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"Automation" of Manufacturing in the Late Nineteenth Century: The Hand and Machine Labor Study

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Over the course of the nineteenth century, the United States experienced its first "industrial revolution." A central feature of this revolution was the mechanization of production, first through water power and later steam power. By the late nineteenth century, the process was well advanced, fostering serious concerns about its effects on labor (Giedion 1948; Hounshell 1984). For example, David A. Wells (1889, p. 68), a prominent US economist of the time, wrote that "the increasing frequency of strikes and industrial revolts ... have been largely prompted by changes in the conditions of production resulting from prior labor-saving inventions and discoveries" and he opined "the depression of industry in recent years has been experienced with greatest severity in those countries where machinery has been most extensively adopted." Indeed, the historical process was so disruptive that it inspired Edward Bellamy's *Looking Backward, 2000–1887* (1888), a utopian science fiction novel, which quickly became the era's third-largest best-seller and provoked extensive political and social discussion.

In the first annual report to Congress, Commissioner of Labor Carroll D. Wright (US Bureau of Labor 1886) drew attention to the problem of the "temporary displacement of labor and to conditions of industry and of society which would

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exist without the presence of power machinery," illustrating with several examples. In small arms production, one worker using conventional hand tools turned and fitted one musket stock per ten-hour day, whereas using specialized machines and dividing the tasks between them, three workers could turn and fit between 125 and 150 musket stocks per day, a 40- to 50-fold gain in labor productivity. Similarly, data from boot and shoe manufacturers suggested an 80 percent savings in labor for machine over handicraft production (US Bureau of Labor 1886, p. 81).

In 1894, Congress requested a fuller investigation, noting "there are works now in existence where the very best and highest grade of machinery is used that formerly employed cruder methods, and the men in charge have knowledge of the old methods as compared with the new; but these men are fast passing away, and the difficulty increases each year of securing the information sought …" (US Congress, House of Representatives 1894). To this end, it directed the Commissioner of Labor to "investigate and report upon the effect of the use of machinery upon labor and the cost of production, the relative productive power of hand and machine labor … and whether changes in the creative cost of products are due to a lack or surplus of labor or to the introduction of power machinery."

The resulting "Hand and Machine Labor" (HML) study took five years to complete, finally appearing as the thirteenth annual report of the Commissioner of Labor (US Department of Labor 1899). [1] The HML study presents its information at a level of detail that was highly unusual not only for its time but even ours, by analyzing the production of highly specific goods (for example, production of circular saw blades with a given number of teeth) at the task level for a matched pair of establishments, one of which produced the product by "hand" (or traditional artisanal) methods and the other using "machine" methods. Among other data, the report specifies the amount of time each task took, the sequence in which these were performed, the characteristics of the workers employed, the tool(s) used, and notably, the source of inanimate power, if any, including steam power, which was the key "general-purpose technology" of that historical period. Brynjolfsson and McAfee (2014, p. 6), for example, describe steam power as the first machine age's "most important" technological development, "overcoming the limitations of

[1] The US Bureau of Labor was established in the Department of the Interior by the Bureau of Labor Act (23 Stat. 60) on June 27, 1884. The Bureau's mission was to collect information about employment and labor. The Act also created the post of US Commissioner of Labor to direct the Bureau. Carroll Wright served as the first US Commissioner of Labor. The Bureau of Labor became an independent (sub-Cabinet) department through the Department of Labor Act (25 Stat. 182) on June 13, 1888. As indicated by the title of the legislation, the Bureau of Labor was renamed the "US Department of Labor" in 1888. The cabinet-level Department of Commerce and Labor was created in 1903 by the Department of Commerce Act (32 Stat. 827) on February 14, 1903. The Act authorized a new "Bureau of Labor" within the Department of Commerce and Labor, which took over the activities of the preceding "Department of Labor." Finally, in 1913, Congress created a separate cabinet-level Department of Labor, within which the "Bureau of Labor" was renamed the Bureau of Labor Statistics. As is clear from this timeline, the 1890s "Department of Labor" is a direct predecessor of the modern Bureau of Labor Statistics, which is why the National Archives stores the extant records of the 1890s department in its Record Group 257 ("Records of the Bureau of Labor Statistics"). The timeline above expands on Rockoff's (2019, pp.147–51) discussion.

muscle power, human and animal" and propelling a "sudden, sharp, and sustained jump in human progress."

The enormously complex Hand and Machine Labor data were published in two large, very dense volumes. We have digitized these data, coding and restructuring them to be tractable to modern econometric techniques. Our analysis here focuses on transitions at the task level from hand to machine production, and on the impact of inanimate power on labor productivity in machine production.

By "transitions at the task level" we mean whether particular tasks in hand production were no longer present under machine production; whether the task content remained the same, even if inanimate power was used under machine production; whether task reorganization occurred in the move from hand to machine labor; or whether entirely new tasks were present under machine labor. Transitions in which the task content remained the same except for the possibility of mechanization—we call these 1:1 transitions—were the most common. However, highly complex task reorganization did occur, and new task creation substantially dominated the abandonment of obsolete hand tasks. Overall, the transition to machine labor brought very large gains in productivity. We show in a regression analysis of the 1:1 transitions that use of steam power explains a large fraction of the productivity gain. Economic historians have been studying the diffusion and impact of steam power for a very long time; but as far as we know, our regressions are the first to show the productivity effects of steam power at the level of individual production tasks in an historical context.

We consider the Hand and Machine Labor data and our findings in the context of the modern "task-based approach" to production (Acemoglu and Autor 2011; Autor 2013; Zeira 1998). This literature develops models allowing technological change to reduce returns to specific factors, which is not possible in standard models of factor-augmenting technological change. We will focus in particular on Acemoglu and Restrepo's (2018) recent model of automation (also discussed in their paper for this symposium). Their model is quite useful in drawing out inferences as to how, in response to technical progress, some tasks are abandoned; others automated, and new, non-automated tasks created. Substituting "mechanized" for "automated" in their framework, we find a similar pattern in the data from the HML study. However, we will also argue that our historical example clearly parts company with Acemoglu and Restrepo in that their model abstracts from the division of labor. Indeed, there is considerable evidence that the diffusion of steam power enhanced the division of labor (Atack, Bateman, and Margo 2008), as Thomson (1989) also shows in the transformation of US boot and shoe production during this time. The underlying issue is the degree to which workers are specialized or not in the tasks they perform, and how this may feed back into human capital investment. Indeed, we will suggest that one of the meaningful differences between nineteenth-century mechanization and the current technological revolution based in robotics and artificial intelligence is that they seem to have quite different implications for the division of labor and thus for human capital investment.

The Hand and Machine Labor Study

Although the title of the 1899 study was "Hand and Machine Labor," Commissioner of Labor Wright cautioned in his introductory remarks that the words were not used in their strictest sense, but rather to characterize two different methods of production. "Machines" were used in "hand" production although these were usually simple hand tools—saws, hammers, chisels, files, knitting needles, screwdrivers, and the like—what he called "the primitive method of production which was in vogue before the general use of automatic or power machines" (US Department of Labor 1899, vol. 1, p. 11). Similarly, some tasks in machine production continued to be performed by hand using these same simple tools, including adjusting the machinery. For Wright, however, a crucial distinction was that, in machine production, "every workman has his particular work to perform, generally but a very small portion of that which goes to the completion of the article"—that is, division of labor was central (p. 11).

The basic unit of observation in the Hand and Machine Labor study was a matched pair of production units: one using hand methods, the other using machine methods to make a particular quantity of product. The products chosen were highly specific—for example, the output of "Unit 71" was described in the report as "SHOES:—100 pairs of men's medium grade, calf, welt, lace shoes, with single soles and soft box toes" (US Department of Labor 1899). Where necessary, production was scaled to industry norms by adjusting the time (and thus the cost) spent on tasks by the appropriate factor, keeping the number of workers unchanged (as we will explain further below). Overall, there are 672 paired units in the HML study: 27 in agriculture, 10 in mining and quarrying, and 9 in transportation, leaving 626 paired units producing manufactures. We focus on these manufactures.

As mentioned, the data were reported in two parts (and volumes). In Part 1, the following was reported for each unit (matched pair of plants producing a highly specific product): an industry classification, an exact description of the product, the standardized quantity of that product, the year in which the production under each method took place, the number of separate tasks of production, the number of different workers employed, and the total number of hours of work to produce the given quantity, the total labor costs, and the average daily hours of operation of the unit. In Part 2, the following information was reported for each mode of producing the product: a brief description of the task in the order in which it was performed; a list of capital goods or machines used in the task; the type of motive power if used; the number of workers assigned to that task; the number, age, gender, and occupational titles of the workers employed in the task; the hours of work by each employee engaged in the task; and the labor cost of each employee engaged in the task along with any miscellaneous comments.

The raw data were collected by trained agents either through direct observation or from written records, following up (sometimes repeatedly) when necessary to resolve inconsistencies and ambiguities. For machine production, the vast majority of the observations pertain to activities conducted in the mid-to-late 1890s (1894–98).

For a few products, the study was unable to find matching hand production from the same year that occurred nearby, presumably because the relevant establishments were no longer in existence. In such cases, the agents assiduously sought out historical records or, in 13 instances, located hand production establishments overseas that they deemed similar to those that no longer survived in the United States. All machine production data, however, was taken from US establishments. Moreover, in the majority of cases, two reports on hand and machine production were secured for establishments/manufacturers from different, widely separated, localities to help spot errors and omissions with "the better and more complete one then selected for presentation" (US Department of Labor 1899, vol. 1, p. 13).

A concrete example illustrates the exceptional (indeed, stupefying) detail in the published study. In making men's medium grade, laced shoes (Unit 71), the study compared production by a bespoke shoemaker producing a single pair of shoes with that of a factory producing 1,500 pairs, scaling the time (and cost) as if each in fact produced 100 pairs of shoes. [2] The shoe size is not specified but is (implicitly) assumed to be different for each pair. The data were tabulated, verso and recto, across several pages, with task identifiers aligning the rows across the left- and right-hand pages and with the numbering sequenced according to the order in which the tasks were performed in machine production.

Hand production of medium grade, laced shoes involved 72 tasks. Selecting and sorting the leather was one task in hand production—presumably so that the uppers for one pair of shoes could come from the same hide—compared with eight separate operations in machine production, for uppers, vamps, quarters, outsoles, insoles, lifts, and counters (machine-molded heel reinforcements), all of which had to be both sorted and matched. In hand production, the individual shoemaker traced each foot to create a cutting pattern and subsequently hand-carved a "last" (a wooden form around which each shoe was molded). These steps were crucial for the fit of the shoe and would be repeated for each individual customer served by the shoemaker. Producing lasts by hand was time-consuming, taking 54 minutes 24 seconds per pair—almost 92 hours for the production run of 100 different pairs of shoes. By contrast, under machine production, the factory skipped these steps, instead purchasing lathe-turned lasts for left and right feet in standard sizes from outside specialist suppliers, which would be used in the fabrication of thousands of pairs of shoes—an example of the subsidiary industries predicted to emerge to meet special needs once a certain scale of operation was achieved (Marshall and Marshall 1881, p. 52).

In the machine production of these shoes, the Hand and Machine Labor study identified 173 separate tasks. These include not only tasks directly related to the manufacture of shoes, like sorting leather, cutting out the vamps (the main part of the shoe between the toe and the laces), quarters (the heel portions), toes, soles, insoles,

[2] Exhibits 1 and 2 in the online Appendix available with this paper at the journal's website reproduce sections of the tables for Unit 71 detailing the tasks in the hand and machine production of men's medium grade, laced shoes from the Hand and Machine Labor report (US Department of Labor 1899).

and heels and sewing these together around the last to form the shoe and punching holes for the laces. Tasks also included finishing the shoes for market by smoothing the welts, waxing and polishing, matching pairs, stamping with the maker's name and size, and boxing for shipment. Moreover, other tasks involved keeping the shoe-making machinery in good order, and maintaining and firing the steam engine that powered the various machines—tasks not directly involved with production but vital to that production. Some of the tasks, like sorting, required nothing more than a good eye. Others, like cutting out the parts, still used basic hand tools (scissors and knives) rather than steam-powered die presses. Eighty of the tasks, however, including trimming, making eyelets, nailing heels, polishing and buffing, made use of steam power driving specialized machines (US Department of Labor 1899, vol. 2, pp. 544–51).

The study investigators carefully linked each operation in hand production to the corresponding operation in machine production via the machine task number. Machine tasks that were a part of several hand tasks had lowercase letters appended to the machine task number. The data showing the connections from hand tasks to machine tasks can be displayed as a "slope chart"[3] relating each of the various hand tasks for shoe-making on the left to the (far more numerous) machine tasks for shoe-making on the right, as in Figure 1. Tasks are numbered in sequence.

Some hand tasks link to multiple machine tasks. Some are performed in quite different sequences between hand and machine production—these lines cross over. A few hand tasks like "selecting and sorting stock" vanish in machine production (we have connected these to "Task 0" in Machine Production on the right hand side). Moreover, the white space on the right-hand axis to which no hand production tasks connect represent new tasks created by mechanization for which there was no hand production analog. In the next section, we discuss these task "transitions."

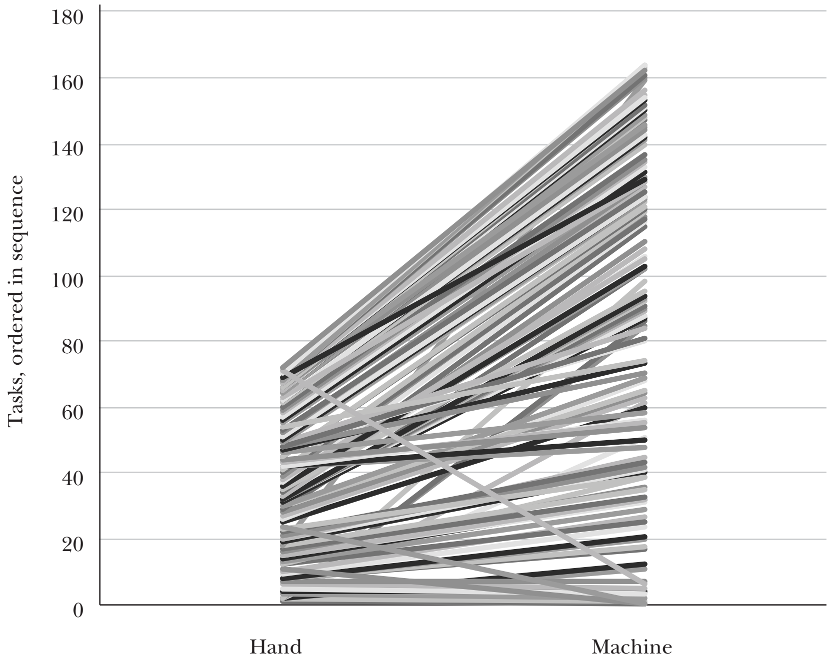
The complexity of the Hand and Machine Labor data overwhelmed statisticians at the time. As Carroll Wright (1900) would later remark: "This report answers in a measure the many demands for information … but no aggregation can be made because it is impossible to carry out calculations through the innumerable ramifications of production under hand and machine methods … although such a summary would be of the greatest possible value in the study of the question of machinery." Its complexity has also largely prevented analysis by modern economic historians until very recently.[4]

Before turning to our findings, we highlight four limitations of the Hand and Machine Labor data. First, although a wide range of goods and industries are covered, the establishments that were included are in no sense a random sample either within or across industries. Second, no information was collected on output prices, revenues, or costs, except those pertaining to the labor involved directly in

[3] For more on slope charts, see Tufte (1983, p. 143), or https://www.edwardtufte.com/bboard/q-and-a-fetch-msg?msg_id=0003nk.

[4] Stanley Engerman has informed us (via personal communication) that he and Robert Fogel included the Hand and Machine Labor study on an unpublished list of key data sources in US economic history that the two prepared in the early 1970s. However, in their view the data were far too complex to digitize and analyze at that time, which was a reasonable judgment until recent advances in information technologies.

Figure 1
Slope Chart Linking Hand to Machine Tasks for Unit 71



Source: Authors.
Note: Figure 1 relates each of the various hand tasks for shoe-making on the left to the (far more numerous) machine tasks for shoe-making on the right. Tasks are numbered in sequence. Some hand tasks link to multiple machine tasks. Some are performed in quite different sequences between hand and machine production—these lines cross over. A few hand tasks like "selecting and sorting stock" vanish in machine production (we have connected these to "Task 0" in machine production on the right-hand side). Moreover, the white space on the right-hand axis to which no hand production tasks connect represent new tasks created by mechanization for which there was no hand production analog.

the production of the product (and its supervision). Consequently, any analysis of productivity, including ours, must rely on the measure provided by the study—the amount of time that it took to complete a task—rather than a measure that would be more conventional for economists like value added per worker. Third, while the agents recorded additional information on the survey form that would have been very useful to have for some analyses—for example, the names of the individual workers, and the address of the establishment—this information was not included in the published study. Moreover, as far as we can determine, the completed survey forms have not survived and so this additional information has been lost.[5] Finally,

[5] We tracked down copies of the original survey instrument which are now stored in Record Group (RG) 257 in the US National Archives (US Bureau of Labor Statistics 1890–1905). The forms asked for additional information that was not published, such as the name and location of the establishment, and the names of the workers employed in the production of the various articles.

as previously noted, the study reported the labor requirements for a standardized scale of production, which enhances comparability. But the number of workers employed and the organization of work may not reflect how producers, especially hand producers, would have operated at that specific scale under realistic time-cost considerations.

Task Transitions and the Role of Steam Power

We focus on three broad features of the Hand and Machine Labor data: transitions of tasks from hand to machine labor; the overall productivity gains associated with machine labor; and the impact of steam power on productivity in machine production for the subset of tasks that were common to both hand and machine labor (tasks in the 1:1 transition category as discussed below).

Task Transitions: From Hand to Machine Production

The data from the Hand and Machine Labor study allow us to see the transition from hand to machine labor at the task level. The agents collecting the data listed tasks in production order under both hand and machine manufacture, adding a column linking hand to machine tasks. This allows us to draw a slope chart as in Figure 1 and to distinguish six types of transitions from hand to machine tasks:

a) Hand tasks that were no longer performed under machine labor, or old tasks, which we label as 1:0 transitions;
b) Tasks whose content was deemed to be essentially the same in hand and machine production, except that the machine task might be mechanized, which we label as 1:1 transitions;
c) A single hand task that was subdivided into M machine tasks, which we label as 1:M transitions;
d) N hand tasks that were combined into a single machine task, which we label as N:1 transitions;
e) N hand tasks were mapped into M machine tasks, with both N and M greater than one, which we label as N:M transitions; and, lastly,
f) Tasks present under machine production but not hand production, or "new" tasks, which we label as 0:1 transitions.

Table 1 presents summary statistics on each different kind of task transition across production units in the study. Table 1A presents these statistics from the point of view of the origin, hand labor, and Table 1B from the point of view of the destination, machine labor. Instead of counts of transitions, we focus on the share of tasks for each type of transition. We normalize within production units either by the total number of tasks (equal weights) or by weighting each task by its share of total production time (time weights); in either case, our estimates of average shares are equally weighted across units. Both panels also show the proportion of tasks that

Table 1
Tasks Transitions, Hand to Machine Labor

Transition	*Share of tasks, equal weights*	*Share of tasks, time weights*	*Share using steam power, equal weights*	*Share using water power, equal weights*	*Share using steam power, time weights*	*Share using water power, time weights*
A: Hand Labor						
1:0	0.044	0.030	0.003	0.002	0.002	< 0.001
1:1	0.673	0.604	0.014	0.017	0.009	0.020
1:M	0.134	0.192	0.023	0.005	0.008	0.006
N:M, $N > 1$, $M > 1$	0.040	0.054	< 0.001	0.010	< 0.001	0.003
N:1	0.108	0.121	0.010	0.018	0.031	0.019
Total	1.000	1.000	0.014	0.014	0.011	0.016
B: Machine Labor						
1:1	0.458	0.563	0.436	0.029	0.461	0.033
1:M	0.146	0.172	0.558	0.058	0.538	0.068
N:M, N>1, M>1	0.024	0.038	0.593	0.070	0.518	0.068
N:1	0.037	0.070	0.757	0.051	0.764	0.060
0:1	0.334	0.158	0.360	0.014	0.333	0.020
Total	1.000	1.000	0.444	0.034	0.477	0.040

Source: Computed from a digitized version of the Hand and Machine Labor study, see text and US Department of Labor (1899).
Notes: The unit of observation is a task as described by the staff of the Hand and Machine Labor study. The basic sample size in Panel A is 7,152 hand tasks from 610 production units. The basic sample size in Panel B is 12,473 machine labor tasks from 610 production units. 1:0 transitions are the hand labor tasks that disappeared in the transition to machine labor. 1:1 transitions are hand labor tasks that have a unique counterpart in machine production. In a 1:M transition, a single hand labor task subdivides into M machine tasks. In an N:M transition, N hand labor tasks transition into M machine labor tasks, with $N > 1$ and $M > 1$. In an N:1 transition N hand tasks combine to a single machine task. 0:1 indicates new tasks under machine labor. For equal weights, observations count equally in determining the average task shares within units. For time weights, observations are weighted by completion time in determining the average task shares within units.

were mechanized, whether by steam or water, similarly weighted. The sample used to compute Table 1 covers 610 of the original 626 manufacturing units.[6] For the most part, our discussion of Table 1 focuses on the equally weighted (rather than the time-weighted) statistics in Table 1.

Although some hand tasks were abandoned in the transition to machine labor, these comprised a small share of hand tasks and of the time spent in hand labor. The largest category of transitions by far was 1:1—that is, the agents were able to match a singleton task in hand production with a singleton task in machine production whose content was deemed to be the same, except that in machine production of the product, the task was far more likely to be mechanized. As can be seen from

[6]We excluded units from foreign countries, those that used horses, and which were otherwise missing data necessary for our analyses.

Table 1B, about 46.5 percent of 1:1 tasks in machine production used inanimate power; of these, 94 percent (0.436/0.465) were steam-powered.

As examples of mechanization in 1:1 transitions, consider the relatively large number of tasks involving trimming excess leather at various stages (for example, operations 33, 117, 133, and 135) or "skiving" leather where it overlapped to reducing bulk (operations 17–21, 54, 63, 71, 82, 88–93, and 135) in the production of boots and shoes, such as in Unit 71. Many patents were issued for tools and machines to facilitate these activities (see, for example, patents issued for leather trimming and skiving prior to 1874 (US Patent Office 1874). Under hand production, these activities were accomplished with a sharp (sometimes specialized) knife, guided by hand and eye. Under machine production, however, the knives were built into powered machines (for example, see US Patent 609868A granted 1898; also see the YouTube https://www.youtube.com/watch?v=Jv-nE1ixiB0 for the mechanics of a belt-driven skiving machine that is more or less contemporaneous with the Hand and Machine Labor study). These operated at high speed, allowing little chance of recovery if the product was wrongly placed, and with considerable risk to the operator. The operation of the trimming machine (and trimmer), for example, is described as follows (in Goldmark 1912, p. 65):

> [It] consists of a sharp knife edge, operating constantly against a sharp edged revolving top. The man who works the machine stands, holding upside down somewhat below the level of his eyes, the partly made, still unsoled shoe. He turns it skillfully and rapidly on the revolving top, against whose sharp edge the second knife-blade operates, cutting off all the surplus crimpled leather. The work is extremely rapid and absolutely uniform. But it takes skill and close attention. The machine could easily cut off too much, or could cut into the upper, if the swift handling of the shoe were not absolutely correct.

The more complex transitions that involved subdividing hand tasks (1:M) or consolidating (N:1) them (or possibly both (N:M)), were less common but by no means unusual. Keeping with the example of producing medium grade, laced shoes (Unit 71), machine production subdivided the selection of stock into several tasks (1, 23, and 35) because the various parts of a pair of shoes no longer came from a single hide as they would for hand-made shoes. Selecting various parts by look and feel so that the pattern and texture of the leather was similar improved the appearance of the finished product, making machine-made shoes look more like their hand-made counterparts. Mechanization, however, sometimes led to the consolidation of separate tasks. For example, the development of a super heavy-duty sewing machine (such as patent US 502873, granted to J. E. Bertrand in 1893) allowed the outsoles to be attached to the welts directly while locking the shoe shank in place. This reduced what had been two separate tasks (124a and 124b) in handicraft production (where the shoemaker used two variations on a single tool—an awl, round for locking the shank in place and square to attach the outsole) to a single machine operation (that is, a *N*:1 transition, or consolidation). From the perspective of hand labor, about 28 percent of hand tasks, on average, fell into the 1:*M*, *N*:*M*, or *N*:1 transitions; the corresponding figure from the perspective of machine labor was smaller, about 21 percent. As Panel B shows, the more complex transitions, especially consolidations, were also more likely to be mechanized by steam.

An important finding in Panel B is that new tasks were one-third of all tasks in machine labor, a much higher fraction than the share of hand labor tasks that were abandoned. Compared with the other tasks performed by machine labor, these new tasks were considerably less likely to use steam power, although the overall rate of steam use in new tasks, about 36 percent, was still substantial in an absolute sense. Many of these tasks were themselves directly related to that power source: engineers and firemen, for example, represented 15 percent of these new tasks. However, the more important group of new nonpowered tasks in machine production were those related to monitoring of the workplace activities (for example, the task of foreman/supervisor) and inspection of the finished product (for example, inspector, examiner, packer, and finisher). These activities made up about 20 percent of the 0:1 tasks and were essential to the smooth flow of the production line and the quality of the final product given that no single worker or group thereof assumed responsibility for the outcome of the production process.

The relative importance of new tasks declines when the data are weighted by time, indicating that many of the new tasks were relatively brief in duration. Even allowing for this, however, new tasks performed by machine labor accounted for a larger share of total production time than the share of time accounted for by old tasks in hand labor. We return to this point later in the paper when we consider our findings in light of Acemoglu and Restrepo's (2018) model of automation.

Although we have focused on task shares in Table 1, it is important to acknowledge that the absolute number of tasks increased from hand to machine labor. This increase is a direct manifestation of the increased division of labor that accompanied mechanization. As we described in detail in Atack, Margo, and Rhode (2017), it is possible to use the information in the Hand and Machine Labor study to compute a summary statistic of the division of labor—specifically, the proportion of tasks performed by the average worker. Multiplying by the number of tasks transforms the statistic into the average number of tasks per worker. The median number of tasks per worker in hand production was two, whereas in machine production, it was just one. In other words, the division of labor in machine production was virtually complete—if the HML study delineated a task, one or more workers were assigned to it and, on average, that was pretty much all they did, as far as the production of the specific good was concerned. As Marshall and Marshall (1881, p. 49) would note, "when the division of [labor] is carried very far a man's whole attention is concentrated on one operation … [and] such operations are performed … with a rapidity and an unerring accuracy …" We return to the division of labor below.

The Productivity Effects of Machine Labor and the Role of Steam Power

The standard way to measure labor productivity is by the flow of output over some period of time (for example, annually) divided by total labor hours over the same period. The Hand and Machine Labor study did not do this. Rather, for a standardized quantity of the specific good, the HML staff computed the amount of time each task took and then summed to get the total amount of time. Because a specific good is held constant (insofar as this is ever possible) while looking at hand and machine production, as is the standardized quantity, the overall productivity gain is simply the difference in total time between machine and hand labor. Given that the range of products considered were so very different, we do not compute the productivity gain in absolute units of time (say, hours) but rather calculate the logarithm of the ratio of machine to labor time, which is then averaged (equally weighted) across units. This average is -1.96. If we take the exponent, it is 0.14 [$e^{-1.96}$]—that is, on average, machine labor reduced total production time by a factor of seven (≈ 1/.14).

What accounts for these remarkable gains in productivity? In Atack, Margo, and Rhode (2017), we concentrated on the role of division of labor (to which we return in the discussion below). In this paper, we shift our attention to mechanization—that is, the use of an inanimate power source, in particular, steam power.

Economic historians have long had a keen interest in the diffusion of the steam engine and its attendant microeconomic and aggregate effects. These include the geography of steam adoption, changes in relative power costs in the face of technological innovation, externalities of steam power such as its role in fostering urbanization, and its impact on aggregate total factor productivity growth (Atack 1979; Atack, Bateman, and Weiss 1980; Kim 2005; Temin 1966). More recently, there have also been studies of how mechanization, whether steam power or electrification, affected the relative demand for different occupations (de Pleijt, Nuvolari, and Weisdorf 2018; Franck and Galor 2017; Gray 2013; Ojala, Pehkonen, and Eloranta 2016). By comparison, the Hand and Machine Labor study allows us to narrow the focus down to the task level for highly specific goods, comparing hand to machine production. This is straightforward to accomplish for the 1:1 overlap tasks; for these, we can difference the data at the task level within production units.

Table 2 reports our productivity regressions. Recall that "productivity" in the Hand and Machine Labor study is measured by the amount of time that it takes to complete a particular task in sequence in the making of a given amount of a specific good. If it is possible to change something to complete the given task more quickly than before—for example, use inanimate power—productivity has increased. We derive the regression specification from the following equation:

$$\ln \mathrm{T}(i, j, k) = \alpha(i, k) + \beta\,(j, k) + \gamma \times (\mathrm{Steam} = 1 | i, j, k) + \delta \times (\mathrm{Water} = 1 | i, j, k) + \varepsilon(i, j, k)$$

The index i refers to the task; the index j, to the type of labor (j = hand or machine); and the index k, to the specific product or equivalently, what the HMLS staff called the "unit." Ln $\mathrm{T}(i, j, k)$ is the log of the amount of time that it takes to complete task

Table 2
The Productivity Effects of Steam and Water Power Use in Machine versus Hand Production: 1:1 Task Transitions

	Dependent variable	
Independent variable	*ln (Time spent in machine task) – ln (Time spent in hand task)* *(1)*	*ln (Time spent in machine task) – ln (Time spent in hand task)* *(2)*
ln (Time spent in hand task)		–0.36 (12.29)
Δ (Steam = 1)	–1.13 (19.29)	–0.84 (15.67)
Δ (Water = 1)	–0.35 (2.86)	–0.28 (2.42)
Adjusted R^2	0.52	0.61

Source: Authors.
Note: The sample consists of tasks in the 1:1 transition category for which there was complete information on the regression variables (N = 4,257). The dependent variable is the difference between machine and hand labor in the log of the amount of time that it took to complete the task. The mean value of the dependent variable is –1.74. See the text for the derivation of the regression equation. Both regressions in the table include unit fixed effects. Standard errors are clustered at the unit level. Absolute value of *t*-statistics shown in parentheses.

i for labor type j in unit k; the greater is T, the longer it took to complete the given task. The parameter α is a task–unit fixed effect; that is, it is indexed for task i and unit k but not for labor type j. In making α dependent on i and k but not j, we are assuming that, while some tasks might take proportionately longer than others for a given product, these relative differences are the same under both machine and hand labor. The parameter β is a labor type–unit fixed effect; it is indexed by j and k but not by i. This allows for the possibility that machine labor was more productive in general and that the productivity gain differed across specific products. Our main interest is in the parameters γ and δ, which are the log effects of steam and water power use and which we assume have the same values under machine and hand labor. If steam or water power use proportionately reduces the amount of time to complete a task, then $\gamma < 0$ and $\delta < 0$.

To estimate this regression, we difference between machine and hand labor within units for all variables measured at the task level. We can do this directly because for every 1:1 task under machine labor there is an exact match to a counterpart task under hand labor. After differencing, we have:

$$\Delta \ln T = \Delta\beta + \gamma \times \Delta \text{ (Steam = 1)} + \delta \times \Delta \text{ (Water = 1)} + \Delta\, \varepsilon$$

For ease of reading, we suppress the indexes but keep in mind that the unit of observation is the task. The dependent variable is the difference between machine and hand labor in the log of the amount of time it took to complete a task,

($\Delta \ln T$). The right-hand side variables are product fixed effects ($\Delta\beta$), the differences in the steam and water power dummies between machine and hand labor at the task level, and the difference in the error terms ($\Delta\varepsilon$). The mean value of the dependent variable is –1.74. If we take the exponent of this mean value, it is 0.18 [= exp (–1.74)] or approximately 18 percent. That is, on average in the set of 1:1 transitions, a task under machine labor took 18 percent of the time to complete as the counterpart task under hand labor, indicating that labor was much more productive in completing the machine task than the equivalent hand task. Note that this mean value, –1.74, is smaller in absolute value than the analogous difference overall between hand and machine labor, -1.96, implying that the more complex transitions in Table 1 were, in an accounting sense, more important in generating overall productivity gains than were the 1:1 transitions.

As shown in column 1 of Table 2, the estimates of γ and δ are negative and highly significant, indicating the use of steam or water is associated with a reduction in time to complete a task. Relative to the mean value of the dependent variable (–1.74), the magnitude of the steam power coefficient (–1.13) in column 1 is quite large, suggesting a very large impact of steam use. By contrast, the coefficient for water (–0.35) is much smaller, although still statistically significant. The impact of water was more modest than steam, probably because of water's seasonality and storage constraints that limited its sustained flow.

Of course we cannot claim that these coefficients are causal; in particular, there may be omitted variables that are correlated with Δ Steam or Δ Water. One way to explore this possibility is to include the log of the amount of time the task took under hand labor as a right-hand side variable, as shown in column 2 of Table 2. If use of steam or water became more likely in machine labor for tasks for which hand labor was particularly unskillful (which we cannot observe directly), we would expect the absolute values of the steam and water power coefficients to be smaller in column 2 than in column 1. While this is the case, the coefficients of steam and water power use remain quite large and highly significant, suggesting that inanimate power use was, indeed, a major factor contributing to higher productivity under machine labor.

Discussion

We discuss our results in light of the recent paper by Daron Acemoglu and Pascual Restrepo (2018, and see also their paper in this symposium), which provides a formal task-based model for analyzing the effects of automation. In Acemoglu and Restrepo's model, tasks are ordered on a continuum along the unit interval from $N - 1$ to N in terms of the productivity of labor relative to capital. At date $t = 0$, capital costs are assumed to be lower than labor costs. Some tasks can be performed by either capital or labor, so if capital is sufficiently cheap, these will already be "automated" at date $t = 0$. However, other tasks might still be performed just by labor, simply because the technology is not sufficiently advanced for automation to occur. An improvement in technology, then, will induce additional automation to the new level of technical feasibility in the unit interval, or to the point where the firm is indifferent, on cost grounds, between capital and labor.

Their model also allows for new tasks to be created that are superior to existing tasks. The process by which this occurs is independent from changes in automation. The assumptions in the model ensure that new tasks will appear at N^*, the new right endpoint of the unit interval, while abandoned tasks will come from the former left endpoint, up to $N^* - 1$. The entire unit interval, therefore, moves to the right.

The key implications of the Acemoglu and Restrepo framework concern the net impacts of automation and new task creation on labor demand. If automation occurs, there is a displacement effect—capital replaces labor in some tasks below the threshold. There is also a productivity effect. If overall output increases sufficiently, demand for labor in non-automated tasks will increase on net. If, on net, new tasks use more labor, labor demand will further increase. However, if new tasks use less labor compared with abandoned tasks, the net impact of task replacement is negative, reducing any positive net effect that automation might have otherwise through productivity gains.

We cannot use the Hand and Machine Labor data to "test" the Acemoglu and Restrepo model literally for three reasons. First, their model orders tasks in terms of labor's comparative advantage at performing them. This is not the same as the order that tasks are actually performed in production. Second, we cannot re-order the HML tasks in terms of labor's comparative advantage because this is not observed in the HML data. Third, tasks in the Acemoglu and Restrepo model are on a continuum, whereas the task descriptions in the HML study are written summaries of discrete activities—in effect, subsets of the tasks in the unit interval of tasks in the Acemoglu and Restrepo model. Even if the HML staff had somehow channeled the logic of an economic model from 125-odd years into the future and managed to collect information on labor's comparative advantage, this would refer to the discrete activity, not to points (tasks) on a unit interval.

Nevertheless, the Acemoglu and Restrepo model is still highly valuable as an interpretive framework. First, their displacement effect is obviously present in the Hand and Machine Labor data; inanimately powered machines did things that were previously done by hand using simple tools. In some cases, the machine task was a sped-up version of what hand labor did—a machine-powered sander or polisher, for example. But as shown by the N:1 transitions, multiple hand tasks were also consolidated into a single machine task, a complicated transition that cannot simply be described as a faster version of a single hand labor activity. As Marshall (1890, p. 112) observed in his *Principles:* "[M]achinery constantly supplants and renders unnecessary that purely manual skill, the attainment of which was, even up to Adam Smith's time, the chief advantage of division of [labor]. But this influence is more than countervailed by its tendency to increase the scale of manufactures and to make them more complex; and therefore to increase the opportunities for division of [labor] of all kinds." Moreover, the displacement effect must have been largest for the *N*:1 transitions, because the *N* hand tasks took nearly twice as long to complete (as a share of total time) than one machine task, a far larger amount of "labor-saving" than is evident in the other transitions. The *N*:1 transitions, as we noted earlier, were the most mechanized—the share of machine tasks using steam or water power—of all the transitions from hand to machine production.

Second, the productivity effect was enormous. While detailed data are lacking, there is little doubt the average annual hours of operation per establishment in manufacturing increased over the nineteenth century (Atack and Bateman 1992; Whaples 1990). Yet, as the Hand and Machine Labor study shows, the amount of time it took machine labor to complete a product was a mere fraction of the time it took machine labor. On an average annual basis, therefore, the increase in total output was an order of magnitude larger than the displacement effect per unit of output, implying a very large positive impact on labor demand.

Third, the net effect of the introduction of new tasks on labor demand appears to have been positive. This is because the share of time taken up by new tasks in machine labor was larger than the share of time associated with hand tasks that were abandoned—indeed, five times larger. Among other activities, these new tasks included maintenance of steam engines, a foreman supervising large numbers of workers (discussed further below), and workers packaging products for distant markets.

The upshot is that the transition from hand to machine labor led to a vast expansion in the size of the manufacturing labor force, both in absolute number and as a proportion of the national aggregate. This was because, not in spite, of an equally vast increase in productivity, such that by the end of the nineteenth century, output per worker in US manufacturing was twice the level in Britain or Germany (Broadberry 1998). As we have noted, a long literature in economic history and economics asserts that the diffusion of steam power was a major factor behind the increase in productivity, but never, until the regression analysis in this paper, has this been demonstrated for individual production tasks.

However, our analysis also shows that steam power was not the full story. In our earlier paper, Atack, Margo, and Rhode (2017), we studied the overall difference in productivity between machine and hand labor at the unit-level, rather than task-level. Because we were analyzing differences across units rather than across tasks within units, we could include measures of the overall division of labor in the relevant regressions. We found that direct measures of the division of labor—specifically, the fraction of total tasks performed by the average worker and the number of tasks—fully account for the positive effects of overall scale, as measured by the number of workers. Unlike the regressions in Table 2 of this paper, those in our earlier paper do not control directly for steam (or water) power, but instead have a dummy variable for hand production. The coefficient of this dummy variable is positive and significant, implying that, once we control for the division of labor, other factors associated with machine labor compared with hand labor, such as greater use of steam power, contributed to overall productivity gains. Our results in Table 2 here are fully consistent with this interpretation.

The point we wish to make here is that, as useful as it is as an overall framing device, the Acemoglu and Restrepo model omits a fundamental feature of historical industrialization—namely, its extensive division of labor. As far as that model is concerned, the individual workers who perform tasks before and after automation could be the same people.

In point of fact, however, they were not the same people. In the tiniest shops that are iconic depictions of hand production in early manufacturing, the artisan was highly skilled in the sense of performing most or all of the production tasks from start to finish, as well as "nonproduction" tasks associated with managing the business. In the transition to machine labor, the artisan shop was displaced by the factory, which was different in many ways that could perhaps be summarized as "more" of everything—more capital, more labor, and more output. Establishments grew in size and complexity, an evolution that spawned the rise of a white collar labor force to oversee it—a "visible hand" in Alfred Chandler's (1977) memorable phase.

Our concern here is not so much the rise of the modern corporation *a la* Chandler, but rather what labor historians call "deskilling." Examples of deskilling are everywhere to be found in the data from the Hand and Machine Labor study. We have already cited the example of shoemaking; another example is blacksmithing—previously, this involved making rakes (Unit 30), most of the assorted carriage and wagon products (units 140–185), tools, and various other metal goods. The "village smithy," fashioning metal objects like pots, pans, plows, and numerous other objects from iron, could be found in small towns and in the countryside all over the United States as late as 1850. Atack and Margo (2019) use census data to study the relative decline of blacksmithing as a "hand trade" over the second half of the nineteenth century. Machine production led to establishments specializing in, for example, agricultural implements. These establishments were much larger in terms of employment than blacksmith shops, and far more productive in making plows, rakes and hoes, and related tools. Faced with such competition, blacksmith shops either shifted away from making objects to fixing them by offering repair services, or simply disappeared. The job of blacksmithing was once considered sufficiently numerous to warrant its own industry classification, but by the very end of the nineteenth century it was dropped from the manufacturing census as no longer worth the trouble to enumerate.

The point we are emphasizing, however, is not deskilling per se, but rather that the extent to which individual workers might be specialized in allocating their labor across tasks has important implications. The massive division of labor documented front and center in the Hand and Machine Labor study dramatically affected the nature of the human capital investment decision facing successive cohorts of American workers contemplating whether to enter the manufacturing sector. Earlier in the nineteenth century, the human capital investment problem such workers faced was mastering the diverse set of skills associated with most or all of the tasks involved in making a product, along with managing the affairs of a (very) small business, an artisan shop. The human capital investment problem facing the prospective manufacturing worker in the 1890s was quite different. There was little or no need to learn how to fashion a product from start to finish; mastery of one or two tasks would do, and such mastery might be gained quickly on the job. The more able or ambitious might gravitate to learning new skills, such as designing, maintaining, or repairing steam engines, or clerical/managerial tasks, the demand for which had grown sharply as average establishment size increased over the century (Katz and Margo 2014).

For many decades in the twentieth century, specialization was economically beneficial to workers—the costs of learning skills were relatively modest and the return on the investment—a relatively secure, highly paid job in manufacturing—made that investment worthwhile. The prospect of widespread automation has arguably changed this calculus. No single "job" is safe and the optimal investment strategy may be very different—a suite of diverse, relatively uncorrelated skills as insurance against displacement by robotics and artificial intelligence. This is perhaps the sense in which the history of how technology affects jobs is not repeating itself, and "this time" really is different.

Concluding Remarks

To understand the effects of automation on jobs, a number of labor economists have turned away from traditional "black box" models of production and their assumptions of relative complementarity or substitutability between capital and different types of labor. Instead, production is modeled as a collection of tasks, some of which might be performed by labor or automated with capital. Empirical assessments of these models have generally been indirect, in part because the data demands are so formidable. Even in today's world awash in "big data," information on production is rarely recorded at the task level. In the absence of such data, analysts must infer the task content of jobs indirectly through the use of, for example, the *Dictionary of Occupational Titles* (US Employment Service 1991).

This paper has reported on some preliminary but ongoing analyses of the US Department of Labor's Hand and Machine Labor (US Department of Labor 1899) study. The study has been long known by economic historians—but almost never used because the data were, until recent advances in information technologies, too complex to analyze. Our analysis of the HML data confirms the modern view that the "machine age" was transformative. It also reveals, however, that current task-based models of automation need elaboration to take into account certain effects of mechanization on labor that were historically relevant, like the division of labor.

The modern debate over automation and labor frequently invokes historical antecedents, most notably the steam engine during the early industrialization. Typically, historical evidence serves as anecdote to provide a context against which qualitative predictions can be made. For example, the steam engine was revolutionary in its time, and in retrospect it is clear that it "destroyed" some jobs but created many others. However, the extent to which the disruptive effects of the mechanization of the past serves as a prologue to the technologies of the present or future, or whether the modern technologies of robotics and artificial intelligence are fundamentally different in some way, remains an open question. It is intriguing to imagine how artificial intelligence might reduce the cost of reassigning and reorganizing tasks, allowing for more efficient dynamic optimization of production in response to changing conditions. Models that allow for such shifts of tasks and alterations in the division of labor may pay a useful role in understanding the technological shifts to come.

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References

Acemoglu, Daron, and David H. Autor. 2011. "Skills, Tasks and Technologies: Implications for Employment and Earnings." Chap. 12 in *Handbook of Labor Economics,* vol. 4B, edited by Orley Ashenfelter and David Card, 1043–171. Amsterdam: Elsevier-North Holland.

Acemoglu, Daron, and Pascual Restrepo. 2018. "The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment." *American Economic Review* 108(6): 1488–542.

Atack, Jeremy. 1979. "Fact or Fiction? The Relative Costs of Steam and Water Power: A Simulation Approach." *Explorations in Economic History* 16(4): 409–37.

Atack, Jeremy, and Fred Bateman. 1992. "How Long Was the Workday in 1880?" *Journal of Economic History* 52(1): 129–60.

Atack, Jeremy, Fred Bateman, and Robert A. Margo. 2008. "Steam Power, Establishment Size, and Labor Productivity in Nineteenth Century American Manufacturing." *Explorations in Economic History* 45(2): 185–98.

Atack, Jeremy, Fred Bateman, and Thomas Weiss. 1980. "The Regional Diffusion and Adoption of the Steam Engine in American Manufacturing." *Journal of Economic History* 40(2): 281–308.

Atack, Jeremy, and Robert A Margo. 2019. "Gallman Revisited: Blacksmithing and American Manufacturing, 1850–1870." *Cliometrica* 13(1): 1–23.

Atack, Jeremy, Robert A. Margo, and Paul W. Rhode. 2017. "The Division of Labor and Economies of Scale in Late Nineteenth Century American Manufacturing." Paper presented at the NBER Development of the American Economy Summer Institute, July 2017.

Autor, David H. 2013. "The 'Task Approach' to Labor Markets: An Overview." *Journal for Labour Market Research* 46(3): 185–99.

Bellamy, Edward. 1888. *Looking Backward, 2000–1887.* Boston: Ticknor and Co.

Broadberry, Stephen N. 1998. "How Did the United States and Germany Overtake Britain? A Sectoral Analysis of Comparative Productivity Levels, 1870–1990." *Journal of Economic History* 58(2): 375–407.

Brynjolfsson, Erik, and Andrew McAfee. 2014. *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* W. W.

Norton.

Chandler, Alfred D., Jr. 1977. *The Visible Hand: The Managerial Revolution in American Business*. Cambridge, MA: Belknap Press.

de Pleijt, Alexandra, Alessandro Nuvolari, and Jacob Weisdorf. 2018. "Human Capital Formation during the First Industry Revolution: Evidence from the Use of Steam Engines." CEPR Working Paper 12987, Centre for Economic Policy Research.

Franck, Raphaël, and Oded Galor. 2017. "Technology-Skill Complementarity in Early Phases of Industrialization." NBER Working Paper 23197.

Giedion, Sigfried. 1948. *Mechanization Takes Command: A Contribution to Anonymous History*. New York: Oxford University Press.

Goldmark, Josephine. 1912. *Fatigue and Efficiency: A Study in Industry*. New York: Russell Sage Foundation.

Gray, Rowena. 2013. "Taking Technology to Task: The Skill Content of Technological Change in Early Twentieth Century United States." *Explorations in Economic History* 50(3): 351–67.

Hounshell, David A. 1984. *From the American System to Mass Production, 1800–1932: The Development of Manufacturing Technology in the United States*. Baltimore: Johns Hopkins University Press.

Katz, Lawrence F., and Robert A Margo. 2014. "Technical Change and the Relative Demand for Skilled Labor: The United States in Historical Perspective." Chap. 1 in *Human Capital in History: The American Record*, edited by Leah Platt Boustan, Carola Frydman, and Robert A. Margo. University of Chicago Press.

Kim, Sukkoo. 2005. "Industrialization and Urbanization: Did the Steam Engine Contribute to the Growth of Cities in the United States?" *Explorations in Economic History* 42(4): 586–98.

Marshall, Alfred. 1890. *Principles of Economics*. London and New York: Macmillan.

Marshall, Alfred, and Mary Paley Marshall. 1881. *The Economics of Industry*. London: Macmillan.

Ojala, Jari, Jaakko Pehkonen, and Jari Eloranta. 2016. "Deskilling and Decline in Skill Premium during the Age of Sail: Swedish and Finnish Seamen, 1751–1913." *Explorations in Economic History* 61: 85–94.

Rockoff, Hugh. 2019. "On the Controversies behind the Origins of the Federal Economic Statistics." *Journal of Economic Perspectives* 33(1): 147–64.

Temin, Peter. 1966. "Steam and Waterpower in the Early Nineteenth Century." *Journal of Economic History* 26(2): 187–205.

Thomson, Ross. 1989. *The Path to Mechanized Shoe Production in the United States*. Chapel Hill: University of North Carolina.

Tufte, Edward R. 1983. *The Visual Display of Quantitative Information*. Cheshire, CT: Graphics Press.

US Bureau of Labor. 1886. *First Annual Report of the Commissioner of Labor, March 1886: Industrial Depressions*. Washington DC: US Government Printing Office.

US Bureau of Labor Statistics. 1890–1905. "RG 257 Records of the Bureau of Labor Statistics, Records of the Department of Commerce and Labor, Reports of Bureau Activities, 1890–1905 Box No. 1, Scrap Book: Memo and Compilations." National Archives and Records Administration.

US Congress, House of Representatives. 1894. *Effects of Machinery on Labor*. Washington DC: US Government Printing Office.

US Department of Labor. 1899. *Thirteenth Annual Report of the Commissioner of Labor, 1898: Hand and Machine Labor*. Washington DC: GPO. Available from HathiTrust.org: http://hdl.handle.net/2027/nnc1.cu08593957.

US Employment Service. 1991. *Dictionary of Occupational Titles*. Washington DC: US Government Printing Office.

US Patent Office. 1874. *Subject-Matter Index of Patents for Inventions*. Washington DC: US Government Printing Office.

Wells, David Ames. 1889. *Recent Economic Changes, and their Effect on the Production and Distribution of Wealth and the Well-Being of Society*. New York: D. Appleton.

Whaples, Robert. 1990. "The Shortening of the American Work Week: An Economic and Historical Analysis of Its Context, Causes, and Consequences." Thesis (PhD in Economics), Graduate School of Arts and Sciences, University of Pennsylvania.

Wright, Carroll D. 1900. "Hand and Machine Labor." In *Gunton's Magazine*, 209–17. New York: Political Science Publishing Co.

Zeira, Joseph. 1998. "Workers, Machines, and Economic Growth." *Quarterly Journal of Economics* 113(4): 1091–117.

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14. Thanh Le. 2024. Robot Revolution and Human Capital Accumulation: Implications for Growth and Labour Income. *SSRN Electronic Journal* **102**. . [Crossref]
15. Mai Vu. 2024. Robot Revolution and Human Capital Accumulation: Implications for Growth and Labour Income. *SSRN Electronic Journal* **102**. . [Crossref]
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24. Toon Van Overbeke. 2023. Conflict or cooperation? Exploring the relationship between cooperative institutions and robotisation. *British Journal of Industrial Relations* **61**:3, 550-573. [Crossref]
25. José#Ignacio Antón, Enrique Fernández#Macías, Rudolf Winter#Ebmer. 2023. Does robotization affect job quality? Evidence from European regional labor markets. *Industrial Relations: A Journal of Economy and Society* **62**:3, 233-256. [Crossref]
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27. Vijay Pereira, Elias Hadjielias, Michael Christofi, Demetris Vrontis. 2023. A systematic literature review on the impact of artificial intelligence on workplace outcomes: A multi-process perspective. *Human Resource Management Review* **33**:1, 100857. [Crossref]
28. Dipankar Das. 2023. Understanding the choice of human resource and the artificial intelligence: "strategic behavior" and the existence of industry equilibrium. *Journal of Economic Studies* **50**:2, 234-267. [Crossref]
29. Jeremy Atack, Robert Margo, Paul W. Rhode. 2023. De-Skilling: Evidence from Late Nineteenth Century American Manufacturing. *SSRN Electronic Journal* **108**. . [Crossref]
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36. Jeremy Atack, Robert A. Margo, Paul W. Rhode. 2022. "Mechanization Takes Command?": Powered Machinery and Production Times in Late Nineteenth-Century American Manufacturing. *The Journal of Economic History* **82**:3, 663-689. [Crossref]

37. José-Ignacio Antón, David Klenert, Enrique Fernández-Macías, Maria Cesira Urzì Brancati, Georgios Alaveras. 2022. The labour market impact of robotisation in Europe. *European Journal of Industrial Relations* **28**:3, 317-339. [Crossref]
38. Quynh Nguyen, Julia Himmelsbach, Diotima Bertel, Olivia Zechner, Manfred Tscheligi. What Is Meaningful Human-Computer Interaction? Understanding Freedom, Responsibility, and Noos in HCI Based on Viktor Frankl's Existential Philosophy 654-665. [Crossref]
39. Jeremy Atack, Robert A. Margo, Paul W. Rhode. 2022. Industrialization and urbanization in nineteenth century America. *Regional Science and Urban Economics* **94**, 103678. [Crossref]
40. Raphaël Franck, Oded Galor. 2022. Technology-Skill Complementarity in Early Phases of Industrialisation. *The Economic Journal* **132**:642, 618-643. [Crossref]
41. Swayam Sampurna Panigrahi, Deepti Chandra. Industry 4.0 Technologies Transforming the Future of Work in Post Pandemic World 311-321. [Crossref]
42. Jéssica de Assis Dornelles, Néstor F. Ayala, Alejandro G. Frank. 2022. Smart Working in Industry 4.0: How digital technologies enhance manufacturing workers' activities. *Computers & Industrial Engineering* **163**, 107804. [Crossref]
43. Ivan Savin, Ingrid Ott, Chris Konop. 2022. Tracing the evolution of service robotics: Insights from a topic modeling approach. *Technological Forecasting and Social Change* **174**, 121280. [Crossref]
44. Martin Fiszbein, Yeonha Jung, Dietrich Vollrath. 2022. Agrarian Origins of Individualism and Collectivism. *SSRN Electronic Journal* **16**. . [Crossref]
45. Luis Guimaraes, P Gil. 2022. Looking Ahead at the Effects of Automation in an Economy with Matching Frictions. *SSRN Electronic Journal* **1**. . [Crossref]
46. David H. Autor, Caroline Chin, Anna Salomons, Bryan Seegmiller. 2022. New Frontiers: The Origins and Content of New Work, 1940–2018. *SSRN Electronic Journal* **113**. . [Crossref]
47. Marvin Goodfriend, John McDermott. 2021. The American System of economic growth. *Journal of Economic Growth* **26**:1, 31-75. [Crossref]
48. James Feigenbaum, Daniel P. Gross. 2021. Organizational Frictions and Increasing Returns to Automation: Lessons from AT&T in the Twentieth Century. *SSRN Electronic Journal* **108**. . [Crossref]
49. John Braxton, Kyle Herkenhoff, Jonathan Rothbaum, Lawrence Schmidt. 2021. Changing Income Risk across the US Skill Distribution: Evidence from a Generalized Kalman Filter. *SSRN Electronic Journal* **4**. . [Crossref]
50. Leonid Kogan, Dimitris Papanikolaou, Lawrence Schmidt, Bryan Seegmiller. 2021. Technology, Vintage-Specific Human Capital, and Labor Displacement: Evidence from Linking Patents with Occupations. *SSRN Electronic Journal* **4**. . [Crossref]
51. J. Carter Braxton, Kyle Herkenhoff, Jonathan Rothbaum, Lawrence Schmidt. 2021. Changing Income Risk Across the Us Skill Distribution: Evidence from a Generalized Kalman Filter. *SSRN Electronic Journal* **4**. . [Crossref]
52. James Feigenbaum, Daniel P. Gross. 2021. Organizational and Economic Obstacles to Automation: A Cautionary Tale from At&T in the Twentieth Century. *SSRN Electronic Journal* **108**. . [Crossref]
53. Yulia Matyuk. 2020. ARTIFICIAL INTELLIGENCE: NEW CHALLENGES AND PROSPECTS. *Advances in Law Studies* **8**:5, 42-48. [Crossref]
54. Bernardo S Buarque, Ronald B Davies, Ryan M Hynes, Dieter F Kogler. 2020. OK Computer: the creation and integration of AI in Europe. *Cambridge Journal of Regions, Economy and Society* **13**:1, 175-192. [Crossref]

55. Andreas Kaplan, Michael Haenlein. 2020. Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons* **63**:1, 37-50. [Crossref]
56. José-Ignacio Antón, Enrique Fernández-Macías, Rudolf Winter-Ebmer. 2020. Does Robotization Affect Job Quality? Evidence from European Regional Labour Markets. *SSRN Electronic Journal* **128**. . [Crossref]
57. Leonid Kogan, Dimitris Papanikolaou, Lawrence Schmidt, Bryan Seegmiller. 2019. Technological Change and Occupations over the Long Run. *SSRN Electronic Journal* **113**. . [Crossref]