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Research Paper

De-skilling: Evidence from late nineteenth century American manufacturing

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ABSTRACT

The longstanding view in US economic history is that the shift in manufacturing in the nineteenth century from the hand labor artisan shop to the machine labor of the mechanized factory led to "labor de-skilling" – the substitution of less skilled workers, such as operatives, for skilled craft workers. Investigating the Department of Labor's 1899 *Hand and Machine Labor Study*, we show the adoption of inanimate power, which we call "mechanization," did induce de-skilling at the production operation level. However, while the treatment effect of mechanization was economically and statistically significant, it accounted for only 16 percent of the de-skilling on average in the sample, using our preferred IV estimator. Broadening the scope of our inquiry, we find that variations in the division of labor, as captured by the share of production tasks performed by the average worker, accounted for a substantially larger fraction.

1. Introduction

Mechanization—the process of assigning production tasks previously performed by hand to an inanimately-powered machine—was a defining characteristic of the first industrial revolution. Did it cause workers to become, in the impassioned words of one contemporary observer, "mere servants to some machine … [whose] skilled artisanship is swept away as a survival of a past which is condemned to disappear" (Kropotkin, 1888, 497). We investigate whether the shift from the "old-fashioned hand process" to the "modern machine methods" led to worker de-skilling at the production operation level using the 13th *Annual Report* of the U.S. Commissioner of Labor (United States. Department of Labor 1899, I: 11). Data from this voluminous and unique report, which is hereafter called the HML study, allow us to examine the occupations of the workers employed in thousands of production tasks performed in the manufacture of hundreds of specific products, referred to as "units" in the study. Our contribution to the de-skilling debate is the superior evidence of the HML study, coupled with an identification strategy that allows us to estimate the causal effect of mechanization (proxied by the use of inanimate power) at the production operation level. We conclude that workers using the machine method were indeed less skilled (as measured by their occupation titles) than their counterparts using the hand method, but that mechanization *per se* accounted for only a fraction of the difference.

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In the early 1890s, the United States Congress ordered the Commissioner of Labor to "investigate and report upon the effect of the use of machinery upon … the relative productive power of hand and machine labor" (United States. Congress 1894). To this end, agents of the Department of Labor collected detailed data on the manufacture of several hundred highly specific products using machine methods, recording the production operations from start to finish in a manner "designed to bring into comparison the operations necessary in producing an article by the old-fashioned hand process and by the most modern machine methods" (United States. Department of Labor 1899, 1: 11). Subsequently, they collected the same information for the same product (or as close as possible) from establishments using the hand methods then "going out of use" (United States. Department of Labor 1899, 1: 6). From these data, the HML staff generated a crosswalk linking the operations from machine method tasks to those for the hand method, ordered sequentially.

Elsewhere, we have used these data to investigate the time savings from switching from hand to machine labor and its causes (Atack et al., 2022). For the analysis in this paper, we map occupational titles in the HML study to 1950 occupation codes (United States. Department of Commerce. Bureau of the Census 1950a; United States. Department of Commerce. Bureau of the Census 1950b). The coded data are then sorted in four bins – white collar, skilled artisans, semi-skilled operatives; and common (unskilled) laborer— from which we compute the share of production time performed by workers with these different skill levels separately for operations that were linked across the hand and machine production processes. Mean values of these shares show a marked shift away from the skilled categories (blue-collar plus white-collar) towards the less skilled (semi-skilled operatives plus common labor). In the vast majority of cases the change was dichotomous – a complete replacement of one skill level for the other at the production operation level. Based on this pattern, we create a binary variable, *De-Skill* that equals one if the share of time performed by semi-skilled operatives and common labor in the operation exceeds the share so performed under hand labor. Overall, the mean value of this variable, 0.357, indicates that de-skilling occurred in almost 36 percent of the production operations analyzed in the paper.

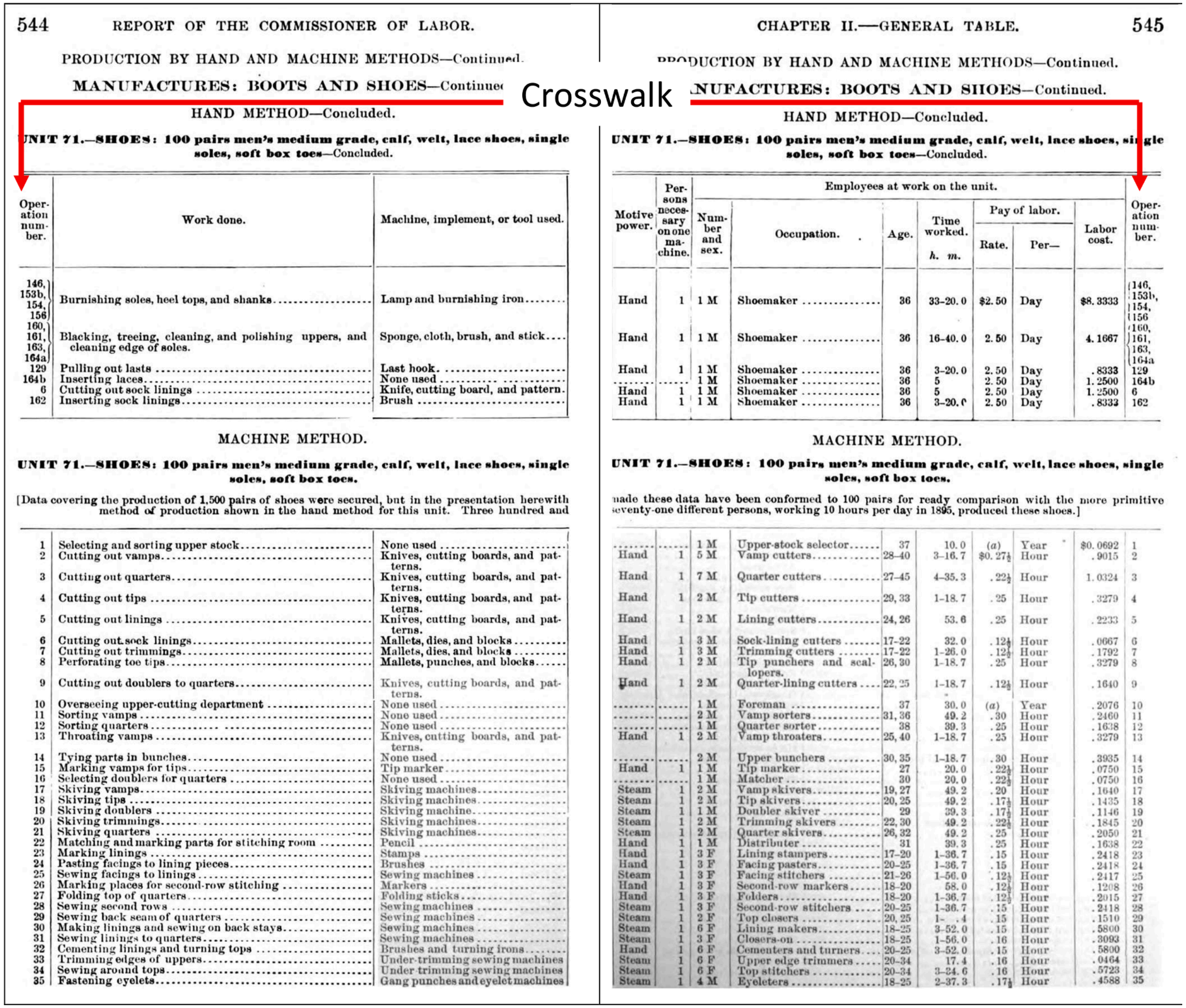
Our identification strategy for estimating the treatment effects of mechanization worker de-skilling uses a text-based instrumental variable, constructed from gerunds appearing in the written description of each task in the hand labor operation. We require an instrument for mechanization because use of inanimate power in the associated machine operation was a choice made by someone in the original establishment, and, therefore, endogenous. We take advantage of the fact that, by the late nineteenth century, scientific and engineering knowledge had advanced sufficiently such that it was technically feasible to mechanize some activities described by these gerunds but not others and this information was exogenous to the decision on the shop floor to use inanimate power. The first stage of our gerund instrument is very strong, and the associated 2SLS coefficient implies that about 16 percent of the mean value of *De-Skill* can be accounted for by the mean level of mechanization in the machine labor units (0.553, or 55.3 percent of machine operations used inanimate power).

Following our prior study of productivity (Atack et al., 2022), we modify our base regression to include additional variables measuring unit level differences between machine and hand labor, the most important of which are measures of scale and of the division of labor. Conceptually, these measures are distinct from mechanization because, for example, increases in the division of labor occurred through an expansion in market access from transportation improvements (Atack et al., 2011). Overall, we find that these additional factors, particularly the division of labor, to be far more important than mechanization *per se* in accounting for de-skilling. This conclusion is significant because the trend towards greater division of labor was clearly underway well before the widespread diffusion of inanimate power in the decades following the Civil War (Fenichel, 1966; Atack et al., 1980).

The historical literature on de-skilling is vast. Our paper is most closely related to studies that infer the presence of de-skilling from estimates of production function parameters using aggregated data from the historical United States Censuses of Manufacturing. A prominent recent example is LaFortune et al. (2019), who find that capital was a relative complement to low-skilled labor before 1890. This is consistent with the idea that the factory system increased the relative demand for low-skilled workers in production at the expense of high-skilled workers.[1] Also related are studies using establishment-level data to correlate proxies for low-skilled labor, such as the proportion of female or child workers or average wages, to measures of scale and/or use of inanimate power (Goldin and Sokoloff, 1982; Goldin and Katz, 1998; Atack et al., 2004. For a critique of this approach, see Bessen, 2011; Katz and Margo, 2014). Other relevant studies use census and related occupational information to document trends in skill levels in manufacturing (Gray, 2013; Katz and Margo, 2014). Katz and Margo (Katz and Margo, 2014, Table 1.4) show that the skilled blue-collar share in manufacturing as a whole declined by 17 percentage points between 1850 and 1910 while the share of operatives and common labor increased by 7 percentage points. Focusing on the early twentieth century United States, Gray (2013) investigates how the adoption of electricity transformed the skill distribution in manufacturing, using a 1956 study on "Worker Trait Requirements" (United States. Department of Labor. Bureau of Employment Security 1956) to classify occupations according to their managerial, clerical, dexterity, and manual task content. Relative demands for these different skills varied with state-level rates of electrification of manufacturing, resulting in a marked decline in demand for dexterity-intensive blue-collar manufacturing jobs.

De-skilling is central to historical debates over the causes and consequences of early industrialization in Europe (see Brugger and Gehrke (2018) for an extensive bibliography). Broadly speaking, this literature has focused on indirect indicators of de-skilling (for example, literacy or schooling) and alternative sources (such as autobiographies), in the absence of manufacturing production data similar to those available for the United States (Nicholas and Nicholas, 1992; Mitch, 1999; Humphries, 2010; Humphries, 2013; de Pleijt and Weisdorf, 2017). In particular, an important recent strand of this literature exploits arguably exogenous geographic variation

[1] LaFortune, Lewis, and Tessada's identification strategy is based on a shift-share instrumental variable constructed from immigration shocks. After 1890 capital became a relative complement of skilled labor through electrification; see also Goldin and Katz (1998), Gray (2013), and Fiszbein et al. (2020).



544 REPORT OF THE COMMISSIONER OF LABOR.

CHAPTER II.—GENERAL TABLE. 545

PRODUCTION BY HAND AND MACHINE METHODS—Continued.

MANUFACTURES: BOOTS AND SHOES—Continued.

HAND METHOD—Concluded.

UNIT 71.—SHOES: 100 pairs men's medium grade, calf, welt, lace shoes, single soles, soft box toes—Concluded.

Operation number.	Work done.	Machine, implement, or tool used.	Motive power.	Persons necessary on one machine.	Employees at work on the unit. Number and sex.	Occupation.	Age.	Time worked. h. m.	Pay of labor. Rate.	Pay of labor. Per—	Labor cost.	Operation number.
146, 153b, 154, 156	Burnishing soles, heel tops, and shanks	Lamp and burnishing iron	Hand	1	1 M	Shoemaker	36	33–20.0	$2.50	Day	$8.3333	146, 153b, 154, 156
160, 161, 163, 164a	Blacking, treeing, cleaning, and polishing uppers, and cleaning edge of soles.	Sponge, cloth, brush, and stick	Hand	1	1 M	Shoemaker	36	16–40.0	2.50	Day	4.1667	160, 161, 163, 164a
129	Pulling out lasts	Last hook.	Hand	1	1 M	Shoemaker	36	3–20.0	2.50	Day	.8333	129
164b	Inserting laces	None used	....	......	1 M	Shoemaker	36	5	2.50	Day	1.2500	164b
6	Cutting out sock linings	Knife, cutting board, and pattern.	Hand	1	1 M	Shoemaker	36	5	2.50	Day	1.2500	6
162	Inserting sock linings	Brush	Hand	1	1 M	Shoemaker	36	3–20.0	2.50	Day	.8333	162

MACHINE METHOD.

UNIT 71.—SHOES: 100 pairs men's medium grade, calf, welt, lace shoes, single soles, soft box toes.

[Data covering the production of 1,500 pairs of shoes were secured, but in the presentation herewith made these data have been conformed to 100 pairs for ready comparison with the more primitive method of production shown in the hand method for this unit. Three hundred and seventy-one different persons, working 10 hours per day in 1895, produced these shoes.]

Operation number.	Work done.	Machine, implement, or tool used.	Motive power.	Persons necessary on one machine.	Number and sex.	Occupation.	Age.	Time worked. h. m.	Rate.	Per—	Labor cost.	Operation number.
1	Selecting and sorting upper stock	None used	....	......	1 M	Upper-stock selector	37	10.0	(a)	Year	$0.0692	1
2	Cutting out vamps	Knives, cutting boards, and patterns.	Hand	1	5 M	Vamp cutters	28–40	3–16.7	$0.27½	Hour	.9015	2
3	Cutting out quarters	Knives, cutting boards, and patterns.	Hand	1	7 M	Quarter cutters	27–45	4–35.3	.22½	Hour	1.0324	3
4	Cutting out tips	Knives, cutting boards, and patterns.	Hand	1	2 M	Tip cutters	29, 33	1–18.7	.25	Hour	.3279	4
5	Cutting out linings	Knives, cutting boards, and patterns.	Hand	1	2 M	Lining cutters	24, 26	53.6	.25	Hour	.2233	5
6	Cutting out sock linings	Mallets, dies, and blocks	Hand	1	3 M	Sock-lining cutters	17–22	32.0	.12½	Hour	.0667	6
7	Cutting out trimmings	Mallets, dies, and blocks	Hand	1	3 M	Trimming cutters	17–22	1–26.0	.12½	Hour	.1792	7
8	Perforating toe tips	Mallets, punches, and blocks	Hand	1	2 M	Tip punchers and scallopers.	26, 30	1–18.7	.25	Hour	.3279	8
9	Cutting out doublers to quarters	Knives, cutting boards, and patterns.	Hand	1	2 M	Quarter-lining cutters	22, 25	1–18.7	.12½	Hour	.1640	9
10	Overseeing upper-cutting department	None used	....	......	1 M	Foreman	37	30.0	(a)	Year	.2076	10
11	Sorting vamps	None used	....	......	2 M	Vamp sorters	31, 36	49.2	.30	Hour	.2460	11
12	Sorting quarters	None used	....	......	1 M	Quarter sorter	38	39.3	.25	Hour	.1638	12
13	Throating vamps	Knives, cutting boards, and patterns.	Hand	1	2 M	Vamp throaters	25, 40	1–18.7	.25	Hour	.3279	13
14	Tying parts in bunches	None used	....	......	2 M	Upper bunchers	30, 35	1–18.7	.30	Hour	.3935	14
15	Marking vamps for tips	Tip marker	Hand	1	1 M	Tip marker	27	20.0	.22½	Hour	.0750	15
16	Selecting doublers for quarters	None used	....	......	1 M	Matcher	30	20.0	.22½	Hour	.0750	16
17	Skiving vamps	Skiving machines	Steam	1	2 M	Vamp skivers	19, 27	49.2	.20	Hour	.1640	17
18	Skiving tips	Skiving machines	Steam	1	2 M	Tip skivers	20, 25	49.2	.17½	Hour	.1435	18
19	Skiving doublers	Skiving machine	Steam	1	1 M	Doubler skiver	29	39.3	.17½	Hour	.1146	19
20	Skiving trimmings	Skiving machines	Steam	1	2 M	Trimming skivers	22, 30	49.2	.22½	Hour	.1845	20
21	Skiving quarters	Skiving machines	Steam	1	2 M	Quarter skivers	26, 32	49.2	.25	Hour	.2050	21
22	Matching and marking parts for stitching room	Pencil	Hand	1	1 M	Distributer	31	39.3	.25	Hour	.1638	22
23	Marking linings	Stamps	Hand	1	3 F	Lining stampers	17–20	1–36.7	.15	Hour	.2418	23
24	Pasting facings to lining pieces	Brushes	Hand	1	3 F	Facing pasters	20–25	1–36.7	.15	Hour	.2418	24
25	Sewing facings to linings	Sewing machines	Steam	1	3 F	Facing stitchers	21–26	1–56.0	.12½	Hour	.2417	25
26	Marking places for second-row stitching	Markers	Hand	1	3 F	Second-row markers	18–20	58.0	.12½	Hour	.1208	26
27	Folding top of quarters	Folding sticks	Hand	1	3 F	Folders	18–20	1–36.7	.12½	Hour	.2015	27
28	Sewing second rows	Sewing machines	Steam	1	3 F	Second-row stitchers	20–25	1–36.7	.15	Hour	.2418	28
29	Sewing back seam of quarters	Sewing machines	Steam	1	2 F	Top closers	20, 25	1– .4	.15	Hour	.1510	29
30	Making linings and sewing on back stays	Sewing machines	Steam	1	6 F	Lining makers	18–25	3–52.0	.15	Hour	.5800	30
31	Sewing linings to quarters	Sewing machines	Steam	1	3 F	Closers-on	18–25	1–56.0	.16	Hour	.3093	31
32	Cementing linings and turning tops	Brushes and turning irons	Hand	1	6 F	Cementers and turners	20–25	3–52.0	.15	Hour	.5800	32
33	Trimming edges of uppers	Under-trimming sewing machines	Steam	1	6 F	Upper edge trimmers	20–34	17.4	.16	Hour	.0464	33
34	Sewing around tops	Under-trimming sewing machines	Steam	1	6 F	Top stitchers	20–34	3–24.6	.16	Hour	.5723	34
35	Fastening eyelets	Gang punches and eyelet machines	Steam	1	4 M	Eyeleters	18–25	2–37.3	.17½	Hour	.4588	35

Fig. 1. Verso and recto pages of part of the hand and machine labor table for unit 71 showing raw data and the HML-generated Crosswalk Source: (United States. Department of Labor 1899, 2: 820–1).

to estimate the causal effect of access to steam power on manufacturing occupations (Diebolt et al., 2017; de Pleijt et al., 2020). Overall, while historical studies for the United States and elsewhere generally find some evidence consistent with de-skilling to varying degrees, none study de-skilling at the level of the production operation and relate it directly to mechanization, as the present paper does.

Our paper also speaks to a large, and ever-growing modern literature on automation and its consequences. A key tool in this literature is the task-based production function (Autor and Acemoglu, 2011; Autor, 2013; Chaney and Ossa, 2013; Acemoglu and Restrepo, 2019, 2020, 2022), which we adopt in theoretically framing our empirical analysis of the HML study data (see Section 3). In particular, Acemoglu and Restrepo's (2018) "displacement" effect which occurs when, say, a robot (or AI) replaces a human being in the performance of a production task, is closely related to the concept of de-skilling studied in this paper.

The modern literature frequently invokes the steam engine as the historical precursor of automation; as Brynjolfsson and McAfee (2014, 6) put it, "steam started it all," overcoming "the limitations of muscle power, human and animal … the "most important" technological development of the era." Echoing the findings of our previous study of productivity (Atack et al., 2022), the results of this paper caution against a monocausal explanation of de-skilling (i.e. "steam [caused] it all"). Instead, we urge recognizing the important roles of changes in scale economies and related organizational innovation that pre-dated the diffusion of inanimate power.

The remainder of the paper is organized as follows. Section 2 introduces the HML study, including a discussion of our coding into skill categories of the listed occupations in the sample of production operations used and preliminary analysis of the skill category production time shares that underpin the measure of deskilling used in the regression analysis. Section 3 sketches our theoretical framework and identification strategy, and presents the base regression results. The regression specification is extended in Section 4 to include measures of scale, division of labor, and other factors. Conclusions are presented in Section 5. Additional information on the industrial composition of the sample, the measure of the division of labor used in Section 4, and robustness checks are presented in the online Supplementary Material: Appendix.

2. The hand and machine labor study: a brief introduction

In this section we present a brief introduction to the HML study. Our goal is to provide readers with sufficient background information to interpret the analysis in this paper. Additional information on the study and its history can be found in our prior work (Atack et al., 2019, 2022, 2023a). We also discuss the occupational information in the study and present our initial analyses of differences in the use of occupational time by skill level between hand and machine labor at the production operation level.

Published in two lengthy volumes of tables and associated text totaling almost 1600 pages, the HML study provided extensive data on the production operations involved in the manufacturing of 672 "units", which were stated quantities of precisely defined goods such as unit #71, "100 pairs men's medium grade, calf, welt, lace shoes, single soles, soft box toes" (see Fig. 1 and United States. Department of Labor 1899, 1: 28–29 and 2: 540–550). Although the 672 units included goods from non-manufacturing sectors such as mining and agriculture, our focus here, as in our prior work, is on the 626 (units #28 - #653) that were manufactures. The core of the operations data is contained in a series of tables stretching across both the left and righthand pages of Volume Two of the report, which we digitized, along with unit level information in Volume One (Atack et al., 2023a).

For each unit, the HML staff visited in person and collected production data from four establishments or related sources, two of which used "hand labor" methods and two "machine labor" methods, choosing "the better and more complete" accounting of each mode of production for the published report (United States. Department of Labor 1899, 1: 13). To guide the collection efforts, the 1894 HML survey instructions to the field agents distinguished between hand and machine labor as follows: "Roughly characterized hand labor was the system of the last century and machine labor is the system of this…" (United States. Bureau of Labor Statistics and United States. National Archives 1890-1905, Instruction form, DL 405, BLS Scrapbook, emphasis added), adding that "[t]he machine schedule should be made for factories where the most highly developed machinery is in use, and the hand schedule should be for establishments using the most old-fashioned and primitive of hand methods" (United States. Bureau of Labor Statistics and United States. National Archives 1890-1905, Supplemental Instruction No. 2, DL 416, BLS Scrapbook).

Commissioner of Labor, Carroll Davidson Wright, went on to clarify that the term "'machine', as applied to a method of production, does not imply that every operation … is performed by machine. On the contrary, it is often found that … work [by] …. hand is necessary in certain operations … even under the most modern machine methods." Further, machine labor differed from hand labor in other ways, most notably in its embrace of a far more intricate division of labor in which "every workman has his particular work to perform, generally but a very small portion of that which goes to the completion of the article" (United States, Department of Labor 1899, 1: 11).

The published report does not describe how specific establishments were chosen. However, Wright had been in charge of the 1890 census which, like other federal censuses of the period, surveyed manufacturing establishments, and whose records contained pertinent information for selecting the establishments. In addition, Wright's personal network in the American business community was vast and deep. Although we have no documentary evidence, it is possible that census records were consulted and then Wright used his network to shape and further data collection efforts. Earlier in his career, he had served as head of the Massachusetts Bureau of Labor Statistics which included directing the state's census of manufactures in 1875 and 1885. It is therefore not surprising that a brief article in the *Daily Evening Item*, a newspaper in Lynn, Massachusetts (then the center of U.S. shoe making), noted that Wright had "been making some preliminary inquiries for the special report … regarding the effect of machinery on production and upon the … condition of labor. Very satisfactory reports have been obtained as to the data available in the industries for which inquiry has been made" (Daily Evening Item. 1895, 7).

The survey forms used by field agents had included the names and addresses of the establishments visited, but these were suppressed in the published report and subsequently destroyed by order of Congress (United States. Congress. House 1906, 2). Except in a few isolated instances from newspaper accounts such as the one from Lynn, we do not know the locations visited by the HML staff (and the HML study itself does not mention Lynn or any other U.S. place). Note that, because we have no systematic information on where the units were produced in the United States, we cannot study or control for geographic variation in our empirical analyses.

Data collection began with machine labor and worked backwards to hand labor. As Wright's introduction to Volume One notes, "[i]n each branch of industry where comparisons could be made, representative articles … were selected as the subject of investigation. The agents of the Department then visited the large establishments … and secured the necessary data from the books and payrolls of the firms … To this was added the expert knowledge of the manager or one or more foremen engaged in supervising the work " (United States. Department of Labor 1899, 1: 13). The agents generally had little trouble securing information on machine labor from the immediate period, as almost all such data pertained to operations in the 1890s. The collection of the hand labor data was more difficult. For roughly a quarter of the hand units, information could be secured from establishments in rural areas close to where the good was produced by machine methods in the metropolitan areas visited by the staff. For the remainder, however, staff "had to hunt for employers or workmen … who had once been engaged in the making of the article in question by old-fashioned hand methods, and draw from them the needed facts" (United States. Department of Labor 1899, 1: 13), in one case from as early as 1813. In a few units, information on hand labor was obtained from foreign sources as no domestic records could be found; as in our prior work (Atack et al., 2022), these units, which are identified by country in the published report, are excluded from the analysis in this paper. All data collected were vetted carefully, compared between the two units using each mode of production, and conflicts and inconsistencies resolved before publication in the final report. Despite the challenges, Wright came close to achieving the goal of documenting "traditional" hand production because only a small fraction of hand operations in the published report involved the use of inanimate power, mostly by waterpower. As in our previous work (Atack et al., 2022) we excluded all units in which any operation in the "hand method" used inanimate power so as to approximate the Bureau's ideal comparison, reducing the number of units analyzed in this paper to 550 (see below).

A principal objective of the HML study was to measure differences in production times for specific operations, and overall, for each unit, between machine and hand labor with the time savings as the measure of productivity. The data on production times collected by the staff demonstrated that machine labor was, on average, significantly more productive than hand labor – to complete the same production operation, it took machine labor, on average, just 17 percent of the hand labor time (Atack et al., 2022). Although the productivity advantage of machine labor was substantial, regression analysis in Atack et al. (2022) shows that only a surprisingly small percentage of the advantage – between a quarter and a third, depending on the estimation method – can be attributed directly to the use of powered machinery. The main reason why is that about half of the production operations under machine labor did not actually use inanimate power. Yet workers performed these tasks more quickly than their counterparts did using hand methods. Further analysis showed that much of this higher productivity in the non-mechanized operations under machine labor could be attributed to other differences between the production methods, especially the greater use of division of labor, a factor that also plays an analogous explanatory role in this paper (see Section 4).

Although the unique nature and extraordinary detail of the HML study data make it worthwhile to analyze for its own sake, it is natural to ask about external validity. Table A.1 in the Supplementary Materials: Appendix classifies the units studied in this paper by broad industrial sector (2-digit SIC code). As can be seen from the table, the units cover the great majority of sectors, which speaks in favor of some external validity; that said, the units cannot be said to be a representative sample of manufactured goods and were not intended as such by the Commissioner of Labor.[2] In Atack et al. (2022) we showed the average difference in productivity between hand and machine labor implied an average annual growth rate of 1.7 percent per year over the nineteenth century. This is slightly higher than the best currently available estimate, 1.5 percent per year, for manufacturing as a whole over the same period (see Atack et al., 2022, footnote 10). Our goal in this paper is to study de-skilling at the production operation level, and, unlike productivity, there are no known alternative sources for comparison purposes. Extrapolating from our previous findings on productivity, however, suggests that the HML data likely overstates the extent of de-skilling at the production operation level, relative to the manufacturing sector as whole. This would be consistent with the study's goal of focusing on the state-of-the-art machine labor establishments of the era. Our main aim is to determine the treatment effect of mechanization on de-skilling, though, and there are no strong reasons to believe the HML study data to be systematically biased on this score.

2.1. *Production operations in the HML Study: Blocks and Block Links*

Volume Two of the HML study reports the hand and machine labor data at the production operation level. This includes a brief description of operations listed in the order in which they were performed, the occupational title(s) of the worker(s), and the time spent performing the operation. These specific data are key to the analysis in this paper – we are interested in whether the time completing the same production operation utilized less "skilled" labor under machine labor than under hand labor. To operationalize this, we describe first what is meant by the "same production operation".

We start with the concepts of a production "block" and a "block-link" as introduced in our previous work (Atack et al., 2019, 2022). Specifically, a block is a collection of production tasks of size H (for hand labor) or M (for machine labor). H and M are non-negative integers and refer to the number of distinct procedures, as identified by the HML staff, such that the intermediate good entering and

[2] For example, certain manufactures which were highly popular at the end of the nineteenth century, like bicycles, were excluded deliberately because they were never produced by hand (see United States. Department of Labor 1899, 1: 12).

exiting the block was in the same stage of completion. The associated block link is a mapping between the hand and machine labor blocks. We transcribed the mappings from the unit-level tables in Volume Two using what we call the HML study's "crosswalk". The crosswalk is illustrated in Fig. 1, which shows a portion of the relevant Volume Two tables from Unit 71 ("100 pairs men's medium grade, calf, welt, lace shoes, single soles, soft box toes").

There are six types of block links – 1:0, 0:1, 1:1; and 1:M, H:1, and H:M, where N and M are greater than one. The 1:0 and 0:1 block links refer to hand labor operations that were not performed under machine labor (1:0) or operations that were novel under machine labor (0:1). As in our prior analysis of productivity (Atack et al., 2022), both types of block links are excluded here, because our interest is measuring the treatment effect of mechanization on de-skilling, holding constant the "output" of the block. This can only be done for those block links that overlap between the two labor modes – 1:1, 1:M, H:1, and H:M – for which underlying content of the work performed (for example, "cutting out sock linings", the 1:1 block link between hand labor operation #5 and machine labor operation #6 in Unit 71, (the latter is also shown in Fig. 1)) is held constant, even if the means to accomplish the task (for example, an inanimately-powered machine versus by a hand tool) differed. This gives us our regression sample (see below) of 4398 block links, approximately 77 percent ($N = 3405$) of which were 1:1 – singular operations under machine labor that the HML staff matched to singular operations under hand labor. Approximately 23 percent of the block links ($N = 993$) required more complex matching by the staff – operations that experienced task reorganization and/or restructuring when performed in the factory compared with the artisan shop. Nearly two-thirds of the non-1:1 block links were 1:M ($N = 619$), in which a singular hand operation was linked to M machine operations – a tell-tale indication of a more intricate division of labor in the factory setting. The remaining third are H:1 ($N = 250$) or H:M ($N = 124$) in which multiple hand operations were linked by the HML staff to a single or to multiple machine operations.

2.2. Coding of HML Study Occupations into Skill Categories

In this subsection we describe our coding of HML occupational titles into skill categories. In brief, the coding derives from the work of Alba Edwards for the 1910 Census (United States. Bureau of the Census, 1910; United States. Census and Hunt, 1914a; United States. Census and Hunt, 1914b; United States. Bureau of the Census, Hunt and Edwards, 1915) and subsequent elaborations culminating in the 1950 occupation codes (United States. Department of Commerce. Bureau of the Census, 1950b). We begin with a brief discussion of the historical background leading up to the 1950 codes, followed by a description of our coding process.

In preparation for the Thirteenth Census in 1910, the U.S. Bureau of the Census undertook an extensive review of the occupational returns from 1900 for several states resulting in a base list of about 13,000 occupational titles. This list was provided to enumerators for the 1910 Census to serve as a guide although it was deemed "far from being all-inclusive, and will need to be supplemented by the addition of the new occupations returned in 1910" (United States. Bureau of the Census, 1910, iii). Subsequently, the Bureau produced a large volume on the occupation statistics (United States. Census and Hunt, 1914a) along with a shorter summary bulletin on the same (United States. Census and Hunt, 1914b) observing "the value of occupation statistics is dependent very largely upon the form in which the occupations are classified" (United States. Census and Hunt, 1914a, 17). The Bureau followed up with its "Index to Occupations: Alphabetical and Classified" written by Edwards who categorized the census data into 215 main occupations and occupation groups, 84 of which were further subdivided to produce 428 separate occupations and occupation groups (United States. Department of Commerce. Bureau of the Census, Hunt and Edwards, 1915). Subsequently, Edwards (1917, 645 and Table 1) classified these many hundreds into nine very broad "Social-Economic Groups," five of which covered manufacturing and thus pertain to the HML study – proprietors, officials, and managers (#1), clerks and kindred workers (#2), skilled workers (#3), semiskilled workers (#4), and laborers (#5).[3] We further narrow the five down to four categories, which we label white-collar (Edwards' categories #1 and #2), skilled blue-collar (#3), semi-skilled operatives (#4) and common labor (#5).[4]

For Edwards (1917, 646), the meaning of "skill" was narrow and specific, "properly applied only to those occupations in which the expenditure of muscular force is one of the chief characteristics. Within this field, those occupations have been considered skilled … [requiring] … a long period of training, or an apprenticeship … and … a degree of judgment, and manual dexterity". Extending this line of argument, his group #4 consisted of occupations for which "only a short period or no period of preliminary training is necessary, and which in their pursuance call for only a moderate degree of judgment or of manual dexterity." He classified as "laborers" occupations requiring "no special training, judgment, or manual dexterity, but supply mainly muscular strength in the performance of coarse, heavy work," that is, by inference, they lacked skill (Edwards 1917, 646).[5] Our definition of "skill" includes white-collar workers, and so is broader than Edwards. Eventually (see below), we collapse the four categories down to two – white-collar/blue-collar and operatives/common labor – in the univariate measure of de-skilling used in the regression analysis (see below).

Over the years, Edwards' original classification evolved and was further refined. For example, the Department of Labor's

[3] The remaining categories were servants (#6), public officials (#7), semiofficial public employees (#8) and professional persons (#9).

[4] Some of the units in the HML study have only a single worker – for example, the shoemaker employed in hand labor Unit 71 (see Fig. 1). In such cases we assigned the worker to the skilled-blue collar category rather than in Edwards' group #1 (proprietors).

[5] A legitimate question is why we did not start with United States. Department of Labor and Hunt (1897) occupational groups, as these are contemporaneous with the HML study. Hunt defined four major categories: proprietors (including farmers), clerical, skilled workers, and laborers. The obvious disadvantage with Hunt is that his skilled category lumps skilled blue-collar workers and semi-skilled operatives together. Edward's innovation was to separate semi-skilled operative workers from skilled and common labor. In the de-skilling debate, which focuses on the shift away from craft-based production, this innovation is crucial.

Employment Service prepared a dictionary of occupational titles with the objective of establishing broad groups of occupations requiring similar skills and abilities, much of it based upon direct observation or job analyses (United States. Department of Labor. Employment Service 1939). It was followed by an alphabetical index of occupations and industries for the Sixteenth Census (1940) again authored by Edwards (United States. Department of Commerce. Bureau of the Census and Edwards 1940) and similar volumes were produced to accompany subsequent censuses, such as the index prepared for the 1950 Census (United States. Department of Commerce. Bureau of the Census, 1950a) and used by IPUMS to generate their "OCC1950" variable found in all IPUMS census samples from 1850 onwards (see https://usa.ipums.org/usa-action/variables/OCC1950#codes_section).

With this background in mind and the goal of creating our skill categories established, we compiled a list of all unique occupational titles appearing in the full digitized version of the HML study covering over 20,000 production operations (Atack et al. 2023a). Where multiple occupations were reported, we adjusted according to function. Thus, for example, the occupation of "canner and labeler" was treated as two different occupations, "canner" and "labeler", whereas a "shank and toe nailer" was simply classified as a "nailer".[6] Overall, we identified 1,703 distinct occupations in the HML study after eliminating those that were compounded by "and" but for which individual occupations were also recorded.

Next, we searched for the closest match to the HML title to those found in the occupational dictionaries and alphabetic indexes mentioned above, primarily the U.S. Department of Labor's *Dictionary of Occupational Titles* (United States. Department of Labor. Employment Service 1939, iii). Once such a title was found we assigned it the appropriate 1950 occupation code (United States. Department of Commerce. Bureau of the Census 1950b), endeavoring to match skill level and function over time. The initial assignments were done by two members of the research team working independently, using a Pivot Table in Excel created for this purpose. The two assignments agreed initially in about 94 percent of cases, and the remaining 6 percent were resolved quickly, without issue. Overall, the most frequent occupation was "machine hand," coded as 690 and, therefore, as semi-skilled.[7]

2.3. *Skill Category Time Shares: Preliminary Analysis*

After classifying occupational titles into the four skill categories, we computed the shares of production time performed by workers in the four skill groups for each block, which gives us eight share variables for each block link, four for each labor mode. Panels A (hand labor) and B (machine labor) of Table 1 show the mean values of the shares, overall (column 2), and classified by mechanization status of the machine labor block (columns 3-4). Panel C shows the differences in the sample means between machine and hand labor. In computing the mean shares (and the differences in means between machine and hand labor) the block-links are equally weighted. Mechanization status refers to the "one-touch" measure of inanimate power use (almost always steam) introduced in our prior analysis of productivity and used here in the regression analysis (Atack et al., 2022). The measure is called "one touch" because it equals 1 if inanimate power was used at any point within the machine labor block, 0 otherwise.

Virtually no white-collar workers and very few common laborers were involved in the production operations covered in the regression sample – that is, the bulk of the labor time, in both types of production, was performed by semi-skilled operatives and skilled blue-collar workers. For white collar workers this is not surprising, given that the purpose of the HML study was to document time in production tasks. White-collar workers overwhelmingly performed non-production tasks such as keeping the books in the front (or back) office rather than on the shop floor – hence, their near complete absence from the HML data. The limited use of common labor might seem more surprising but the most likely explanation is that most of the laborers employed in the establishments making the HML units were primarily performing non-production tasks (and therefore, not documented in the HML data) such as moving raw materials onto and off of the shop floor (rather than between tasks), or cleaning the premises.

In interpreting the mean shares it is important to keep in mind that, if a single worker performed the task (or a group of workers with the same occupational title), the share corresponding to the worker's skill category will be equal to one, and the others equal to zero – "corner" solutions. Thus, for example, an average share of 0.8, for semi-skilled workers in machine labor does not imply that, on average, 80 percent of the production time in the average block was assigned to operatives but rather, in 80 percent of the blocks, the work was performed by operatives. To this end, Panels A and B includes rows showing the number (and proportion) of block links for which the mean occupation share was identically one if workers in the skill category were employed in the block. Again, note that, if this was the case, the other occupation shares would be zero. As shown in the final column in Panels A and B, 94 percent of the block-links in both hand and machine labor have this characteristic.

Under hand labor, skilled blue-collar plus white collar had an average time share of about 0.44 (44 percent), almost all of which was skilled blue-collar. Under machine labor, the corresponding average time share was about 0.13 (13 percent). Thus, the (machine –

[6] When a person was listed with two or more occupations, we ensured that there was a singular occupational entry for each occupation. For example, "Shaft and Pole trimmer" was separated into "shaft trimmer" and "pole trimmer". In this example, the skill set used for classification is defined by "trimmer". However, if the two occupations differed with respect to skill, we assigned the worker to the higher skill category. Thus, for example, the person whose occupation was given as "matcher and foreman" was assigned the supervisory code for a foreman rather than the operative code for a matcher. Where the term "assistant" or "helper" was used in conjunction with a skilled blue-collar title, we treated these individuals as apprentices, assigning them the appropriate 4-digit code (#6020 – 6150). This protocol differs slightly from that used in the 1950 Alphabetical Index (United States. Department of Commerce. Bureau of the Census 1950b), where such workers would be coded 690 (= operatives). Note, however, that apprentices/helpers are still ultimately classified into our semi-skilled category based on the 1950 code for apprentices

[7] During the coding process the research team members occasionally used information on wages in the HML study to separate out problematic cases requiring further review, but did not use wages *per se* to assign skill categories.

Table 1
Mean values of occupation time shares and mechanization, regression sample.

Panel A: Hand Labor Time Shares.	White-collar	Skilled blue-collar	Semi-skilled operative	Common laborer	Sample size
Mean, Overall	0.005	0.431	0.505	0.059	4398
N = 1 if Time Share > 0	21	1780	2094	254	
	[0.955]	[0.883]	[0.895]	[0.944]	{0.943}
Machine Labor Block Mechanized	0	0.440	0.501	0.059	2432
Machine Labor Block Not Mechanized	0.011	0.419	0.510	0.060	1966
Difference, Row 3 – Row 4	−0.011	0.021	−0.009	−0.001	
Panel B: Machine Labor	White-collar	Skilled blue-collar	Semi-skilled operative	Common laborer	Sample size
Mean, Overall	0.004	0.124	0.833	0.038	4398
N = 1 if Time Share > 0	17	443	3525	150	
	[0.850]	[0.664]	[0.932]	[0.769]	{0.940}
Machine Labor Block Mechanized	0	0.083	0.896	0.021	2432
Machine Labor Block Not Mechanized	0.009	0.175	0.756	0.060	1966
Difference, Row 3 – Row 4	−0.009	−0.092	0.140	−0.039	
Panel C: Machine Labor – Hand Labor	White-collar	Skilled blue-collar	Semi-skilled operative	Common laborer	Sample size
Overall	−0.001	−0.307	0.328	−0.021	4398
N, Complete De-Skilling					1332
					[0.303]
Machine Labor Block Mechanized	0	−0.357	0.395	−0.038	2432
N, Complete De-Skilling					834
					[0.343]
Machine Labor Block Not Mechanized	−0.002	−0.244	0.246	0	1966
N, Complete De-Skilling					498
					[0.253]
Difference, Row 3 – Row 5	0.002	−0.113	0.149	−0.038	[0.09]
Panel D: Unit-Level Weighted Occupation Time Shares, Regression Sample Block Links	White-collar	Skilled blue-collar	Semi-skilled operative	Common laborer	
Hand Labor	0.003	0.363	0.570	0.065	
Machine Labor	0.004	0.157	0.812	0.027	
Machine – Hand	0.001	−0.206	0.242	−0.038	
Panel E: Unit-Level Weighted Labor Cost Shares, Regression Sample Block Links	White-collar	Skilled blue-collar	Semi-skilled operative	Common laborer	
Hand Labor	0.003	0.384	0.550	0.064	
Machine Labor	0.002	0.170	0.802	0.026	
Machine – Hand	−0.001	−0.214	0.252	−0.038	

Source: computed from digitized HML study (United States. Department of Labor 1899). Notes: Panels A-C: block links are equally weighted in computing the mean values (Panels A and B) and differences (Panel C). Panels A and B: N = 1, Time Share > 0: number of blocks for which the time share = 1, if time share > 0 ([ ], proportion in which time share = 1)); { }: share of block links in which one of the time shares = 1 and the others = 0 (N = 4,419 hand blocks and N = 4,135 machine blocks). Panel C: Complete De-Skilling: number of blocks [(share in [ ]) for which ((Time Share, Semi-Skilled + Common in Hand Labor) = 0 & (Time Share, Semi-Skilled + Common in Machine Labor)] = 1. Panel D: Sample size is 4398 block links. Block links are weighted by block link time shares within units (weights sum to one within units) in computing the mean values. Panel E: The sample of block links for Panel D is slightly smaller (*N* = 4393) because of missing data on labor costs for five block-links. Occupation group time shares are replaced by group's labor cost time shares; block links are weighted by block link time shares within units (weights sum to one within units).

hand) labor difference is −0.31 (computed from Panel C, row 2, columns 2 and 3), a marked reduction in the use of skilled blue-collar time, in favor of a greater use of semi-skilled time (approximately 0.33) and slight less common labor time (−0.02), in machine labor than in hand labor. This is direct, unmistakable evidence of de-skilling at the production operation level, of an exceptionally high quality (that is, for specific goods, holding constant the underlying production activity) otherwise wholly unavailable from historical sources, for any country. We clarify this point further in the rows in Panel C labelled "N, Complete De-Skilling" which show the number (and proportion) of block links for which the share of semi-skilled and common labor was zero under hand labor and one under machine labor. Overall, fully 30 percent of the block-links fall into this category – again, direct evidence of de-skilling. In Section 3 we return to the apparent binary nature of de-skilling in the HML study data.

Rows 3 and 5 of Panel C show that the decreased use of skilled blue-collar and white-collar time – or equivalently, the increased average use of semi-skilled and common labor time – was disproportionately larger, approximately 0.11 (11 percentage points), in block links that were mechanized under machine labor, compared with block links that remained unmechanized. Rows 4 and 6 show that much of the 11 percent points is accounted for by the block-links in which complete de-skilling occurred. In Section 3 we develop an identification strategy to argue that the positive relationship between mechanization and de-skilling suggested by this comparison is also causal. Here, we emphasize that use of skilled time was also much lower in the non-mechanized block links under machine labor than under hand labor. This, plus the observation that a significant fraction of machine labor blocks – approximately 45 percent [= (1966/4398) x 100] in the regression sample – were non-mechanized suggests that mechanization cannot be the sole cause of de-skilling, a point that we explore further in Section 4.

In Panel D, we report sample means of the time shares weighted by the block's overall share of total production time in the unit, restricting the calculation to the time spent in the completion of blocks in the regression sample (that is, excluding the 1:0 and 0:1 block links). Weighting in this manner mutes the shift towards semi-skilled operatives and away from skilled blue-collar workers. In our earlier study of productivity (Atack et al., 2022) we showed that mechanization reduced the time needed to complete a block under machine labor. As we shall demonstrate econometrically in Section 3, the shift towards semi-skilled operatives was positively related to mechanization. Thus, machine labor blocks using semi-skilled operatives were completed more quickly than the corresponding block under hand labor; this is reflected in the weighting in Panel D, thereby muting the shift towards semi-skilled operatives and away from skilled blue-collar.

Finally, in Panel E, we provide a complementary perspective to Panel D, by substituting (unit weighted) labor cost shares by occupation category for (unit weighted) time shares. The cost of the additional capital used in machine production was covered in part by higher labor productivity, but also by wage "saving" because machine labor used less skilled blue-collar time, which was more costly than semi-skilled time. Hence, we expect a decrease in the labor cost share of skilled blue-collar and an increase in the semi-skilled cost share, comparing machine to hand labor – which is exactly what we see in Panel E. Elsewhere (Atack et al., 2023b) we use the unit-level data from the HML study show that within-unit variance in labor cost across production operations was substantially higher for machine labor than hand labor, which is largely explained by the higher degree of division of labor in the machine units (see also Section 4).

3. Regression analysis: de-skilling and mechanization

In this section we present a regression analysis of the block-link sample represented in Table 1. The goal of the analysis is to estimate the causal effect of mechanization on de-skilling We begin with a brief discussion of the economic theory behind the analysis, followed by the empirical definition of de-skilling (the dependent variable), our identification strategy, and the estimation results.

3.1. Theoretical framework

As a point of departure for the theoretical framework, we begin with a task-based production function, as described by Acemoglu and Restrepo (2018). In a task-based production function, the completion of a task yields an intermediate good which is a function of the task technology and the task inputs. These inputs are capital and labor inputs in the current task, plus the intermediate good from the prior task. At the task level, Acemoglu and Restrepo impose a partial Leontief or "fixed coefficients" structure such that labor and capital are perfect substitutes for each other. Aggregating across all tasks to final output – as in a conventional neoclassical production function – labor and capital will be imperfect substitutes.

In writing down the task production function, Acemoglu and Restrepo specify the task ordering in terms of labor's comparative advantage, rather than sequential completion from start to finish. The ordering of comparative advantage is along the unit interval, from low to high. Somewhere in the interval there is a point, I^*, such that for tasks below I^*, capital is sufficiently productive such that, depending on its user cost, it can be used alone to produce the intermediate output, or what Acemoglu and Restrepo call "automation." Above I^*, however, capital is insufficiently productive such that it will never be used to perform the task – only labor is used. Suppose that a firm is at I^* and that technology improves at the margin, causing I^* to shift to the right by the amount $d(I^*)$, $I^{**} = I^* + d(I^*)$. The improvement in technology causes tasks in $d(I^*)$ previously were performed by labor to being performed now entirely by capital. This generates a reduction in the labor input, what Acemoglu and Restrepo call labor "displacement." For tasks in the sub-interval $d(I^*)$, the share of task time performed by labor changes from exactly one, before the new automation, to exactly zero, post-automation – a dichotomous change.

Recognizing that, unlike today, there were no robots in the nineteenth century – someone had to operate the machinery – Acemoglu and Restrepo's displacement effect bears similarity to historical de-skilling, insofar as the combination of the operative-*cum*-machine was viewed as a perfect (or nearly so) substitute for the skilled artisan-*cum*-hand tool. In fact, this is suggested by the patterns in Table 1, which we further confirm below; in the HML data, de-skilling was overwhelmingly binary at the production operation level, in line with the displacement effect in Acemoglu and Restrepo's 2018 model. That said, the analogy to the displacement effect is not fully satisfactory because the 2018 model does not incorporate scale economies – in particular, division of labor (Atack et al., 2019). As far as the model is concerned, the person operating the machinery might just as well have literally been the same artisan who previously performed the task by hand. However, in reality, the operative was typically a different person, less "skilled" overall than the artisan whom they replaced because the artisan had the knowledge and experience to perform a wider range of tasks versus, in the extreme, the single task performed by the operative.[8]

It is beyond the scope of this paper to extend Acemoglu and Restrepo's 2018 model to incorporate scale economies, but we can draw on the existing literature to sketch the relevant economics at play. For this purpose, we refer to the "production chain" model of Chaney and Ossa (2013). In Chaney and Ossa's model, consumers have a "love of variety" utility function defined over a set of goods, Q_j, each of which is produced by a monopolistically competitive firm, historically akin to the "endless novelty" identified by Scranton (1997). Final output Q_j is produced by having workers in firm j complete tasks arrayed sequentially along a continuous interval which is the production chain. The firm hires workers who are then assigned to a subset of tasks in the interval. Each worker has a "core competency" – a range of tasks the worker can perform centered around some point c in the interval. The cost of acquiring the core competency is F_j. The marginal cost of production is lowest (equivalently, task productivity is highest) at c, and then rises (task productivity declines) at an increasing rate for tasks further away in from point c. Firms choose the number of workers and their assignment to tasks along the interval to minimize total production costs for a given level of Q_j.

Chaney and Ossa derive the conditions for the optimal number of workers and their assignment to tasks – equivalently, the optimal degree of division of labor. The optimal division of labor depends on Q_j – that is, on scale – and on F_j. A rise in Q_j – for example, because of an increase in overall market size – creates an incentive for the firm – a bigger market for its product – to increase the optimal division of labor which, given the model assumptions, requires more workers, each of whom performs a narrower share of tasks in the production chain.

Although not emphasized in their paper, inspection of Chaney and Ossa's eq. 4 (2013, eq. 4, p. 178) reveals that a reduction in F also increases the optimal division of labor – intuitively, if it is cheaper for workers to acquire core competencies, it will pay the firm to hire more workers and reduce the share of tasks each performs on average. For the purpose of our empirical analysis, the motivating argument is that the cost of acquiring the core competency of a task is reduced by the technological innovation of powered machinery. That is, for most manufacturing workers at the time, it was easier (less costly) to learn to operate the machine productively than to learn to perform the equivalent task by hand (see Atack et al., 2008 for a related argument). As Joseph Roe (1926, 31) put it when discussing the contributions of machines innovated by Bentham and Brunel in the Portsmouth (U.K.) shipyard, "these machines were thoroughly modern in their conception and constituted a complete range of tools, each performing its part in a definite series of operations. By this machinery ten unskilled men did the work of 110 skilled workmen". Thus, in the transition from hand to machine labor, the mechanized task should more likely be performed by a less skilled worker – equivalently, one whose range of tasks performed is narrower than a skilled artisan – relative to tasks that are not mechanized.

3.2. Identification strategy and instrumental variable analysis

Our base regression specification is given by Eq. (1):

$$\textit{De-Skill}(a,j) = \beta(j) + \gamma(a) + \lambda^{*}\textit{Mechanized}(a,j) + \varepsilon(a,j) \tag{1}$$

The index *j* refers to the unit, and *a* to the block link. The *β(j)* are unit fixed effects. We include these because the manufactured goods produced by the various units were very different. Because the unit fixed effects soak up all unit level variation, we cannot include any unit level variables directly (for example, the difference between the hand and machine units in the year to which the data pertain) in [Eq. (1)]. In Section 4 we substitute four-digit SIC industry codes for the unit fixed effects, which allows us to include unit level variables in the regression. Our base specification also includes dummy variables for the block link types, γ(a), to control for the complexities introduced by multi-operation grouped tasks which, as noted in Section 2, accounted for slightly less than a quarter of the blocks.[9]

We could define *De-Skill* to be the continuous difference (Δ) between machine and hand labor in the sum of the semi-skilled and common labor time shares, or Δ (share of block production time, semi-skilled operative + common labor) which, on average, is positive (0.307). Instead, we elected to define *De-Skill* to be a 0–1 binary variable, as follows:

$$\textit{De-Skill} = \textit{Prob}[\Delta(\text{share of block production time, semi-skilled} + \text{common labor} > 0)]$$

Measured as a binary variable *De-Skill* takes the value 1 if the share of semi-skilled operative plus common labor time is higher in the machine labor block than the corresponding hand labor block, 0 otherwise. As discussed in our theoretical framework, if the operative-*cum*-machinery was a perfect substitute (or nearly so) for the skilled artisan-cum-hand tool, we should see a "displacement" effect that is mostly dichotomous. This is consistent with the results in Table 1 showing that approximately 30 percent of the block links exhibit complete de-skilling (binary *De-Skill* = 1). Further evidence is displayed in Fig. 2, which exhibits the histogram of the continuous version of *De-Skill*.

The distribution is, in fact, almost completely dichotomous. Virtually all observations (92 percent) are either identically zero – no change in de-skilling – or one – which suggests that the binary version of *De-Skill*, empirically speaking, conveys nearly the same information as the continuous version. To be sure, the binary definition ignores variation in the positive values in Fig. 2 between 0 and 1 as well as obscuring the negative values, which are examples of "up-skilling" (substitution of more skilled labor in machine

[8] Under the displacement effect interpretation, even if the machine task is performed by the same artisan who previously performed the task by hand, the artisan is no longer using the hand skill on a regular basis, and thus has been "de-skilled" in that sense. However, this is clearly different from a scenario in which the operative never learns how to perform the hand labor task in the first place.

[9] The values of *β(j)* and γ(a) are available on request. The left-out block-link dummy is 1:1.

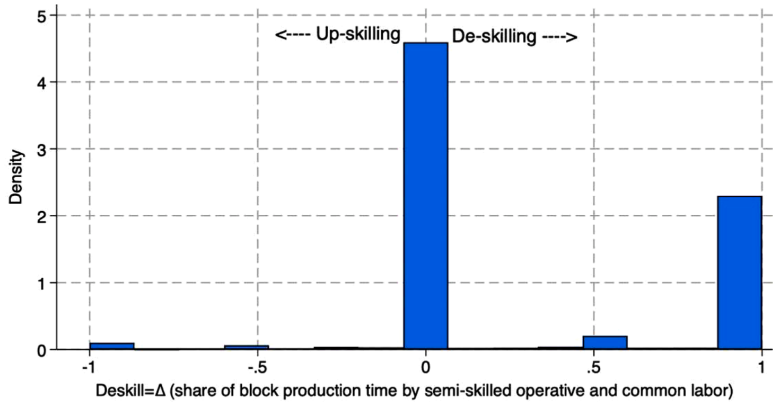


Fig. 2. Histogram of continuous measure of *De-Skill* source: see text. Notes: figure shows the histogram of the continuous measure of *De-Skill* = Δ (share of block production time, semi-skilled operative plus common labor). $N = 4398$ block links.

production compared with hand production) and which are grouped with the zeroes in the binary measure, but these observations are a tiny share of the total.

In section D of the Supplementary Materials: Appendix we use the continuous measure of de-skilling as the dependent variable and re-estimate the regressions in the paper, finding results very similar to those reported in the text tables. We therefore adopt the dummy variable version as the dependent variable. Given that the mean value of the binary measure (0.354) is far from either endpoint (0 or 1) and that our treatment variable (the one-touch measure of mechanization) is also binary, we follow conventional practice and specify [Eq. (1)] as a linear model (Angrist and Pischke 2009).

OLS estimation of λ will be unbiased and consistent provided that the treatment variable, *Mechanized*, is uncorrelated with the error term (Angrist and Pischke 2009). However, the HML staff did not randomly assign inanimately powered machinery to the machine labor operations that used them (indeed, the staff would not have known what this meant). The decision to use inanimate power was made by someone in the original manufacturing establishment, presumably an owner or manager, and presumably because mechanization was expected to be profitable – an endogenous choice.

To assess the magnitude, if any, of endogeneity bias, we need an instrumental variable (IV) for *Mechanized* at the block link level. We follow the same identification strategy used in Atack et al. (2022). This makes use of the textual descriptions of production operations appearing in the "General Table – Production by Hand and Machine Methods" in the column titled "Work Done," organized by unit number and production method (see Fig. 1), in Volume Two of the HML study. We briefly describe the construction steps here; additional details can be found in Atack et al. (2022). First, we extracted all unique occurrences of gerunds appearing in the "Work Done" columns. The first word in these descriptions is usually a gerund describing the principal action taking place in the operation, so we call this the "principal gerund."[10] Next, a member of our research term with specific knowledge in the history of technology was given just the list of gerunds and asked to sort them into two bins without consulting the HML study. Based solely on the expert's historical knowledge, if the expert believed there was some technical feasibility of mechanization worldwide by the end of the nineteenth century, the relevant gerunds were sorted into one bin (bin #1), while those for which there was little or no feasibility were sorted into the other (bin #0). The classification of gerunds into the two bins is shown in Panel A of Table 2. The five most common activities in bin #0 were "making", "putting", "overseeing", "finishing", and "marking." For each, human judgement was crucial and the activity idiosyncratic, impossible to mechanize in the nineteenth century (and until recently with the invention of AI, not possible to automate today). By contrast, the five most common activities in bin #1 were "cutting", "sewing", "smoothing", "stitching", and "conveying". These are repetitive activities for which special-purpose machinery had been invented in the nineteenth century. For the 1:1 and 1:M block links there is a direct mapping from the bins to our instrument, which is the "one-touch" analogue to *Mechanization, MECHABLE* = 1 if principal gerund was sorted into bin #1, or 0 (if sorted into bin #0). For the H:1 and H:M block links there is an intermediate step because when $H > 1$ there may be more than one principal gerund (Atack et al., 2022).

As discussed in our earlier article (Atack et al., 2022), the motivation for the instrument derives from the Acemoglu's and Restrepo's 2018 model of automation. By the late nineteenth century, science and engineering had advanced to the point where the mechanization of certain physical production activities – as captured by the relevant gerunds – was technically feasible. Conditional on the unit to be manufactured, therefore, the fraction of operations that, in principle, could be mechanized under machine labor depends on the classification of the relevant gerunds into the two bins. The classification corresponds to variation in the cost of mechanization which, by construction, is exogenous, because it depends on technical feasibility, beyond the control of the owner or manager deciding on whether to mechanize or not, thus implying that our instrument satisfies the exclusion restriction.

Panel B of Table 2 reports coefficient estimates and regression statistics. The first stage is very strong, as indicated by the highly

[10] A gerund is an English verb to which "-ing" has been appended. Additional gerunds, if present, are closely related to the main activity described by the principal gerund.

Table 2
Regression and decomposition analysis of *De-Skill*.

Panel A: the top-five activities (principal gerunds) in hand production 1:1 and 1:M block-links in the regression sample: bin #0 (mechanization infeasible/unlikely)) versus bin #1 (mechanization feasible)

Bin #0	Number	Bin #1	Number
Making	170	Cutting	677
Overseeing	169	Sewing	138
Putting	133	Smoothing	92
Finishing	44	Stitching	80
Marking	33	Conveying	71
Total count in Bin #0	775	Total count in Bin #1	3245

Source: See text.
Notes: The table shows the distribution of the five most common principal gerunds classified into bin #1 (some feasibility of mechanization) versus bin #0 (little or no feasibility of mechanization) for the 1:1 and 1:M block links in the regression sample.

Panel B: OLS and 2SLS coefficients and percent explained, binary measure of *de-skill*

	Variable	Coefficient (s.e.) or Statistic	Mean Value (s.d.) of *Mechanized*	Percent Explained of Mean Value of *De-Skill*
OLS	*Mechanized*	0.044	0.553	6.8 %
		(0.018)	(0.497)	
Adjusted R-2		0.669		
2SLS	*Mechanized*	0.101	0.553	15.6 %
		(0.038)	(0.497)	
First Stage	*MECHABLE*	0.315	0.819	
		(0.020)	(0.385)	
Kleibergen-Paap F-Statistic		239.09		

Notes: $N = 4398$ block links, s.e. = standard error, s.d. = standard deviation. Mean value of binary *De-Skill* = 0.357 (s.d. = 0.479). Percent Explained of mean value of *De-Skill* is computed by multiplying the OLS or 2SLS coefficient of *Mechanized* by the mean value of *Mechanized* (0.553) and dividing the product by the mean value of *De-skill* (0.357). The regression also includes dummy variables for block link types and for units (see the text). Standard errors of coefficients are clustered at the unit level (550 units).

significant value of the Kleibergen-Paap F-statistic. The 2SLS estimate of the coefficient of *Mechanized*, 0.101, is positive, as hypothesized, and significant (s.e. = 0.038) at the 5 percent level. Column 5 of Table 2 shows the "percent explained" of the mean value of *De-Skill* by the treatment effect, which is the estimate of λ multiplied by the mean value of *Mechanized*, divided by the mean value of *De-Skill*. Using the 2SLS coefficient, the percent explained is 16 percent. For comparison purposes, we also show the OLS coefficient, 0.044, also positive and significant (s.e. = 0.018), but smaller in magnitude than the 2SLS coefficient, and, therefore, the percent explained, about 7 percent, is lower.

The IV analysis indicates that the OLS bias is downward.[11] Measurement error could cause a downward bias, but this is almost certainly not present given the careful nature of the HML study and the fact that our measure of mechanization is "one-touch" – that is, we only require that the HML staff to have correctly observed the use of inanimate power and nothing more. A more plausible explanation is reverse causality. In Atack et al. (2022) we argued the OLS estimation of the treatment effect of mechanization on the (ln) difference in production time between machine and hand labor was biased upwards. Our explanation in the earlier paper was that use of inanimate power was more likely when it was more profitable, and it was more profitable if the savings in production time was especially large. But if this is true, the share of production time that was mechanized under machine labor will be smaller than if mechanization were randomly assigned, an unobservable factor that will bias *De-Skill* towards zero. Correcting for this bias results in a larger estimate of λ in [Eq (1)] when IV is used instead of OLS.

4. Further analysis of de-skilling: scale, division of labor, and other factors

At the production operation level, machine labor used a far smaller share of skilled blue-collar time than hand labor. The higher degree of mechanization under machine labor is part of the reason. However, the majority of de-skilling, 84 percent, is not accounted for by mechanization *per se*. What accounts for the unexplained portion?

To answer this question, we follow the strategy in Atack et al. (2022), which uses the detailed text descriptions of the HML units to map them into 70+ four-digit SIC codes. We substitute these SIC code dummies for the unit fixed effects, which results in [Eq. (2)]:

$$De\text{-}Skill = \eta(s) + \gamma(a) + \lambda^{*}Mechanized(a,j) + \Delta X(j)^{*}\gamma + \varepsilon(a,j) \tag{2}$$

The η(s) are coefficients of the 4-digit SIC fixed effects. Because Eq. (2) does not include unit fixed effects, we can add unit level variables, Δ *X(j)*, provided these can be constructed from the information reported in the HML study. Identification of the coefficients – the vector γ – of the unit level difference variables is achieved through variation across units within the 4-digit SIC codes. The Δ *X(j)* variables are not reported (or cannot be calculated from the available information) for all units in the original regression sample,

[11] The 95 percent confidence interval around the 2SLS estimate of λ includes the OLS estimate so we cannot reject the hypothesis that the 2SLS and OLS estimates statistically are the same.

Table 3
IV regressions of *De-Skill* with 4-digit SIC code dummies.

Independent variable	Coefficient (s.e)	Coefficient (s.e)	Coefficient (s.e)	Coefficient (s.e)	Mean value of independent variable (s.d)	Percent explained (column 5 coefficients)
Mechanized	0.086 (0.047)	0.088 (0.048)	0.058 (0.045)	0.055 (0.045)	0.555 (0.497)	8.0
Unit level differences (Δ) between machine and hand labor in:						
Δ Ln *Q*		0.048 (0.009)	0.025 (0.008)	0.024 (0.009)	2.735 (2.308)	17.2
Δ Percent_Oper			−0.418 (0.057)	−0.438 (0.058)	−0.397 (0.375)	45.6
Δ Ln *(Daily Hours)*				0.208 (0.174)	−0.030 (0.073)	−1.6
Hand Unit Better quality				0.065 (0.050)	0.030 (0.172)	0.5
Δ Ln *(Year)*				2.945 (1.683)	0.014 (0.009)	10.8
First stage:						
MECHABLE	0.306 (0.021)				0.820 (0.384)	
Kleinbergen-Paap F-statistic	220.72					

Notes: The dependent variable is the binary measure of *De-Skill*. Mean value of dependent variable = 0.382 (s.d. = 0.486). *N* = 3871 block links. Coefficients are 2SLS estimates, s.e. = standard error, and s.d. = standard deviation. *Mechanized* is the endogenous variable, and MECHABLE is the instrument Δ = difference between machine and hand labor. Ln *Q*: natural log of actual quantity produced in the unit. *Percent_Oper*: percent of total production operations performed by the average worker. Ln *(Daily Hours)*: natural log of average daily hours of operation. *Hand Unit Better Quality* = 1 if HML staff believed the hand unit to be of better quality than the quality of the machine unit. Ln *(Year)*: natural log of year to which the production data pertain. Block-link and 4-digit SIC dummies are included in all regressions (coefficients not reported). Standard errors of coefficients are clustered at the unit level (501 units).

consequently the sample size for [Eq. (2)], is smaller (3871 block links) than in Panel B of Table 2.

To motivate the choice of the unit level differences variables, we refer back to our discussion of the Chaney and Ossa (2013) model, which points to the role of scale, keeping in mind that we are controlling for mechanization at the block-link level. For scale, we introduce unit level differences in two variables. The first is the variable $\Delta \ln Q$. When the HML study agents collected the production operations data, they were careful to note the quantity of final output that was actually produced in the unit, and subsequently scaled the production times to make the hand and machine production times comparable. In almost all units, however, the actual quantity produced was considerably greater in machine labor than in hand labor. This is revealed by the mean value of $\Delta \ln Q = 2.735$ (see Table 3), which implies that the typical "production run" was 15.4 [= exp (2.735)] times larger for machine labor units than hand labor, a testament to the much higher level of labor productivity under machine labor (Atack et al., 2022). We expect the coefficient of this variable to be positive.

The second is called Δ *Percent_Oper*, which is the difference between machine and hand labor in the fraction of total production operations performed by the average worker in the unit. An extraordinary feature of the HML study is that there is sufficient information to compute this variable, the details of which can be found in section D of the Supplementary Material: Appendix. In level terms, *Percent_Oper* is closely related to "core competency" measure of the division of labor in the Chaney and Ossa (2013) model. Its value lies within the half open unit interval (0, 1]. If a single worker performed all tasks – that is, zero division of labor – *Percent_Oper* = 1. If the division of labor is extensive – there are many tasks and many workers, each performing a small fraction of the tasks – *Percent_Oper* will be close to zero.

As shown in Panel A of Table D.1 of the Appendix, the mean value of *Percent_Oper* was 0.487 for the hand method versus 0.091 for the machine method; on average, a worker in the hand unit performed close to half of the production operations in the regression sample whereas, in the machine unit, a worker performed 9 percent. The difference, −0.396, indicates are far higher degree of division of labor in the machine units, a consequence of the much larger number of workers and the finer delineation of tasks. As shown in Panel B of Table D.1 in the Supplementary Materials: Appendix, *Δ Percent_Oper* is negatively and significantly related to $\Delta \ln Q$ – the greater the (proportional) difference in the scale of production between machine and hand labor, the greater was the difference in the division of labor, consistent with Chaney and Ossa (2013). The correlation with the difference in scale is essentially explained by the differences the number of workers and tasks; once these variables are controlled for, magnitude of the scale coefficient in absolute value is close to zero and loses statistical significance. We expect the coefficient of *Δ Percent Oper* in [Eq. (2)] to be negative – as the value of *Δ Percent_Oper* becomes more negative on average in the unit, de-skilling at the production operation level should become more likely.

To estimate [Eq. (2)] we use the same instrumental variables strategy as in Table 2. Results are shown in Table 3. As in Table 2, the first stage is very strong and the associated Kleinbergen-Paap F-statistic well above the critical level. Moving to left to right in Table 3, we include additional unit level differences variables in the regression. In column 2, there are no such variables at all, so this specification is comparable with Eq. (1), except for the replacement of the unit fixed effects by the 4-digit SIC codes. The 2SLS estimate of λ, 0.085, is slightly smaller than the analogous coefficient in Table 1 (=0.101) but lies squarely within a conventional confidence interval around it.[12] In column 3, we add the first scale variable, Δ ln *Q*. The coefficient of this variable is positive (0.048) and highly significant (s.e. = 0.009), indicating that the greater the difference in scale between the machine and hand labor unit, the greater the extent of de-skilling at the production operation level. Column 4 then adds Δ *Percent_Oper*; its coefficient is negative (−0.418), as hypothesized, relatively large and highly significant (s.e. = 0.057), and including it reduces the magnitude of the coefficients of *Mechanized* and, especially, Δ ln *Q*.

In column 5 we add three additional unit level differences, the first of which is Δ Ln *(Daily Hours)*, the difference between machine and hand labor in the natural log of average daily hours. If worker fatigue at the end of a long working day set in more quickly for skilled than unskilled labor – for example, because of the greater range and physical requirements of skilled tasks), the coefficient of this variable should be positive – a longer working day would favor greater use of unskilled labor. The mean value of the difference, −0.03, indicates that, on average, the working day was about 3 percent shorter in the machine labor units compared with hand labor, which is consistent with the known downward trend in average daily hours over the nineteenth century (Atack and Bateman 1992; Atack et al., 2003). The relevant coefficient is positive, as hypothesized, but imprecisely estimated.

In designing and implementing the HML study, Wright and his staff attempted to select products such that quality differences were either no different between the machine and hand units, or else favored machine labor, knowing that poor quality machine goods could be made more quickly and with "cheaper" (less skilled) labor. The quality differences, as observed by the staff, were recorded in the text of the report, which we also digitized and coded. For the most part, the staff concluded there was either no relevant difference or a difference in favor of the machine labor version of the good, consistent with the goals of the study. For a small fraction of units, the hand product, however, was deemed to be of better quality, which allows us to test the assumption implicit in the study design – namely, we should see more de-skilling. The dummy variable – *Hand Unit Better Quality* = 1 if the hand unit was of better quality, 0 otherwise – captures this idea. Consistent with the hypothesis, the coefficient is positive, but small and imprecisely estimated.

We include the variable Δ *(Ln Year)* in the regression, the difference between machine and hand labor in the natural log of the observation year (the year to which the production data pertain). On average, this difference is positive – the hand labor data were older than the machine labor data. The coefficient of this variable is positive, 2.945, and significant (s.e. = 1.683) at the 8 percent level, indicating that the older the hand labor data was relative to machine labor, the greater the relative use of skilled labor in hand production of the unit, other factors held constant. The positive coefficient is sensible because earlier hand labor establishments were likely closer to the "old-fashioned" methods that Wright had in mind as the yardstick.

In column 7 we report the "Percent Explained" figures for the various independent variables for the specification in column 5, which includes all of the unit level differences variables. Here, the most important finding pertains to our division of labor variable, Δ *Percent_Oper*. The coefficient remains relatively stable in magnitude across the columns and always highly significant; even when we control for the other unit level variables, Δ *Percent_Oper* accounts for a large fraction, about 45 percent, of the mean value of *De-Skill* on its own. We stress that we are controlling for mechanization at the block-level – hence, the effect of division of labor at the unit level in the regression must explain why so much de-skilling is apparent in the non-mechanized tasks under machine labor, a point that we raised earlier in our discussion of Table 1.

We cannot and do not claim that the unit level coefficients are causal, as we have no way of instrumenting separately for the variables. That said, the fact that we can measure these variables at all, particularly the division of labor, goes far beyond what is currently possible with any other nineteenth century manufacturing data. The unit level variables account for about 72 percent of the mean value of *De-Skill*, compared with 8 percent for mechanization *per se* in the column 5 regression in Table 3– a total of 81 percent overall, leaving relatively little left to explain.

5. Concluding remarks

Economic historians have long hypothesized that de-skilling occurred during the first industrial revolution but have been largely stymied in determining if the diffusion of inanimate power was primarily responsible, mainly because of the lack of suitable data. This paper has turned to a unique and unusually detailed source, the United States Department of Labor's 1899 *Hand and Machine Labor* study. The HML study allows us to measure de-skilling directly at the production operation level and relate it to the use of inanimate power. We find that de-skilling in this sense was quite common in the mechanized factory of the late nineteenth century compared with traditional artisan hand production, and that greater use of inanimate power led to greater de-skilling. However, by itself magnitude of the mechanization effect was relatively modest.

De-skilling in production operations was part and parcel of a vast growth in the division of labor over the nineteenth century. While we cannot measure the change in division of labor continuously over the nineteenth century, it is clear from the HML study that this change was strongly correlated with scale. Our modified regression analysis of the HML data including unit-level differences variables show that de-skilling was strongly increasing in the scale of production, in main part because the division of labor was increasing.

The HML study did not investigate why the division of labor increased in the transition from hand to machine labor but there is little doubt that the transportation revolution was a crucial factor (Atack et al., 2011; Donaldson and Hornbeck 2016). The transportation

[12] The difference here is mainly due to the smaller sample size, not the use of SIC code dummies. If equation (1) is estimated on the Table 3 sample, the 2SLS coefficient of *Mechanized* is 0.088 (s.e = 0.041), virtually identical to the estimate in Table 3.

revolution expanded market access and in so doing, made a larger scale of operation and the enhanced division of labor associated with it more profitable – as the saying (from Adam Smith) goes, "the division of labor is limited by the extent of market". As the division of labor increased, production workers became more specialized in what they did on the shop floor, and the "average worker" was, in effect, a (convex) combination of individuals – some using powered machinery, others not – performing different operations according to comparative advantage, much more productive than a single artisan performing all tasks from start to finish. Compared with such artisans, the typical nineteenth century factory operative had less overall to learn on the job. Although advances in technology and emerging complementarity with capital increased the skill demands on factory workers, this calculus remained much the same until well into the twentieth century when the forces of automation eventually caught up, making operatives highly vulnerable to displacement by automation (Goldin and Katz, 1998; Acemoglu and Restrepo, 2018).

Declaration of Competing Interest

None.

Data availability

Replication files (STATA code and necessary data file) are available at https://www.openicpsr.org/openicpsr/project/194857/version/V1/view.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.eeh.2023.101554.

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