsigma > 1$. The above specification features a lower bound on the difficulty, $\underline{c} \cdot c(l|\rho)$, which is independent of r. In the functional form given by (7) we have that $\sigma = \varsigma$. ■

3.3 Performers

So far we have discussed two key differences between performers: ρ and σ. The former determines the ease with which a performer addresses problems of increased complexity. The latter summarizes the tolerance of a performer to an increase in rate. In general, these characteristics vary between performer types (human vs. machine) and among performers of the same type. For example, different machines can be characterized by their level of generality and rate-sensitivity. Humans may also differ from each other along these dimensions.

The use of the aggregator D defined in the previous section implicitly assumes that performers are heterogeneous along a single-dimensional ability level (denoted with a). When assigning an operator to a step, the ability level of the performer needs to be commensurate with the difficulty of the step. Formally, for a performer of type $o \in \{m, h\}$ with degree of generality ρ is capable of executing a step of length l with rate r if $a \geq D(c(l|\rho), r|o)$.[55]

Divisibility

The final dimension characterizing performers is performer divisibility. Performers vary in the degree to which they can divide their time and reallocate their effort. A highly divisible human performer is able to complete additional tasks once the initial tasks associated with their job are completed. For example, a human computer programmer can quickly switch to answering emails once their programming tasks are completed. This performer therefore is not idle even when they can finish their tasks quickly (r is high), but can be reallocated to other productive tasks. In contrast, a robotic welding machine cannot switch to other tasks when the welding tasks are completed. The firm must pay for the performer (the rental price of capital in this case) even when they are idle.[56] Unlike ρ and σ, the degree of divisibility is influenced not only by the type of performer but also by exogenous policy such as minimum shift labor laws.[57]

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[55] In our model the ability of a worker is single dimensional. We abstract from explicitly modeling workers characterized by multidimensional abilities. Refer to Lindenlaub (2017) and Ocampo (2018) for work in this area.

[56] The inability to fully use the capacity of a performer is a common concern in the systems engineering literature. Refer to Hopp and Spearman (2011) for an extensive analysis.

[57] The divisibility of performers can also be affected by institutional and organizational constraints. For example, Schmitz and Teixeira (2008), when analyzing the Brazilian iron ore

In general there are two additional types of indivisibility of performers: the minimum time a performer can be allocated to the task, and the incremental amount that a performer can allocate to a task above the minimum (for example, a worker might work a minimum of four hours with hourly increments). We focus on the minimum time a performer can be allocated to the task. When encoding this restriction we assume that any higher rate of work provides no benefit. This restriction is summarized in the function: $g(R, r)\colon \mathbb{R}_{+} \times \mathbb{R}_{\geq 1} \rightarrow \mathbb{R}_{+}$.[58]

The function g takes into account the rate at which a step is performed, r, and adjusts the fraction of performers needed per unit output accordingly. A higher r denotes a shorter amount of performer time is devoted to the step, thus a lower performer cost for the step. The function g also takes into account the number of products produced R. The reason for this dependency is due to the fact that the benefit of raising r depends on the number of products to be processed and on the ability to reallocate the performer to a different task. To fix ideas we give two examples taken from Hopp and Spearman (2011):

1. **Perfectly divisible performer.** In this case we have:

$$g^{div}(R, r) = \frac{1}{r}.$$

In this case, any increase in r translates into a proportionate reduction in the costs associated with the performer completing the assigned step. For this case, cost reductions from higher r are independent of R.

2. **Indivisible performer**. This is the case of a performer that cannot be reallocated to a different task when idle. For this type of performer we have:

$$g^{ndiv}(R, r) = \frac{1}{R}\left\lceil\frac{R}{r}\right\rceil.$$

In this case, the gains from higher rate r are limited by the number of products produced, R.

In general the function $g(R, r)$ is assumed to have the following properties:

Assumption 3 *For human ($o = h$) and machine ($o = m$) performers, the function $g^{o}(R, r)$ is such that:*

1. For all R, there exists an $\overline{r}(R)$ such that $g^{o}(R, r) = g^{o}(R, \overline{r}(R))$ for all $r \geq \overline{r}(R)$. In addition $\lim_{R\rightarrow 0}\overline{r}(R) = 0$;
2. $\lim_{R\rightarrow\infty} g^{o}(R, r) = 1/r$;
3. If $r > r'$ then $g^{0}(R, r) \leq g^{o}(R, r')$ for all R;

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industry, document the productivity impact of organizational changes within the firm; specifically, they document how allowing repair staff to perform repairs outside their job classification (increasing the divisibility of the performer) increased labor productivity of these workers.

[58] Restriction on the incremental divisibility of workers would also be encoded in g. For analytical tractability, we do not assume a restriction on incremental work.

4. If $R' > R$ then $g^0(R,r) > g^o(R',r)$ for all $r > \overline{r}(R)$;
5. For all R, $\overline{r}_h(R) \geq \overline{r}_m(R)$.

Condition 1 in the above Assumption formalizes the idea that, above a certain level of rate there are no further returns. This insight is commonly represented in the engineering literature by assuming that performers are dedicated" to a process or to a step, meaning that their unused capacity cannot be productively used elsewhere. We refer to $\overline{r}_i(R)$ as the specific minimum divisibility threshold for the performer. When $r > \overline{r}$, all output is produced with a single performer within the minimum time increment, and so increasing r further cannot reduce the costs associated with the performer. *Condition 2* states that as the output quantity grows, the constraint on the minimum time a performer can be allocated to the task becomes non-binding. Finally, *Condition 5* encodes the idea that moving a human performer to a different task is easier than re-tasking a machine performer.

We can now determine the total cost of assigning a performer to a step. Total step-costs are determined by the ability-price of the performers, $w(a)$ for humans and $k(a)$ for machines, as well as the cost saving associated with increasing the rate in which a step is executed, $g(R,r)$. We have that the price of a performer to complete a step with ability a, rate r, and total number of products produced R is given by:

$$p(a,r,R|o_i) = \begin{cases} w(a)g^h(R,r), & \text{if } o_i = h \\ k(a)g^m(R,r), & \text{if } o_i = m \end{cases}. \tag{8}$$

We assume the following conditions for functions $w(\cdot)$ and $k(\cdot)$:

Assumption 4 *The functions $w(\cdot)$ and $k(\cdot)$ are: positive, strictly increasing and weakly convex.*

We now have all the model ingredients needed to define the problem of the firm.

3.4 Firm Optimization

The firm chooses how to subdivide the production process by choosing the number and positions of steps and which performer to assign a given step. For each step, the firm also determines the required completion rate. We begin by taking the number of steps T as given and finding the cost minimizing step thresholds, s_i, operator, o_i, ability, a_i, and rate, r_i, for each step i. We impose a lower bound of rate $\underline{r}$ for later analysis, with the intuitive reasoning that there are technical limitations on each performer producing arbitrarily small fractions of a unit output.

$$C(R,T) = \min_{\{s_i\}_{i=1}^T, \{r_i, a_i, o_i\}_{i=1}^T} \sum_{i=1}^T p(a_i, r_i, R|o_i) + \sum_{i=1}^T f(s_i, o_i) \tag{9}$$

subject to:

$$l_1 = s_1; \quad l_i = s_i - s_{i-1}, \quad \forall\ i = 2, \dots, T; \tag{10}$$

$$a_i \geq D(c(l_i|\rho_{o_i}), r|o_i), \qquad \forall\ i = 1, \dots, T; \tag{11}$$

$$s_i \in [0, \overline{v}]; \qquad s_i \leq s_{i+1}; \qquad o_i \in \{h, m\}; \qquad r_i \geq \underline{r}, \qquad \forall\ i = 1, \dots, T; \tag{12}$$

$$s_0 = 0; \qquad s_T = \overline{v}. \tag{13}$$

The two terms in (9) represent the performer and fragmentation costs associated with a given choice of T (and performer characteristics). The per-unit cost of producing R units is then determined by choosing the cost minimizing number of steps T.

$$C(R) = \min_{T \in \mathbb{N}_+} C(R, T). \tag{14}$$

We assume that firms take as given $w(\cdot)$ and $k(\cdot)$.

4. Analysis

We analyze the environment of the model in four sections. First we analyze the conditions for the division of tasks to occur, finding that division can be driven by the structure of wages or by production volume. Second we analyze the relationship between step length and ability demand, rate, and wages. Third we analyze the conditions for firms to automate steps. We show how the effect of automation varies with production volume, showing polarization of skill demand at low volumes and up-skilling at high volumes.

We conclude by analyzing the effect of changes in fragmentation costs on the division of production and the distribution of ability demand. We show first that variation in fragmentation costs over tasks is necessary for variation in demand for performer type and ability, then we show how changes in process technology can affect the inequality between the highest and lowest wages.

4.1 The Structure of Production: Division of Tasks

The production problem described earlier provides a rich set of possibilities on how the structure of production can be organized. The organization is impacted by the cost associated with performers and with fragmenting production. In this section, we discuss conditions under which the firm finds it optimal to divide tasks across performers. For simplicity, we refer to human performers with wage rates w. However, the wage rate can simply be replaced with the rental price of capital to extend the discussion to the division of tasks among machines.

Since the price of performers is strictly increasing in their ability, it follows that constraint (11) binds at the optimum. This result implies that a necessary condition for production tasks to be divided into more than one step is the existence of at least one $0 < l < \overline{v}$ and r', r'' such that:

$$p(D(c(\overline{v}|\rho_h), r^*|h), r^*, R|h) > p(D(c(l|\rho_h), r'|h), r', R|h) + p(D(c(\overline{v} - l|\rho_h), r''|h), r'', R|h) \tag{15}$$

where r^* is the optimal r without any division of tasks. The above inequality is strict since fragmentation costs are nonzero. We explore two forces that lead firms to divide tasks. The first is the effect of convex wages. The intuition for why convexity of wages lead to fragmentation is straightforward. A sufficiently convex wage in ability makes it extremely expensive for a firm to hire a worker to execute a large non-fragmented step. Formally, this is described as follows.

Proposition 1 *Suppose that $f(\cdot,h)$ is sufficiently low and that $w(\cdot)$ is sufficiently convex. Then division of tasks is optimal.*

Proof. If fragmentation costs $f(\cdot,h)$ are sufficiently low, then the condition described in (15) is also sufficient. Suppose that, by contradiction, for all $l \in (0,1)$ and all r', r'' we have:

$$p(D(c(\overline{v}|\rho_h),r^*|h),r^*,R|h) \leq p(D(c(l|\rho_h),r'|h),r',R|h) + p(D(c(\overline{v}-l|\rho_h),r''|h),r'',R|h).$$

To reach a contradiction, set $l = \overline{v}/2$, using (8) we have:

$$w(D(c(\overline{v}|\rho_h),r^*|h))g^h(R,r^*) \leq w(D(c(\overline{v}/2|\rho_h),r'|h))g^h(R,r') + w(D(c(\overline{v}/2|\rho_h),r''|h))g^h(R,r''),$$

setting $r' = r'' = r^*$ the above implies:

$$w(D(c(\overline{v}|\rho_h),r^*|h)) \leq w(D(c(\overline{v}/2|\rho_h),r^*|h)) + w(D(c(\overline{v}/2|\rho_h),r^*|h)). \qquad (16)$$

If w is sufficiently convex, the function $\widetilde{w}(l) = w(D(c(l|\rho_h),r^*|h))$, reaching a contradiction with equation (16). ■

The previous result considered division of tasks as a way to reduce the cost of production for sufficiently convex wages, trading off against fragmentation costs. The notion of connecting division of tasks to increases in production efficiency dates to Adam Smith in the Wealth of Nations in his discussion of the division of labor (Smith 1776). Smith himself argues that the degree of specialization may also be limited by market size; we turn to this channel for division of labor next. The following proposition sharpens the trade-off present between fragmentation costs (related to cross-step coordination) and the size of output (related to the size of the market).

Proposition 2 *Suppose that: $f(\cdot,h)$ is sufficiently low; R is sufficiently high. If $D'_r = \frac{\partial D}{\partial r}$ is sufficiently small (or $\overline{v}$ is sufficiently large), then division of tasks is optimal.*

Proof. If fragmentation costs $f(\cdot,h)$ are sufficiently low, then the condition described in (15) is also sufficient. Suppose that, by contradiction, for all $l \in (0,1)$ and all r', r'' we have:

$$p(D(c(\overline{v}|\rho_h),r^*|h),r^*,R|h) \leq p(D(c(l|\rho_h),r'|h),r,R|h) + p(D(c(\overline{v}-l|\rho_h),r''|h),r'',R|h).$$

Set $l = \overline{v}/2$, using (8) we rewrite the above as:

$$w\big(D(c(\overline{v}|\rho_h),r^*|h)\big)g^h(R,r^*) \leq \qquad (17)$$
$$w(D(c(\overline{v}/2|\rho_h),r'|h))g^h(R,r') + w(D(c(\overline{v}/2|\rho_h),r''|h))g^h(R,r'')$$

Set the values of $r' = r'' = \hat{r}$ so that $D(c(\overline{v}|\rho_h),r^*|h) = D(c(\overline{v}/2|\rho_h),\hat{r}|h)$. From (5) we get:

$$\hat{r} = r^* + \frac{c(l|\rho)}{\partial l}\frac{D'_l}{D'_r}\frac{\overline{v}}{2}, \qquad (18)$$

From Assumption 3, for R sufficiently high, we have $g(R,r) \approx 1/r$ for all r. We rewrite (17) evaluated at $r' = r'' = \hat{r}$ as $\hat{r} < 2r^*$. From (18) we see that this condition is violated when D'_r is sufficiently small or $\bar{v}$ is sufficiently large thus reaching a contradiction. ■

4.2 Ability and wages

In this section we explore the demand for ability in the production process. The demand for ability is determined by the length and the rate at which a step is completed. Since the latter can be adjusted in the short-run, we first provide a result linking length and rate. Then we provide a condition linking the length of a step and the overall ability level. The relationship between length and ability is a key property of the model, because it underlies the ability demand effects of automation and of division of tasks. To simplify the analysis for some of our results we assume the following structure for $g(R,r)$:

Assumption 5 *For human ($o = h$) and machine ($o = m$) performers, $g^o(R,r)$ is given by:*

$$g^o(R,r) = \begin{cases} 1r, & \text{if } r \le \bar{r}_o(R) = R\bar{r}_o \\ 1R\bar{r}_o, & \text{if } r > \bar{r}_o(R) = R\bar{r}_o \end{cases},$$

with $\bar{r}_h > \bar{r}_m$.

In the above we can see that $\bar{r}$ is the rate at which the total amount of time required to produce the quantity R is equal to the minimum time increment that can be allocated to a performer. We also assume that the ability-price for performers (either human or machine) is well-behaved so that a unique rate level emerges for any step length. The following assumption guarantees this:

Assumption 6 *The function $\mathbf{w}$, defined as:*

$$\mathbf{w}(x, o_i) = \begin{cases} \frac{xw\prime(x)}{w(x)}, & \text{if } o_i = h \\ \frac{xk\prime(x)}{k(x)}, & \text{if } o_i = m \end{cases},$$

is increasing for all $x > 0$.

The next proposition considers the impact of step length on the optimal rate and ability level for a constant performer type.

Proposition 3 *Suppose Assumptions 4, 5 and 6 hold. In addition, assume the following: (a) D is separable between its two arguments and (b) $\sigma > rD'_r/D$ for all r. Given two steps i and j with the same performer, denote with r_i (a_i) and r_j (a_j) the optimal choice for rate (ability) in step i and j. Then if $l_i > l_j$, we have that (i) $r_i \le r_j$, (ii) if $r_i, r_j \in (\underline{r}, R\bar{r}_h)$ then $r_i < r_j$, and (iii) $a_i > a_j$.*

Proof. Suppose that $o_i = o_j = h$ (similar arguments follow for a machine performer). From (9), for step length l the choice for r solves:

$$\min_{\underline{r} \le r \le R\bar{r}_h} \frac{w\big(D(c(l|\rho_h), r|h)\big)}{r}. \tag{19}$$

We begin with the proof of *(i)*. Suppose by contradiction that $r_i > r_j$. The case in which $r_j = R\bar{r}_h$ is obvious as it is not optimal to increase rate in step i (doing so would raise the ability requirement of the step without benefiting from a lower usage of operator time). Consider now the case in which $r_j < R\overline{r}_h$. If $r_j > \underline{r}$ we then have the following first order condition (from Assumption 4, the second order condition is verified) holding for both steps:

$$\mathbf{w}(D(c(l_s|\rho_h), r_s|h)) = \frac{D(c(l_s|\rho_h), r_s|h)}{rD'(c(l_s|\rho_h), r_s|h)}, \qquad s = i, j. \tag{20}$$

Let function g be defined as follows:

$$g(r_s) = \frac{D(c(l_s|\rho_h), r_s|h)}{rD'(c(l_s|\rho_h), r_s|h)},$$

note that given Assumption (a) in the statement of the Lemma, function g is independent of step length. We then have that:

$$g'(r) = \frac{r(D'_r)^2 - DD'_r - rDD''_r}{(rD')^2},$$

given Assumption (b) in the statement of the Lemma, we have from (6), that $\sigma = 1 + r\frac{D''_r}{D'_r} > \frac{rD'_r}{D}$ so that $g'(r) < 0$ for all r and all l. Hence:

$$\frac{D(c(l_i|\rho_h), r_i|h)}{rD'(c(l_i|\rho_h), r_i|h)} < \frac{D(c(l_j|\rho_h), r_j|h)}{rD'(c(l_j|\rho_h), r_j|h)}.$$

With the above, we then reach a contradiction with condition (20) since given the contradicting assumption together with Assumption 6, we have that $\mathbf{w}(D(c(l_i|\rho_h), r_i|h)) > \mathbf{w}\big(D(c(l_j|\rho_h), r_j|h)\big)$.

The case with $r_j = \underline{r} < r_i$ can be analyzed in a similar fashion as the interior case above. In this case we have that the first order condition is given by:

$$\mathbf{w}\big(D(c(l_j|\rho_h), r_j|h)\big) \geq \frac{D(c(l_j|\rho_h), r_j|h)}{rD'(c(l_j|\rho_h), r_j|h)}.$$

The contradiction is reached in a similar manner as the previous case.

We next show that *(ii)*: if $r_i, r_j \in (\underline{r}, R\overline{r}_h)$ then $r_j > r_i$. In this case we have that (20) holds for both steps. Given the previous result, we need to rule out $r_i = r_j$. In this case we have $g(r_i) = g(r_j)$. However, by Assumption 6, $\mathbf{w}$ is strictly increasing, it follows that $D(c(l_i|\rho_h), r_i|h) = D(c(l_j|\rho_h), r_j|h)$ reaching a contradiction since $l_i > l_j$.

We next show *(iii)*: $a_i > a_j$. If $l_i > l_j$, from the previous result we have that $r_i \leq r_j$ with the inequality strict if $r_i, r_j \in (\underline{r}, R\overline{r}_h)$. Starting from this interior case we have (using the shorthand $\mathbf{w}_j = \mathbf{w}\big(D(c(l_j|\rho_h), r_j|h)\big)$.)

$$\mathbf{w}_j = g(r_j) < g(r_i) = \mathbf{w}_i, \tag{21}$$

where the two equalities are from (20) and the assumption of interior r_i, r_j. While the inequality follows from the properties of g discussed above together with $r_i < r_j$. From (21) we have that $D(c(l_i|\rho_h), r_i|h) > D(c(l_j|\rho_h), r_j|h)$. Since constraint (11) in the firm's optimization problem is binding, it then follows that $a_i > a_j$.

Next consider the cases that involve either $r_i = r_j = \underline{r}$ or $r_i = r_j = \overline{r}_h$. In this case $a_i > a_j$ follows from $l_i > l_j$. Finally, we need to consider separately two remaining cases. First let $r_j = \overline{r}_h$ and $r_i < r_j$. In this case we have:

$$\mathbf{w}_i \geq g(r_i) > g(r_j) \geq \mathbf{w}_j, \tag{22}$$

where the weak inequality originates from the first order condition of (19) and the possibility that the upper bound for r_j or lower bound for r_i might be binding. As before from (22) we conclude that $a_i > a_j$. The remaining case has $r_i = \underline{r}$ and $r_j \in (\underline{r}, R\overline{r}_h)$ so that $r_i < r_j$. This case proceeds as before noting that now the second weak inequality in (22) is now an equality. ∎

The conditions on D in the previous Proposition hold for the simpler example with D given by (7). In this case separability is immediate and we have that (recall $\sigma = \varsigma$ for this functional form): $\varsigma > \frac{\varsigma r^{\varsigma}}{\underline{c}+r^{\varsigma}}$ whenever $\underline{c} > 0$.

4.3 Automation

In this section, we describe the conditions under which a firm automates a step by choosing a machine performer rather than a human. We show how automation impacts labor demand by showing that step length (l) and production quantity (R) is a key determinant for the patterns of automation. This section proceeds in three parts. We first show the existence of an upper bound on the length of automated steps, then show the existence of a lower bound; these results establish a region of automation and give us the effect of automation on the distribution of human performer ability demand. We then show how the range of steps automated evolves with production quantity (R). Specifically, we show that if a step of a given length is automated for a given R it is also automated for all $R' > R$. This result is key in showing that the range of steps automated grows as R increases. Combining the results of this section leads to a pattern of automation in (R, l) space as displayed in Figure 14. In this Section we assume that fragmentation costs for machines are higher than for humans.[59]

Assumption 7 *For all $s_t \in \mathcal{V}$, $f(s_t, h) < f(s_t, m)$.*

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[59] Difficulties in machine-machine interactions transferring work in progress are well documented (Korsah, Stentz and Dias, 2013), though this property is not essential for results of this section.

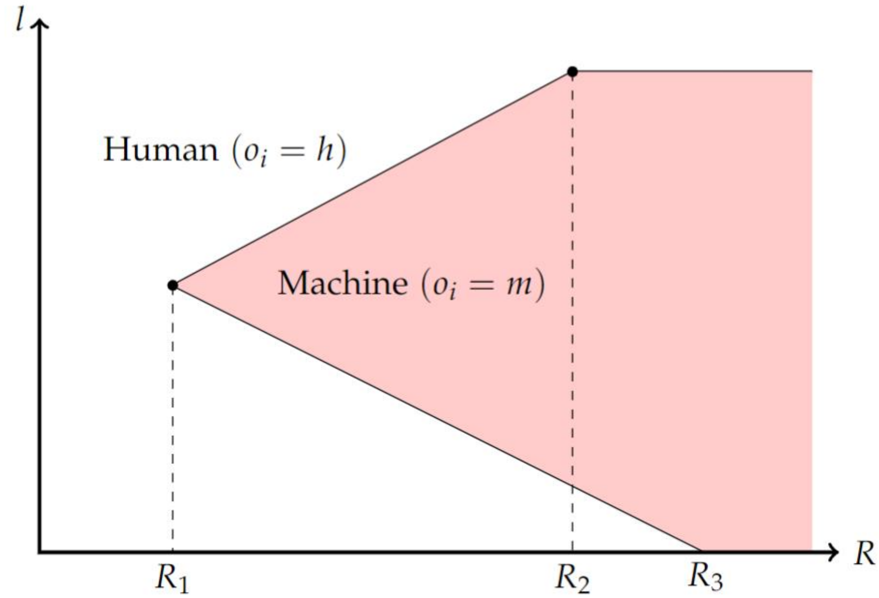

Figure 14 Automation Patterns: Volume and Step Length

As we show below, if a step is long enough then it will not be automated, giving us the upper bound of a region of step lengths automated. This result is driven by the relatively higher generality (higher ρ) of humans.

Proposition 4 (Upper Bound on Automation) *There exists $\bar{l}$ such that $o_i = h$ for all i with $l_i > \bar{l}$.*

Proof. Suppose not, then for all $\bar{l}$ there exists a j with $\tilde{l}_j > \bar{l}$ such that $o_j = m$. (Recall $f(s_j, m) > f(s_j, h)$ from Assumption 7.) This implies that:

$$k(a_j^m) g^m(R, r_j^m) < w(a_j^h) g^h(R, r_j^h). \tag{23}$$

Since $k(\cdot)$ and $w(\cdot)$ are increasing, given Assumption 3 Part 1, the optimal r for either performer is always $\underline{r} \leq r \leq \overline{r}$. We then have $D(c(l_j|\rho_h), r_j^h|h) = a_j^h \leq D(c(l_j|\rho_h), \overline{r}|h) \equiv \overline{a}(l_j)$, and $D(c(l_j|\rho_m), r_j^m|m) = a_j^m \geq D(c(l_j|\rho_m), \underline{r}|m) \equiv \underline{a}(l_j)$. Substituting the previous inequalities in (23) we have:

$$k(\underline{a}(l_j)) < w(\overline{a}(l_j)) \frac{g^h(R, \overline{r})}{g^m(R, \underline{r})}. \tag{24}$$

For l sufficiently high, the probability of drawing a small number of issues is small. We can then approximate step difficulty in (2) as:

$$c(l_i|\rho) \approx \sum_{n=\underline{n}}^{\infty} P_n(l) \mathbf{X}(n|\rho)$$

with $\underline{n}$ sufficiently high. We can then use the approximation of $\mathbf{X}(n|\rho)$ in (1) and substitute into (24) so that we have:

$$k\left(D\left(\tilde{n}_j^{1/\rho_m} E[X^{\rho_m}]^{1/\rho_m}, \underline{r}|\rho_m\right)\right) < w\left(D\left(\tilde{n}_j^{1/\rho_h} E[X^{\rho_h}]^{1/\rho_h}, \overline{r}|\rho_h\right)\right) \frac{g^h(R, \overline{r})}{g^m(R, \underline{r})}.$$

Since $\rho_h > \rho_m$ (and $k = w$) the above is violated for n_j sufficiently large, reaching a contradiction. ■

The previous result is stated in terms of l sufficiently high for a given step. A similar result holds for any l if λ is instead sufficiently high. In both cases the step will feature a likely high number of issues.

We now consider the case of automation of small steps. This lower bound of automated step-lengths is driven by the lower divisibility of machines than humans, such that $\bar{r}_m < \bar{r}_h$ (defined in Assumption 5). The result holds as long as step difficulty for small steps is not affected by varying rate. To define notation, let $r_h(l_i, R)$ and $r_m(l_i, R)$ be the optimal rate for humans and machines given the constraints $\bar{r}_h$ and $\bar{r}_m$, and $r_h^*(l_i)$, and $r_m^*(l_i)$ be the unconstrained optimal rate for human and machine respectively for a step of length l_i with output R.[60] Similarly, o_i denotes the optimal choice of performer for step i. In the proposition that follows, we assume that human wages are sufficiently low for low ability levels.

Proposition 5 (Lower Bound on Automation) *Suppose there exists a step i with l_i sufficiently small. Suppose also that $lim_{c,r\to 0} w(D(c,r|h)) \leq k(D(c,r|m))$. Then if R is sufficiently low, we have that $o_i = h$.*

Proof. Suppose not, then:

$$k(D(c(l_i|\rho_m), r_m|m))g^m(R, r_m) < w(D(c(l_i|\rho_h), r_h|h))g^h(R, r_h). \tag{25}$$

If R is sufficiently small we have that $r_m = \bar{r}_m(R) < \bar{r}_h(R) = r_h$. This implies that $g^h(R, r_h) < g^m(R, r_m)$. From (25) it follows that $k(D(c(l_i|\rho_m), r_m|m)) < w(D(c(l_i|\rho_h), r_h|h))$. If l_i is sufficiently small, we then have that $c(l_i|\rho) \approx 0$; in addition, from Assumption 3 part 1 we have that $\lim_{R\to 0} r_j = 0$ for $o_j = h, m$. We then reach a contradiction with the assumption in the Proposition stating that $\lim_{c,r\to 0} w(D(c,r|h)) \leq k(D(c,r|m))$. ■

The proof is straightforward and relies on the idea that, for low R, the advantage of a machine performer operating at high rate is eliminated. This of course requires a minimum wage for workers that is sufficiently low. At the opposite end, with high R, we expect the presence of automation since in this case the optimal machine rate is higher than the human rate. For this to occur we need the symmetrical assumption on costs assumed in Proposition 5:

$$\lim_{c\to 0}[\lim_{r\to\infty} w(D(c,r|h))] \geq \lim_{c\to 0}[\lim_{r\to\infty} k(D(c,r|m))].$$

Between the upper and lower bounds of automated step lengths, automation is driven by the lower sensitivity of machines to rate. For sufficiently short steps in which the constraint on machine rate is not binding, the lower rate-sensitivity of machines allows them to achieve lower cost than humans. We next consider the optimality of automation as the product quantity increases. For the next proposition, we keep the interval length fixed as we raise output R. This result is useful when comparing similar plants that operate at different scale. It

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[60] That is $r_j(l_i, R) = \operatorname{argmin}_{r\leq R\bar{r}_j}\left\{\frac{w\left(D(c(l_i|\rho_j), r|j)\right)}{r}\right\}$; $r_j^*(l_i) = \operatorname{argmin}_r\left\{\frac{w\left(D(c(l_i|\rho_j), r|j)\right)}{r}\right\}$. When not a source of confusion, the dependency of r_j^* and r_j on l_i and R is omitted.

also can provide insights on the optimal automation response of a plant faced with an increase in demand but not redesigning the entire production process. We have the following:

Proposition 6 *Suppose the g function satisfies Assumption 5. Suppose that $k(\cdot) = w(\cdot)$. Then if there exist i such that $o_i = m$ for a given R, then $o_i = m$ for all $R' > R$.*

Proof. Since step i is automated and $k(\cdot) = w(\cdot)$ it implies that:

$$\min_{r \le R\bar{r}_m} \left\{ \frac{w\big(D(c(l_i|\rho_m), r|m)\big)}{r} \right\} < \min_{r \le R\bar{r}_h} \left\{ \frac{w\big(D(c(l_i|\rho_h), r|h)\big)}{r} \right\}, \tag{26}$$

The proof proceeds by contradiction. Suppose that with $R' > R$ the step of length l_i is not automated. The contradicting assumption implies that:

$$\min_{r \le R'\bar{r}_m} \left\{ \frac{w\big(D(c(l_i|\rho_m), r|m)\big)}{r} \right\} \ge \min_{r \le R'\bar{r}_h} \left\{ \frac{w\big(D(c(l_i|\rho_h), r|h)\big)}{r} \right\}, \tag{27}$$

Let $\tilde{r}$ be defined as the rate such that $D(c(l_i|\rho_m), \tilde{r}|m) = D(c(l_i|\rho_h), \tilde{r}|h)$. This $\tilde{r}$ exists and is unique given conditions (3) and (4) in Assumption 2. For any $r < \tilde{r}$ we have that:

$$\frac{w\big(D(c(l_i|\rho_m), r|m)\big)}{r} > \frac{w\big(D(c(l_i|\rho_h), r|h)\big)}{r},$$

hence we have that for (26) to hold it must be the case that $\tilde{r} \le R\bar{r}_m$. Given (3) and (4), it also follows that $D'_r(c(l_i|\rho_m), r|m) < D'_r(c(l_i|\rho_h), r|h)$ and $D''_r(c(l_i|\rho_m), r|m) < D''_r(c(l_i|\rho_h), r|h)$ for all $r \ge \tilde{r}$. Since difficulty increases with respect to r at a faster rate for human relative to machine performers, we reach a contradiction with (27).

■

The previous results look at patterns of automation when changing the length of a step or separately when changing the size of the output. We next consider the interaction between these two components as we will see below as the output size increases (R goes up) so does the region of step-lengths that is optimal to automate. The end result is a *cone of automation* as highlighted in Figure 14.

It is useful to define for a given R the maximum and minimum length of a step that will not be automated. The maximum length denoted with $\bar{l}(R)$ is the maximum l_i such that:

$$\min_{r \le R\bar{r}_m} \left\{ \frac{w\big(D(c(l_i|\rho_m), r|m)\big)}{r} \right\} = \min_{r \le R\bar{r}_h} \left\{ \frac{w\big(D(c(l_i|\rho_h), r|h)\big)}{r} \right\}.$$

The minimum length $\underline{l}(R)$ is similarly defined. In general, cases with no automation present will feature $\underline{l}(R) = \bar{l}(R) = 0$. Automation occurs whenever $\underline{l}(R) > \bar{l}(R)$ or $\underline{l}(R) = \bar{l}(R) > 0$. An immediate implication of Proposition 6 is that for any $R' > R$ we have $\bar{l}(R') \ge \bar{l}(R)$ and $\underline{l}(R') \le \underline{l}(R)$. We sharpen the characterization of the region of automation with the following result:

Proposition 7 *Let the assumptions of Proposition 6 hold. Consider two output levels R, R' with $R' > R$. Consider a step of length $l_i = \bar{l}(R)$ or of length $l_i = \underline{l}(R)$. We have two cases of interest:*

• Suppose $r_m(l_i, R) = r_m^*(l_i)$, then in the R' scenario the step is not automated: $o_i(R') = h$;

• Suppose $r_m(l_i, R) < r_m^*(l_i)$, then in the R' scenario the step is automated: $o_i(R') = m$.

Proof. We focus on the case $l_i = \bar{l}(R)$. The case for $l_i = \underline{l}(R)$ follows in a similar manner. *(i)* Suppose not. We then have $o_i(R') = m$. In addition, $r_m(l_i, R') = r_m(l_i, R) = r_m^*(l_i)$, so that

$$\frac{w\big(D(c(l_i|\rho_m), r_m|m)\big)}{r_m} < \min_{r \le R'\bar{r}_h} \left\{\frac{w\big(D(c(l_i|\rho_h), r|h)\big)}{r}\right\},$$

since the $l_i = \bar{l}(R)$, the step was not automated so we also have that

$$\frac{w\big(D(c(l_i|\rho_m), r_m|m)\big)}{r_m} \ge \frac{w\big(D(c(l_i|\rho_h), r_h(l_i,R)|h)\big)}{r_h(l_i,R)},$$

Since the choice of $r_h(l_i, R)$ is available for the scenario with $R' > R$ the two above equations lead to a contradiction.

(ii) Suppose not. We then have:

$$\frac{w\big(D(c(l_i|\rho_m), r_m(l_i,R')|m)\big)}{r_m(l_i,R')} \ge \frac{w\big(D(c(l_i|\rho_h), r_h(l_i,R')|h)\big)}{r_h(l_i,R')}.$$

As a fist step we show that $r_h(l_i, R) > r_m(l_i, R)$. Since $l_i = \bar{l}(R)$ we also have:

$$\frac{w\big(D(c(l_i|\rho_m), r_m(l_i,R)|m)\big)}{r_m(l_i,R)} = \frac{w\big(D(c(l_i|\rho_h), r_h(l_i,R)|h)\big)}{r_h(l_i,R)}. \tag{28}$$

Since $r_m(l_i, R) < r^*(l_i)$ it also follows that

$$\frac{w\big(D(c(l_i|\rho_m), r_m(l_i,R')|m)\big)}{r_m(l_i,R')} < \frac{w\big(D(c(l_i|\rho_m), r_m(l_i,R)|m)\big)}{r_m(l_i,R)}.$$

If $r_h(l_i, R) = r_h(l_i, R')$ the previous three equations lead to a contradiction. It then follows that $r_h(l_i, R) < r_h(l_i, R')$ and hence $r_h(l_i, R) < r_h^*(R)$. This implies that both human and machine operators assigned to step l_i with output R are constrained: $r_m(l_i, R) = R\bar{r}_m$ and $r_h(l_i, R) = R\bar{r}_h$. From Assumption 5 it then follows that $r_h(l_i, R) > r_m(l_i, R)$. From (28) since $r_h(l_i, R) > r_m(l_i, R)$ we have that $D(c(l_i|\rho_h), r_h(l_i, R)|h) > D(c(l_i|\rho_m), r_m(l_i, R)|m)$. From Assumption 2, it follows that an increase in r will raise difficulty for the human performer more than for the machine performer. Consider now a level of output $R'' = R + \varepsilon$ with $\varepsilon > 0$ and small. Since the increase in difficulty is higher for the human performer and the gain of an increase in r is smaller for the human performer (recall that $r_h(l_i, R) > r_m(l_i, R)$) we then have that $o_i = m$ at R''. From Proposition 6 it also follows that $o_i = m$ at $R' > R''$, reaching a contradiction. ∎

4.4 Fragmentation Costs And Division of Tasks

In Section 2 we discussed how a significant source of technological change is the change in fragmentation costs. The goal of this section is to explore the relationship between changes in fragmentation costs and the implied changes in the division of tasks and changes in ability demand.

The production environment allows for an arbitrarily complex pattern of fragmentation costs. To make progress, this section considers two benchmarks: a uniform fragmentation cost case, and then an arbitrary fragmentation cost case affected by a uniform change in fragmentation costs. As a first step we show that variation in fragmentation costs over production tasks is a necessary condition for wage inequality. Without variation in fragmentation costs, step length is uniform and hence so is the ability demand for performers.

Lemma 3 *Suppose that the Assumptions of Proposition 1 and Proposition 3 hold. Consider the case in which* $f(\cdot,\cdot) = \overline{f}$. *Then* $l_i = \overline{l}$ *and* $a_i = \overline{a}$. *for all* $i = 1, \dots, T$.

Proof. Suppose not, then there exist two consecutive steps i, j such that without loss of generality $l_i > l_j$. Consider the alternative allocation with $\overline{l} = (l_i + l_j)/2$. For this allocation not to be optimal it must be the case that: $p(D(c(l_i|\rho_h), r_i|h), r_i, R|h) + p(D\big(c(l_j|\rho_h), r_j|h\big), r_j, R|h) \leq 2p(D(c(\overline{l}|\rho_h), \overline{r}|h), \overline{r}, R|h)$. The contradiction is then reached as in the proof of Proposition 1 exploiting sufficiently convex wages. The result for ability follows from Proposition 3. ■

While constant fragmentation costs do not create heterogeneity in skill demand, the level of skill is impacted by the level of fragmentation costs, even when these costs are homogeneous. As a first step we show that a general reduction in fragmentation cost leads to an increase in the number of steps.

Lemma 4 *Suppose that the Assumptions of Proposition 3 hold. Suppose also that the function* $w(\cdot)$ *and* $k(\cdot)$ *are strictly convex. Consider an arbitrary profile for fragmentation costs* f *with an associated* T *thresholds. Consider an alternative profile for fragmentation costs* f' *so that* $f'(t,\cdot) = f(t,\cdot) - \overline{f} > 0$ *for all t. Let* T' *be the optimal number of thresholds under* f'. *We have that (i)* $T' \geq T$. *Suppose now that* $w(\cdot)$ *and* $k(\cdot)$ *are sufficiently convex, then: (ii) If* f' *sufficiently lower than* f, *then* $T' > T$; *(iii) For* f' *sufficiently low, then* T' *is arbitrarily large; (iv) let* l_{min} *(*l'_{min}*) be the length of the shortest step given* T *(*T'*), then for* $\overline{f}$ *sufficiently large,* $l_{min} > l'_{min}$.

Proof. We first establish that convex $w(\cdot)$ and $k(\cdot)$ implies $p(a,r)$ is convex in length. From Proposition 3, a_i minimizing $p(a,r)$ in (9) is increasing in l, so that by Assumption $w(a)$ or $k(a)$ is convex in length. Note also that r is weakly decreasing in l, so that for $g(R,r)$ weakly increasing and convex in r, $p(a,r)$ is also convex in length. This convexity holds even if the choice of performer changes in length: take any $l_i > l_j$ such that $o_i \neq o_j$, with $w(\cdot), k(\cdot)$ sufficiently convex by assumption. Then by cost-minimization, $p(a_i, r_i|o_i) \geq p(a_j, r_j|o_j)$, so that by $p(a,r|o)$ convex in l, o_j preserves convexity of p for steps of different length. The convexity of costs in length by Assumption and Proposition 3 holds even if there exists a constant $\underline{D}$ such that $a(l = 0) > 0$. By the proposition, a is strictly increasing in l: for sufficiently convex w, any $a(l_i) - a(l_j) > 0$ ensures that $p(a,r)$ remains convex in length. For sufficiently convex $w(a)$ and $k(a)$, we can also ensure $p(a,r)$ is sufficiently convex in length.

The proof of *(i)* follows by contradiction: Suppose not. Then $T' < T$. This implies that $C(R,T'|c') < C(R,T|c')$. Since the original allocation under cost c is feasible, it follows that:

$$C(R,T'|c') = \sum_{i=1}^{T'} p(a'_i, r'_i, R|o'_i) + \sum_{i=1}^{T'} f'(s'_i, o'_i) < \sum_{i=1}^{T} p(a_i, r_i, R|o_i) + \sum_{i=1}^{T} f'(s_i, o_i)$$
$$= C(R,T|c) - T \cdot \overline{f}.$$

From the statement of the Lemma given the optimality of T we have:

$$C(R,T|c) = \sum_{i=1}^{T} p(a_i, r_i, R|o_i) + \sum_{i=1}^{T} c(s_i, o_i) \leq \sum_{i=1}^{T'} p(a'_i, r'_i, R|o'_i) + \sum_{i=1}^{T'} c(s'_i, o'_i)$$
$$= C(R,T'|c') + T' \cdot \overline{f}.$$

Combining the two previous equations we get $0 < \overline{f} \cdot (T' - T)$, reaching a contradiction if $T' < T$.

The proof of *(ii)* and *(iii)* follows the proof of Proposition 1: First note that $l_{min} \leq \frac{\bar{v}}{T}$. If not $\sum_{i=1}^{T} l_i > \bar{v}$, reaching a contradiction. From *(iii)* for sufficiently high f', we have we have T' sufficiently greater than T to ensure $l_{min} > l'_{min}$.

■

The previous Lemma enables us to determine the changing demand for ability as fragmentation costs change. As fragmentation costs decrease, an immediate implication of Lemma 4 and Proposition 3 is a decrease in the lowest ability demanded. The following corollary formalizes this statement.

Corollary 1 *Suppose the Assumptions of Lemma 4 hold. Consider an arbitrary profile for fragmentation costs* f*. Consider an alternative profile for fragmentation costs* f' *so that* $f'(t,\cdot) = f(t,\cdot) - \overline{f}$ *for all t. Let* a_{min} *and* a'_{min} *be the lowest ability demanded under fragmentation cost* f *and* f'*, respectively. If* f' *sufficiently lower than* f*, then* $a'_{min} < a_{min}$*.*

The last result in Lemma 4 shows how a sufficiently large reduction in fragmentation costs results in a decrease in the minimum step length. There is not an equivalent property for the maximum step length in a process. Indeed it is possible for the maximum step length to increase due to an increase in T, even if the total cost of production decreases. The following example makes this point.

Example 2 *In this example we show how it is possible for the longest step length to increase as the number of steps increases. Let fragmentation costs be arbitrarily high for all t, except for three points,* t_a, t_b, t_c*, with* $f(t_a,\cdot) = f(t_c,\cdot)$ *and let* $f(t_b,\cdot) = f(t_a,\cdot) + d$*, with* $d > 0$*. Let* $t_a < t_c - t_b$ *and* $t_b > \frac{\bar{v}}{2}$*. For* $T = 1$ *we have* $s_1 = t_b$*, the more centrally located cut. This is the case whenever the convexity of costs with respect to length dominates the higher fragmentation costs at* t_b*.*

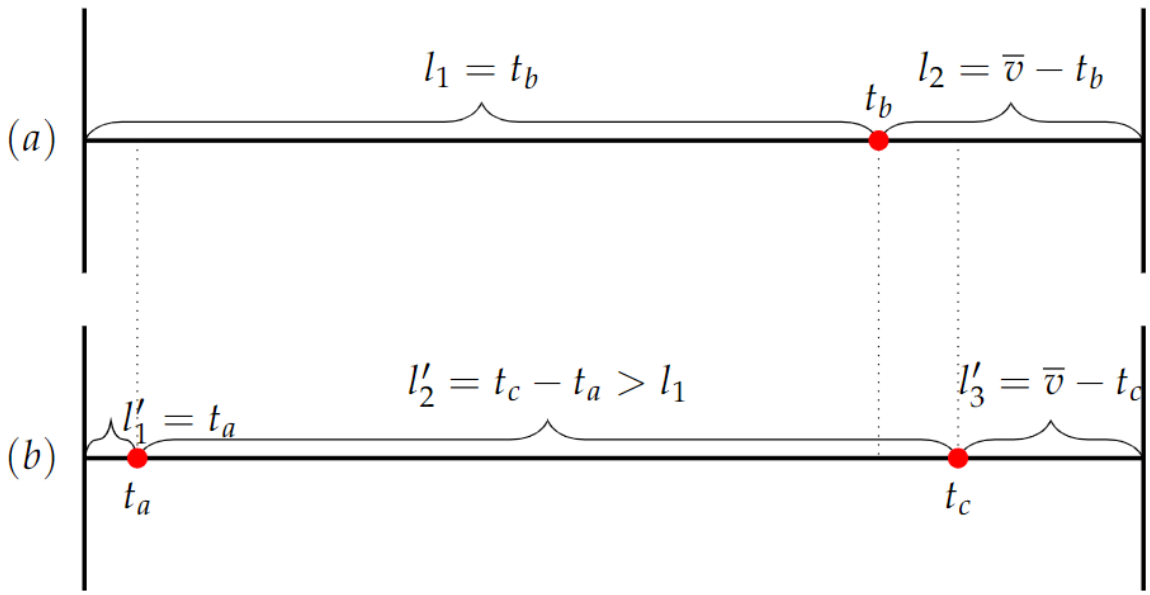

Figure 15 Maximum Step Length and T. (a) Case T=1, (b) Case T=2.

For $T = 2$ we have $s_1 = t_a$ and $s_2 = t_c$. This occurs if the reduction in performer costs from placing step thresholds at t_a, t_b or t_b, t_c relative to t_a, t_c are less than a. Figure 15 summarizes the example when $T = 1$ and $T = 2$. The parametric scenario with $p(l) = l^{1.088}$, $t_a = .4, t_b = 7, t_c = 7.5, \bar{v} = 10, d = 0.05$ delivers the required properties for the example.[61]

While the effect of a change in fragmentation costs on the maximum step length is indeterminate under arbitrary conditions, we can place additional structure on fragmentation costs to restrict the effects on maximum length. If there exists any interval of tasks $V = [t_i, t_j]$ such that $f(t)$ is arbitrarily high for $t \in V$, then the maximum step length will never be less than $t_j - t_i$. In this case we refer to V as a set of *lumpable-tasks*. It is natural to think of maximum step lengths being defined by regions of tasks which are indivisible or have arbitrarily high fragmentation costs, such as in highly controlled processes (e.g. material deposition as described in Combemale, Whitefoot, Ales and Fuchs (2021), continuous processing (e.g. in steel production as in Goldin and Katz (1998)), or highly interconnected tasks (e.g. indivisible loads in computing as in Berenbrink et al (2015)). Under this additional structure, maximum step length is insensitive to reductions in fragmentation cost, while the minimum step length is not. It is thus possible for technological changes to affect the upper and lower bounds of step complexity independently. These independent effects, as we show next, allow for technological changes that change the difference between the least and highest ability demand.

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[61] Formally, we require t_a, t_b, t_c be such that $p(t_b) + p(\bar{v} - t_b) < \min\{p(t_c) + p(\bar{v} - t_c) - a, p(t_a) + p(\bar{v} - t_a) - a\}$. Let t_a, t_c be such that $p(t_c - t_a) + p(\bar{v} - t_c) < p(t_c - t_b) + p(\bar{v} - t_b) + a$ and $p(t_c - t_a) + p(t_a) < p(t_b - t_a) + p(t_b) + a$.

Changes in Issue Arrival

Important historic technological changes have simultaneously affected the complexity and divisibility of processes.[62] Within the framework presented in this paper these technological changes can be described by a simultaneous change in fragmentation costs f and in the parameter governing the average number of issues λ. [63] In what follows, we consider the ability demand implications of a change in technology which increases issue arrival and sufficiently decreases fragmentation costs. We show that this change generates an increase in the upper bound of ability demanded and hence upward pressure on the highest wages in labor market equilibrium.

Corollary 2 *Suppose that the Assumptions of Proposition 3 hold. Suppose there exist a set of lumpable tasks $\hat{V}$ of length $\hat{l}$. Suppose also that under issue arrival λ, the maximum step length is $\hat{l}$. Consider an issue arrival $\lambda' > \lambda$. Let a_{max} and a'_{max} be the lowest ability demanded under fragmentation cost λ and λ', respectively. If the performer for the longest step remains the same, we then have $a'_{max} > a_{max}$.*

Proof. Since $\hat{V}$ is lumpable, the maximum step length cannot be smaller than $\hat{l}$ under any technological change. From the definition of complexity in (2) we observe that step length and issue arrival are perfect substitutes in their effect on complexity. The result then follows the proof of Proposition 3 substituting changes in l with changes in λ. ■

The previous Corollary requires a constant performer type for the longest step. If the longest step is sufficiently long, then by Proposition 4 this Assumption is automatically satisfied, as human performers are assigned to this step before and after the change in issue arrival rate.

The previous Corollary together with Corollary 1 imply that in the presence of technological change that simultaneously lowers fragmentation costs and raises issue arrival, we will expect an increase of within-plant inequality. Together Corollary 1 and 2 provide a theoretical basis to understand how within-firm inequality might increase or decrease given different types of technological change.

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[62] For instance, the development of the assembly line in manufacturing permitted a much finer division of tasks but entailed a more complex overall process with greater logistical and managerial requirements (Hounshell (1985), Chandler (1990)). The more recent phenomenon of design modularity in programming and other design allows for easier separation of work but increases system complexity (Baldwin, 2008). The inverse of this trade-off is also possible. In modern manufacturing, parts consolidation, when formerly discrete parts are fabricated as one piece, makes dividing tasks more costly but also reduces the number of issues that might arise in assembly (Selvaraj, Radhakrishnan and Adithan, 2009; Combemale, Whitefoot, Ales and Fuchs 2021).

[63] Technological change affecting multiple dimensions are also intuitive from an adoption perspective. For example, a firm will not adopt a technology increasing fragmentation costs or issue arrival without an opposing effect reducing costs, such as reduced fragmentation cost or fewer issues.

5. Empirical Analysis

In this section, we provide empirical counterparts to the theoretical results of the preceding section. First, increasing complexity of production requires performers with higher ability working at lower rates. Second, a reduction in fragmentation costs leads to an increase in the number of steps. Third, a reduction in fragmentation costs and an associated increase in issue arrival rates leads to an increase in the upper bound of ability demand, and a decline in the lower bound of ability demand. Fourth, a cone of automation forms where automation substitutes for workers of middle ability at low volumes, and the range of ability substituted widens as volume increases until automation substitutes for all but high ability.

5.1 Data Sources

In this section we use three datasets. Each dataset used provides detailed information on production operations. The three datasets are the *Hand and Machine Labor Study* of 1898; data on optoelectronic semiconductor manufacturing taken from (Combemale, Whitefoot, Ales and Fuchs, 2021); and data on contemporary auto-body assembly taken from (Fuchs, Field, Roth and Kirchain, 2008).

The Hand and Machine Labor Study.

The first dataset comes from the Hand and Machine Labor (HML) study (Wright, 1898).[64] The original data collection for this study was conducted by the Bureau of Labor Statistics between 1894 and 1898, with the goal of investigating the effect of the use of machines on labor. The study covers 672 products across the agricultural, manufacturing, mining, and transportation sectors. Detailed descriptions are provided for all products, which vary from harvesting hay to watch manufacturing to road repair and cargo loading. Processes range from one step to hundreds. Every step of every production process is coded in the data in terms of its motive power (e.g. hand, steam, water). Every product recorded in the hand and machine labor study is produced by exactly two separate processes: a "hand" process (a process that is relatively more manual), and a "machine" process (a process that is relatively more mechanized). The two processes represent a change in process structure and performer type to produce the same good with identical characteristics.[65] The data characterizes each process step-by-step, analogously to the structure of steps in our model: for example, the hand process for producing hay consists of 1) mowing grass, 2) tending hay, 3) raking hay, 4) cocking hay, 5) hauling hay, 6) bailing hay and 7) weighing hay. The data includes the occupations employed in each step, the number of employees for each occupation for the step, the task content of the step and the motive power used in the step (e.g. hand, or different types of machine power such as water, steam, or electricity). Wages and operations data consist of the time worked per step cycle, the output per cycle of a process step, the number of workers required per step and the number of workers required per workstation. Each process step has a detailed task description, and coding to identify which step (or steps) in the hand process contains the same

[64] The dataset is also described in Atack, Margo and Rhode (2019).

[65] The original authors note rare exceptions, such as slabs of granite of different final weight or an 8-inch versus 9-inch pipe. These products are of the same composition, but different dimensions.

tasks as the machine process. For example, the machine process for making a sleigh (Product 183) includes steps coded 2 and 3 for sanding panels and setting up the sleigh body, while the hand process has a step for setting up and sanding the body, coded as (2,3) to indicate that it contains the same tasks as the other process but combined into one step. Refer to Appendix 8 for further details on this unique dataset.

Direct Measurement of Production

The remaining two datasets are direct measurement of plant-level production processes. This data is collected to identify the technical parameters of a highly detailed production model. These models, called Process Based Cost Models (PBCMs) in the industrial engineering and operations literature, are used across a variety of industries to inform engineering and production decisions. PBCMs describe the production of a single product in individual process steps and map characteristics of the product design (e.g. geometry) and process design (e.g. level of automation) to production outputs. This modeling approach provides the additional benefit of isolating the effects of technology changes at the level of individual process inputs, for example the effect of using a human or a machine to perform a specific production step on output. See (Combemale, Whitefoot, Ales and Fuchs, 2021) not for a detailed description of these models and the data collection process.

Optoelectronic Semiconductor Manufacturing

The first production process is the production of optoelectronic semiconductor transceivers for communications. We use data from the fabrication of semiconductor components to their assembly into a final package. The optoelectronic semiconductor industry is a useful case study for the effects of technology change because optoelectronic transceivers have a common form factor and end-use, so that they are functionally homogeneous while varying significantly in their internal design and method of production (i.e. in terms of the technological parameters in our theory). The optoelectronic semiconductor manufacturing dataset was originally collected and presented in (Combemale, Whitefoot, Ales and Fuchs, 2021). This dataset allows us to compare step-level demand for worker skills (captured using the same methodology as the O *NET database) under different technological scenarios. These scenarios vary in the level of automation and the level of consolidation of product designs (increasing in the number of internal components which are jointly fabricated).

Automobile Body Fabrication and Assembly

The final dataset is from automobile body fabrication and assembly. This dataset was originally collected and presented in Fuchs, Field, Roth and Kirchain (2008). The data which we use in this paper characterize process flow and step-level process inputs for automobile body assembly. For each assembly process step, the data includes capital and labor inputs (demand, price) for each process cycle as well as operations parameters, specifically batch size and cycle time. The dataset also includes data for each step on the number of welding joins required for each part of the automobile body.

5.2 The Relationship Between Ability, Rate and Complexity

In this Section, we use the optoelectronic semiconductor and automobile body production data to provide an empirical analogue to Proposition 3, which relates rate (r) and ability (a) to step length (l). Following Remark 1, we use value added per step as a proxy for step length (this approximation relies on the second result in Proposition 3 relating ability and step length: longer steps have higher performer costs and hence higher value added). Assuming a competitive market for inputs and outputs (see (Combemale, Whitefoot, Ales and Fuchs, 2021) for discussion of competitive market assumptions in optoelectronic semiconductor manufacturing), we calculate value added per step from the cost of labor and capital inputs to produce a unit of output from a step. Human performer costs are given by the compensation of workers divided by the worker time needed per unit output. Machine performer costs are given by the cost of the machine used, scaled by the time of use per part and the length of service life of the machine. The empirical results from both contemporary contexts, presented in Figure 16, are consistent with Proposition 3 by showing that rate is decreasing in step length. In the optoelectronic semiconductor context, the same wire-bonding machine takes longer to complete more complex configurations while preserving the same proportion of successful versus failed outputs. In the automobile body assembly context, more complex welding operations require more expensive machines (see Figure 15 in Appendix 10) or require the same machines to operate more slowly (in the case of human operators more complex steps are often associated with more expensive tooling).

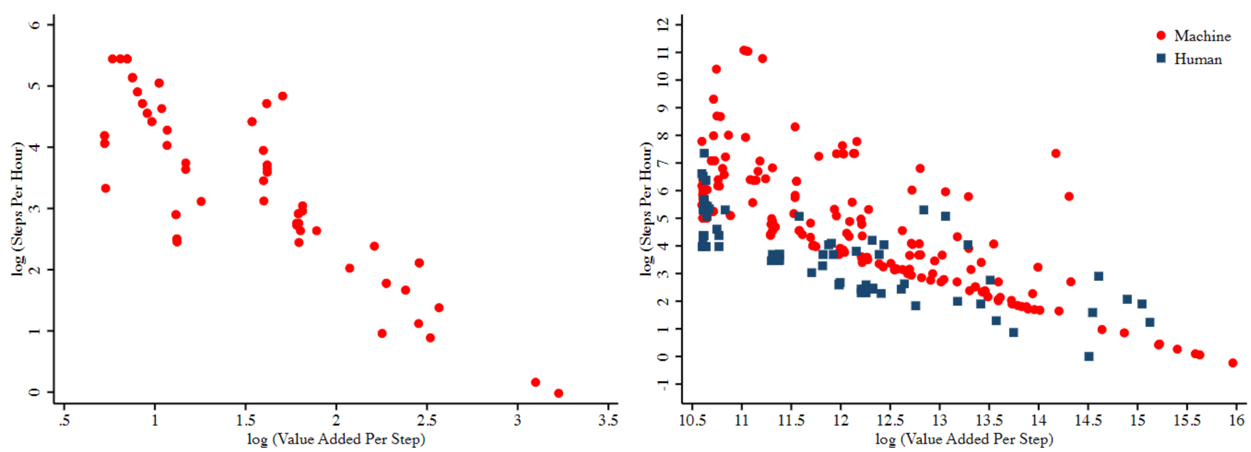

Figure 16 Log rates of production steps of increasing log value added. Data for (a) is from Fuchs, Field, Roth and Kirchain (2008). Data for (b) is from Combemale, Whitefoot, Ales and Fuchs (2021).

We next use the step-level worker dexterity skill measures from the optoelectronic semiconductor data to explore the relationship between a and l. Recall that Proposition 3 provides conditions in which a is strictly increasing in l. For this exercise, we proxy step length l on value added, specifically the value added by human performers from wage-costs per unit output.[66] In practice, production activity is shared in many steps between humans and machines, so to isolate the relationship between l and human ability demand we consider only steps in which human labor costs are at least 70 percent of value added (the following results are robust to reducing minimum value added share to 60 percent). We compare across all steps in the dataset which have either a dexterity ability-level rating of 1 (the lowest value) or a level of 5 (the highest value recorded in the data).[67] For context, level 1 indicates that the task is easier than putting coins into a parking meter, and level 5 means that it is harder than assembling small knobs onto stereo equipment in an assembly line. The distribution of labor costs associated with steps of high and low skill is consistent with Proposition 3 that highlights a negative relationship between ability and length. We have that average labor cost per unit for the low-skill steps (19 observations) is \$0.19, while the average labor cost per unit for the high-skill steps is \$0.52.

5.3 Fragmentation Costs and Division of Tasks

The time period covered by the HML dataset is characterized by a reduction of fragmentation costs.[68] This dataset thus offers a useful empirical counterpart to the results of Section 4.4. As a first step we look at how the historical general reduction in fragmentation costs leads to changes in the number of production steps. In the HML dataset we look at mappings between hand and machine process steps to capture intervals which are affected by an increase in the division of tasks (for detailed information on the processing of data, refer to Appendix 9.2). We focus on the overall distribution of step lengths across all processes, because the HML dataset does not contain direct information on the fragmentation costs for each process. The results are displayed in Figure 17.

[66] Due to limitations of the data, we use a constant operator wage across all steps based on the average at each plant.

[67] As a check for robustness to skill type, we also performed a comparison between all steps whose maximum skill was 1 across the skills captured in the data (operations and control, dexterity, near vision) and steps whose maximum skill was 5. We found comparable results.

[68] For a historical account of the implications of technological change on manufacturing refer to Hounshell (1985) and Chandler (1990).

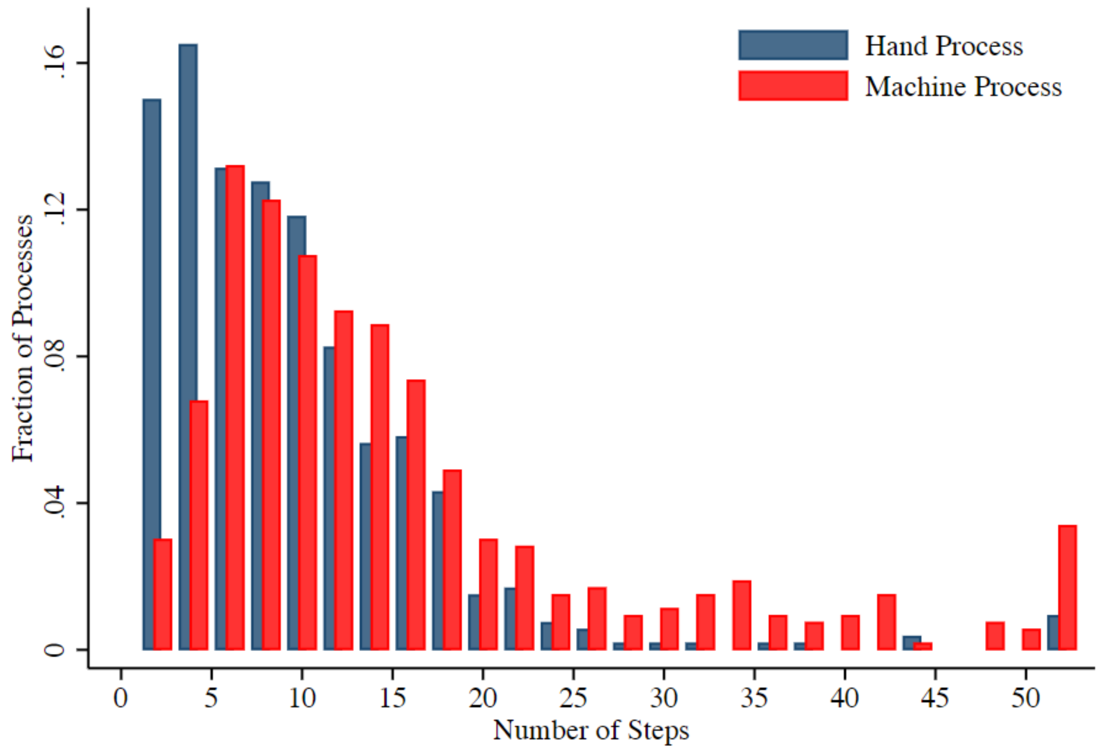

Figure 17 Fragmentation costs and step divisibility. (HML data).

The figure displays a reduction in the number of processes that feature a small number of steps, consistent with the increased division of tasks provided by Lemma 4. In the context of our theory (see Lemma 4) this phenomenon is rationalized by a reduction in fragmentation costs.

We next move to wages. Figure 18 is based on the HML data set. In this figure we restrict the analysis to steps with constant performer type (i.e. manual motive power regardless of whether the process is characterized as a hand or machine process). The figure displays the moments of four distinct distributions. With the leftmost two box charts, we compare the distribution of relative wages for tasks in which changing from the hand to the machine process does not incur changes in number of steps to perform those tasks (constant T). Relative wages are calculated using the wage of a performer divided by the average wage in their empirical plant.[69] With the rightmost two box charts, we look at the case of tasks for which changing from the hand to the machine process leads to an increased number of steps (T increasing). In either case we compare the distribution of relative wages in the case of hand and machine processes.

In Figure 18 the behavior of wages and ability is consistent with Corollary 1. For the case of increasing T, we observe a decrease of the lowest wages. As wages are monotone in abilities

[69]We use relative wages to narrow in on plant-level distributions of wage and (indirectly) ability demand, as automation decisions occur within production plants.

this also suggests a decrease of ability demanded.[70] The Corollary emphasizes how in the presence of decreasing fragmentation costs we expect downward pressure in demand for the lowest skills. To confirm that the changes in wages are indeed driven by changes in the number of steps, in the left panel we also consider products for which the number of steps did not change as the process moved from hand to machine. In this case, the widening of the distribution of relative wages is much smaller than the case of increasing T.

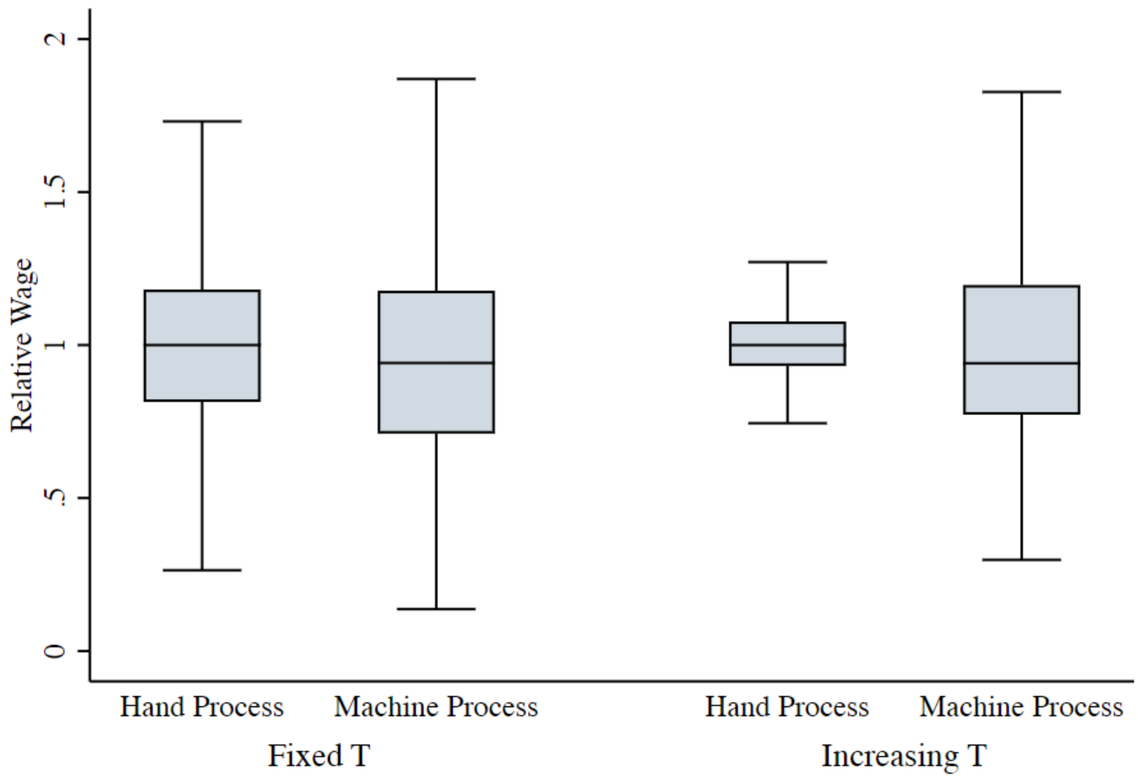

Figure 18 Fragmentation costs and wages. (HML data).

In Figure 18, for the case of increasing T, we also observe an increase in the relative wages at the top. Following the result in Corollary 2, this phenomenon can be rationalized by an increase in issue arrival.

The HML dataset has the advantage of covering a variety of different industries and products. A downside is the lack of precise controls on the nature of fragmentation cost and lack of precise measurements of ability levels. To overcome these limitations we next look at the data from the optoelectronic semiconductor and automobile assembly. This modern production data allows for direct observation of ability and precise control over the changing nature of the process as fragmentation costs and average number of issue change. The optoelectronic semiconductor production data features adoption of different levels of

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[70]This pattern appears in direct industry observations. For example Womak, Jones and Roos (1990) confirm the shortening of steps as the Automotive industry moved away from the hand process. The cycle time of workers between 1908 and 1913 decreased from 514 to 2.3 minutes. Similarly the training required for workers declined also to a few minutes.

automation and consolidation. For all levels of automation and consolidation, the final products are functionally homogeneous and perfect substitutes on the market. Changing the level of consolidation of the design drives step consolidation: the more consolidated the design, the fewer the step thresholds (T). Consolidation of parts leads to an increase in fragmentation costs (f) but also a reduction in assembly requirements, captured in our theory by reduced issue arrival (λ). The case of consolidation allows us to look for an empirical analogue of Corollary 1 and Corollary 2 for constant performer type. Taking these two Corollaries together, we expect a convergence in ability demand (decline at the top and at the bottom), as fragmentation costs increase and issue arrival decrease (this is the opposite scenario as the one studied in the HML dataset). We use the skill-ratings collected for each step by (Combemale, Whitefoot, Ales and Fuchs, 2021) as a measure of a. Holding performer type constant across levels of consolidation, Figure 19 shows the effects of two changes in consolidation (from low to medium consolidation and then from medium to high consolidation) on the distribution of skill demand. We see that with consolidation skill demand converges toward middle skills. This is similar to the convergence in ability demand predicted by Corollary 1 and 2.

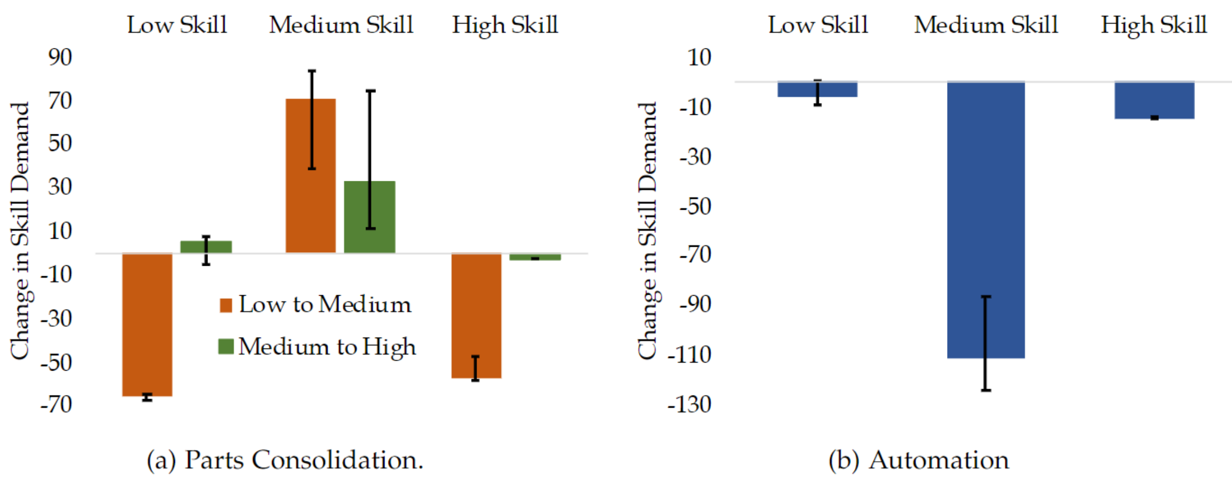

Figure 19 Impact of technological change on skill demand.
Data from (Combemale, Whitefoot, Ales and Fuchs, 2021).

5.4 Automation

The next set of empirical results relates to which steps in a production process are most likely to be automated. The results in Section 4.3 provide guidance on what steps are more likely to be automated when considering steps of different length or production processes with different levels of output. Together, the results of Section 4.3 describe what we refer to as a *cone of automation* where automation is more likely for higher level of output and for middle length steps (see Figure 14). In the following section, we consider the HML data and the optoelectronic semiconductor to find evidence for this pattern of automation. We also use the connections between our theory and HML empirics to suggest insights for understanding the finding from aggregate data presented in the introduction that low utilization industries experienced polarization of occupational demand in the period 2000-2019 while high utilization industries experienced a more "upskilling" shift toward high wage occupations.

We begin with the HML dataset. Ideally, to look at an empirical analogue for Figure 14, we need precise measurement of step length and observations of the production process at different output levels. The HML dataset provides a proxy of step length using wage data; in our theory, the longer the step, the higher the ability demanded for a constant performer type (e.g., human), and so the higher the wage. Unfortunately a process is observed at only one output level. Nevertheless, the HML dataset can be used for an empirical counterpart of Figure 14. The key insight, described below, is to use the capacity utilization of each step as a proxy for the overall output level. The variety of processes observed across different products (correctly scaled) then provides variation in capacity utilization across steps. Before proceeding note that Figure 14 describes strict upper and lower bounds on automation for a given set of structural parameters. In the approach that follows, we compare different products in the HML dataset. Intuitively, the different products are heterogeneous in the production structural parameters (for example, they might differ in ρ or σ). Given this unobserved heterogeneity we expect to observe a probability of automation that varies as we vary wages and capacity utilization as opposed to a strict demarcation.

In the model, changes in R impact the firm choices by affecting the cost of performers. This occurs through the function $g(\cdot,\cdot)$. As can be observed in Assumption 3, the role of R is symmetric to the role of the minimum divisibility threshold of the performer $\overline{r}$. So that an impact of an increase in R can be achieved by an increase in $\overline{r}$. With this logic, the results of Section 4.3 and the pattern in Figure 14 can be recast in terms of $\overline{r}$ as opposed to R. The intuition for the existence of $\overline{r}$ is that performers are underutilized. We develop a proxy of how close performers are to $\overline{r}$ by their level of utilization: if a worker is highly underutilized, then it is likely that so will be a machine, and the constraint on r^m will bind as in Proposition 6 and 7. This reasoning is helpful since the HML data, while not providing observation for different R allows us to recover the utilization of each performer in each process. We can then look at each manual step and determine how close the rate of the operator is to the minimum divisibility threshold. Using the same logic as Section 4.3, steps with high capacity utilization of human performers are more likely to be automated.

Wage Bin	1	2	3	4	5	6	7	8
8	17%	29%	17%	25%	30%	33%	44%	40%
7	25%	21%	35%	14%	47%	58%	63%	74%
6	25%	52%	50%	40%	52%	48%	58%	93%
5	17%	N/A	30%	57%	63%	40%	78%	91%
4	35%	60%	56%	70%	62%	68%	76%	91%
3	38%	53%	59%	44%	67%	68%	91%	91%
2	39%	42%	40%	35%	72%	71%	76%	77%
1	30%	41%	40%	41%	29%	65%	65%	64%

Step Utilization Bin

Figure 20 Patterns of automation over wage and utilization bins. Numbers in each cell denote the percentage of steps automated in each step. (HML data).

We next briefly describe how $\overline{r}$ is identified in the HML data (see Appendix 9.2 for additional details). The dataset provides information on the number of workers involved in a step and the amount of time the step requires in order to be completed. For each process, following (Hopp and Spearman 2011), we identify the bottleneck in production by looking at the step that requires the longest time to be completed. We determine the fractional utilization of a step by comparing its completion time to the completion time of the bottleneck. For example if a bottleneck requires 10 hours to be completed and a preceding step requires 1 hour to be completed, the fractional utilization of the preceding step is 1/10. Finally using the information on the number of performers on a given step we recover the fractional utilization of performers in a step. In the previous example, if the step has two workers assigned to it, it implies that the fractional utilization of performers in the step is 1/5 of a worker. This fractional performer utilization rate can be compared across steps and across processes and is used as one of the two key drivers for automation in Figure 20.

The second dimension driving automation in Figure 14 is step length. The connection of this dimension to the data is more straightforward. Proposition 3 establishes a direct relation between step length and ability. As ability is not observed in the HML dataset we proxy this characteristic using worker wages (in the optoelectronic semiconductor data below we instead directly observe ability). For each production process, wages for each step are normalized by the average wage observed in that process.

In the HML dataset, for each product we consider pairs of steps with identical task content between the hand and machine processes. We select steps from hand processes that were performed manually. We then measure whether a step has been automated in the machine process using a binary indicator of a change in motive power.[71] Figure 20 displays the results. In the figure, each cell is ordered in terms of percentile of performer utilization and wage of the performer. The number in each cell denotes the percentage of steps in each range of utilization and wage that is automated. As expected from Figure 14, the pattern that emerges displays characteristics of a *cone of automation*: automation occurs more often at middle wage steps, and the range of middle wage steps that are likely to be automated becomes progressively larger for higher utilization steps. Intuitively, the most automated steps in the HML data are the ones in which a large fraction of worker time is devoted to a step thus allowing a machine in that step to be less rate-constrained. Additionally automation is more likely when wages are not too high or too low (so that machines are not executing a too complex step and as before are not rate-constrained).

The application of the aggregate trends described in Figure 13 to the HML case also gives potential insights into the differences in occupational demand change between high and low utilization industries in Figure *13* in the motivation section. In keeping with Figure 14 from our theory and the relationship between utilization and rate constraints described above, we would expect industries with high levels of utilization to be further along the cone of automation than industries with low levels of utilization. This difference would imply that given

[71] We do not observe any instances of a hand step shifting to a less mechanized form of motive power in the equivalent step in the machine process. For additional details refer to Appendix 8.2 and 8.3.

exposure to new automation technology, low utilization industries would tend to see labor substitution at middle wages, shifting the share of demand toward low and high wage jobs. While we do not measure exposure to information technologies or other possible sources of automation in Figure *13*, the change in occupational demand share for lower utilization industries is consistent with this feature of the theory. Our theory would also predict that higher levels of utilization should mean substitution across a broader range of wages, first driving demand toward the lowest and highest wage jobs and ultimately toward the highest wages. Again, we see this pattern in the change in occupational demand from 2000 to 2019, so that our theory could help explain the difference in demand evolution across industries.

We next turn to optoelectronic semiconductor data. In this dataset we observe different production scenarios with different levels of automation.[72] This level of detail allows us to precisely determine if a step has been automated or not. In addition, the available data allows us to determine the ability of each operator without relying on data. The data provides information on ability levels as defined in the O *NET database.[73] In Figure 19 we display the results as we move from a low to medium level of automation. The data displayed is for a single output level. This figure can then be considered as a vertical slice of Figure 14 in a region where automation occurs. The vertical axis denotes the number of displaced workers being automated at a given skill level. As anticipated by our theory, the impact of automation is more evident for middle-skill workers.

6. Concluding Remarks

In this paper, we provide a general theory relating technology change and labor demand. We emphasize three dimensions of the problem of the firm which are affected by technology change: the ease of fragmenting the production process into smaller steps (with associated changes in process complexity); the costs of allocating the same performer (human or machine) to multiple steps; and the trade-off between step complexity and rate of completion, where humans tend to solve more complex steps than machines but tend to have a slower completion rate.

We find that implications of the theory are supported by empirical evidence across a wide range of technologies and industry contexts from the late 19th century and contemporary production. Human performers are favored against machines in high complexity steps, or at low output quantity, so that automation has a polarizing effect on skill demand at low output and an upskilling effect at higher output. The theory also offers insights for understanding aggregate changes in occupational demand not anticipated or explained by prior theory, such as the differential patterns of demand polarization versus upskilling in low versus high utilization industries. Technology changes that reduce fragmentation costs and increase process complexity can increase the spread of labor abilities demanded. Such technological changes put

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[72] The change in level of automation is characterized using a taxonomy of automation, For additional details refer to Combemale, Whitefoot, Ales and Fuchs (2021).

[73] A skill of 1 is rated low, a skill of 5 or greater (levels 6 and 7 were not observed) high, and 2-4 medium. As shown in Combemale, Whitefoot, Ales and Fuchs (2021), this result is robust across different types of skills and without aggregation of skill rankings.

upward pressure on wage inequality. Conversely, we also find that technologies that increase fragmentation costs and lower complexity reduce the spread of labor abilities demanded, putting downward pressure on wage inequality.

The theory offers multiple broad insights for technology change and the division of labor. First, the division of production into different steps is the origin of heterogeneous ability demand. Heterogeneous ability demand will not occur unless some steps are more costly to divide than others, and technological change can affect wage inequality by altering these fragmentation costs. Second, as machines become more divisible (e.g. through cloud computing), the effect of automation becomes less skill-polarizing and more upskilling. Third, the singularity point where all human labor is replaced by machines occurs when machines are general enough and cheap enough such that they no longer have a relative disadvantage in solving complex problems nor simple problems compared to humans, even in low output production processes.

The theory also offers a unified explanation of technological change, capable of rationalizing a large number of empirical regularities observed in empirical data. In Table *7* we provide a mapping between major technological trends of the last two centuries captured empirically in this paper and deep parameters and functional forms of our model.[74] Based on the theory, a taxonomy of technology change can be developed. A technology change may be described in terms of its effects on process complexity (λ), task separability (f) and performer characteristics such as divisibility (g), sensitivity of performers to rate (related to σ) and generality (related to ρ). The classification of technology changes into their effects on these parameters suggests the resulting impacts of the technology on labor demand.

Table 7 General Theory Applied to Empirically Captured Technology Changes

Technology Change	Period	Theory Interpretation	Labor Impact
Mechanization: Substitution of human performers by machines	1870s-1890s	Machine performers repeat tasks faster than humans but unable to perform highly varied work: $\rho^m < \rho^h$ and $\sigma^m < \sigma^h$. Machines less divisible than humans, $\bar{r}_m < \bar{r}_h$.	Human ability demand polarized. Empirically: growth of higher skill professional jobs (Chandler 1990), more demand for unskilled labor (Atack, Margo and Rhode 2019)
Interchangeable Parts and Assembly Line: Increased standardization of parts and process to facilitate transfer of	1870s-1910s	Increased process complexity, leading to $\lambda \uparrow$, but facilitation of transfer and reduced post-processing of parts driving $f \downarrow$	Upper bound of human ability demand increases, lower bound of demand decreases. Empirically: creation of new managerial jobs and of

[74] A more extensive table of technologies whose labor implications as documented in the literature match the theory (but without corresponding empirical analysis in this paper) is provided in Appendix 12.

work and minimize refitting requirements			very simple production jobs. (Hounshell (1985); Womak, Jones and Roos (1990))
Consolidation of Parts: Formerly discrete parts fabricated as one	1970s-2010s	Joint fabrication of parts makes some fabrication tasks indivisible, driving $f\uparrow$, allows simpler design and reduced assembly, driving $\lambda\downarrow$	Upper bound of human ability demand decreases, lower bound increases. Empirically: convergence of skill demand from low and high to middle, reduced division of production (Combemale, Whitefoot, Ales and Fuchs, 2021)
Automation and Computerization: Substitution of human labor by computer and machine performers	1960s-2010s	Machine performers able to repeat tasks faster than humans but unable to perform highly varied work: $\rho^m < \rho^h$ and $\sigma^m < \sigma^h$. Compared to mechanization, performers are more general ($\rho\uparrow$), intense ($\sigma\downarrow$) and divisible ($\bar{r}\uparrow$)	Polarization of worker ability demand at low volumes, shifting to high skill at high volumes. Empirically: up-skilling of skill demand (especially in manufacturing), aggregate polarization in conjunction with lower automation in services (Goos, Rademakes, Salomons and Vandeweyer (2019); Willcocks and Lacity (2016))

While the model is rich enough to model the skill demand implications of an unprecedented variety of technology changes, we also anticipate a number of extensions. A natural extension is to relax the assumption in the model that firms set their ability demand to ensure that a step is completed in expectation. This extension would allow firms to choose ability greater or less than difficulty at the cost of higher or lower successful completion (e.g., yield) rates. This extension could help explain certain empirical cases where high costs of failing to solve issues in a specific step would warrant higher demand for operator ability so that failure is less frequent. An additional extension could be imposing additional costs associated with the reorganization of a process. This extension would allow us to distinguish the effects of technology change with and without process reorganization, and could be extended to understand the incentives for different strategies of technology adoption across different firms or regions.

Chapter 3: How Task Characteristics Affect the Automation of Steps

1. Introduction:

This chapter refers to and offers an extension on the model described in "How It’s Made." An important feature of the model given in Chapter 3 is the ability to explain differential task-performer complementarities. It is widely observed that while machines are competitive with humans in many physical tasks, they are not currently competitive in many social tasks. The model as currently constructed could account for this difference in terms of different characteristics of tasks and the contexts in which they are performed. Most basically, if the number of issues (issue arrival rate) is greater for social tasks than physical tasks, then we would anticipate a lower rate of automation.

If social tasks are generally less divisible than physical tasks, high fragmentation costs could explain why machines are more competitive in physical roles. Similarly, an occupation with tasks that have low fragmentation costs would be more susceptible to automation than one with high fragmentation costs. If the volume of production differs significantly across task contexts, it could also drive differential rates of automation for different types of tasks in the model: note for instance that customer support tasks such as directory assistance experienced high automation despite being social (e.g. Premkumar et al. 2002)

Another feature of tasks discussed in the literature (Autor and Dorn 2013; Bessen 2016) is whether they are "routine," with the relevant prediction that routine tasks are more readily automated. It is possible to reflect this conception in the model by changing the variance of the number of issues in tasks. As we show next, the properties of performer generality and our assumptions on performer price suggest that a more generalist performer should become more cost-effective relative to a less generalist performer as the variance of number of issues increases, even as expected number of issues remains constant.

To study the implications of greater variance in the number of issues, we analyze how performer generality affects the curvature of complexity in number of issues. We show in the following lemma that the difference in complexity between low and high generality performers is convex in the number of issues, for sufficiently high n. This property will allow us to show in a subsequent proposition that high variance in number of issues changes the difference in expected complexity between high and low generality performers and hence changes the cost of using humans or machines.

2. Model

This section builds on the model described in Combemale et al (2022: How It’s Made), with specific departures noted throughout. The extension made herein capture how issues of different types may occur depending on the type of task to be performed, with associated types of difficulty and performer ability to characterize differences in performer demand from new technology (e.g. effects of automation).

Each task has a type $\psi(t) \in \mathcal{N}$, belonging to the set Ψ. Within a step, issues arise for each type of task according to the random process described in Sections 3.1 and 3.2 Combemale et al

2022, giving n^{ψ} issues of given type with magnitude X_i^{ψ} for $i = 1,..,n^{\psi}$. The span of tasks of type ψ in a step is given by a type-specific length l^{ψ} with a corresponding expected complexity value $c(l^{\psi}|\rho)$ and hence difficulty D^{ψ}. Each performer, in turn, has an ability associated with each type given by a_j^{ψ} for performer j, with a vector of abilities A^{Ψ}. A step is not completed if performer ability of any type is less than difficulty of the corresponding type.

For analytical progress in some cases, we call on two assumptions of independence across task type: firstly that issues across types are independent in their number and magnitude, and second that wages or capital prices are increasing in ability of all types, and that greater ability of one type weakly increases the derivative of price with respect to other types of ability.[75]

Assumption 1 *The number of issues n^{ψ} and issue magnitudes x^{ψ} are independent across different task types ψ*

Assumption 2 *Performer price is given by $w(A^{\psi}) = k(A^{\psi})$, increasing in a^{ψ} for all ψ and with $\frac{dw(A^{\psi})^2}{d\psi_i d\psi_j} \geq 0$ for all i,j*

To make analytical progress, we will define a random variable $Y \in \mathcal{N}$ with mean 0. "High variance" steps will have number of issues $\hat{n} = n + Y$. Let $E(n)$ be sufficiently high that $p(\hat{n} < 0) \approx 0$.[76] In the following proposition, we consider two steps of equal length, one of high variance and the other not, analogous to the idea of non-routine and routine work.

Remark 1 *The model could be further extended to make variance a property of tasks rather than steps: each task has a type $\psi(t) \in \mathcal{N}$ with a corresponding random variable $Y(\psi)$ with mean 0 and different variance for all ψ (and a constant $Y(0) = 0$ as a baseline level of issue variance in tasks). Aggregating across tasks in a step i, for any draw of number of issues n, there is a corresponding probability that any distribution $Y(\hat{\psi})$ will be used to generate $\hat{n}_i = n + Y(\hat{\psi})_i$. The probability is given by $p(Y(\hat{\psi}))_i = \int_{t \in S_i, \psi(t)=\hat{\psi}} t\ dt$, the share of tasks of type $\hat{\psi}$: a step with many tasks of a high variance type will thus also be high-variance. The step-level difference in variance considered in our analysis would be equivalent in this construction to an interval in which $\psi(t) = 0$ for all $t \in S$ for the low-variance case, and $\psi(t) = 1$ for all $t \in S$ for the high-variance case.*

3. Analysis

To study the implications of greater variance in the number of issues, we first analyze how performer generality affects the curvature of complexity in number of issues. In this subsection,

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[75] By allowing heterogeneity in $\frac{dw(A^{\psi})^2}{d\psi_i d\psi_j}$ for different i,j, it is possible to capture complementarities across abilities in terms of price.

[76] One approach to modeling differences in variance of tasks while satisfying this condition is to impose some constant minimum $\underline{n}$ for any step, so that $\hat{n} = n + \underline{n} + Y$: this feature would be analytically similar to the property of minimum difficulty $\underline{D}$ provided in our functional specification of step difficulty.

we assume for analytical simplicity that steps have one type of issue (but still allow issue type and corresponding properties to vary between steps).

Assumption 3 $\psi(t_m) = \psi(t_n)$ *for all* $t_m, t_n \in S$ *and* $|\Phi_i| = 1$ *for all* S_i.

Remark 2 *Given Assumption 3, the cost minimization problem of the firm in this model is equivalent to the problem of the firm given by Equation 16 in Combemale et al 2022.*

We show in the following lemma that the difference in complexity between low and high generality performers is convex in the number of issues, for sufficiently high n. This property will allow us to show in a subsequent proposition that high variance in number of issues changes the difference in expected complexity between high and low generality performers and hence changes the cost of using humans or machines.

Lemma 1 *Let* $E(n)$ *be sufficiently high so that* $X(n|\rho) \approx n^{1/\rho}(E[X^\rho])^{1/\rho}$ *(see Equation 1 Combemale et al 2022) and let Assumption 3 hold. Let* $\Delta\boldsymbol{X}(n|\rho_1,\rho_2) = n^{1/\rho_1}(E[X^{\rho_1}])^{1/\rho_1} - n^{1/\rho_2}(E[X^{\rho_2}])^{1/\rho_2}$ *be the difference in complexity between two performer types with generality* ρ_1, ρ_2. *Then* $\Delta\boldsymbol{X}(n|\rho_1,\rho_2)$ *is convex and increasing in* n.

Proof. We know already from Lemma 1 (main paper) that $X(n|\rho_h) < X(n|\rho_m)$, such that $\Delta\mathbf{X}(\rho_1,\rho_2) > 0$. To establish $\Delta\mathbf{X}(\rho_1,\rho_2)$ convex and increasing in n, we want to show that $i)$ $X(n|\rho)$ is increasing and concave in n, $ii)$ $\frac{d^2X(n|\rho)}{dnd\rho} < 0$ and $iii)$ that $\frac{d^3X(n|\rho)}{dn^2d\rho} < 0$.

If $i - iii)$ hold, then $\frac{dX(n|\rho_m)}{dn} > \frac{dX(n|\rho_h)}{dn} > 0$, giving $\frac{d\Delta\mathbf{X}(\rho_m,\rho_h)}{dn} = \frac{dX(n|\rho_m)}{dn} - \frac{dX(n|\rho_h)}{dn} > 0$.

We also have $\frac{d^2X(n|\rho_h)}{dn^2} < \frac{d^2X(n|\rho_m)}{dn^2} < 0$, giving $\frac{d^2\Delta\mathbf{X}(\rho_m,\rho_h)}{dn^2} = \frac{d^2X(n|\rho_m)}{dn^2} - \frac{d^2X(n|\rho_h)}{dn^2} > 0$, so that $\Delta\mathbf{X}(\rho_1,\rho_2)$ is convex and increasing.

$i)$ For convenience, let $f(\rho) = E(X^\rho)^{\frac{1}{\rho}}$. We first derive with respect to n:

$$\frac{d\mathbf{X}(n|\rho)}{dn} = \frac{n^{\frac{1}{\rho}-1}}{\rho}$$

$$\frac{d^2\mathbf{X}(n|\rho)}{dn^2} = (\frac{1}{\rho^2} - \frac{1}{\rho})n^{\frac{1}{\rho}-2}f(\rho)$$

We have $X(n|\rho)$ increasing and concave in n.

$ii)$ $\frac{d^2X(n|\rho)}{dnd\rho} = \frac{n^{\frac{1}{\rho}}}{\rho}[f'(\rho) - \frac{f(\rho)}{\rho} - \frac{ln(n)f(\rho)}{\rho^2}]$. By the properties of p-norms, we have $f'(\rho) < 0$, so that $f'(\rho) - \frac{f(\rho)}{\rho} - \frac{ln(n)f(\rho)}{\rho^2} < 0$, hence $\frac{d^2X(n|\rho)}{dnd\rho} < 0$.

$iii)$ We now show that $\frac{d^3X(n|\rho)}{dn^2d\rho} < 0$.

$$\frac{d^3\mathbf{X}(n|\rho)}{dn^2\rho} = \frac{n^{\frac{1}{\rho}-1}}{\rho}[(\frac{1}{\rho} - 1)f'(\rho) + f(\rho)(\ln(n)(\frac{1}{\rho} - 1) + (\frac{1}{\rho} - \frac{2}{\rho^2}))]$$

For $\rho = 1$, the result is trivial: $(\frac{1}{\rho} - 1)f'(\rho) + f(\rho)(\ln(n)(\frac{1}{\rho} - 1) + (\frac{1}{\rho} - \frac{2}{\rho^2})) = -f(\rho) < 0$. For $\rho > 1$ and for n sufficiently high, $(\ln(n)(\frac{1}{\rho} - 1) + (\frac{1}{\rho} - \frac{2}{\rho^2}) < \frac{1}{\rho} - 1$. Substituting, we find $(\frac{1}{\rho} - 1)f'(\rho) + f(\rho)(\ln(n)(\frac{1}{\rho} - 1) + (\frac{1}{\rho} - \frac{2}{\rho^2})) < (\frac{1}{\rho} - 1)(f(\rho) + f'(\rho))$. Note that $f'(\rho)$ is negative, but as a p-norm, $E(X^\rho)^{\frac{1}{\rho}}$ is positive, decreasing and convex in ρ for $\rho > 1$, so that $f(\rho) > |f'(\rho)|$, giving us $(\frac{1}{\rho} - 1)(f(\rho) + f'(\rho)) < 0$. ■

We show that a sufficiently large increase in variance makes it economical to use human performers in steps that would otherwise be automated. This result is consistent with current theory on the greater feasibility of automating routine work than non-routine. It also suggests a means of comparing different types of tasks on a continuum from routine to non-routine, in terms of the variance of successful performance (indicative of greater variance of issues). Finally, and consistently with work on occupational content (e.g. Brynjolfsson et al), it suggests how the content of work may change if workers have mixed variance in the number of issues across their responsibilities: for example, low-variance work such as answering commonly asked questions (an FAQ) can be automated, while high-variance among uncommon questions requires a customer support worker.

Proposition 1 *Let the assumptions of Lemma 1 hold, and let Equation 16 in Combemale et al be solved such that there exist steps i, j such that tasks $t \in [s_{i-1}, s_i]$. Let the number of issues in i be given by $\hat{n} = n + Y$ (with $\mu Y = 0$ and variance ςY), while the number of issues in j is only n. Let $E(n)$ be sufficiently high, so that $X(n|\rho) \approx n^{1/\rho}(E[X^\rho])^{1/\rho}$ (see Equation 1). Let machine be the optimal choice of performer for step j: if ςY sufficiently large, then the optimal performer for step i is a human.*

Proof. For convenience, we define the difference in expected complexity of humans and machines as: $\Delta c(l|\rho_m, \rho_h) = c(l|\rho_m) - c(l|\rho_h)$ or $\Delta c(l|\rho_m, \rho_h, \hat{n})$ for the high variance case. By Lemma 1, $\Delta\mathbf{X}(n|\rho_1, \rho_2)$ is convex and increasing in n: $\Delta c(l|\rho_m, \rho_h, \hat{n})$ is the expected value of a convex function over the random variable $\hat{n}$, and hence is increasing and unbounded in ςY. It follows that there exists ςY sufficiently great that the cost of a machine is greater than a human. ■

We now turn to the implications of variance for the cone of automation defined by $\underline{l}$ and $\overline{l}$ in R. We show that for greater variance of issues, $\underline{l}$ is increasing and $\overline{l}$ is decreasing, narrowing the cone of automation. We would thus expect polarization of worker ability demand resulting from automation in high variance contexts to be less extreme in that the gap between the upper and lower bounds of automation is reduced.

Remark 3 *While variance in the number of issues increases the difference between human and machine complexity, it also reduces expected complexity for performers. Let the assumptions of Proposition 1 hold, with steps i, j such that $\hat{n}_i = n + Y$ and $\hat{n}_j = n$. For $\rho = 1$, $\boldsymbol{X}$ is linear in n: hence for any variance in $\hat{n}$ with $E(\hat{n}) = n$, $c = E(\boldsymbol{X})$ is constant. For $\rho > 1$, $\boldsymbol{X}$ is strictly concave in n: hence, for greater variance of Y, c_i is decreasing and strictly less than c_j.*

Proposition 2 *Let the assumptions of Proposition 1 hold. For Y constant, let the greatest lower and least upper bounds of step length automated be given by $\underline{l}$ and $\bar{l}$. Let $\underline{l}'$ and $\bar{l}'$ satisfy the conditions for the highest lower and least upper bounds of automation given $\varsigma(Y) > 0$. Let $\rho_m, \rho_h > 1$. Then for $\varsigma(Y)$ sufficiently great, $i)$ $\underline{l}' > \underline{l}$ and $ii)$ $\overline{l'} < \bar{l}$*

Proof. $i)$ By contradiction, suppose that $\underline{l}' \le \underline{l}$ such that $p(\underline{l}'|\rho_m, \varsigma(Y) > 0) < p(\underline{l}'|\rho_h, \varsigma(Y) > 0)$ but $p(\underline{l}'|\rho_m, \varsigma(Y) = 0) > p(\underline{l}'|\rho_h, \varsigma(Y) = 0)$. Note as in Remark 2 that $c(\underline{l}|\varsigma(Y) = 0) > c(\underline{l}|\varsigma(Y) > 0)$: by property of $\underline{l}$, all $l < \underline{l}$ is manual, which is equivalent to all $c(l) < c(\underline{l})$. Note that by Lemma 1, for l_i, l_j such that $c(l_i|\rho_m, \varsigma(Y) > 0) = c(l_j|\rho_m, \varsigma(Y) = 0)$, we have that $c(l_i|\rho_h, \varsigma(Y) > 0) < c(l_j|\rho_h, \varsigma(Y)$.

This result implies that if $p(\underline{l}'|\rho_m, \varsigma(Y) > 0) < p(\underline{l}'|\rho_h, \varsigma(Y) > 0)$, then $p(\underline{l}'|\rho_m, \varsigma(Y) = 0) < p(\underline{l}'|\rho_h, \varsigma(Y) = 0)$, generating a contradiction.

$ii)$ For any $\bar{l}$, Proposition 1 implies there exists $\hat{\varsigma}(Y)$ such that $p(\bar{l}|\rho_m, \varsigma(Y) > 0) > p(\bar{l}|\rho_h, \varsigma(Y) > 0)$. In such a case, (proof of Prop. 4 main paper) implies $p(l_i|\rho_m, \varsigma(Y) > 0) > p(l_i|\rho_h, \varsigma(Y) > 0)$. Hence, $\bar{l}'$ satisfying the conditions of a least upper bound of automation given $\varsigma(Y) > 0$ is less than $\bar{l}$. ■

The implications of the propositions given in this section are depicted in the following figure, adapted from Figure *14* in Combemale et al (based on Propositions 4-7 of that paper). Steps for which a machine performer with $\sigma^m < \sigma^h; \rho^m < \rho^h; \bar{r}^m < \bar{r}^h$ would be of lower cost are colored, indicating that a machine performer would be chosen instead of human; steps that would remain manual are in white. The dashed lines represent an "inner cone" of automation formed by the upper and lower bounds of automation given high variance of the number of issues within steps: note that when tasks are of high variance, the cone is constricted by shifting the upper and lower bounds of automation inward. This shift also results in polarization of ability demand occurring at higher production volumes than for low variance tasks.

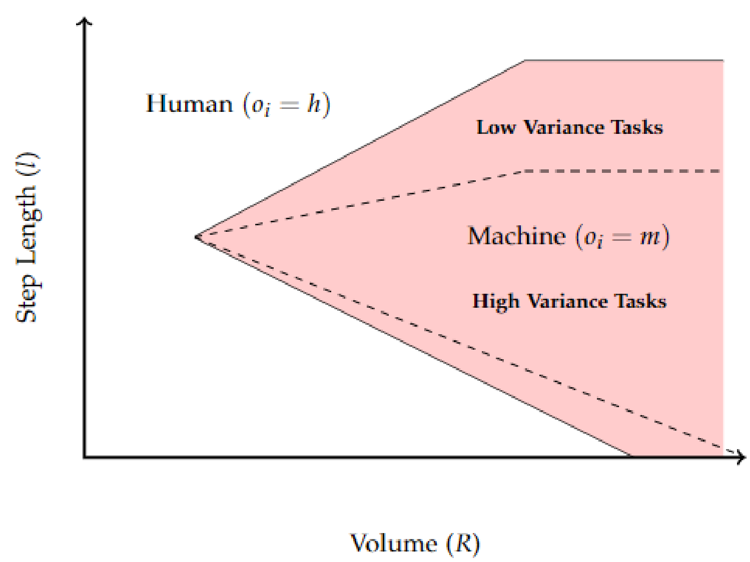

Figure 21 Cone of Automation Contracts with Higher Variance of Issues

4. Concluding Remarks

In this paper, we develop an extension to the model described in Combemale et al (2022) to describe tasks of different types with corresponding differences in production issues. This new feature allows us to consider differences in tasks that are informative for understanding task-biases in technology change, such as automation. We show within the model that the ability-demand profile of steps that are cost-minimizing to automate varies with the task-characteristics of steps. We provide a formal method for describing the variability of steps (similar to the qualitative idea of “routineness” in prior literature) and show, consistently with prior theory, that steps with less variance of production issues are more cost-effective to automate. However, our results are nuanced with respect to the distribution of steps that are automated: we show in the model that the implications of issue variance by task type differ with production volume (or equivalently utilization). At low volumes, higher variance of issues within tasks can lead to reduced (narrower) polarization of ability demand due to automation, but at higher volumes the effect of automation under such conditions of high variance could *remain* polarizing while instead being upskilling under conditions of low variance. This result demonstrates that the effect of automation on the distribution of skill demand depends not only on volume and variability of issues across types of tasks, but on the interaction of these characteristics of production.

Chapter 4: Sorcery at the Technical Frontier: How Embedded Knowledge on the Production Line Can Give Workers a Role in Innovation

1. Introduction

Technological change in the United States has historically been associated with significant changes in skill and labor demand across the economy, with strong patterns of displacement and skill demand polarization in the manufacturing sector: workers can view technological change as a threat to their employment or that of future generations, leading to frustration or fear. Manufacturing in the US in particular is affected by powerful economic forces – including globalization and technological change – that have dramatically changed labor market outcomes for workers. The U.S.'s manufacturing value added grew by $587 billion (40%) from 1999 to 2014 (World Bank); however, since the mid-1980s, the number of U.S. manufacturing employees manufacturing has declined (U.S. Bureau of Labor Statistics). Scholars have tried to pinpoint the source of this trend – to offshoring, automation, or both – but none have done so definitively (Autor and Dorn 2013; Goos et al 2014). Overall, across all industries there has been a polarization of labor demand with more jobs at the top and at the bottom of the income distribution and relatively fewer in the middle (U.S. Bureau of Labor Statistics). Technical change due to emerging technologies can directly alter the demand for worker skills (Combemale, Whitefoot, Ales and Fuchs 2021) and may thus further accelerate these trends.[77]

Manufacturing, in addition to being strongly affected by technological change, is a significant epicenter of industrial research and development activity, accounting for 66% of Industrial R&D spending in the United States in 2015 (NSF 2018). This interaction of innovation and sectoral change raises the question of what role workers currently have or may have in process of innovation. With continued technological change a major part in potentially unstable

[77] Significant literature exists on skill-biased technological change and its influence on employment, wages, international trade, and productivity (Autor et al 2003; Card and DiNardo 2002; Bartel et al 2007; Acemoglu and Restrepo 2017). Research, however, has been limited in its ability to directly measure different types of simultaneous technology change, and their possible relation to labor demand. The current approach in economics linking technical change and labor outcomes (c.f. Ales, Kurnaz, Sleet 2015) is mostly retrospective and top-down: dependent on aggregate historical data, it focuses on past episodes of technical change and works largely with coarse groups of workers ranked by historic occupational wages (Card and Dinardo 2002; Bresnahan and Brynjolfsson 2002; Autor, Levy and Murnane 2003; Acemoglu and Autor 2011; Pedro and Lee 2011; Autor and Dorn 2013). Traditional quantitative approaches may not be adaptive to technological or policy changes that displace firm behavior outside of a narrow band of historic factor substitutions captured by statistical data (Chenery 1949; Lave 1966; Pearl and Enos 1975; Wibe 1984; Smith 1986). Such limitations present challenges in anticipating the effects of emerging technologies on labor outcomes, complicating policy efforts to mitigate associated labor market failures.

or uncertain employment conditions for many workers, especially over the long term (Brynjolfsson, Mitchell and Rock 2018), and common feelings of frustration and helplessness in the face of perceived future technological placement (Ananat et al 2017), a participatory role for workers in innovation offers an important contrast and potential alternative to a passive or adversarial labor experience of technology change.

In this paper, we present qualitative insights from the optoelectronics industry on different innovation arrangements and the roles that these allow (or prevent) for production workers as participants in technological change. We identify organizational characteristics surrounding these arrangements and suggest mechanisms within firms which may generate more participatory roles in innovation for workers. We then provide a discussion of potential policy directions and needed future work to develop our findings.

2. Literature Review

The level of vertical integration by a firm is informative in anticipating the scope of innovation in which the firm (and its workers) may participate.

The structure of a design architecture or of a firm have related implications for innovation outcomes. In the modularity literature, modularized designs allow local, more incremental innovation to occur while affecting only the elements of a single module, while more significant innovations may need to cross module boundaries, with greater associated costs (Baldwin and Clark 2000). This conceptualization links naturally with the theory of the firm, shifting modular boundaries for interfirm boundaries: a disaggregated value chain may be able to host incremental innovations, but costs are incurred when transacting across the chain (Chandler 1993), potentially impairing the returns to innovation, and in particular imperfect contracts will impose costs for innovation involving multiple elements of the value chain (Antras 2005).

Firms' level of integration may also influence access to knowledge: if issues in innovation occur outside of the firm's scope of activity, it must obtain and manage knowledge from elsewhere. However, the more uncertain the technical circumstances, the more tacit the knowledge and the more difficult (or costly) it will be to transfer across the firm boundary, and the more uncertain the firms' investments in innovation (Chesbrough 2004).

Existing linkages between structure and innovation are informative in thinking about the possibility space for worker participation. However, the literature has not generally linked the role of workers in innovation to firm structure. In this paper, we build on the innovation literature by examining a multilateral association among workers, innovation, and firm structure. We show how firm structure may alter the possible interactions between workers and innovation happening outside their role, and hence the scope for their participation.

3. Methods

This paper draws on grounded theory-building principles (Glasner and Strauss, 1967; Eisenhardt, 1989; Yin 1989) to explore associations between the role of production workers in innovation and characteristics of firms employing them. We draw on qualitative evidence from a case study that we conducted of the optoelectronics industry at a time of ongoing but heterogeneous technological change across the industry.[78] Our results draw primarily on over 30 semi-structured interviews with employees at 12 different firms and organizations in the industry across the United States, Europe and East Asia, covering every step of transceiver production as well as product and process development (the device manufacturers accounted for 42-44% of industry volume at the time of our study). Our firm sample captured the range of technological variation in the industry, allowing us to contrast mature technologies with efforts at the technical frontier: broadly we observed variation in two central technologies – automation (substitution of machines for workers), consolidation (formerly discrete parts replaced by a single part with their collective functions).

We spoke to engineers, senior technical officers, trainers, supervisors, and operators: our broad sample allowed us to capture the content and scope of production work and characterize the interface between workers and technological development in-house at each firm. In addition to interviews, we performed line observations across the production processes for five different optoelectronic device designs (three in the U.S. and two in Asia). The principal data for our subsequent qualitative analysis were the 1) types of technologies in use at each firm (along dimensions of consolidation and automation), 2) whether or not firm leaders considered their production processes to be technically well understood by engineers, 3) whether or not production workers were involved in process or product development, 4) whether or not there was equipment-specific knowledge that affected production outcomes, 5) firm geographic location (possibly varying between segments of the value chain under one firm), and 6) the organization of the firm, namely which segments of the industry value chain the firm occupied.

4. Case Industry and Sample Firms: Optoelectronics Manufacturing

Our case industry, optoelectronics, is forecast to reach $53 billion in global annual revenue in 2025 (MarketsandMarkets 2020): this industry, while a small subset of the $515 billion global semiconductor industry (Deloitte 2020), is both growing and sufficiently diversified to allow us to capture a variety of organizational types and technological regimes within our firm sample. The industry is distributed heavily across East Asia, India, the U.S., and Western Europe, with a value chain in four broad segments: component fabrication (and testing), component assembly into final product (and associated testing, subassembly, etc.), process design and product design. In the United States, all stages of the value chain are represented, though within our firm sample and the industry more broadly the U.S. has relatively more of the industry's product and process design sites than it does, for instance, assembly.

Optoelectronic devices combine electronic and photonic (optical) elements for a variety of applications, broadly in sensory instruments (automotive, medical, aerospace), precision lighting (LEDs) and telecommunications (NAS 2013). Telecommunications dominate the current optoelectronics market, and optoelectronic transceivers are manufactured in the millions annually (Yole 2016). Transceiver devices use light to send and receive information and electronic components to convert information to and from light for transmission or procession. Transceivers must first have their components fabricated (using a process of material

[78]See Combemale, Whitefoot, Ales and Fuchs 2021 for our quantitative work on this same industry around the labor implications of different technologies.

deposition and etching to achieve desired structure), and then each component must be assembled into the whole: thus, different transceiver designs affect the requirements for fabrication by changing component characteristics and also affect assembly work by changing how components must fit together.

Broadly, two of the central technological changes ongoing in optoelectronics are automation and consolidation: automation in our sample occurs mostly in assembly (fabrication is already highly automated) and consists of introducing machines to substitute for manual tasks. Consolidation involves the fabrication of formerly discrete components as single parts, thereby changing the content of fabrication and the structure and extent of assembly (Fuchs et al 2008).

Because optoelectronic devices combine electronic and photonic elements, they pose a number of challenges in design and fabrication which differ from traditional electronics. The materials used for optical components (lasers) are often not the traditional silicon of electronics: common materials such as Indium-Phosphide have differing crystalline structures from silicon which add complexity to the interactions between them and limit co-fabrication (NAS 2013). Differences in the behavior of photons and electrons also mean that traditional semiconductor design solutions are not always well-suited to optoelectronic applications: one technical expert in our study noted: “The problem is that electrons will more or less follow the path you want them to [in a device], and photons don’t.” Indeed, CAD and other computer design solutions are not readily transferrable from electronics to optoelectronics in many cases, and while there is an emerging industry space for commercial optoelectronic design software, all firms in our sample relied at least partially on proprietary software developed in-house to accommodate their design technologies. Despite these differences there are broad overlaps in fabrication, and many optoelectronic producers rely on fabrication equipment designed for electronics.

The firms in our sample vary significantly in their degree of vertical integration: qualitatively, we measure integration by the segments of the value chain in which a firm performs its primary activities. [79] These segments are product design, process design, component fabrication and assembly. The most integrated firms in our sample perform all four segments. Several firms in the sample are design-focused, specializing in the development of new transceiver designs, often with no fabrication capabilities: these are instead provided by foundries, which offer contract manufacturing services (often these same foundries serve the wider semiconductor industry as well).

[79]It may be possible to think of a firm’s position in the industry into terms of outsourcing rather than vertical integration. However, outsourcing assumes that a firm performs a segment of the value chain, outsources the next and then eventually re-integrates outsourced work into its own production sequence: many firms in our sample may be destinations for outsourcing rather than outsourcers themselves, and hence a focus on which segments of value-added a firm performs is more informative for our analysis.

5. Qualitative Findings

The differences between optoelectronics and electronic semiconductors give the industry two important characteristics. Firstly, a lack of industry-specialized education. Second, a higher degree of technical uncertainty concerning product design and process. These two characteristics are associated with the importance of worker experience, firm structure and ultimately the role of shop floor workers in innovation.

5.1 On the Job Training and the Role of Worker Experience

The optoelectronics industry is affected generally by a lack of specialized education: national entities such as the American Institute of Manufacturing Photonics (AIM-Photonics) seek to address a perceived lack of technical training for production workers, especially in fabrication: for now, the firms in our sample rely heavily on training on the job and worker experience to make up for traditional educational resources.[80] Interviewees from senior technical staff to supervisors who began as line workers consistently describe to us a premium in their hiring decisions on worker experience within the industry, frequently citing the lack of formal training or educational alternatives.

The majority of trained engineers, who usually come into optoelectronics from a more traditional electronics background, must undergo a significant degree of on-the-job learning not only about the firm's specific processes or designs, but also about the technical characteristics of optoelectronics. Multiple interviewees across different firms indicate that even PhD-level engineers usually do not come to the optoelectronics industry with full technical knowledge, and that adaptation could take a year or longer in some cases.

Shop floor workers perform tasks in the fabrication and assembly stages of value added, though they have potential roles in design. On the shop floor, our sample firms employ workers in consistent broad categories: operators, responsible for production tasks and interacting with or monitoring machines during production, technicians, responsible for setting up and calibrating machines (though some job-setup is typically performed by operators) and for intervening when machines fail and cannot be restored by operators, supervisors, responsible for organizing and often training operators (though training is sometimes performed by more experienced or "lead" operators), and equipment and process engineers, responsible for solving high level process issues (often but not always in dialogue with workers). Typically, an operator's role is fairly scheduled, performing well defined tasks throughout the shift, while technicians, supervisors and engineers often performed more ad-hoc functions. Our focus in this paper is primarily on operators.

On the job training at all levels of employment is a feature in all manufacturing firms in our sample. Among shop floor operators, training is generally between two and eight weeks (with two the mode) for a given assembly task, while in fabrication training times are often much longer, sometimes lasting up to 6 months for a line worker to become qualified on a single type of fabrication equipment.

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[80] AIM-Photonics Technician certification program: https://aimphotonics.academy/workforce/workforce-training/technician-certification

In both fabrication and assembly, training general begins with a manual outlining both equipment and (in the case of assembly) manual work procedures that the worker will perform, as well as general introductory training to the work environment. Optoelectronic components in both fabrication and assembly are highly sensitive to material contamination and damage from static discharge, and in addition to the motions of their primary work, shop floor employees must learn protocols to minimize the risk of foreign contaminants. While some procedures such as switching into static-deterring slippers to step onto an assembly line are relatively trivial, more exacting standards in sensitive clean-room environments require full cleanroom body suits (affectionately referred to as "bunny suits" by several engineers and lead operators in our sample). Workers must learn not only how to change in and out of the suits in a timely fashion,[81] but how to operate effectively within the constraints of the suit, which interviewees with cleanroom experience attested can be both a physical and a psychological challenge. Though all cleanroom employees receive demonstrations, instruction is not sufficient, and for fabrication workers especially,[82] learning how to operate in the cleanroom suit is one of the first markers of the cleanroom experience that several firms in our sample value highly in manufacturing employees.

The format of worker training after basic instruction is strongly associated in our sample with the scale of production at a plant. Workers typically receive active instruction on a piece of equipment, often from a more experienced worker or supervisor but, at the largest production scales, from trainers. In the transition from instruction to experience-building, depending on the scale of production, the equipment may on-line or off the production line. Whether from equipment off the production line or being used less efficiently by a less experienced worker, the cost of training in terms of "idle capital" is lower when work is principally manual (e.g. attaching an optical fiber): it may not be cost-effective for firms to dedicate high capacity, high-cost equipment to a small flow of trainees. However, at the largest scale of operations, some firms in our sample maintain internal training programs with full time training staff and training-purposed multi-step equipment and workstation layouts. These layouts can also be reconfigured to train workers for specific processes or to retrain workers for novel processes.

Except for the largest training programs with worker testing protocols, the best indicator of successful training is successful work, embedding the measurement of a worker's skill in their direct job performance. Workers who begin to perform production activities on the line typically graduate from training to a probationary status (usually 3 months to a year and longer in fabrication than in assembly: see Table 8 for details) after demonstrating a certain number of proven good parts coming from their station. Probationary workers typically work under conditions with a greater ratio of supervisors to workers, or in smaller groups with a core of experienced workers. The involvement of supervisors or more experienced workers in the work of the trainee can be constructed through limitations on the tasks that the trainee or probationary worker is permitted to perform (such as calibrating a machine at the beginning of

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[81] A senior engineer in our sample noted that he could do it in two minutes but knew of employees who could change in "about 30 or 45 seconds."

[82] Though some highly sensitive assembly steps may also be performed in a cleanroom.

a shift), but it supervisor and senior worker involvement can also be at the discretion of more junior workers as they refer production problems up the managerial hierarchy.

Table 8 Education, Training and Experience of Optoelectronic Shop Floor Operators

Occupation	**Education**	**Training & Probation**	**Average Experience**
Assembly Operator	High School (Less in developing nations)	2-6 weeks training 3-6 months probation	1-3 Years
Fabrication Operator	High School or Technical Degree[83]	1-3 months training 3 months - 1 year probation	5-10 Years

Unlike in industries such as automotive assembly, where workers may be cross-trained across different equipment (Jordan, Inman and Blumenfeld 2004), optoelectronic shop floor operators tend to be dedicated to a specific type of equipment or (in the case of testing) class of equipment types. Equipment-specific expertise is narrower in fabrication, where a worker may be responsible for a single, specific machine and the jobs for which it is calibrated. Greater levels of qualification across the firms in our sample corresponded with greater worker autonomy: a fully qualified operator might be responsible for multiple machines, prepare them for jobs without technician support and serve as the first interrogator of equipment in the event of failure. Shop floor operators in optoelectronics are almost always at least high-school educated in the U.S. and developed world, sometimes less so in contexts such as developing East Asia. Assembly is usually a higher turnover environment than fabrication (and, hence, mean experience tends to be lower), but both have a wide variety of experience across workers, often less than five years in assembly but commonly up to ten or twenty years in both assembly and especially fabrication. Generally in our sample, an assembly operator's performance gains from experience plateau after two to three years (based on observations at four plants), while the greater variety and complexity of equipment in fabrication can extend the gains from experience over years – an operator in fabrication typically works more years before an internal promotion (e.g. to lead operator) than does an assembly operator. Experience can manifest as a higher rate of performance with fewer errors committed by a worker (as in the example of cleanroom suits), but it also appears in problem diagnosis and solving: for instance, an experienced operator can learn to visually identify inputs that are likely to cause production errors in a machine, or can learn to recognize and solve failure states that are not identified by the manufacturer or, indeed, result from nonstandard applications of equipment in a novel production process.

Internal promotion for operators based on experience and performance is common throughout our sample, though more so in fabrication than assembly. First, the classification of "lead" operator usually is used to reflect operators whose experience and skill make them

[83] Most fabrication operators in our sample were high-school educated, but all interviewees confirmed at least some fabrication operators on their shop floor with technical degrees.

suited to train others, but also to handle one or more complex pieces of equipment with greater autonomy and, often, to serve as a second line of problem-solving after less experienced workers. Many firms also have a strong pipeline from operators to technicians, waiving or reducing formal educational requirements for workers who develop expertise on specific machines: for U.S. workers, a promotion from operator to lead operator to technician means a shift in wages from about $14/hour for entry-level assembly workers to about $20/hour for more senior operators up to $28/hour for technicians, usually with a further premium for fabrication workers. This pipeline is especially important in firms that make use of custom or customized equipment, where outside training and certification are not useful measures of qualification.[84] Most direct hires in technician roles have at least a two-year degree, though in practice the workforces in each firm are about equally split internally between high school and technical degrees, reflecting a significant level of advancement through experience. Higher supervisory roles and even engineering positions can also be reached through experience in some firms, though formal education becomes a stricter requirement for engineering in all the cases we observe: equipment and process engineering teams in our sample features some cases of individuals with a two-year technical degree, but we observe no cases of engineering-level workers with only a high school degree. Moving from process to product engineering, we observe a mixture of bachelor and master level engineers: master's and doctoral-level engineers and material scientists are predominant in the firms we observed at the leading technological edge of the industry.

5.2 Technical Uncertainty and Firm Structure

The second industry characteristic, technical uncertainty, means both that production failures are frequent (and potentially quite expensive) and that the outcomes of design changes or new production processes in terms of productivity, skill requirements or labor demand are uncertain at the outset. From the firm perspective, the process of innovation begins with a change in product design (often to meet a specific client's need), which is performed by several design engineers of various specializations, from more general roles such as layout design (how components fit together into a system) and circuit simulation to component-specific work such as laser or waveguide design: their product is then passed to fabrication engineers, who judge the feasibility of production and then engage production workers (the same process is later repeated for assembly).

Production failures, investigation and rework or redesign are common at these stages: indeed, our firms reported at least one and often two iterations of experimentation and redesign stretching from operators back to design engineering roles: iterations might take a month, but often stretched for six months to a year, with full development cycles from initial design to full production on the order of two to three years for new material platforms and typically a year even for incremental product innovations. Several firms cite continued technical uncertainty until the first 100,000 units of a new platform have been shipped, sometimes a year or more after the beginning of production "ramp-up." All firms in our sample

[84] Notably, however, more customized equipment sometimes means that some technician roles are subsumed to the equipment engineers who designed the equipment.

describe a learning experience in production with each new design, and as we will expand in the next subsection, a sometimes-central role for production workers.

The structure of firms in our sample is also associated with different levels of technical uncertainty, bearing out the innovation literature and also helping to inform how technical conditions and firm structure may interact to in turn affect the role of workers. Table 9 lays out the key organizational forms that occur in the industry and in our sample and maps these to the broad value chain described in section 4, and then to the level(s) of technical uncertainty faced by corresponding firms in our sample.

Broadly, there are three categories of firm models: transceiver manufacturers (fabless, meaning without fabrication capabilities in-house, or with in-house fabrication), which span product design and at least some production, contract manufacturers (foundries and contract assembly), and consultants and equipment manufacturers, which directly (consultants) or indirectly (equipment manufacturers) participate in design of product or process but not production. Transceiver manufacturers self-defined in our sample based on performing product design, which differentiates them from contract manufacturers (foundries and assembly). Equipment manufacturers implicitly set some of the conditions for process design, and in our sample also designed specific operational protocols for their machines, sometimes collaboratively with customers. In addition, though not a model for firm organization, the optoelectronics industry hosts the American Institute of Manufacturing Photonics (AIM-Photonics), which performs an industry-support role similar to a cutting-edge foundry or contract manufacturer for experimental product and process development (Manufacturing USA 2020): such manufacturing institutes suggest a possible public analogue to the firm structures and their implications discussed in this paper.

Table 9 Technical Uncertainty and Firm Integration Along the Optoelectronics Value Chain

Organization Type(s)	Product Design	Process Design	Fabrication	Assembly	Technical Uncertainty	Number of Processes in Sample
Integrated Transceiver Manufacturers	Yes	Yes	Yes	Yes	Low (Legacy) to High	3
Fabless Transceiver Manufacturers	Yes	Yes*	No	Yes*	Low (Legacy) to High	2
Foundries	No	No**	Yes	No	Low	1
Contract Assembly	No	Yes	No	Yes	Low	4
Design Consultants	Yes***	Yes***	No	No	High	3
Equipment Manufacturers	No	Yes	No	No	Low to Medium	2

*Some firms observed performed limited outsourcing of process design and assembly functions but all kept at least a majority (by cost) of these activities in-house.

**The significant capital outlays for foundry equipment and relatively small capacity demanded by most foundry clients make it very rare for foundries to make any change in production process outside of the allowable process parameters established by the foundry's Process Design Kit (PDK). However, experimental work within the constraints of a PDK is often performed by a Foundry on behalf of a client.
***Design Consultant processes studied accommodated both process and product design, varying according to the client's needs.

The configuration of a firm's position along the optoelectronic value chain is associated in our sample with the level of technical uncertainty under which the firm may operate. Contract manufacturers need high volume processes that can be readily adapted to the needs of new customers, and thus tend (especially in the case of fabrication) to engage in production at low technical uncertainty. The exception to this role is the case of experimental services offered by these firms, usually providing small batch production to facilitate product design at a client firm: in these cases, however, the contract manufacturer can provide feedback but did not usually perform a technical design role (e.g. in the manner of a design consultant). All CMs must resolve some uncertainty concerning the adaptability of their standard production processes to new customer demands: the level of customization available to clients sets the level of technical uncertainty. Foundries have well-defined Process Design Kits (PDKs) which they offer their clients: documents or software which lay out the parameters under which the foundry's equipment and workers are rated to operate and which serve as a first constraint on the designs that customers may attempt to produce: assembly CMs are often more flexible, and thus take a more active role in process design, though even here the level of process and equipment customization is much lower than at transceiver manufacturers that assemble in-house.

Design consultants and equipment manufacturers may specialize in a specific set of processes or product characteristics, but their rule is usually to offer solutions to firms without in-house capabilities in certain parts of design. Thus, the design consultant and equipment manufacturers will often tend to serve smaller firms, potentially without the resources to fully integrate their production activities. Design consultants are not typically engaged in incremental work on existing platforms – more often, the processes we studied had to do with leading-edge designs and novel materials, such as highly consolidated devices (multiple components fabricated as one without assembly) or new material platforms to more easily co-fabricate components. These design consultants are nevertheless typically separate from shop-floor production, often performing design work and material science work away from the customer's facilities. Equipment manufacturers, in contrast, typically provide varying types of equipment for established functions – they are not usually developing equipment for entirely novel processes and designs, as these tend to be firm-specific and thus a narrow share of the industry and market.

Transceiver manufacturers, then, would appear to have the greatest range of value added activities in their sphere and thus the greatest tendency to produce under technical uncertainty. Indeed, many transceiver manufacturers choose to integrate certain production activities for finer control and a less constrained design space for their products. However, some of the industry's leading-edge firms in design are fabless, suggesting that a significant degree of innovation is possible without direct control over the entire value chain. Meanwhile, certain "legacy" designs, meaning products on well-established platforms with procedures and component designs relatively unchanged in the last fifteen years,[85] are produced by vertically integrated firms, following well-understood processes with little further innovation in design or process around the legacy product. Technical uncertainty is thus associated with but not fully married to the degree of integration: rather, the resources available to a firm in pursuing innovation differ according to its position on both dimensions.

In the following figure, we summarize our analysis to show how the organizational models of the optoelectronics industry map onto the dimensions of technical certain and firm vertical integration.

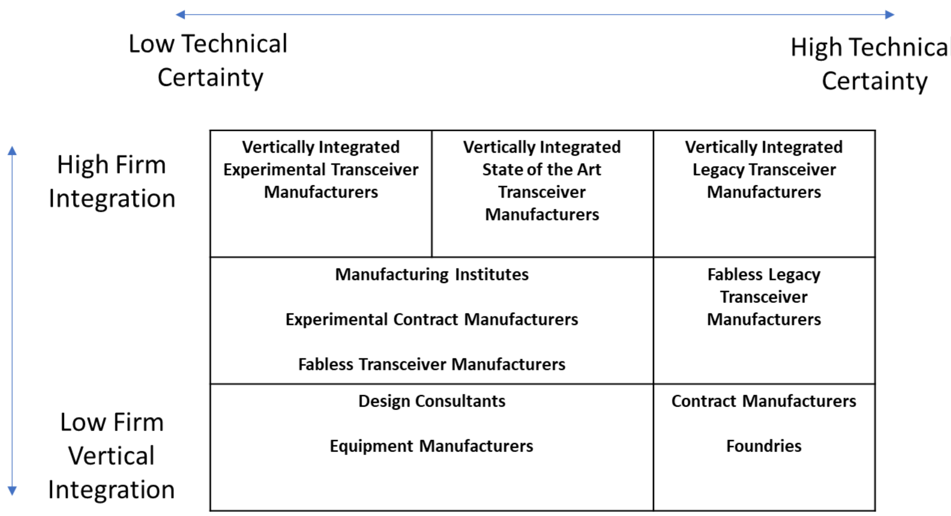

Figure 22 Distribution of Technical Certainty and Integration Across Organizational Models in Optoelectronics

5.3 Embedded Knowledge and Worker Interfaces with Technology Change

The fabrication of optoelectronic chips, laser diodes, waveguides and other components that make up optoelectronic transceivers involves a dozen or more unique pieces of equipment used in a process of hundreds of production steps. Some individual machines may be applicable in dozens of production steps but will be dedicated to just a handful of steps. In some cases, the reason is simply one of capacity – the relevant process steps demand sufficient equipment time that a machine can be fully dedicated without being underutilized, and keeping the machine calibrated for the same small set of steps saves time for engineers, technicians and operators. In assembly, we observed that it is common for workers to be dedicated to specific manual tasks: the number of employees hired for such tasks suggest that this dedication was possible because such tasks demanded enough person-hours to fully occupy a worker.

However, not all equipment dedication falls neatly into the logic of capacity: there are facilities with individual machines on a full production line for a mature design with a history of

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[85] Because many optical device applications have a standardized industry form factor and many device consumers put a premium on an established history of product reliability, legacy designs can survive for extended periods of time even against competition from new devices with the same form factor but different internal design.

hundreds of thousands or millions of units running below capacity (we have captured some at half capacity or less) working on an often small subset of the steps in which they could be applied, while a different machine of the same type handles other steps: the scale of production does not explain such underutilization, and the dedication of equipment to steps would seem to rule out the use of duplicate equipment to take over during production failures and unscheduled downtime. Calibration time (that is, "transition costs" from one step to another) provide one explanation, but across multiple companies and fabrication sites, engineers have often described another reason: they simply do not know how to replicate the parameters under which a given piece of equipment operates economically. Under such conditions, a machine and its neighbor of identical manufacturer and model are nevertheless not interchangeable.

In optoelectronic fabrication, processes are "qualified" (similarly to workers within a process) after they reach certain standards of scale, uniformity of output and minimal rates of failure or unexpected downtime: often, however, equipment is also qualified for a given process. That is, the process is not universally qualified for use either with other equipment or under contract fabrication with a foundry:[86] the process meets standards when performed on the exact machines on a production line, often in an exact order. This idiosyncrasy of capital is the "sorcery" (among other colorful descriptions given by interviewees) mentioned by at least one engineer at every facility or firm we have visited.

To develop a reproducible process from these first black-box procedures on idiosyncratic equipment, some firms adopt an experimental line approach, using a dedicated production environment to test and develop new processes, often using the most experienced operators and giving them an active role in innovation. Another configuration of production with a similar function to the experimental line is the dedicated training line used by some firms: when adopting a new processes, especially in high process-turnover environments such as contract manufacturing, retraining may have an experimental role in the transmission from process design to practice, as experienced workers identify (and perhaps resolve) the flaws of a new process while learning it.

While idiosyncratic equipment is seemingly more common in experimental contexts in our sample (owing to technical uncertainty and lower reproducibility of working processes and equipment), it is a very real phenomenon even moving outside of the laboratory or experimental line and onto the fab floor. Something in the machine's history, its path to qualification, gives it the specific qualities to perform exactly the operations needed for a successful fabrication step and cannot easily be imported whole cloth to its neighbor. When fabs do gain the capability to replicate operations across equipment, they will often impose very strict design limitations for clients and in-house designers on what can be produced on the equipment: outside of those parameters, one engineer tells us, "they cannot guarantee a good

[86] While foundry customers can specify quality standards and perform their own quality control procedures, such as product sampling, and they can negotiate (usually on the basis of their product volume) for limited exceptions to the Foundry's PDK, they have relatively little direct control in the standard foundry model over which procedures and configurations the Foundry will accept.

part." These processes can be tamed, but often they remain poorly understood, and deviations can trip back over into the domain of "sorcery," where the quirks of nominally standardized equipment and the intuition of the machine operators become an indispensable part of production that is sometimes unaccountable by rationalized process management.

The uncertainty and specificity of such processes and equipment demand embedded knowledge, often not only of a process but of a specific piece of equipment. While a process remains uncertain and potentially difficult to reproduce, highly specialized, deeply contextual worker knowledge may be crucial to successful operations. This unique knowledge may also require worker skillsets that differ from those of workers within operations that are reproducible *de novo* outside of equipment history and calibration path-dependency. The practitioners of "sorcery" may be line workers as much as engineers.

Multiple firms that we interviewed note, unsurprisingly, that the degree of embedded knowledge was greatest with machine operators and technicians, then among process engineers (some of whom were involved in building custom equipment), then among design engineers. These differences widen considerably depending on the degree of vertical integration: the most highly integrated firms that we study report a close interface between development engineers and technicians or production workers, who often supply feedback on machines under development. In this manner, workers can have an active influence over the nature of their future work, by affecting the characteristics of future equipment, in which they will again develop specialist expertise. Here, the degree of customization plays an important part: when equipment is purchased from a general semiconductor or other industrial line, the role of the engineer in adapting it may be lower and the opportunity for the worker to engage in the development of future work reduced. Even firms that we interviewed with a focus on providing process solutions for manufacturers had an emphasis on designing a process in-house (with their own dedicated team of higher-skilled operators and technicians) and then teaching it to workers at a client firm, contrasted with the more dynamic interface between process development and worker that we observed in integrated firms.[87]

On the other hand, when a firm is disintegrated (as several in our sample are), the possibility for interfaces between workers and the firm's technological development is often reduced. Workers at contract manufacturers must work within carefully fixed parameters to meet promised specifications: in turn, the constraints on allowable operations in these disintegrated environments limit the design space for firms and constrain their technological development. Put otherwise, environments with greater roles for workers in innovation may also provide greater technical flexibility to designers.

In our firm sample, the embedded knowledge of workers becomes less sought after for innovation when considering manual production tasks. Manual work in optoelectronics includes the delicate art (so-described by a trainer) of attaching optical fibers at an angle and degree of

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[87] At a higher level, interactions between workers and process engineers will inform reworking of broader assembly processes and indeed changes in product architecture if fabrication or assembly prove unsuccessful in their initial state.

precision that to-date has not been fully automatable in any context we observe. Not all workers possess the manual dexterity for such a task, and multiple firms noted the importance of experience and precision: yet such processes, while demanding, have much lower technical uncertainty than the “black box” of the fabrication environment. The skill and experience of the worker appears more disconnected from a role in innovation in our sample when the technical facts are well understood.

The implications of technological uncertainty for worker participation in innovation may also be connected to the scope of uncertainty. Consolidation and automation in optoelectronics are an illustrative case. Consolidation, as a large-scale design change, requires simultaneous outlays of capital to modify large segments of production from fabrication to assembly, and in turn the consequences of technical uncertainty can be far-reaching, affecting the entire production process (Combemale, Whitefoot, Ales and Fuchs 2021). Automation, in contrast, carries some technical uncertainty but is more local, as individual process steps can be automated, sometimes (though not always) independently of the rest of the production process. The difference in scope of uncertainty between the two technologies is reflected in the experimental lines used by some larger firms, primarily for testing the production of new designs rather than for equipment automation: whereas automation might be more easily offloaded to engineering or indeed outside firms, handling a specific sub-process, the broad technical uncertainty associated with consolidation means that capturing the effects of design change requires a working example of every production step affected. These experimental lines, especially in their lack of mass standardization of equipment and procedures, allow workers an active and potentially more autonomous role as participants in technical innovation.

6.. Discussion

We summarize and synthesize our findings concerning worker participation in innovation in the following figure. Note that the level of “integration” influences how far the production worker’s presence on the value chain extends up toward product designers: the least integrated employer would only accept production orders from clients, with little to no customization or adaptation of process outside of a standard offering, thus allowing no context for a change in technology to be informed by the worker’s embedded knowledge. At a high level of integration, the firm would operate from the shop floor to the product design room, with direct linkages at least between workers and process engineers if not up to the design stage. As we have seen in the case of manual labor in assembly compared with fabrication, the degree of technical certainty of the firm, more so than whether a task is manual or not, is associated in our sample with the degree of engagement of the worker in innovation: uncertainty was the recurring theme in contexts where firms engaged significantly with production workers as direct participants in the firm’s technology development efforts.

Thus, we propose two axes associated with the level of worker participation in technological development: technical certainty and level of integration. In the next figure, we build on our analysis of the distribution of optoelectronic organization models to show how technical certainty and level of vertical integration are associated with worker participation in innovation. Both axes increase the degree of worker participation: more integration gives the worker potentially farther-reaching influence on development, while less technical certainty makes the worker's knowledge more urgent to avoid costly failures.

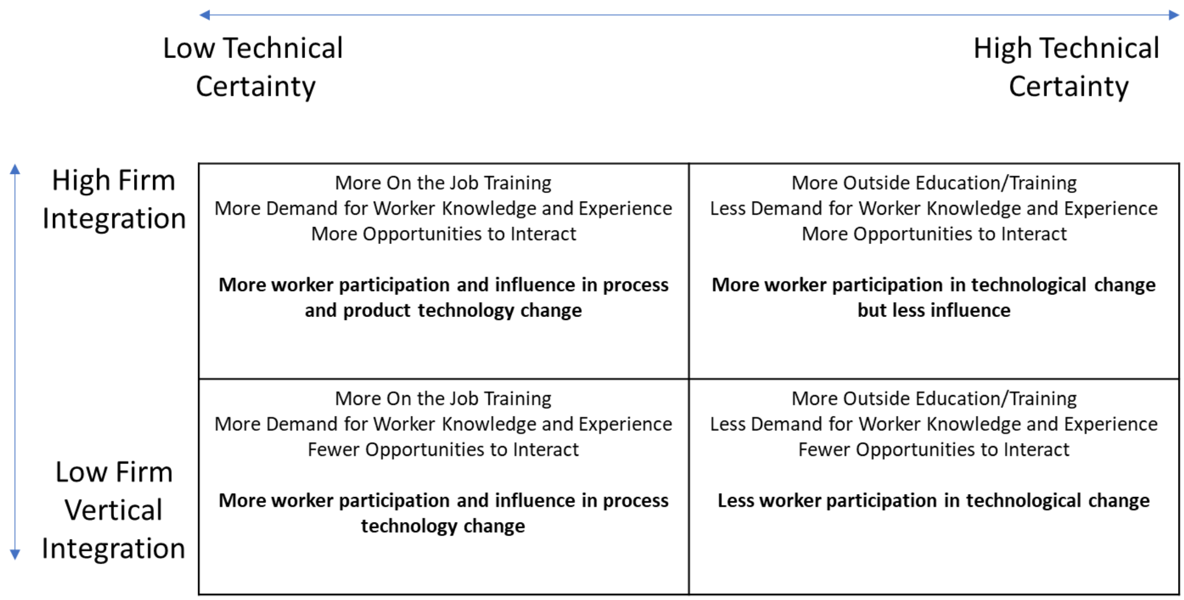

Figure 23 Worker Participation in Innovation by Level of Firm Value-Chain Integration and Technical Certainty

These findings are drawn from recurring themes in interviews with optoelectronics industry members at all levels of employment, and they are consistent in the U.S. and abroad, but further empirical work will be needed to separate these associations from other firm characteristics, and to collect the necessary outcome information to test them as mechanisms for worker participation. Further research is also needed to determine the extent to which participation as alternative to passiveness or conflict in worker experiences of technology indeed results in different employment, wage and psychological outcomes (e.g. a greater sense of ownership over a process of technological change which in current literature is associated with fear and frustration).

Optoelectronics has a high variety of vertical integration and technical certainty, but another important trait as noted in our analysis is its lack of formal educational resources, resulting in greater firm reliance on worker experience and on the job training. These traits are not universal in manufacturing, and we show in stylized form in Figure 24 how other industries may map onto dimensions of technical uncertainty and vertical integration. We also note a third dimension from our analysis, sector-specific technical education: this dimension is more helpful for inter-industrial comparison, as educational resources are generally limited across optoelectronics. In industries such as Aerospace and Automotive manufacturing, with less technical uncertainty than optoelectronics and greater technical educational resources in both secondary and tertiary education (Lloyd 1999; Lin, Chen and Chen 2008)), we would expect a reduced premium on worker experience and on the job training, and potentially reduced reliance in innovation on the localized “sorcery” of workers expert in the operation of specific equipment and uncertain processes.

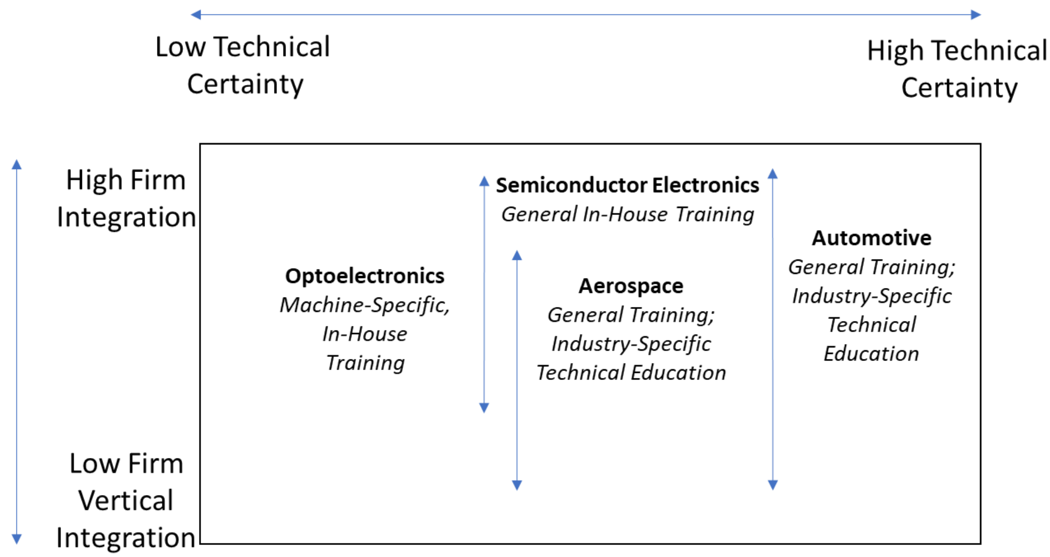

Figure 24 Stylized Industry Distributions by Range of Vertical Integration, Technical Certainty and Educational and Training Programs

With the association between the level of vertical integration, technical uncertainty and worker roles in innovation comes a possible new dimension for policy: policy mechanisms which encourage reshoring of production, firm integration or interfirm collaboration on technical issues also have implications for the part that workers will be enabled to play in the innovations that affect their work and the economy at large.

7. Conclusion

This paper draws on extensive interviews with optoelectronics employees with experiences from the shop floor to product design and senior management, in order to study variations in the scope of worker participation in technological change. We find associations in our qualitative data between high levels of firm integration, high levels of technical uncertainty and the demand from firms for active worker participation as a contributor of knowledge and co-performer of innovative activity. Integration allows interfaces for worker knowledge to be adopted and uncertainty makes the worker’s embedded knowledge a crucial counterpart to imperfect technical understanding in engineering. With the influence of technological change on worker feelings of employment insecurity in many contexts, it is important for labor policy to identify opportunities for workers to take on a more participatory role in technological change, and to recognize that policy implications for firm vertical integration and interfirm innovation collaboration may also have direct implications for the role of labor as participatory in innovation rather than only recipient of its consequences. An important insight of our findings is that firm characteristics could affect their incentives to engage workers as co-innovators, suggesting opportunities for a cooperative approach that can benefit workers and firms. Further research is needed to establish more clearly if the associations described in this paper can be used to inform policy mechanisms, and indeed to evaluate empirically the benefits to workers of participation in the process of technological change.

Dissertation Summary and Conclusions

The four chapters presented in this dissertation offer novel data, technological nuance, and new theoretical underpinnings to our understanding of the labor effects of technological change, such as skill demand, management structure and worker displacement.

In the first chapter, we find across industries and times that not all technologies are equal in their implications for worker outcomes: for example, among shop floor workers in semiconductor manufacturing for communications, we find that skill demand is polarized away from the middle under automation, but that it converges toward middle skills when parts are consolidated as one. We also show that these very different outcomes for skill demand can have similar cost ranges. This evidence suggests that technology change need not lead to greater inequality, and it suggests a choice for decisionmaking around technology and labor outcomes.

In the second chapter, we develop a general theory relating technology change to ability demand through the division of production tasks within a firm. In the theory, technology change affects the problem of the firm on five dimensions: 1) cost of dividing production tasks (fragmentation costs), 2) process complexity, 3) cost of dividing performers across steps (divisibility of performer), 4) sensitivity of performers to rate of production and 5) sensitivity of performers to number of tasks in a step (generality of performer). These dimensions can be used by firms and policymakers to interrogate new or emerging technologies, by seeking technical or operational evaluations of how each dimension may be changed by features of the technology.

This work provides a formal structure for identifying and explaining ways in which technologies can have *different* effects on labor outcomes such as inequality, and for characterizing the dependencies between characteristics of production context and technological effects. A major finding is that polarization due to automation is dependent on the reallocation constraints on machines and hence on the volume of production in processes being automated: automation substitutes for mid-skill workers at lower production volumes (driving skill polarization toward ability and high ability workers) but substitutes for all but high ability at higher production volumes. We also show that design innovations, such as parts consolidation, lead to reduced inequality between the highest and lowest levels of ability demand by reducing process complexity but making tasks harder to separate (inversely to interchangeable parts historically).

The third chapter of this dissertation extends the theoretical approach in the second chapter to understand how technology change interacts with characteristics of different tasks. We show in our model that polarization of demand due to automation interacts with the characteristics of production tasks. We show theoretically that polarization is greater when tasks have lower variation in the number of issues, but that at sufficiently high volumes automation in low-variance contexts can result in upskilling where high-variance tasks would still see polarization. These findings suggest different consequences from automation across industry and indeed occupational contexts with different levels of issue variance.

Future work building on this extension to the model will adapt and expand the task-type construction to study the origins of occupational bias and managerial hierarchy changes from new technology. In the envisioned model, after aggregating production tasks into steps, firms choose how many layers of issue-solving to use within each step and the type (human or machine) and abilities of performers (or sets of abilities across types of issues) assigned to each layer. Heterogeneous issues arise and progress from one layer to the next until they are solved by a sufficiently able performer. Technology change alters the cost-minimization problem of the firm by affecting characteristics of performers, types of issues or referral costs. This relationship will give rise to mechanisms for technology change to affect choice of managerial structure, inequality of skill demand within managerial hierarchies and generate occupation and task-biased productivity changes.

Potential insights from this expanded theory include identifying implications for inequality of skill demand within a hierarchy when technology (or other) changes allow greater flexibility of manager reallocation. We seek to ground the theory empirically by measuring how different technologies alter the structure of problem-solving and the division of labor across occupations. We focus on automation versus consolidation of parts in the optoelectronic semiconductor industry as examples of innovations that change the inputs to production and the structure of production, respectively. In anticipation of this extended work, I revisited and expanded my industry contacts in optoelectronic semiconductors and collected a new dataset from nine firms on direct, indirect and supervisory labor in over 90 manufacturing activities and in over 100 activities in process or product design, in-house or as a service.

The fourth chapter offers a qualitative investigation of relationships between organizational structure and the productivity returns to worker experience under technological uncertainty, drawing on extensive observations and interviews from the optoelectronics context. Our findings suggest that firms integrating between technical design and production are better able to draw on embedded worker knowledge to solve “black box” problems, but that lower transferability of embedded expertise can leave such workers especially vulnerable to future technological disruption.

The general theory of tasks and technology change presented in the second chapter offers significant opportunities for future work by relaxing assumptions or expanding mechanics of the model. A natural extension of this general theory work is to relax assumptions on production failure. The model assumes that firms set ability demand for each process step to solve a series of stochastic production issues in expectation. However, factors such as safety, material losses and scheduling costs drive firms to reduce rates of production failure.

I plan to develop an extended model that endogenizes the rate of production failure as a firm choice, allowing me to study how technology change (e.g. testing methods) and worker skills interact with the optimal choice of operations regimes (e.g. make-to-order) and the safety or quality characteristics of products (Appendix 13 provides a preliminary sketch of model extensions to capture these features). The operations data I collected for prior papers directly capture production characteristics such as yield rate and the cost of non-performer inputs (e.g. materials) that may be lost with production errors. This work, in conjunction with my work on organizational structure, will allow me to study the relationship between technological change and industry structure by modeling task separation and quality management at the boundary of the firm.

The general theory in the second chapter provides insights into multiple technological changes, but it can characterize a much wider range of phenomena. A natural extension is in my ongoing work to develop a taxonomy of technological change, formalizing the implications of all possible parameter changes in the model for the division of tasks and demand for workers. This avenue for future work could support two main objectives. The first is to build out a body of formal propositions whose implications will give academics and non-academic decisionmakers an "off the shelf" framework for readily dissecting the labor demand implications of technology change. This framework will also support analysis of technology adoption within existing steps (a non-organizational change) and the reorganization of tasks to adapt to new technology (organizational change). The second objective is to develop a suite of econometric methods for the estimation of parameters of the model in aggregate data, allowing the theory to be taken from detailed operations data to a wider selection of public data (such as the U.S. Survey of Manufacturers), expanding its research applicability (see Appendix 14 for a discussion of possible empirical identification strategies for key parameters of the general theory).

The propositions of the taxonomy could also be developed to support analysis of the implications of strategy or policy choices with respect to technology change. One future paper I envision is assessing the labor implications of union policy, such as rules to prevent employers from reassigning workers to tasks outside of negotiated job descriptions. Such rules may reduce the divisibility of workers. In the general theory, lower divisibility can raise demand for given performers, but the higher divisibility of workers is an important advantage over machines.

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Appendix

Appendix 1: Equations for Process Based Cost Model in Chapter 1

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:

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

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

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

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

$\omega_s \in \mathbb{R}^+$ 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):

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

$u(v_s)$ 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 $\mathrm{l_s}$ is the line time required in step j to meet effective production volume (as in Fuchs and Kirchain (2010)) and $\mathrm{a_s}$ 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):

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

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

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 $\mathrm{D_s}$ 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:[88] 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:

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

[88]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.

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 $\overrightarrow{p(\imath_s)} \in \mathbb{R}^n$. A demand for input factors $\overrightarrow{D(\imath_s)} \in \mathbb{R}^n$ 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.

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

Thus the range of overall production costs is given by:

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

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:

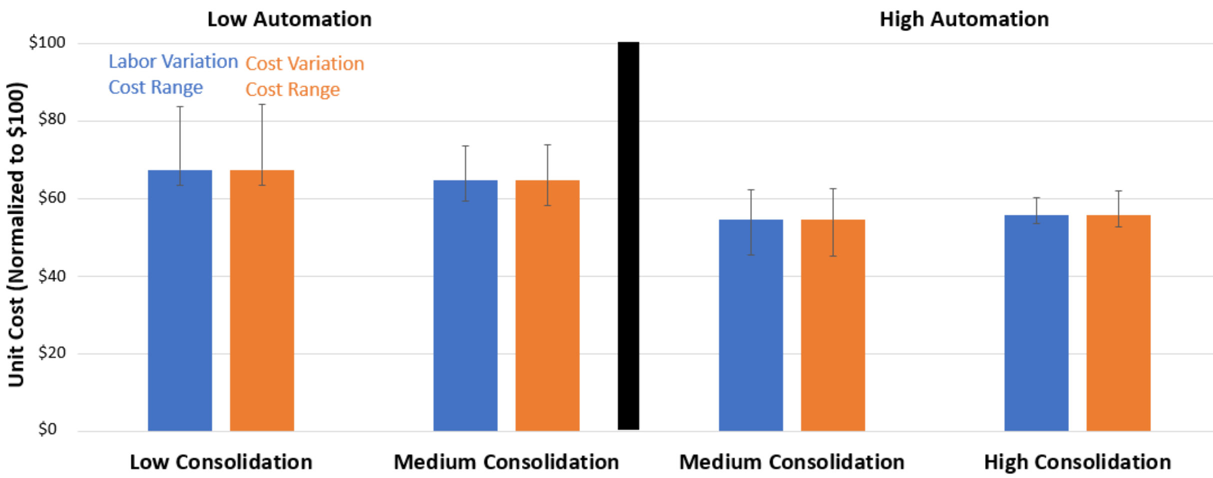

Figure 25 Cost Range Comparisons of Interfirm Labor and Cost Variation Inputs

Appendix 1.2: 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):

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

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

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:

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

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:

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

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

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 10 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 11 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 12 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 13 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 14 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[89]	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 15 and Table 16, 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 15 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)

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

Table 16 Sample of Empirical Validations of Labor Quantity Estimates

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

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

Appendix 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).[90] 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).

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[90] 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

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).[91] 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.[92] 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.

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.

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

[92] 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).

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 (

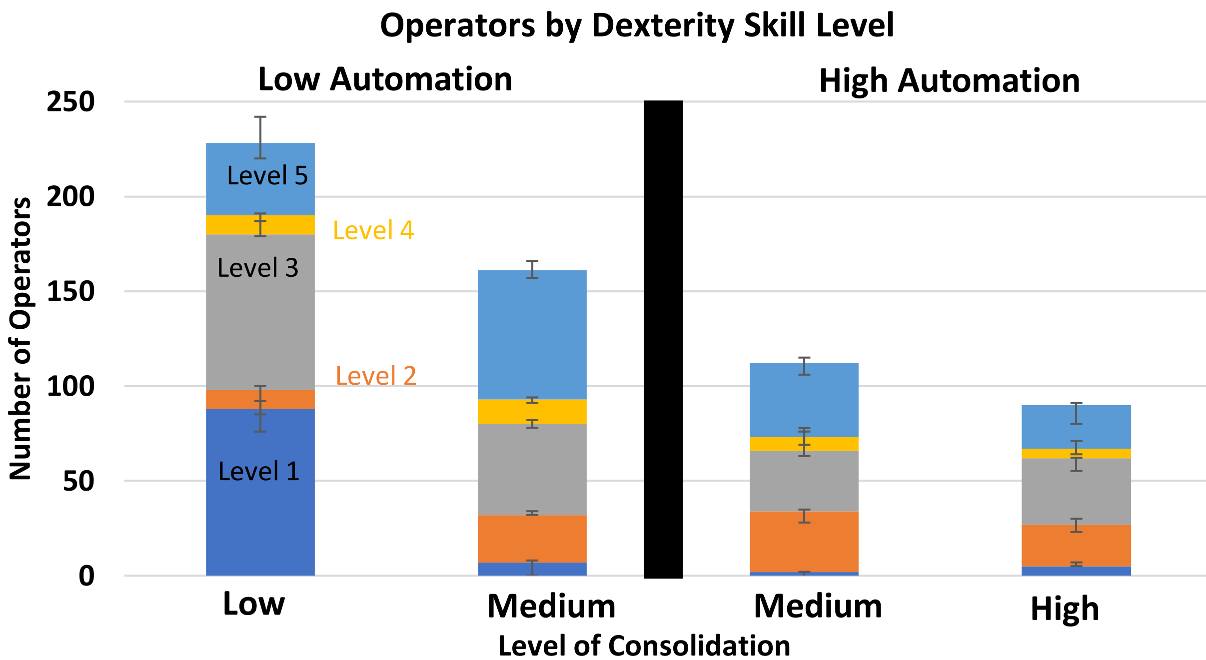

Figure *26* Number of Operators by Scenario and Dexterity Requirement (Median APV)

) and share (**Error! Reference source not found.**) 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 (

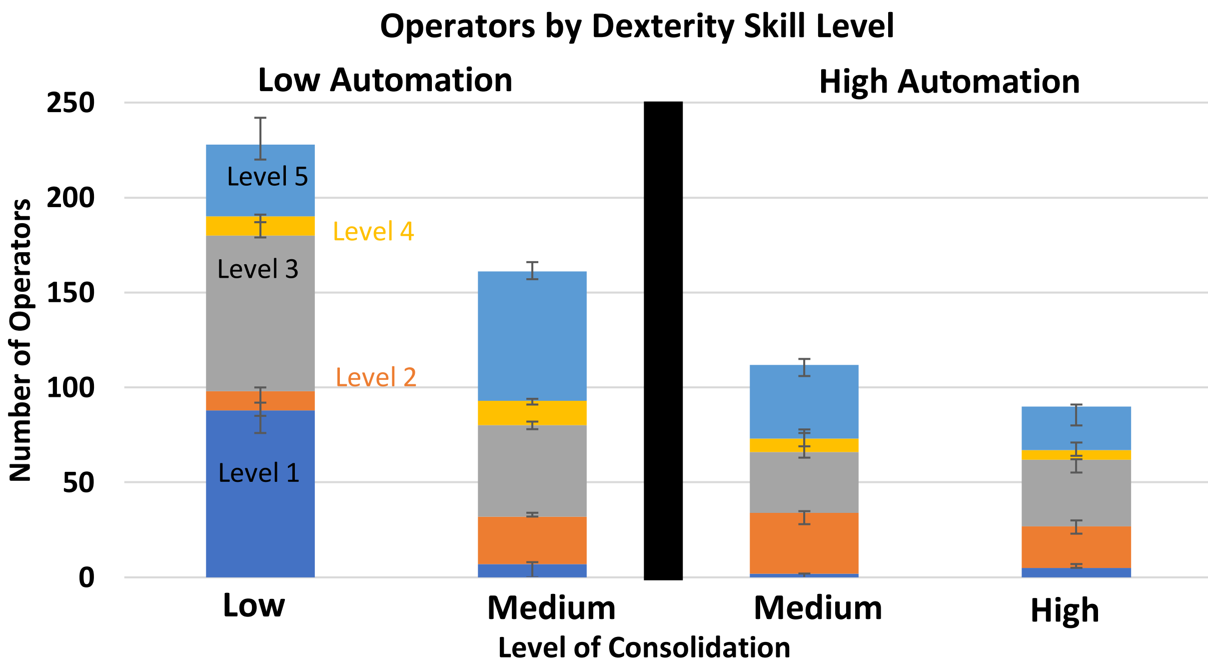

Figure *26* Number of Operators by Scenario and Dexterity Requirement (Median APV)

) as well as proportionally (**Error! Reference source not found.**). 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.

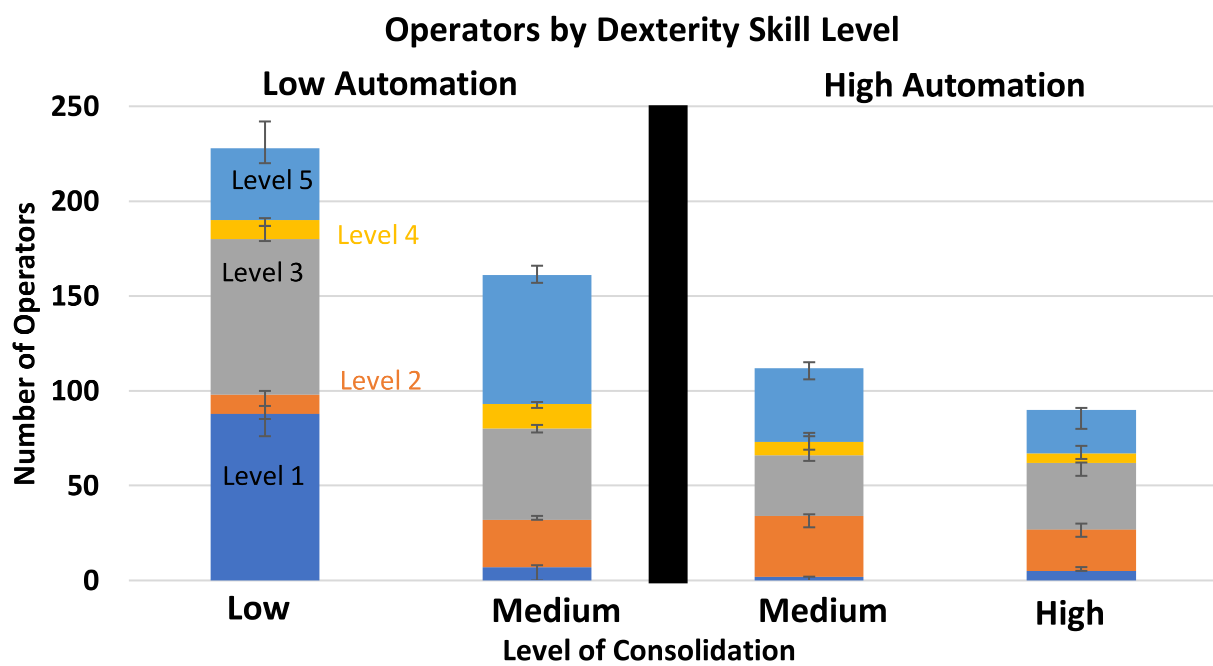

Figure 26 Number of Operators by Scenario and Dexterity Requirement (Median APV)

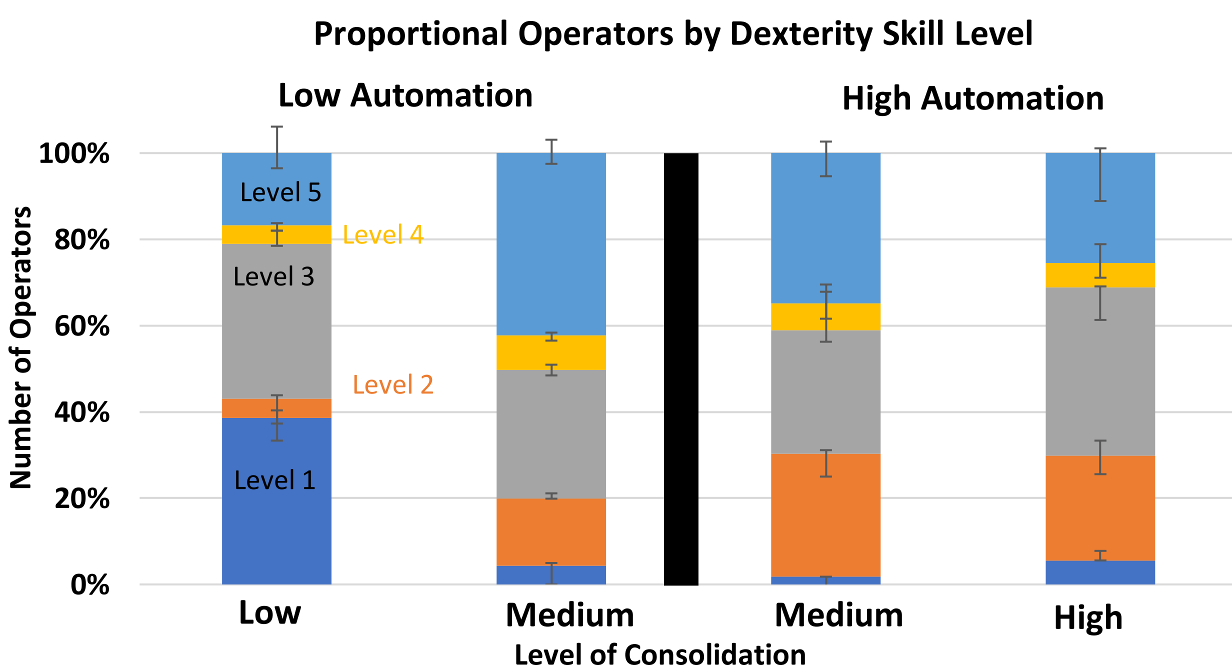

Figure 27 Share of Operators by Scenario and Dexterity Requirement (Median APV)

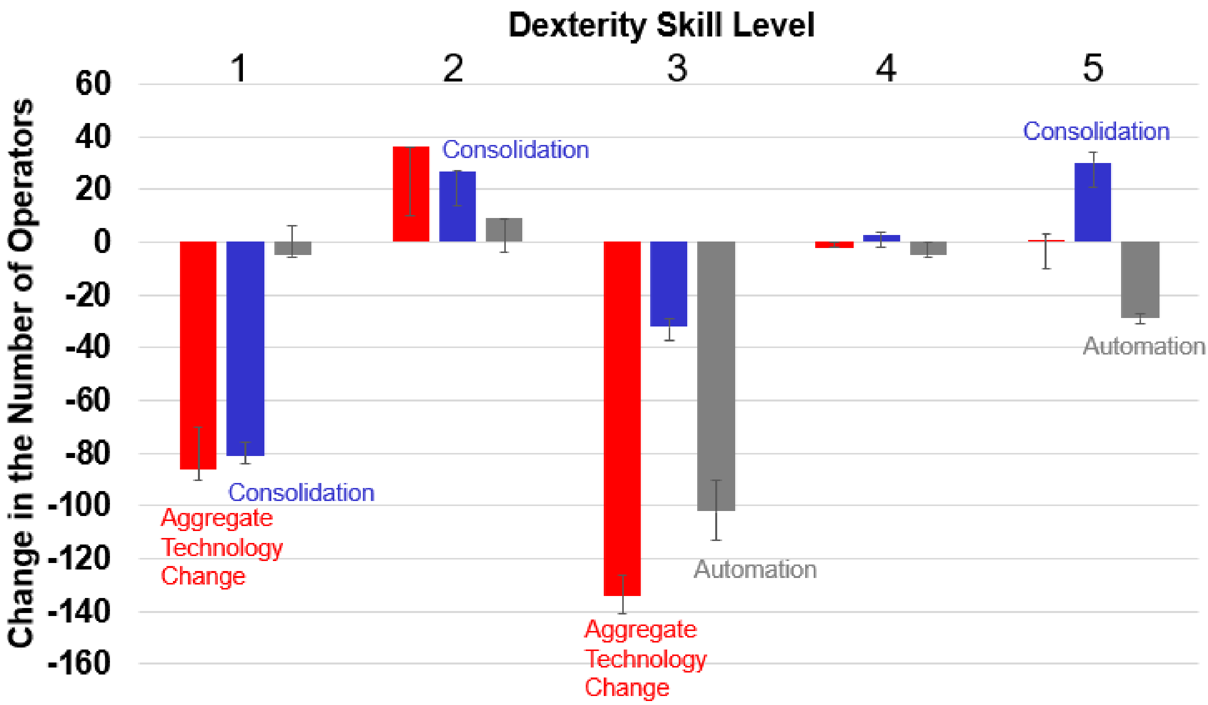

Figure 28 Aggregate Dexterity Skill Effects of Disaggregated Automation and Consolidation: Shifting from Low Consolidation, Low Automation to Medium Consolidation, High Automation

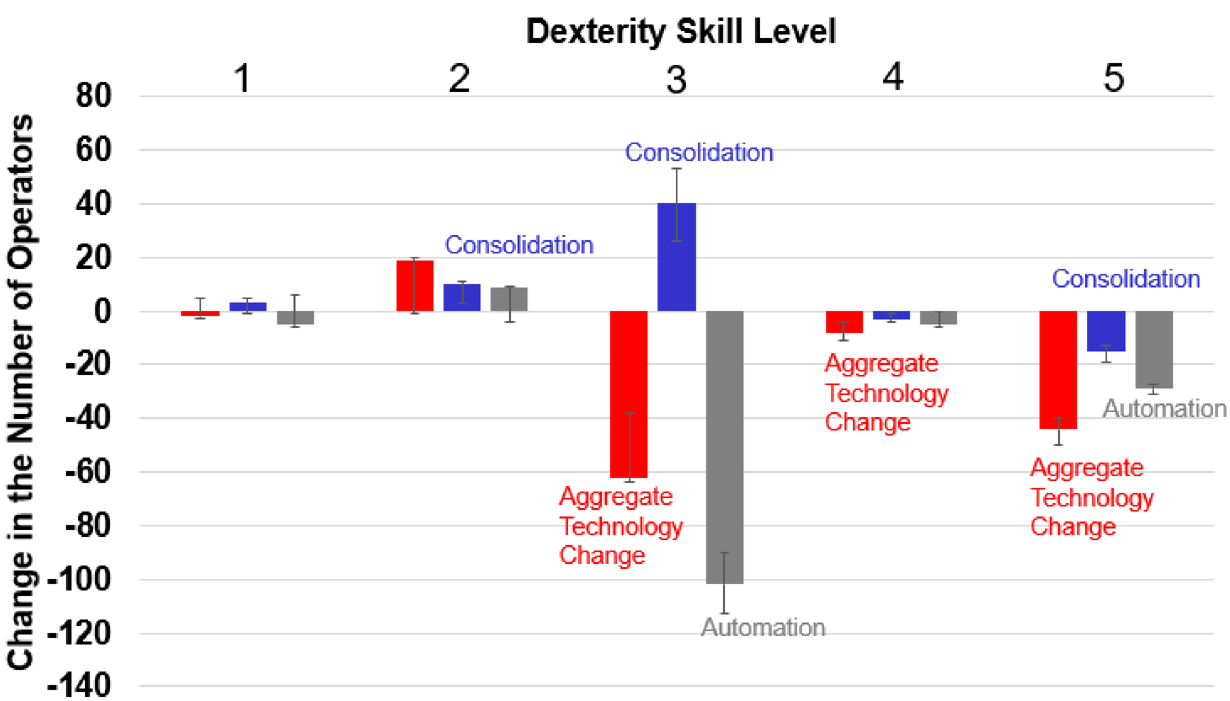

Figure 29 Aggregate Dexterity Skill Effects of Disaggregated Automation and Consolidation: Shifting from Medium Consolidation, Low Automation to High Consolidation, High Automation

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 30) and proportionally (Figure 31) 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 30) and share (Figure 31) 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.

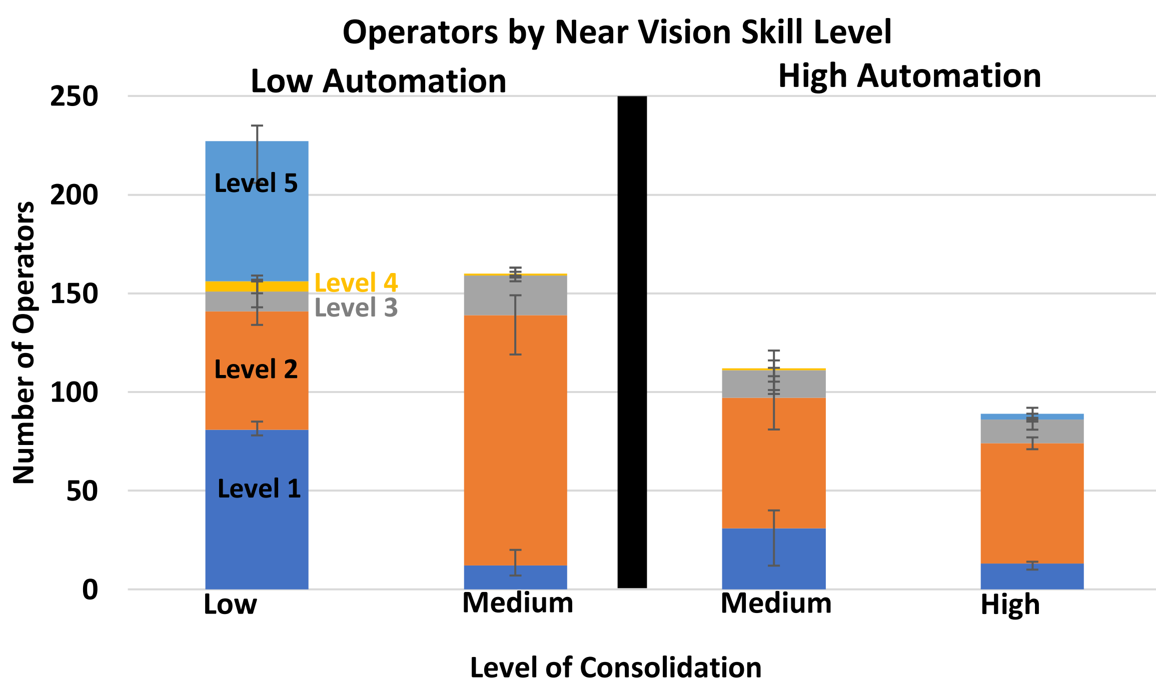

Figure 30 Number of Operators by Scenario and Near Vision Requirement (Median APV)

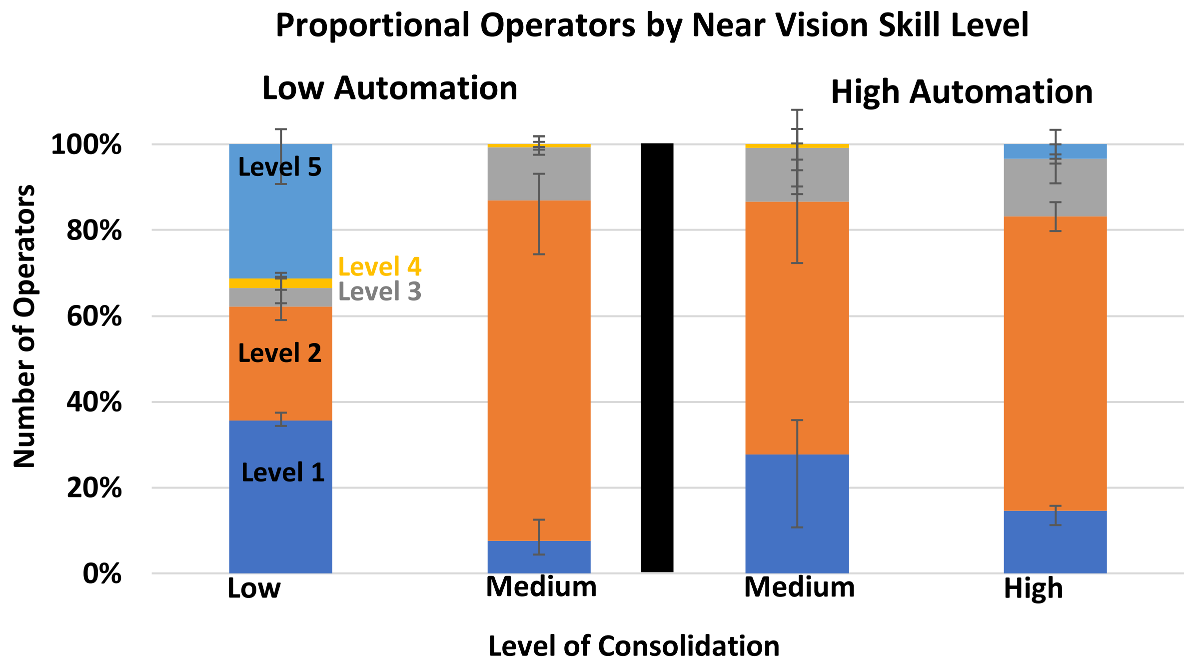

Figure 31 Share of Operators by Scenario and Near Vision Requirement (Median APV)

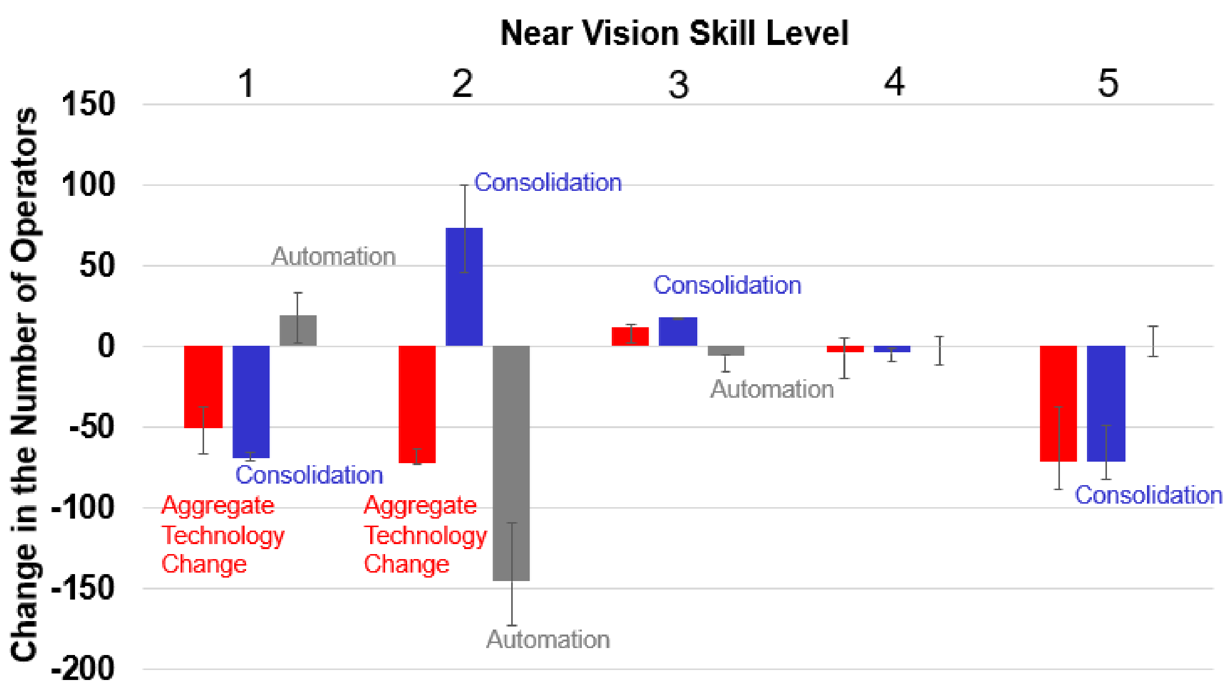

Figure 32 Aggregate Near Vision Skill Effects of Disaggregated Automation and Consolidation: Shifting from Medium Consolidation, Low Automation to High Consolidation, High Automation

3.1.3. Operations and Control Requirements for Operators

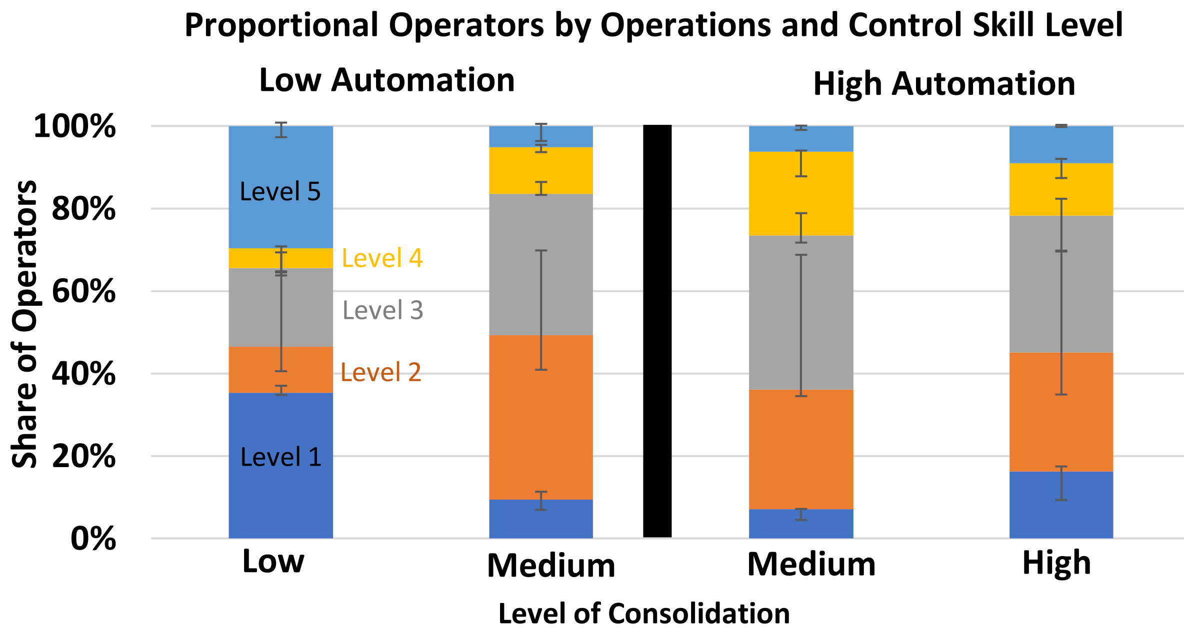

Figure 33 Share of Operators by Scenario and Operations and Control Requirement (Median APV)

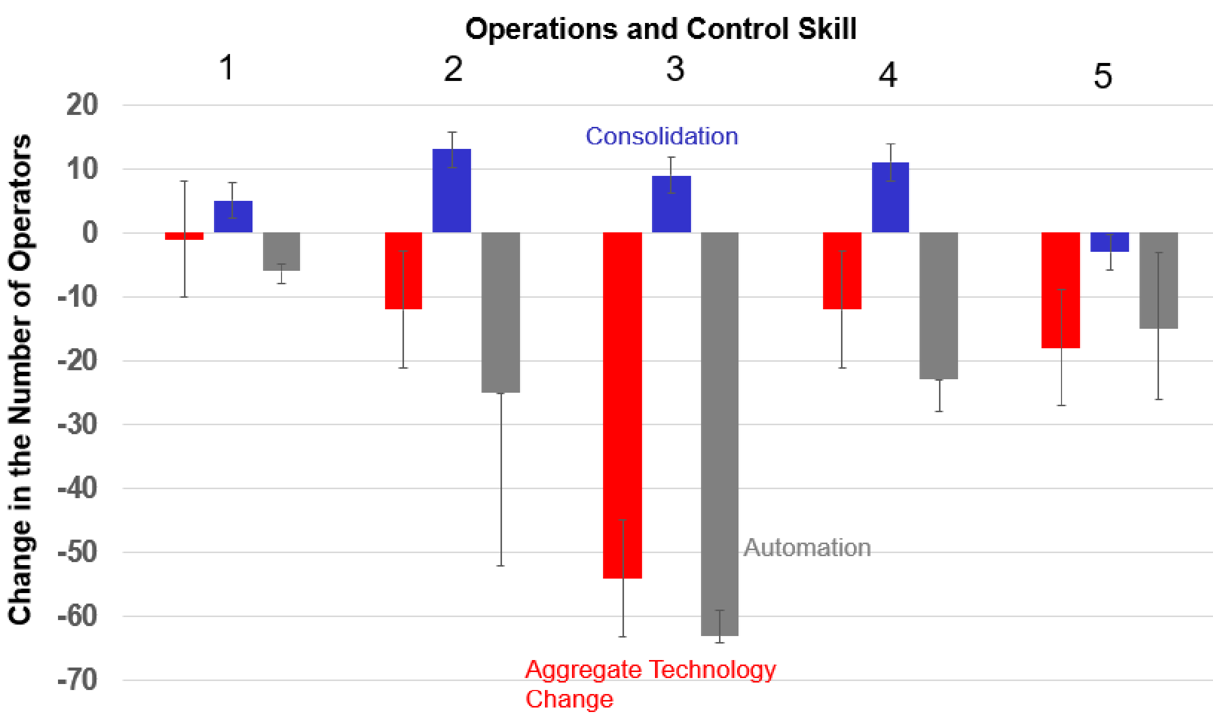

Figure 34 Operations and Control Skill Effects of Disaggregated Automation and Consolidation: Shifting from Medium Consolidation, Low Automation to High Consolidation, High Automation

3.1.4: 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.

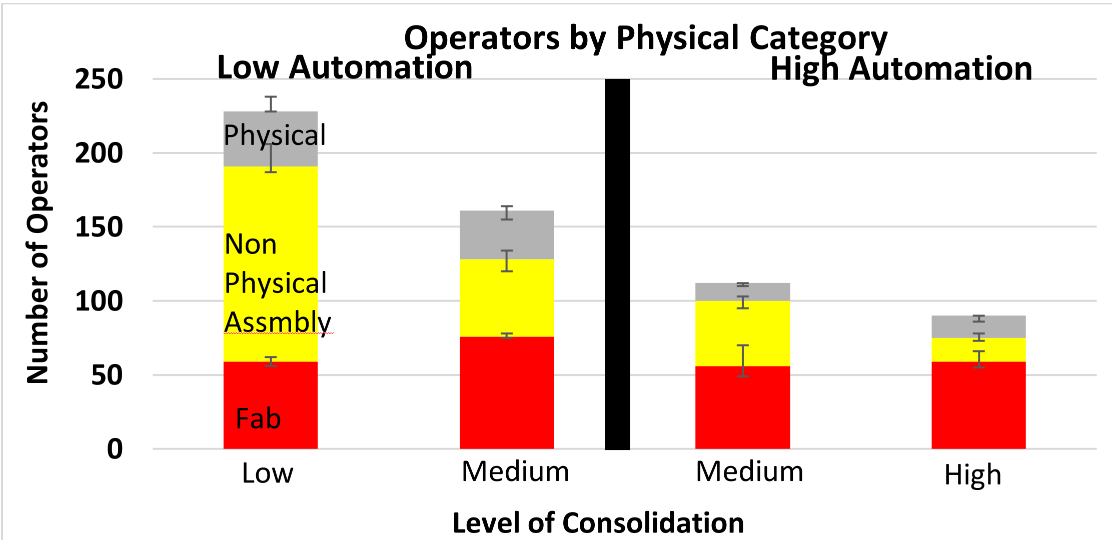

Figure 35 Physical, Nonphysical Assembly Operators, Total Fabrication Operators

This result 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

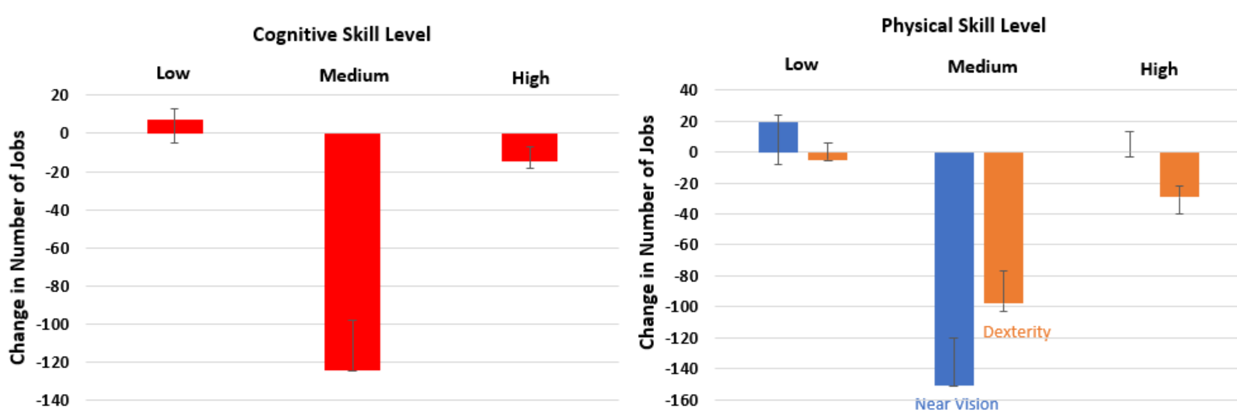

Figure 36 Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level under Automation

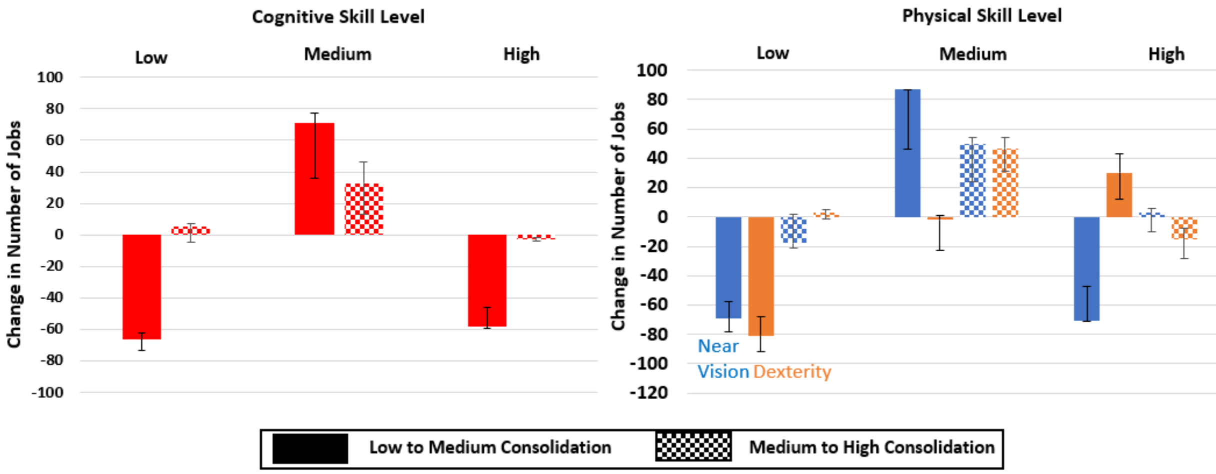

Figure 37 Aggregate Change in Operator Jobs by Cognitive, Near Vision and Dexterity Skill Level under Consolidation

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 (Fuchs and Kirchain 2010; Fuchs, Kirchain and Liu 2011). Figure 38 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.

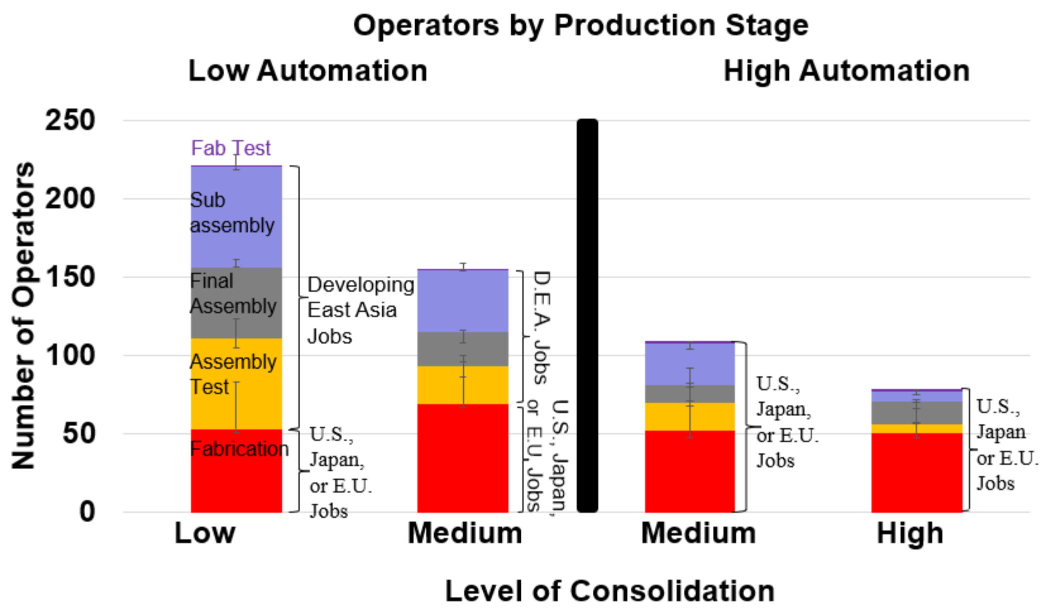

Figure 38 Probable Global Location of Jobs by Production Stage and Scenario

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), 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 39 (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.

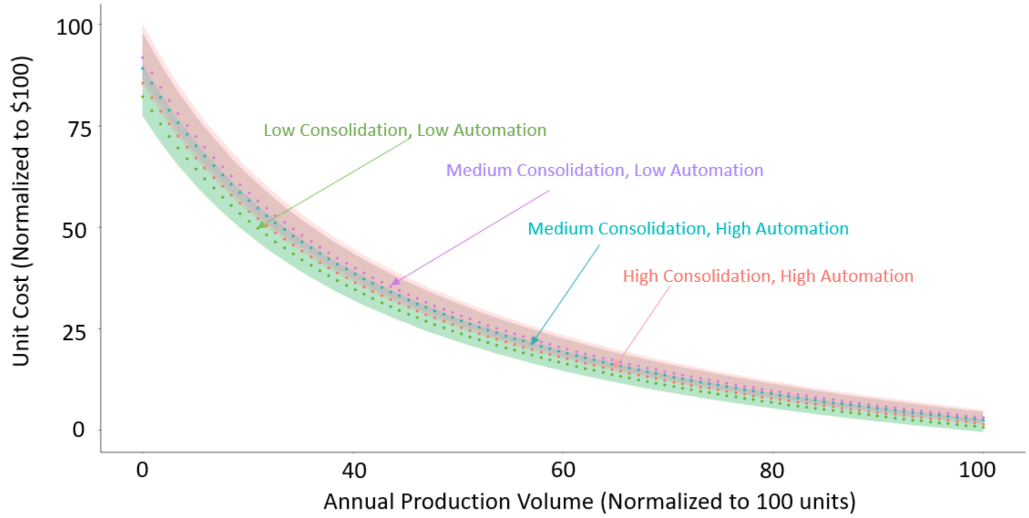

Figure 39 Cost Ranges for Automation and Consolidation Scenarios in Developing World

Appendix 3.4: Joint Skill Distribution Shifts

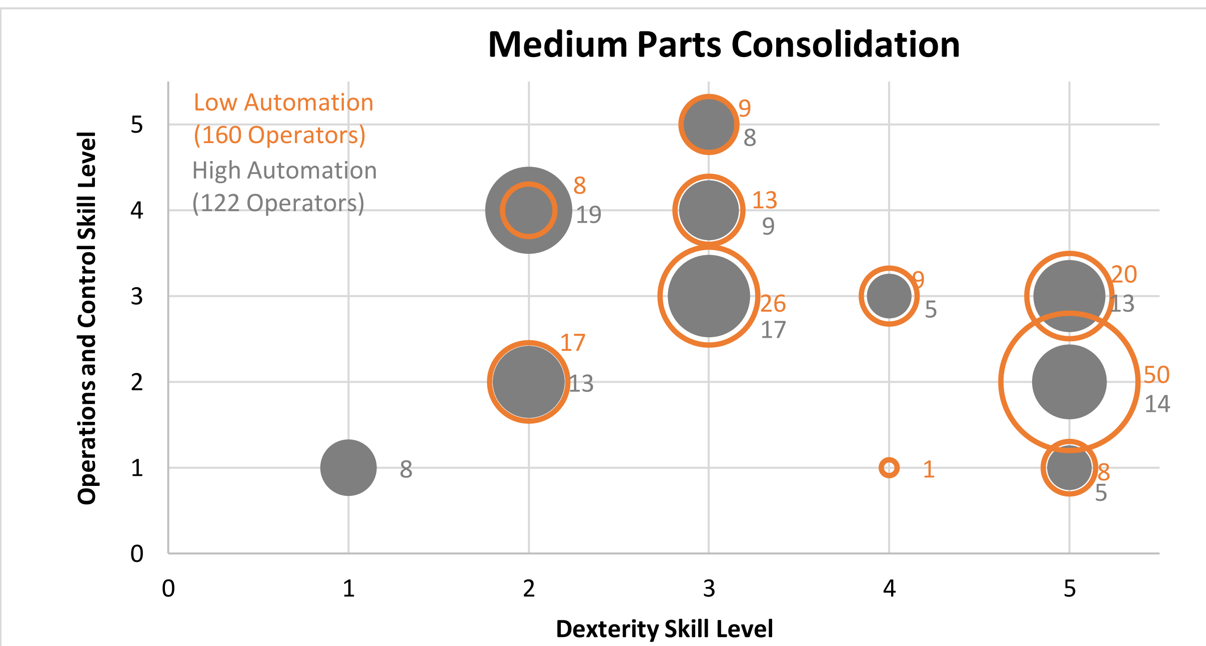

Figure 40 Automation from Low to High, Under Medium Parts Consolidation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

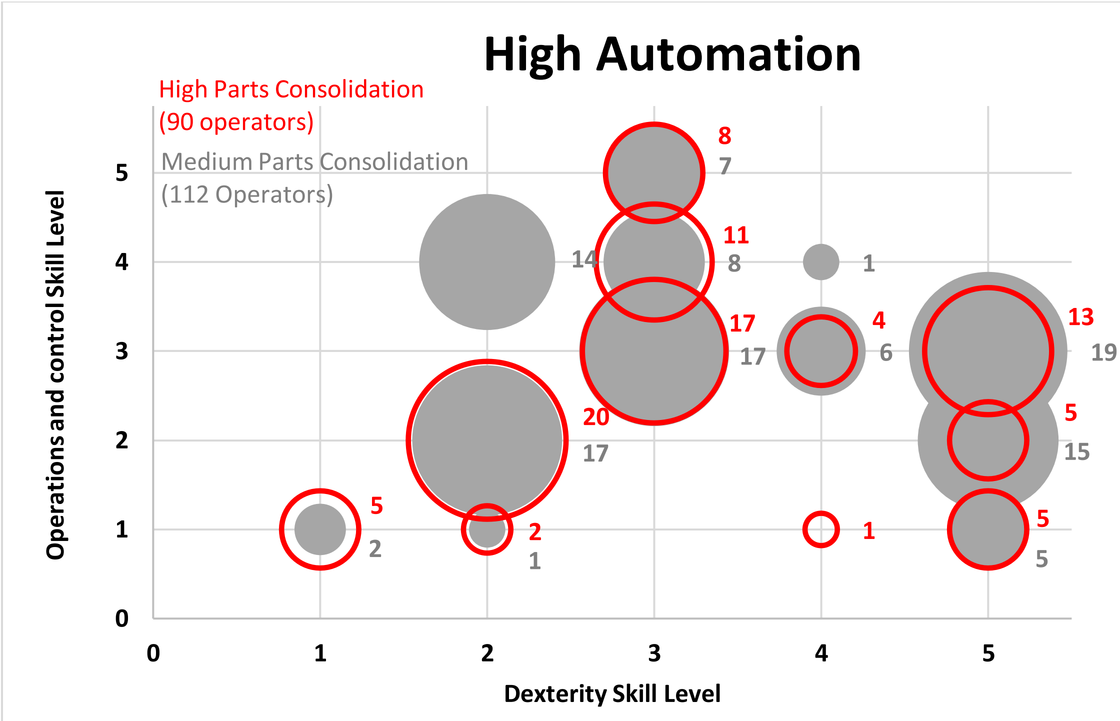

Figure 41 Parts consolidation from Medium to High, Under High Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

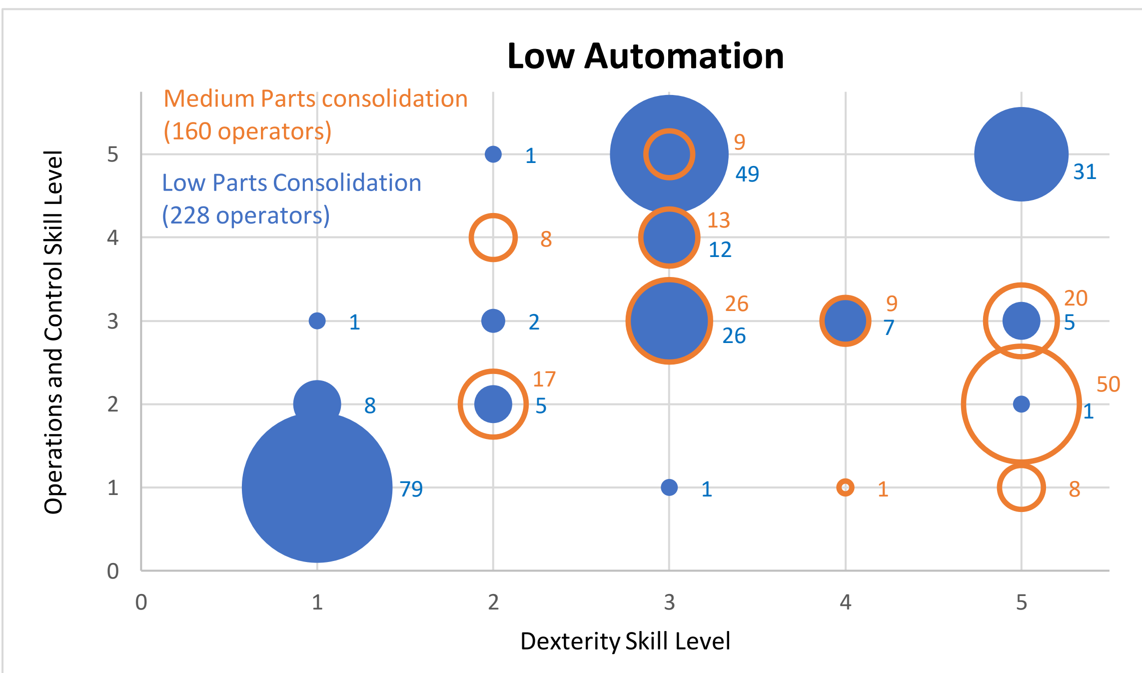

Figure 42 Parts Consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Dexterity Skill

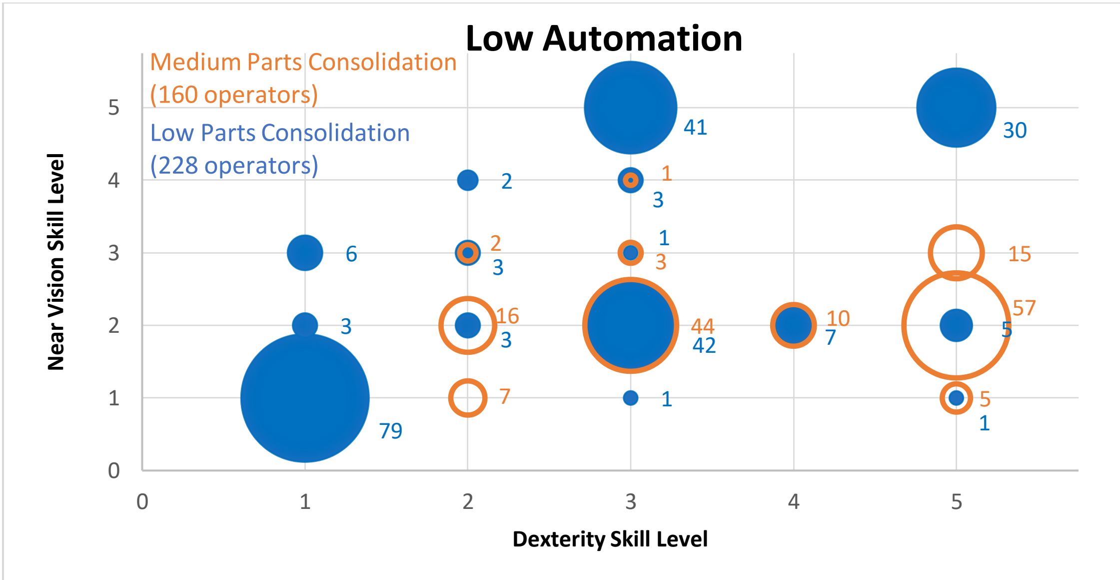

Figure 43 Parts consolidation from Low to Medium, Under Low Automation: Shifts in the Joint Distribution of Near Vision and Dexterity Skill

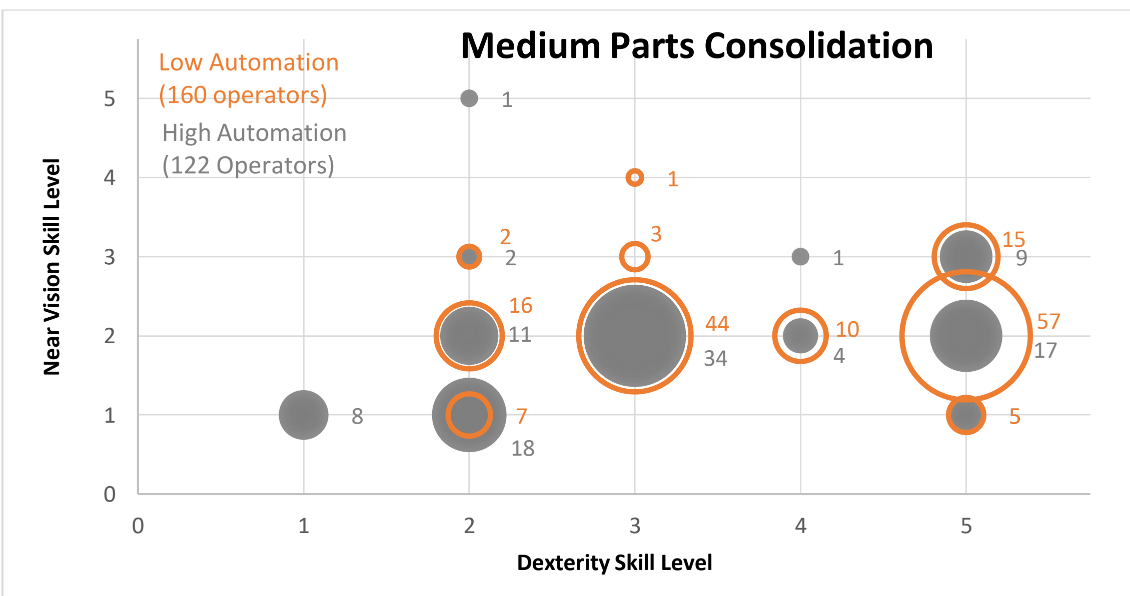

Figure 44 Automation from Low to High, Under Medium Parts consolidation: Shifts in the Joint Distribution of Near Vision and Dexterity Skill

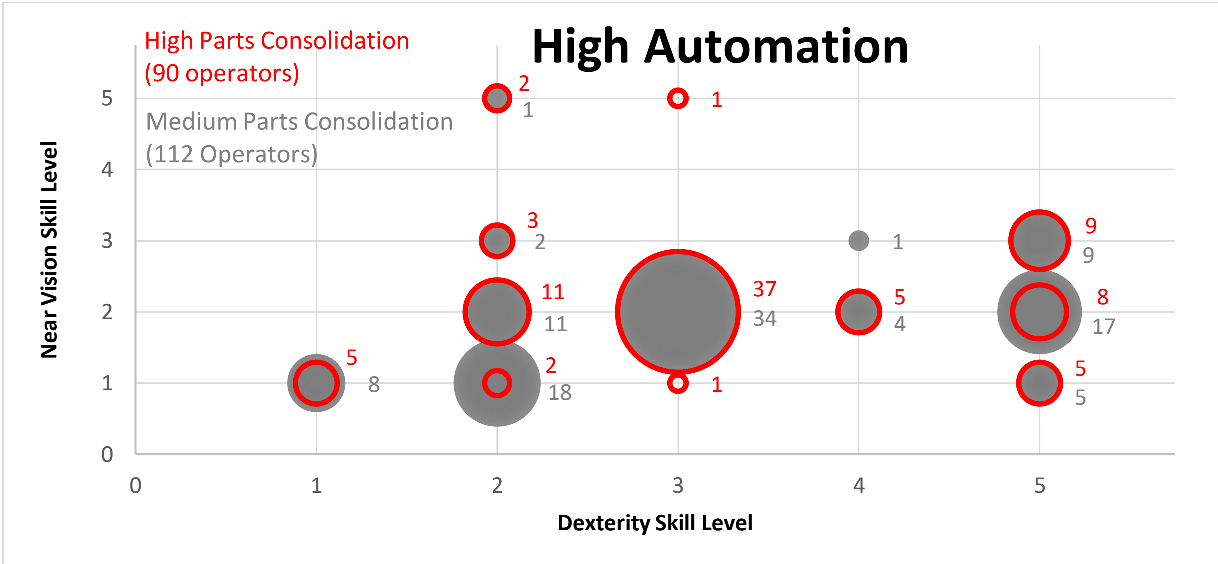

Figure 45 Parts Consolidation from Medium to High, Under Low Automation: Shifts in the Joint Distribution of Near Vision and Dexterity Skill

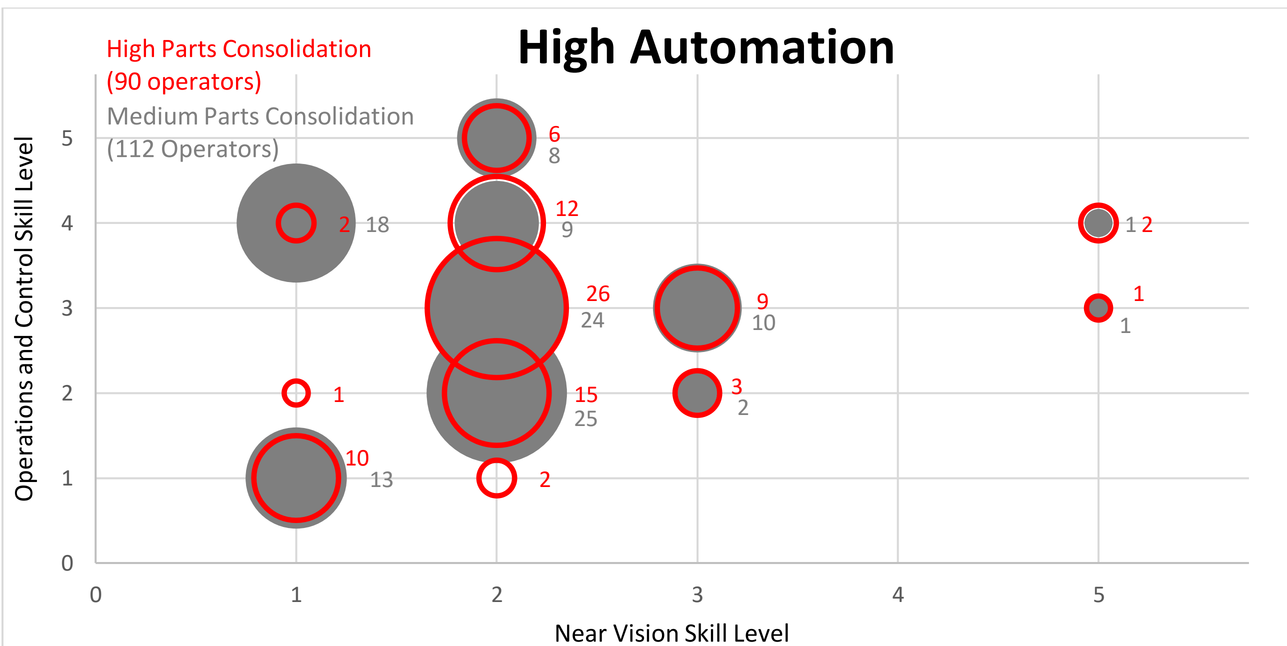

Figure 46 Parts Consolidation from Medium to High, Under Low Automation: Shifts in the Joint Distribution of Operations and Control and Near Vision Skill

Appendix 3.5: Unit Cost Breakdowns at median annual production volume

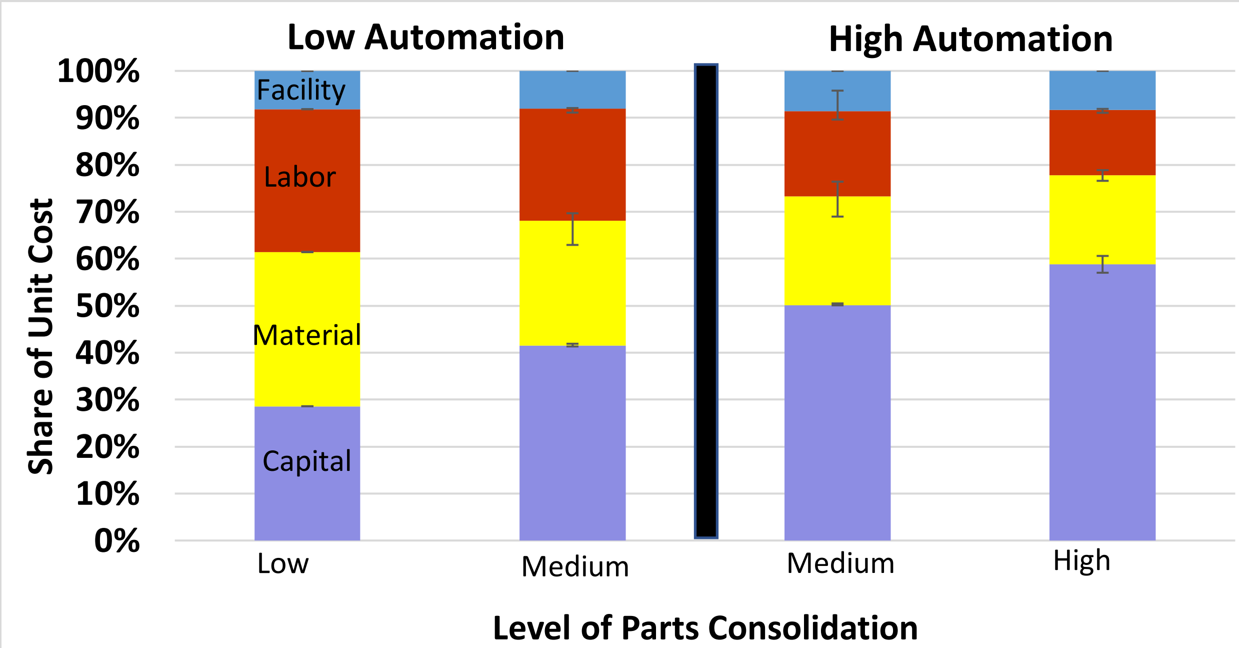

Figure 47 Unit Cost proportions by Cost Category

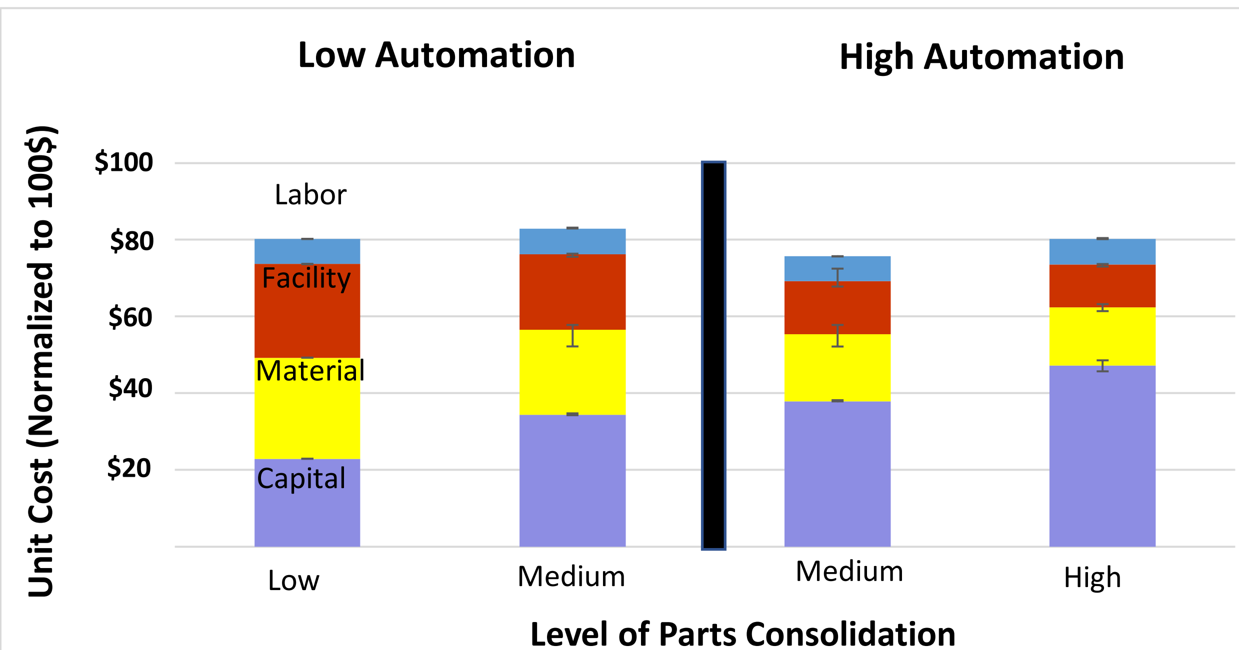

Figure 48 Unit Costs by Cost Category

Appendix 4: Fabrication Analysis

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 17 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 18 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 6: 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 19. 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 20 and Table 21 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 20) The large majority (91%) of process steps with automated tasks include an automated execution task (Table 21), with few cases of monitoring automated alone (9%) and no cases of preparation automated alone.

Table 19 Task Categories and Examples

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

Table 20 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 21 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%

Appendix 7: Structure and Theory of O*NET

The O*NET dataset is organized according to a content model, with six overarching categories: Worker Characteristics, Worker Requirements, Experience Requirements, Occupation-Specific Information, Workforce Characteristics and Occupational Requirements.

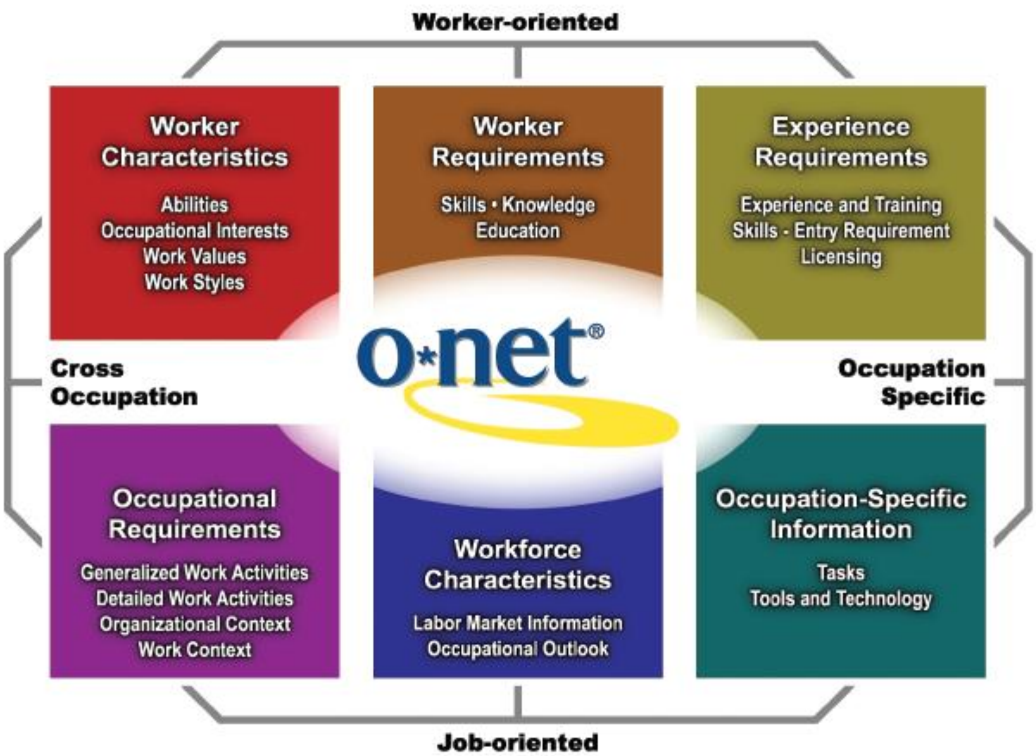

Figure 49 O*NET Content Model (source: National Center for O*NET Development)

Worker Abilities and Worker Skills are captured in this model as subcategories; Worker Abilities are a subcategory of Worker Characteristics, and Worker Skills are a subcategory of Worker Requirements. Worker Skills are acquired through formal education, experience and on-the job training,[93] whereas Worker Abilities are "enduring" characteristics that allow workers to perform tasks; the theoretical distinction between skills and abilities is somewhat loose in the content model (NAS 2010), resting mostly on the process of acquisition – skills are acquired through education, training or experience (i.e. learned to some extent), whereas abilities may or may not be innate (the content model and survey instrument is agnostic on this point for any given ability). Abilities may feed into skills (Burtch et al 1982) or the ease of skill acquisition (Bartel and Lichtenberg 1987; Kanfer and Ackerman 1989), but the content model does not presume such mappings. The restriction on skills as acquired capabilities, with more ambiguity for abilities, appears to be the primary distinction (NAS 2010), and it is also reflected in past literature (Carrol 1993) and in past Department of Labor measures (DOT US DOL 1991). As our study focuses on task-level capability requirements but not the acquisition of skills or abilities for meeting those requirements (and firms in our study do not have programs in place for skill development outside of very task-specific training), skills and abilities are both relevant labor characteristics and potential distinctions in their acquisition are not immediately in-scope to our research questions around shifting labor demand under technological change.

Thus, skills and abilities influence worker performance and form part of the spectrum of requirements for certain occupations or tasks.[94] These skills and abilities are more general than the occupation specific information section of the content model, which includes "tasks and tools" as descriptors of work; these descriptors allow a qualitative mapping of detailed, station or machine level work characterizations to the more aggregate "occupations" measured by O*NET.

The O*NET taxonomy was devised based on taxonomic methods common in the literature (Meehl and Golden 1982; Carrol 1993) and reflects a continuation of interest and capability typologies used in past aptitude 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.

Appendix 8: Proofs of Chapter 2 Section 3

Proof of Lemma 1

Proof. For any realization of $\{X_i\}_{i=1}^{n}$, from Lemma 2.1 in [35] we have that:

$$\left(\sum_{j=1}^{n} (X_j)^{\rho_h}\right)^{\frac{1}{\rho_h}} < \left(\sum_{j=1}^{n} (X_j)^{\rho_m}\right)^{\frac{1}{\rho_m}},$$

---

[93] However, experience and training as occupational credentials or requirements in their own right also fall under "experience requirements"

[94] Relating O*NET to the task-based framework in e.g. Acemoglu and Autor (2010)

the result then follows immediately. ■

Proof of Lemma 2

Proof. We have that for all n

$$\frac{dP_n(l)}{dl} = P_n(l)\left(\frac{n}{l} - \lambda\right).$$

Since $\mathbf{X}(n|\rho)$ is strictly increasing in n, we have that:

$$\frac{dc(l)}{dl} = \sum_{n=1}^{\infty} P_n(l)\left(\frac{n}{l} - \lambda\right)\mathbf{X}(n|\rho) > \sum_{n=1}^{\infty} P_n(l)\left(\frac{n}{l} - \lambda\right)\mathbf{X}(1|\rho),$$

so that:

$$\frac{dc(l)}{dl} > \mathbf{X}(1|\rho)\left[\frac{1}{l}\sum_{n=0}^{\infty} nP_n(l) - \lambda(1 - P_0(l))\right] = \mathbf{X}(1|\rho)\lambda P_0(l) > 0.$$

We next show concavity. Since $\mathbf{X}(0|\rho) = 0$ and since $\frac{n}{l}P_n(l) = \lambda P_{n-1}(l)$, we have that

$$\frac{dc(l)}{dl} = \lambda \sum_{n=0}^{\infty} P_n(l)(\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho)) > 0,$$

so that:

$$\frac{d^2c(l)}{dl^2} = \lambda \sum_{n=0}^{\infty} P_n(l)\left(\frac{n}{l} - \lambda\right)(\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho)),$$

so that:

$$\begin{aligned}\frac{d^2c(l)}{dl^2} &= \lambda^2 \sum_{n=0}^{\infty} P_{n-1}(l)\big(\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho)\big) - \lambda^2 \sum_{n=0}^{\infty} P_n(l)\big(\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho)\big)\\ &\le \lambda^2 \sum_{n=1}^{\infty} P_n(l)[(\mathbf{X}(n+2|\rho) - \mathbf{X}(n+1|\rho)) - (\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho))] < 0.\end{aligned}$$

Where the first inequality holds since $\lambda^2 P_0(l)(\mathbf{X}(1|\rho) - \mathbf{X}(0|\rho)) > 0$ and the second inequality holds since $\mathbf{X}(n+1|\rho) - \mathbf{X}(n|\rho)$ is decreasing in n. ■

Appendix 9: Hand and Machine Labor Data

Appendix 9.1: Overview

For each product, the Hand and Machine Labor (HML) dataset includes general information on the process as well as detailed information on the steps required to create the product either using different methods: either by hand or using a machine. Products vary greatly in the complexity of production: the observed number of steps range from one to over two hundred and fifty. The data used in this paper comprise 247,482 step-level entries and 11,862 process-level entries. The HML data is publicly available in a non-digitized form. The entire dataset was digitized from scanned and physical copies of the data by undergraduate students at Carnegie Mellon University between 2019 and 2021.[95]

The type and definition of variables present in the HML dataset are described below. Table *22* describes process-level variables, which apply across all steps and methods. For ease of comparison between processes of each method, the dataset reports observed production volumes for each process. The dataset also reports the input requirements to meet a conformed volume which is consistent across the hand and machine methods. Table *23* describes variables which are reported for each step.

Table 22 Process variables in HML data.

Variable Name	Definition	Example
Unit	Product name	Potatoes
Unit Volume	Volume of product captured for each full cycle of process	880 bushels
Conformed Volume	Volume of product per cycle used in presentation of step-level data	220 bushels
Method	Level of process mechanization	Hand/Machine
Total Employment	Number of people employed in process	4 people
Total Animals	Number and type of animals used in process	2 horses
Time Worked	The number of hours worked per day	10 hours
Year	Date of production process	1893
Unit Characteristics	Additional product details	From grafts

[95] Approximately 90% of products in the Hand and Machine Labor Study have been digitized so far.

Table 23 Step variables in HML data.

Variable Name	Definition	Example
Operation Number	Identifying code for the set of tasks in a process step	{2, 3}
Work Done	Description of the activities performed in a step	Planting Seed
Machine, Implement or Tool Used	Description of primary equipment used to complete step	Steam shovel
Motive Power	Source of power for operations described	Steam; Horse
Persons Necessary on One Machine	Number of workers required per machine or station	2 workers
Animals Necessary on One Machine	Number of animals required per machine or station (type recorded in motive power)	2 horses
Number of Workers	Number of workers required in a process step across all stations	4 workers
Sex	Sex of workers	M, F
Occupation	Occupational title of workers	Laborer
Age	Age (or age range) of workers	21-30
Time Worked	Total person-hours and minutes to complete step	1hr 15m

Animal Time Worked	Total animal-hours and minutes to complete step	2hr 30m
Worker Pay Rate	Rate of pay (nominal dollars) for payment period	$1.00
Animal Pay Rate	Cost of animal (nominal dollars) for payment period	$0.375
Worker Pay Period	Payment cycle for workers	1 Day
Animal Pay Period	Cost cycle for animals	1 Day
Labor Cost	Total labor cost of producing conformed volume	$.125
Animal Cost	Total animal cost of producing conformed volume	$.0938

Appendix 9.2: Mapping Hand and Machine Processes

We next describe the steps taken to map the data to the model. In the original data, entries concerning animal labor in production are given a distinct line with otherwise identical step information (tools, task content). Since there are never animals used in production without workers, we condense animal information into the same step as the human workers that manage them. Some steps also include workers with multiple occupational titles. When this occurs the dataset provides separate entries in the data. When mapping the task content between hand and machine methods, distinct occupations are kept as separate steps with the same task content. Any step containing multiple occupations (7.6 percent of steps observed) is excluded from our analysis of step automation or changes in the division of tasks among steps, because the division of tasks within occupations within a single step is not specified (and to avoid double-counting steps).

For all products, we build a mapping between hand and machine processes. We index the tasks in hand and machine processes as $\mathcal{V}^H$ and $\mathcal{V}^M$ respectively. In terms of notation, H, M indicate either hand or machine process-types. Every step i contains a set $\mathcal{S}_i$ of tasks. Note that it is possible for two steps $i \neq j$ to exist such that $\mathcal{S}_i^M \cap \mathcal{S}_j^M \neq \varnothing$: for example, steps with content 1a and 1b in Hand are identical in task content to step 1 in Machine, and to each other. Any given step belongs to exactly one of the following six possible cases:

1. **1 to 1:** Steps i^H and j^M belong to this case if they have the same task content and do not share task content with any other steps: $\mathcal{S}_i^H = \mathcal{S}_j^M$. For any $n \neq i$ then $\mathcal{S}_n^H \cap \mathcal{S}_j^M = \varnothing$, and for any $m \neq j$ then $\mathcal{S}_i^H \cap \mathcal{S}_n^M = \varnothing$. A 1 to 1 mapping is useful when analyzing a change in performer type or performer characteristics, independently of changes in the division of production.

2. **1 to 0:** a step i^H belongs to this case if $\mathcal{S}_i^H \cap \mathcal{V}^M = \varnothing$. These steps capture activities that are no longer performed in the machine case (e.g. post-processing work made unnecessary by process improvement).

3. **0 to 1:** a step i^H belongs to this case if $\mathcal{S}_i^M \cap \mathcal{V}^H = \varnothing$. These steps represent activities which are new to a process (e.g. firing a boiler, which would be unnecessary in a hand process without a steam engine).

4. **1 to N:** step i^H belongs to this case if: *(a)* $\mathcal{S}_i^H \subset \mathcal{V}^M$ (all of its tasks are contained in the machine process), *(b)* $\exists m \neq n$ such that $\mathcal{S}_n^M, \mathcal{S}_m^M \subset \mathcal{S}_i^H$ (tasks in the hand step are contained in more than one machine step), and *(c)* $\forall j$ such that $\mathcal{S}_j^M \cap \mathcal{S}_i^H \neq \varnothing$ we have $\mathcal{S}_j^M \cap (\mathcal{V}^M \backslash \mathcal{S}_i^H = \varnothing)$ (no machine step with a task set intersecting the hand step contains tasks that are contained in any other hand step:[96]) Step j^M belongs to this case if $\mathcal{S}_j^M \subset \mathcal{S}_i^H$ such that i^H satisfies the above conditions. This case allows us to capture an increase in the division of tasks.

5. **M to 1:** a step j^M belongs to this case if: *(a)* $\mathcal{S}_j^M \subset \mathcal{V}^H$, *(b)* $\exists m \neq n$ such that $\mathcal{S}_n^H, \mathcal{S}_m^H \subset \mathcal{S}_j^M$ and *(c)* for any i such that $\mathcal{S}_i^H \cap \mathcal{S}_j^M \neq \varnothing$, $\mathcal{S}_i^H \cap (\mathcal{V}^m \backslash\ \mathcal{S}_j^M) = \varnothing$. Step i^H belongs to this case if $\mathcal{S}_i^H \subset \mathcal{S}_j^M$ such that j^M satisfies the above conditions. This case allows us to capture a decrease in the division of tasks.

6. **M to N:** any remaining step not included above belongs to this case.

Table *24* reports the number and share of process steps for each method which belong to each of the six cases described above. We see that 78.6% of Hand steps and 83.4% of Machine steps belong to mappings which can be interpreted as changes in T for fixed $\mathcal{V}$, allowing them to be used to explore technological cases which vary or hold constant the division of tasks.

Table 24 Mapping between steps of different methods recovered from HML data.

Process Mapping	Hand Steps	Share of Hand	Machine Steps	Machine Share
0 to 1	0	0	2948	.333
1 to 0	204	.042	0	0
1 to 1	2375	.484	2375	.269
1 to N	639	.130	1921	.217
M to 1	639	.130	131	.015
M to N	1039	.212	1469	.166
Missing Alternate	9	.02	0	0
Total	4896		8844	

[96] Including tasks which occur in both step i^H and another hand step.

The *Missing Alternate* row indicates steps from processes which do not have a corresponding process of the opposite method: in our data, one hand process had a counterpart machine process for which the authors of the Hand and Machine study could not compare task content and thus could not encode operation numbers.

Appendix 9.3: Measuring Automation & Division of Tasks

To look at the impact of automation, we focus on the rate of automation of steps belonging to the 1:1 case described in the previous section (so to keep the task content of each step constant across the human and machine scenarios). As multiple products in the HML dataset are used for this analysis, a superscript $p \in P$ is used to denote different products. We denote the motive power of step i (e.g. hand power, mule power, steam power, etc.) as ω_i^p. Next we construct an indicator of automation, i.e. a change in motive power between the hand and machine process. The HML dataset features no observations of motive power in hand processes such as steam or water shifting to less mechanized motive powers such as hand or animal power in the respective machine processes. Given this we treat all changes in motive power as a shift toward automation. Formally, for two 1:1 mapped steps $i^{H,p}$, $j^{M,p}$, the index of automation is given by the difference in motive power between the steps:

$$\theta = \begin{cases} 1 & \text{if} \quad \omega_i^p \neq \omega_j^p \\ 0 & \text{if} \quad \omega_i^p = \omega_j^p \end{cases}.$$

To look at the implications of $\bar{r}$ on the rate of automation, we construct a measure of the utilization of performers in each process step, $u = \frac{R}{r}$. The lower the utilization of performers, the lower the returns to increasing rate and the closer the performer is to $\bar{r}$. To compare between process steps which were or not automated, we use the parameters of a step's performer in the hand process to determine utilization given the volume in the machine process, as a proxy for $\bar{r}$. While the data does not include empirical production volume, we can recover an upper bound on the possible output of each process step: $R_j^{H,p} = r\mu$, where r is the rate of output per performer shift and μ is the number of performers demanded per shift. The maximum effective output of any step in a production process cannot be greater than the maximum output of every other step (bottlenecks), giving us $\overline{R}_i^{H,p} = \min_{i=1}^{i=N}(R_i^{H,p})$.

We next look at the division of tasks. To remove the effect of other changes beyond the division of tasks, we control for task content and for the level of automation. For the former we only consider the case of steps mapping from 1 to N (the decrease in the division of tasks is characterized by a M to 1 mapping. As fewer than 20 steps exhibit this property, we do not consider this scenario). To control for the level of automation we further restrict the sample selection to steps in which the motive power is unchanged.

Appendix 10: Additional Results on Cost and Complexity

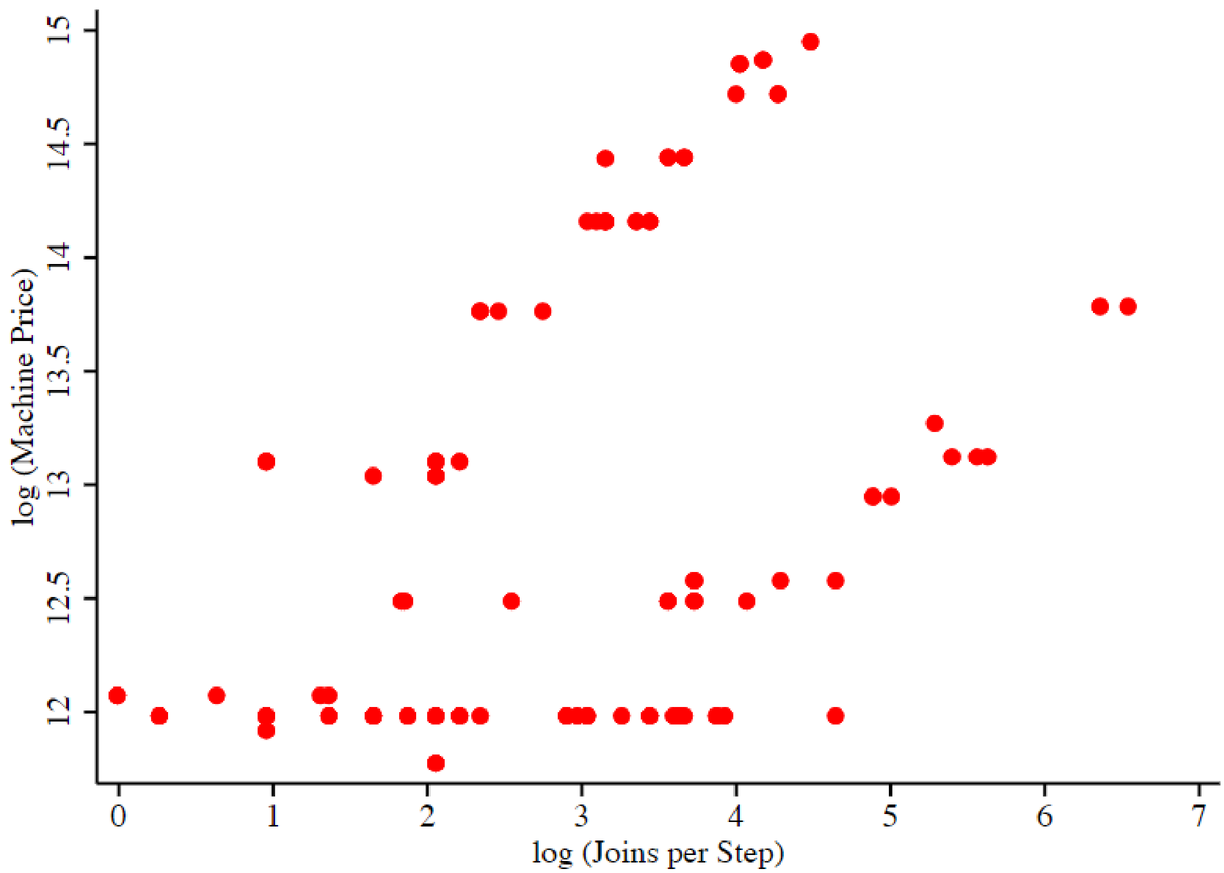

Figure 50 Performer cost and step complexity. Prices in 2006 Dollars. For information on the data refer to Fuchs, Field, Roth and Kirchain (2008).

Appendix 11: Aggregate Occupational Demand Trends

11.1: Empirical Analysis

To produce the aggregate occupational demand result in Chapter 2 Section 2, we employ an approach based on the LOESS smoothing method used in Autor and Dorn 2013, using IPUMS census data on individual employees. Our objective is to recover the share of employees in an industry who belong to different occupations with high or low average wages, and to characterize how these shares changed between 2000 and 2019. Differently from Autor and Dorn, to allow industry-level analysis, we use 2000 rather than 1980 as our basis (NAICs classification is implemented in the IPUMs dataset for the year 2000 and later).

We classify industries based on whether they are above or below the median level of utilization in 2000: finer classifications (e.g utilization quartile) are highly inconsistent between 2000 and 2019. The utilization data provided by the Federal Reserve (G.17: Industrial Production and Capacity Utilization) is available only for manufacturing industries and covers 27 mutually exclusive NAICs codes at the 3 to 5 digit level. Due to these data limitations, we restrict our analysis of the IPUMS data specifically to manufacturing employees as defined by the NAICS code associated with the industry employer for each observation in the data.

We construct a percentile ranking of occupations in the year 2000 based on their average log wage. For each industry (using the NAICs codes reported in IPUMs) we calculate the share of industry workers in each occupation. We repeat this operation for observations in the year 2019, but keep the occupation percentile rankings from 2000 for comparison. We then calculate the absolute change in occupational labor share for an industry by subtracting the 2000 share from the 2019 share; we construct our relative measure of change in demand share by dividing the absolute share by the occupation share in 2000. We then use a LOESS regression method to estimate a smoothed relationship between occupational wage percentile and change in demand share, using a span of 0.8 (though the result is still apparent with spans as low as 0.5).

Table 25 Industry Utilization (2000) (U.S. Federal Reserve 2022)

Descriptions:	2000
Communications equipment (NAICS = 3342); n.s.a. CAPUTL	91.916
Automobile and light duty motor vehicle (NAICS = 33611); n.s.a. CAPUTL	89.8088
Semiconductor and other electronic component (NAICS = 3344); n.s.a. CAPUTL	89.6532
Petroleum and coal products (NAICS = 324); n.s.a. CAPUTL	89.4463
Plastics material and resin (NAICS = 325211); n.s.a. CAPUTL	88.3867
Electrical equipment, appliance, and component (NAICS = 335); n.s.a. CAPUTL	85.8824
Paper (NAICS = 322); n.s.a. CAPUTL	84.6345
Primary metal (NAICS = 331); n.s.a. CAPUTL	83.0869
Plastics and rubber products (NAICS = 326); n.s.a. CAPUTL	82.3746
Textile product mills (NAICS = 314); n.s.a. CAPUTL	81.8054
Computer and peripheral equipment (NAICS = 3341); n.s.a. CAPUTL	81.7871
Apparel (NAICS = 315); n.s.a. CAPUTL	80.8795
Artificial and synthetic fibers and filaments (NAICS = 32522); n.s.a. CAPUTL	80.8331
Nonmetallic mineral product (NAICS = 327); n.s.a. CAPUTL	79.896
Textiles and products (NAICS = 313,4); n.s.a. CAPUTL	79.3221
Fabricated metal product (NAICS = 332); n.s.a. CAPUTL	78.9735
Wood product (NAICS = 321); n.s.a. CAPUTL	78.1871
Machinery (NAICS = 333); n.s.a. CAPUTL	77.7868
Furniture and related product (NAICS = 337); n.s.a. CAPUTL	77.4929
Food, beverage, and tobacco (NAICS = 311,2); n.s.a. CAPUTL	77.356
Printing and related support activities (NAICS = 323); n.s.a. CAPUTL	76.9995
Synthetic rubber (NAICS = 325212); n.s.a. CAPUTL	76.8691
Miscellaneous (NAICS = 339); n.s.a. CAPUTL	76.7938
Chemical (NAICS = 325); n.s.a. CAPUTL	76.4093
Beverage and tobacco product (NAICS = 312); n.s.a. CAPUTL	72.2087
Leather and allied product (NAICS = 316); n.s.a. CAPUTL	70.495
Aerospace and miscellaneous transportation eq. (NAICS = 3364-9); n.s.a. CAPUTL	66.9831

In Table 25, we reproduce the capacity utilization of industries captured by the Fed Data and IPUMs Data, aggregated the highest-level most common NAICs code (some industries are reported in the Fed tables at multiple 4 to 6 digit NAICs levels).

11.2 Supplemental Results

While we use a relative measure of change in demand share to account for industry-level biases in initial occupational demand, we find similar results for the case of absolute change in demand share by industry utilization, as presented in the following figure. Note that while both high and low utilization industries show polarization in absolute terms, the shift toward high wage occupations is much more pronounced in the high utilization industry. As we would expect from the cone of automation in our theory, we observe a net decline in demand share for low-wage occupations under high utilization, in contrast with the increase in share for low-wage occupations in low utilization industries.

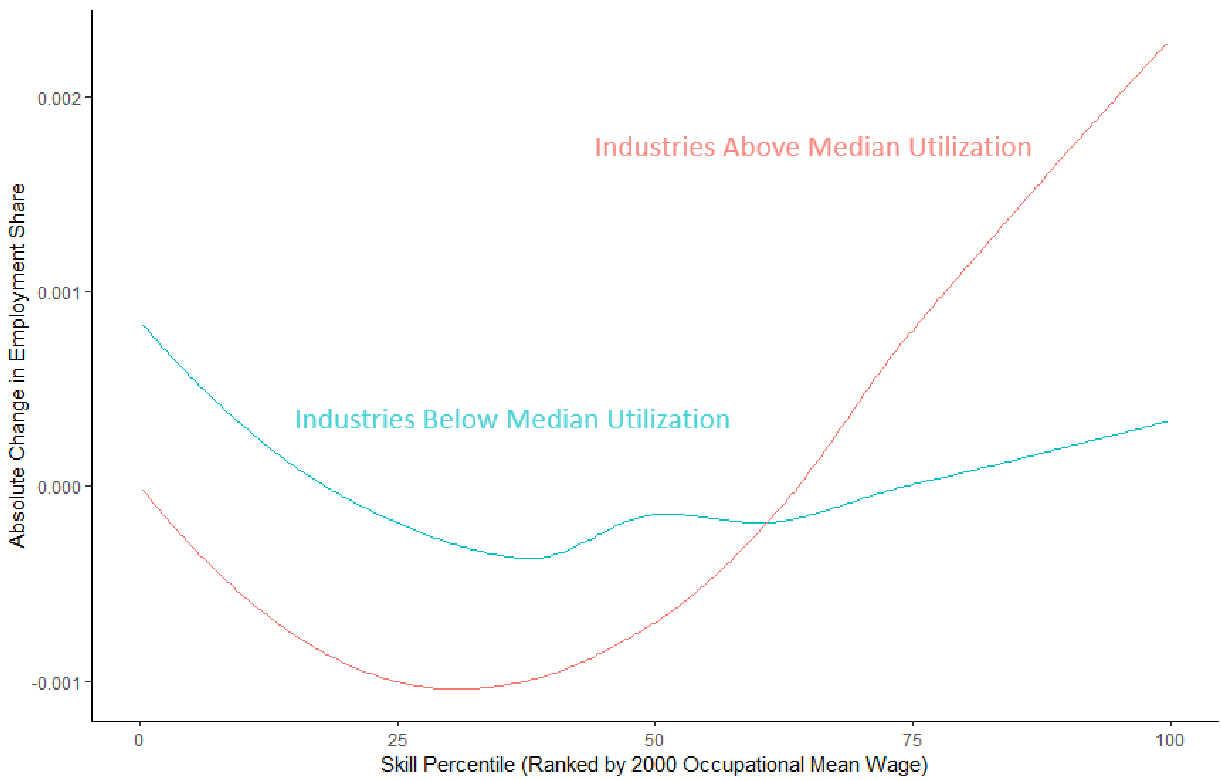

Figure 51 Change in Occupational Demand (2000-2019) by Industry Utilization

Aggregating the industries used to recover changes in occupational demand by level of industry utilization, we find an overall pattern of polarization from 2000 to 2019, presented in Figure 52. This polarization resembles the findings of Autor and Dorn for the period 1985-2005, albeit with a more pronounced "upskilling" pattern of demand toward the highest wage occupations. This result suggests that while polarization remains a pattern of demand change (most strongly, as we show, in low utilization industries), it may be shifting toward a phenomenon of outright upskilling, with an overall decline in demand share for not only middle but low wage occupations in the industries we capture.

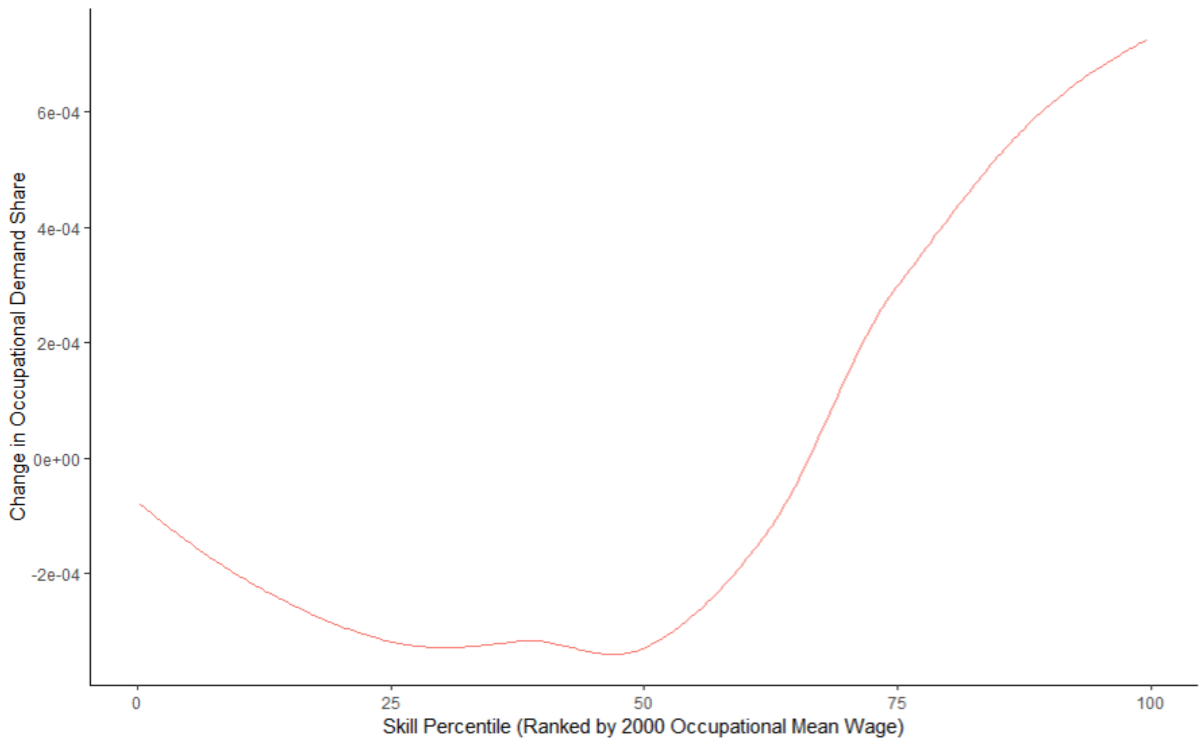

Figure 52 Change in Occupational Demand (2000-2019) Across Industry Utilization

11.3 Industry Specific Results

Our analysis focuses on three key manufacturing industries well represented in the IPUMs data: airplane manufacturing, automobile and light duty motor vehicle manufacturing and boat and ship manufacturing. All three industries experienced automation in this period (e.g. Min 2008; Heping et al 2009; Angerer et al 2011), and are characterized by high numbers of employees per establishment relative to manufacturing overall near the beginning and end of the period 2000-2019 we analyze from IPUMs data (the latest detailed Statics of U.S. Businesses at time of writing date to 2018): on average, airplane manufacturing had 727 workers per establishment in 2000, 501 per establishment in 2018; automobile and light duty motor vehicle manufacturing had 617 workers per establishment in 2000, 787 per establishment in 2018; boat and ship manufacturing had 83 workers per establishment in 2000, 93 per establishment in 2018; compared with manufacturing overall with 46 workers per establishment in 2000 and 41 workers per establishment in 2018 (Statistics of U.S. Businesses, U.S. Census 2018)

As the following figure illustrates, these industries differ in how their occupational demand distributions have evolved. All three industries experienced demand polarization (commonly attributed to automation in the literature (cite, cite)), but the polarization was most acute in aerospace in terms of the magnitude of share change, followed by boat and ship manufacturing. Automobile and light duty motor vehicle manufacturing also saw a different domain of polarization, with shifts away from the second and third quintiles of occupational wages, while airplane manufacturing saw the greatest shifts away from the third and fourth quintiles. Current theory does not explain why low-wage occupations are preserved in industries heavily exposed to automation, nor why an industry like aerospace should both see greater preservation of lower wage occupations and more intense polarization at middle-to-higher wage occupations.[97]

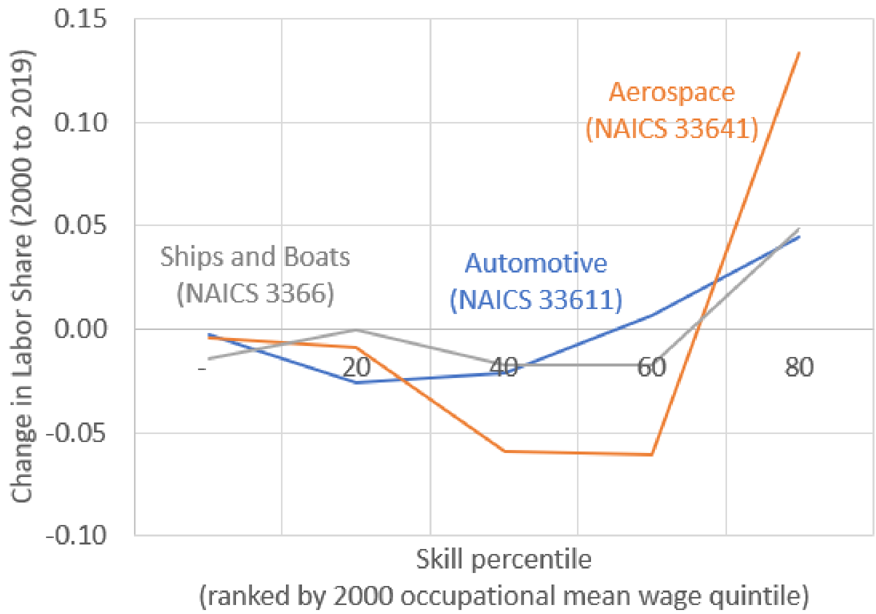

Figure 53 Change in Occupational Skill (Wage) Demand Share by Industry: Aerospace, Automotive and Ships&Boats (2000 to 2019)

We also consider the case of two overlapping industry categories: machine shops and metal fabrication. Machine shops are a subset of metal fabrication, consisting of smaller establishments (15 employees per establishment in 2000) than the metal fabrication category overall (29 employees per establishment in 2000). The Machine Shop industry shows polarization of labor demand from 2000 to 2019, while the metal fabrication overall shows upskilling: as with the aerospace, automotive and ship manufacturing cases, current theory does not suggest why machine shops and metal fabrication should differ in the change in occupational demand.

[97] If, for instance, the exposure to automation is different across industries, it would not suggest a reason for demand for some wage classes to change more than others.

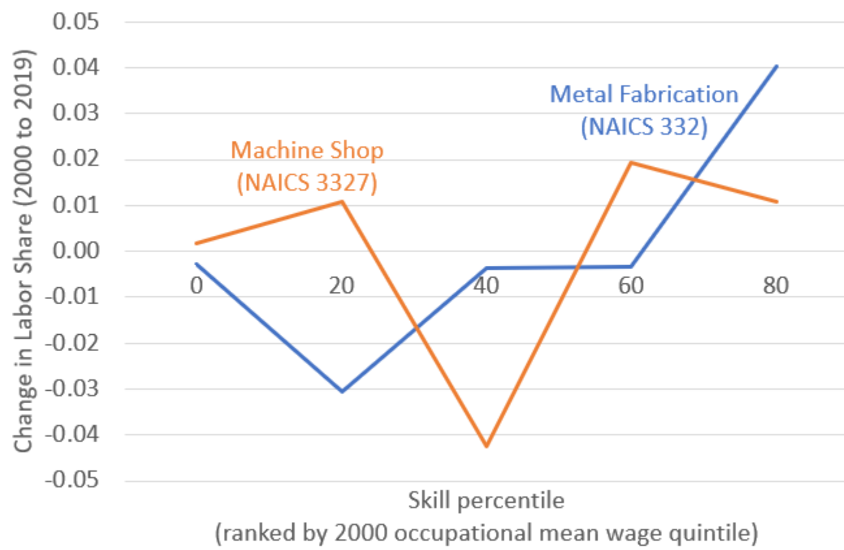

Figure 54 Change in Occupational Skill (Wage) Demand Share by Industry: Machine Shops and Metal Fabrication (2000 to 2019)

Our theory provides an explanation for the different changes in the distribution of occupational demand across industries, from the view that each is exposed to automation.

Aerospace and automotive manufacturing are among the largest employers in the U.S. manufacturing sector, both with significant historical automation and large establishments. However, production volume is much lower in aerospace (e.g. Boeing delivered fewer than 400 aircraft in 2019 (Statista 2021)) than automotive (e.g. Ford sold over 2.4 million vehicles in the U.S. alone from Q4 2020 to Q4 2021 (Statista 2021)).[98] Boat and ship manufacturing is chosen as an intermediate case, with higher volume than aerospace but much lower than the automotive industry. Our theory predicts that automation polarizes worker ability demand at low volumes of production, but that as volume increases the domain of automation shifts to become wider and eventually becomes upskilling rather than polarizing. Matching this prediction, the boat manufacturing industry shows greater polarization than automotive but less than aerospace.

[98] Regulatory requirements for aerospace production place a high cost on the adoption of new production technologies, such as automation, though there is not a reason that these regulatory costs should be heterogeneous along the occupational wage domain and drive the difference in distribution.

Appendix 12: Expanded Technology Change and Theoretical Interpretation

Table 26 General Theory Applied to Historic and Contemporary Technology Changes

Technology Change	Period	Parameter Changes	Labor Impact
Mechanization: Direct Substitution for Human Performers by Machines	1870s-1890s	Machine performers able to repeat tasks better than humans but unable to perform highly varied work: machines less general and more intense, introducing $\rho^m < \rho^h$ and $\sigma^m < \sigma^h$	Growth of managerial and professional jobs (high skill) (Chandler 1990), more demand for unskilled labor (Atack Margo and Rhode 2019)
Continuous Processing: materials produced without interruption, involving constant motion of product	1870s-1890s	Interruptions from division of tasks are more disruptive to process flow, driving f ↑	Upskilling (Goldin and Katz 1998)
Interchangeable Parts and Assembly Line: increased standardization of parts and process layout to facilitate transfer of work in progress and minimize refitting requirements	1870s-1910s	Increased process complexity from assembly and logistics, leading to λ ↑, but facilitation of transfer and reduced postprocessing of independent parts driving f ↓	Growth of managerial and professional jobs (high skill), decline of artisanal labor (middle skill) Hounshell 1985; Chandler 1990)
Continuous Integration Software: tests independently developed code for reintegration into master code	2010s	Software-based testing of code significantly reduces time and error from code integration, reducing cost of multiple programmers working on copies of master code and hence f ↓	Greater division of tasks (Vasilescu et al 2015)
Consolidation of Parts: formerly discrete parts fabricated as one	1970s-2010s	Joint fabrication of parts makes some fabrication tasks indivisible, driving f ↑, but allows simpler design and reduced assembly and logistics, driving λ ↓	Convergence of skill demand from low and high to middle, reduced division of production (Combemale et al. 2021)
Mainframe Operating Systems: supports scheduling of tasks and division of system	1960s	By allowing computers to divide their resources between tasks at much lower costs, drives $\bar{r}$ ↑	Higher utilization of computers allowing them to economically perform more and

resources by a computer			narrower tasks (Hansen 1973)
Automation and Computerization: substitution of human labor by computer and machine performers	1960s-2010s	Machine performers able to repeat tasks better than humans but unable to perform highly varied work: machines less general and more intense, introducing $\rho^m < \rho^h$ and $\sigma^m < \sigma^h$. Compared with earlier mechanization, performers are more general ($\rho \uparrow$), intense ($\sigma \downarrow$) and divisible ($\bar{r} \uparrow$).	Upskilling of skill demand; polarization in conjunction with lower automation in services (Autor and Dorn 2013)
Additive Manufacturing: production of parts by material deposition rather than subtraction	1980s-2020s	Material deposition allows highly complex parts to be made by one machine, driving $\rho^m \uparrow$, and flexibility of deposition methods allows machine reallocation, driving $\bar{r}^m \downarrow$; motions of deposition can be harder to accelerate than subtractive processes, driving $\sigma \uparrow$	Additive Manufacturing is implemented more in low volume or high complexity production steps (Atzeni and Salmi 2012)
Cloud Computing: sharing high system capacities among many individuals	1990s-2020s	Increased divisibility of system resources drives $\bar{r}^m \uparrow$	Decline in low skill clerical jobs (Dhar 2012)

Appendix 13: Managing the Cost of Failure

The model described in Combemale et al. 2022 (How It's Made) assumes that firms set ability demand for each process step to solve a series of stochastic production issues in expectation. However, factors such as safety, material losses and scheduling costs drive firms to reduce rates of production failure. The following builds toward an extended model that endogenizes the rate of production failure as a firm choice, allowing us to study how technology change (e.g. testing methods) and worker skills interact with the optimal choice of operations regimes (e.g. make-to-order) and the safety or quality characteristics of products.

Operations data from prior papers can directly capture production characteristics such as yield rate and the cost of non-performer inputs (e.g. materials) that may be lost with production errors.

Key extensions to "How It's Made":

- Explicit ordering of steps, driving cost of failure up/downstream
- Introduction of step fixed costs (e.g. material inputs) to drive failure costs
- Variance in ability to solve problems (humans have higher variance)
- Optimal choice of a (additional decision) building in probability of failure

Three broad categories of failure cases are described in the following equations. These equations will give structure to our analysis of how task inter-dependency and material intensity, and performer characteristics such as precision can generate bias in ability and performer demand.

Repeating a Step:

$$E(C(R,T)) = \sum_{i=1}^{T} \frac{p(a_i,r_i,R|o_i)+f(s_i,o_i)}{p(a_i \geq D_i)}$$

Repeating Prior Steps:

$$E(C(R,T)) = \sum_{i=1}^{T} \frac{p(a_i,r_i,R|o_i)+f(s_i,o_i)}{\Pi_{j\geq i} p(a_i \geq D_i)}$$

Paying Fixed Cost:

$$E(C(R,T)) = \sum_{i=1}^{T} p(a_i,r_i,R|o_i) + f(s_i,o_i) + bp(a_i \geq D_i)$$

The cost of production in a step is given $p(a,t,l,r,R,m)$, which is assumed to be convex in a.

Every task has a material intensity m – the material inputs to a step are given by $\int_{s_{i-1}}^{s_i} m(t)\, dt$

Appendix 14: General Theory Parameter Estimation Methods for Aggregate Data

We are interested in recovering the relationship between length, rate and ability demand. Depending on the availability of measures, there are strategies available for the direct estimation of model parameters and for reduced form relationships.

In order to directly estimate ρ and σ, we assume the functional form $D = (\underline{D} + C(l|\rho))r^{\sigma}$. Measures of r may be obtained directly from operational data (e.g. on a per-step basis) or imputed from the ratio of volume to performer demand: e.g. $\hat{r} = \frac{R}{N}$ where N is the number of performers.[99] Some tasks have readily measurable length, such as if the parameters of tasks to be completed are quantifiable and uni-dimensional. For instance, the automotive assembly data measures of the number of joins required for a step give a direct approximation of l for assembly steps. To estimate ρ or σ, a measure of D is also necessary; by assumption in the model, firms choose $a = D$. Measures of a for a given step include education, or direct elicitation of ability demand using the O*NET Survey Instrument; wages do not support direct estimation of ρ and σ without prior recovery of the functional form of $w(a)$.

From any measure of r and controls for l, it is possible to directly estimate σ from the equation $\sigma = \frac{ln(D)-ln(\underline{D}+C(l|\rho))}{ln(r)}$. To obtain a direct estimation of ρ, we also require parameter values for issue arrival rate λ and the distribution of issue magnitude χ. These parameters are unlikely to be separable from ρ or l in aggregate data, but can be approximated from deep

[99] Note that this ratio represents the lower bound of rate; it is possible for higher rates to be demanded than the minimum to satisfy volume, for instance if demand is heterogeneous in time, or uncertain.

operations-level data using the rate of production failures or recorded incidents for performers on steps of different lengths, controlling for performer ability.

We now describe reduced form approaches that get at the essential tradeoffs between length, rate and ability demand with fewer and more aggregate measures. From l and a alone (given controls for r) it is possible to obtain $C(l|\rho)$ for any constant performer type; hence it is possible to indirectly capture a change in ρ by showing a change in $C(l|\rho)$.[100]

In addition to direct measures of l, it is possible to recover the length-ability demand relationship using only a and controls for r, if two jobs (or steps) whose ability requirements are known are merged together into a new job whose ability requirements are also known. For instance, if $\rho = 1$, then for constant rate the ability requirements of the job should be equal to the sum of the requirements of its components. If $\rho \to \infty$, then for constant rate the ability requirements of the job should be equal to the highest requirement of its component tasks.

Without a measure of a or specification on the functional form of $w(a)$, it is not possible to recover estimates of ρ and σ, but the margins between rate, complexity and wage can still be obtained in a reduced form and are governed by the same mechanisms in the model. An aggregate approximation of step length can be obtained from value added (see footnote X on use of value added as proxy of step length): in a relatively labor intensive (e.g. manual) step, step length can be approximated $\hat{l} = \frac{w}{r}$. Likewise, a relatively capital-intensive step may have step length approximated $\hat{l} = \frac{k}{r}$.

The model has certain implications for representation within classical production functions, which are detailed below:

1. In Cobb-Douglas, the g function is intuitively connected to the returns to scale. The less divisible a performer, the more convex the production function. The intuition of factor complementarity (e.g. labor, capital or different skill levels of labor) given in Cobb-Douglas is connected to our model by the reasoning that given a certain number of performers, the firm will first assign them to the steps for which they are optimal, then to steps in which they are less optimal (e.g. machines fill middle-length steps first, then diminishing returns to capital absent increasing labor come from machines filling low and high length steps).

2. Predictions for elasticity of substitution: as machines increase in ρ, they become more substitutable with humans (especially at higher length i.e high skill labor L^H). Volume affects elasticity of substitution between labor and capital (more elastic substitution of capital for labor at high volumes), and $\bar{r}$ (divisibility) governs the degree to which volume affects elasticity of substitution. The theory suggests that CES assumptions may largely hold past sufficiently high volume, but that they are unlikely to hold in smaller firms that make up much of the economy.

[100] Without assuming or observing the underlying rate of issue arrival and magnitude distribution, it is not possible to characterize ρ except indirectly by the curvature of $C(l)$. For instance, if $C(l|\rho)$ is approximately linear, then $\rho \to 1$.

3. Differences in intuition when process organization is static versus adaptive. For example: if low skill labor increases, and the firm is able to reorganize production into smaller steps, for which performer types is the low skilled labor substituting?