'MECHANIZATION TAKES COMMAND'?: POWERED MACHINERY AND PRODUCTION TIMES IN LATE NINETEENTH CENTURY AMERICAN MANUFACTURING

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MANUFACTURING

Abstract: During the nineteenth century, U.S. manufacturers shifted from the
"hand" to "machine labor," fundamentally changing production tasks, jobs, and
job requirements. This paper uses digitized data from an 1899 US Commissioner
of Labor report to estimate the frequency and impact of the use of inanimate
power on production times. About half of production operations were
mechanized; and use of inanimate power raised productivity, accounting for one-
quarter to one-third of the overall productivity advantage of machine labor.
Additional factors, such as the increased division of labor and adoption of high-
volume production, also played important roles in raising productivity.

Popular observers often place the adoption of inanimate power, especially steam power,
at the heart of the first Industrial Revolution. For example, in their influential book on the future
of work, Erik Brynjolfsson and Andrew McAfee (2014, p. 6) state that "steam started it all,"
overcoming "the limitations of muscle power, human and animal … [t]he Watt steam' engine
was the "most important" technological development of the era, one that "underlie[s] the sudden,
sharp, and sustained jump in human progress." They are hardly alone in treating the steam
engine as the prime mover of industrialization (see, for example, Rosenberg and Trajtenberg
2004) but economic historians are generally more cautious recognizing, for example, the earlier
development of waterpower and the potential importance of scale economies and related
organizational changes (Chandler 1977; Hilt 2015; Hunter 1979; Hunter 1985; Hunter and

Bryant 1991). The analysis in this paper provides quantitative support for our profession's

wariness of monocausal narratives of complex historical events such as industrialization, while

providing fresh evidence on the productivity impact of mechanization across a wide swath of

manufacturing. In this paper, we will equate "mechanization" in nineteenth century

manufacturing with the use of steam or water powered machinery.[1]

To conduct this investigation into the relative importance of mechanization, we analyze

the remarkably detailed data in the US Commissioner of Labor's 13th Annual Report (United

States. Department of Labor. 1899) on *Hand and Machine Labor* (hereafter HML study). This

report was commissioned by the US Congress in 1894 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, it recorded all individual tasks from start to

finish associated with the production of over 620 highly specific manufactured goods using

"machine methods" in the late nineteenth century, along with those involved in the production of

the same good by the traditional "hand methods". The observations were paired by production

method, and the HML staff generated a crosswalk for the operations listed for hand and machine

labor. It is a subset of these (n = 4,405) which are analyzed in this paper. The extraordinarily

complex structure of the HML study overwhelmed statisticians at the time, preventing the

computation of even summary productivity figures, let alone any kind of systematic analysis.

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[1] A source of motive power is cited by contemporaries as a *sine qua non* for mechanization (see,

for example, Willis 1841, p. 1). We recognize that some machines at the time were driven by

muscle, either directly or through stored energy; wind power; and, very late in the century,

electricity. The quote in the title is a nod to Giedion (1948).

Nor did the Cliometrics Revolution solve the challenges posed by the HML data until recent advances in computing and econometrics allow the analyses that Carroll Davidson Wright (the Commissioner of Labor), his team of agents, and prior generations of scholars were unable to deliver.

We employ a "task-based," or production operations approach to investigate the reductions in time devoted to specific production activities (Acemoglu and Restrepo 2018). This was the HML study's measure of labor productivity. Our main regression analysis of the HML operations data uses ordinary least squares (OLS) with fixed effects for the specific individual goods (called "units" in the HML study).[2] We find that (i) the more frequent use of inanimate power in factory production had significant positive effects on labor productivity, but that (ii) these effects accounted for just one-third of the average difference in production operation times between hand and machine labor. Further probing using an instrumental variables estimator

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[2] The empirical analyses in this paper differ from our previous work with the HML study data in several important ways. The analysis here focuses on productivity differences between hand and machine labor at the production operation level, unlike in Atack, Margo and Rhode (2017) which examined differences at the unit level. The main purpose of Atack, Margo, and Rhode (2019) was to study task transitions (referred to as "block-links" in the present paper) in the context of Acemoglu's and Restrepo's (2018) model of automation. Our 2019 paper included an OLS regression of the effect of mechanization on productivity differences at the operation level like the specification in Table 2 in this paper, but the analysis in the 2019 paper was limited to a subsample of observations (the 1:1 block links, see the text below) and did not consider endogeneity, or the role of additional factors such as the division of labor.

suggests that this OLS effect of mechanization is likely biased upwards compared with the true causal impact. We then conduct a broader, if less exacting, study of the roles of other factors measured in the HML study, including the division of labor, and the adoption of high-volume or "quantity" production. We find that these additional factors are of roughly similar importance in accounting for the average difference in productivity between hand and machine labor. Because the HML study focused on what it called the "most modern" of machine labor, the average difference in productivity in the sample may overstate the true difference in the economy. However, there is no reason to believe that the relative explanatory power of mechanization is misstated, and the superior quality of the HML data makes our findings more convincing than the usual growth accounting studies of aggregate time series or conventional production function estimation based on census of manufacturing data.

The Hand and Machine Labor Study

Published in two volumes totaling almost 1,600 pages, the HML study detailed the tasks (including what, and how) involved in the production of what the study termed "units." These units were specific quantities of precisely defined goods such as "50 dozen regular taper, triangular saw files, 4 inches long, tapering 23/64 inch" (United States. Department of Labor. 1899, 1: 241-6 and 2: 1026-9). The report covered 672 units in various economic sectors including transportation services, mining and quarrying, and agriculture. Ninety-three percent of the units —626 (units 28-653) of 672 —were manufactures. Although the products in the study embrace almost the entire range of broadly defined manufactured goods (2-digit SIC codes 20-39), including those in the first industrial revolution as well as the second, in no sense can it be claimed that they are a representative sample of manufacturing at the time (see online Appendix Table 1).

For each unit, the HML staff collected production data from multiple establishments that were using "hand labor" or "machine labor".[3] For confidentially reasons, the HML staff anonymized the information in the published report. We never know the names of the establishments and, except in few instances, do not know their location except that 15 of the hand labor establishments were foreign.[4]   The HML staff was aware of the widely held belief

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[3] The product descriptions were identical for the hand and machine labor goods for 524 of the units. Differences in the remaining descriptions varied from words like "dairy" v "creamery" or "30 ½" v "30 5/8" to "iron" v "steel." In all cases, though, the product served the same purpose. The HML staff first collected data from two machine labor establishments and then two matching hand establishments, before selecting "the better and more complete" accounting of each mode of production for publication (United States. Department of Labor. 1899, 1: 13), sometimes also tracing a significant intermediate input purchased from elsewhere that was used in one type of production but manufactured in house in the other.

[4] Contemporary newspapers sometimes carried brief notes regarding the cities being visited by the agents conducting the survey (see, for example, Evening Star 1895) but the establishments to be visited were not specifically named. The original survey forms recorded fuller details such as the address of the business along with the names or initials of individual workers (as evidenced by blank forms retained in Record Group 257, entry 8, box 3 in the National Archives), but these were suppressed in the published study and the completed survey forms themselves were subsequently destroyed (U.S. Congress. House. 1906). Indeed, in preparing their report, the HML staff went to considerable lengths to anonymize the information having promised the respondents anonymity in return for their cooperation.

that the machine methods yielded a lower quality product than the hand methods and they

expended great efforts to find units producing factory goods that were not of inferior quality to

artisan products. Based on textual comments regarding quality in the report, the Bureau was

remarkably successful in keeping with the goal of the study.[5]

In collecting data, the HML staff took the actual output of the establishment as a given.

However, because the machine labor output almost always exceeded that of hand labor, the staff

scaled all production times to match a standardized output level. This normalization varied

across units but in a manner that would be "recognized and commonly used in the trade" (United

States. Department of Labor. 1899, 1: 15).[6] Virtually all machine production data were

contemporaneous with the report. For hand production, however, the HML staff found

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[5] The text of the HML study discusses quality differences, from which we were able to

categorize whether the staff thought the quality was better for product when made by hand or

vice versa; or no difference was detected, or no opinion was expressed. For the sample of

operations (n = 4,405) analyzed in Table 2 (see below), 63.2 percent pertain to operations in

units where the machine labor product was judged to be superior in quality; 5.7 percent, in units

in which the hand good was of better quality; and no difference for the remainder. See also the

discussion of quality effects in Table 5.

[6] The HML staff were, in effect, holding establishment size fixed and varying the number of

establishments to reach the desired standardized quantity. While some sort of rescaling is

necessary to make the data interpretable, it should be kept in mind that these are "out of sample"

predictions; it is entirely possible that the optimal establishment size (hand or machine) would be

different at the standardized quantity.

contemporaneous matching observations from the 1890s for only a quarter of the units. For the remainder, the staff assiduously sought out historical records, one of which was as early as 1813.[7]

The central goal of the HML study was to measure differences in production times for specific operations, and for each unit overall, between the "most modern machine method[s]" compared with the "old fashioned hand process … in vogue before the general use of automatic or power machines" (United States. Department of Labor. 1899, 1: 11). The HML staff had no trouble finding machine establishments such that all units in the machine method used inanimate power at some point in production. Perhaps more surprisingly, the staff came fairly close to achieving its goal for hand production "before the general use of … power machines" because only a small fraction of hand operations involved use of inanimate power, mostly by waterpower. We have excluded all units in which any operation in the "hand method" used inanimate power to approximate the Bureau's ideal comparison. This reduces the sample size from the 626 manufacturing units in the published report to 551, which we call our base sample.

Our regression analysis uses a subset of "paired" production operations from this base sample where the HML staff were able to match operations between hand and machine labor and reported the time taken to complete each. This complex matching procedure, which involves the "HML crosswalk", is discussed below. Figure 1 displays a histogram of the unit-level mean

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[7] Data for just three machine establishments predate the joint resolution authorizing the study, one by six years. On average, the hand labor observations predate those for machine labor by about three decades. The implications of this are explored in Table 5. Foreign establishments in the study are excluded from our analysis.

values of the dependent variable used in the regression analysis. This variable is $\Delta\ ln\ T,$ the log difference between hand and machine in the time to complete the <u>matched</u> production operation. The overall mean value across all units is shown by the dark line, -1.761. The associated geometric mean, 0.172 [= exp (-1.761)] implies that, on average, it took just 17.2 percent of the labor time to complete operations producing the same intermediate product using machine labor methods that it took using hand labor—an almost 6-fold productivity gain. We emphasize that these are the total labor times of all workers involved in the operation (or "block link" as discussed momentarily in the text); that is, the total labor input. Because the HML study holds "output" fixed (literally), the geometric mean (or, equivalent, $\Delta\ ln\ T$) is an exact index number of the inverse of labor productivity.[8] The overwhelming majority of the differences are negative, indicating that machine labor almost always took less time than hand labor. The support of the distribution is very large, suggesting a degree of variation across units that is unlikely to be explained by any single factor.

By the early twentieth century the vast majority of value-added in manufacturing was produced in mechanized establishments whereas to a first approximation, almost none was at the start of the nineteenth century.[9] To reach a mean (ln) gap in production operation times of the

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[8]The variable $\Delta\ ln\ T$ is a far superior measure of labor productivity than is normally available for the nineteenth century -- typically, nominal value added per worker deflated by an aggregate index of output prices (real value added per worker), with no adjustment for output mix or labor time; see, for example, Sokoloff (1986).

[9] We estimate that approximately 94 percent of the value of manufacturing output in 1904 was produced in establishments using inanimate power, almost all by steam; see the online Appendix.

size (-1.761) shown in Figure 1, labor productivity in US manufacturing would have to have grown steadily at about 1.8 percent per year over the entire nineteenth century. A back-of-the-envelope estimate of the actual growth rate is 1.5 per year, which suggests that the machine labor establishments surveyed by the HML staff were somewhat more productive than the average such establishment in the late nineteenth century, consistent with the study's goal.[10]

The HML study provided a cornucopia of anecdotal examples of machine labor operations that were sped up through use of powered machinery but also many examples of operations that were not mechanized. "The term 'machine'," Wright acknowledged, "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". He also conceded that machine labor differed from hand labor in other ways, most notably in its embrace of a far more intricate division of

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[10]According to Sokoloff (1986, Table 13.4, p. 695, unweighted B estimates), real value added per (equivalent) worker in manufacturing grew at 2.6 percent per year between 1820 and 1860 versus 1.4 per year from 1870 to the end of the century; see Kendrick (1961, p. 265). A weighted average (the weight is the number of years) of the two estimates is 2.1 percent per year. For the 1800-20 period little is known, but it seems unlikely that there was much, if any, change so we assume a growth rate of zero. For 1860-70, the annual growth rate was 1.0 percent per year, based on Gallman's (1960, Table A-1, p. 43) estimates of real value added and counts of manufacturing workers from the 1860 and 1870 censuses (United States. Bureau of the Census. 1975, 2: 666, Series P-5). A geometric weighted average of the estimates gives 1.5 percent per year.

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).[11] Hence, in addition to quantifying the overall difference in productivity, Wright hoped to pin down the extent of mechanization of machine labor as well as the proportion of the difference in productivity that could be attributed to operations that were mechanized under machine labor.

Wright knew, however, that he and his staff lacked the mathematical tools to do any of these computations.   "This report," Wright lamented, "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" (Wright 1900, p. 211).

The HML Crosswalk, "Blocks", and "Block-Links"

The tables in Volume One of the HML study summarize the data in terms of industry categories and product descriptions, the actual and standardized outputs, the reference year, the number of operations, the number of different workers employed in producing the good, total hours worked, total labor costs, and daily hours at the unit level. Volume Two then breaks down the hand and machine production data to the operation level, providing a brief description of

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[11] To achieve a more intricate division of labor, on average, the machine labor establishments hired 4.5 times as many workers (34.8 vs. 7.7) and identified 80 percent more tasks to be performed (17 vs. 9.5). The average worker in the machine labor establishment also performed a smaller share of total operations than in the hand establishments; see Table 5.

operations in the order in which they were performed; a list of tools or machines used; the type

of motive power; the number of workers assigned to that operation; some information on the

worker characteristics; the time spent on the task; and the labor cost of each employee engaged

in the operation along with any miscellaneous comments.[12]

These data lie at the heart of our analysis in this paper. Consider, for example, data on

the production of 14-tooth steel garden rakes by machine labor (see Unit #30, United States.

Department of Labor. 1899, 2: 480) was originally gathered from a plant that produced a batch of

300 rakes through 16 distinct operations done by 6 adult males, but the data were normalized to

the production of a dozen rakes by dividing the actual time spent on each operation by 25

(=300/12). The first, operation #1, was "cutting iron into sizes" using shears and waterpower by

a forty-year-old who was paid $3.00 per day would have taken 2 minutes and 24 seconds to yield

the pieces to make a dozen rakes. The last, operation #16, was "inspecting rakes and overseeing

the establishment" done without any tools or assistance, again, by a forty-year-old male, paid

$3.00 a day taking the operative a total of 24 minutes. The HML staff assigned consecutive

numbers to each of these (1-16) machine labor operations in the "Operation Number" column.

The HML staff then followed the same protocol for recording the hand labor data, once

again arranging the data in the order in which it was performed. This order was not necessarily

the same as that in machine production. The information in the Operation Number column,

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[12] Information on gender and age is reported for many, but not all workers. The regressions in

the text (Tables 2, 4, and 5) exclude gender and age. But, as discussed in the online Appendix

and in footnote 23, including age and gender variables does not affect the substantive

conclusions.

however, now consisted of letters, numbers, or combinations thereof; each with a distinct

interpretation but a number always referred to the analogous operation in machine production.

These assignments were made by the HML staff based on their detailed knowledge and

observation and provide a crosswalk between the hand and machine operations within units.

The HML crosswalk is the key to our empirical analysis of the operations-level data. To

understand how we use the crosswalk, it is helpful to employ the concepts of an operation

"block" and an operation "block link." An operation block is a collection of underlying

operations of size H (for hand labor) or M (for machine labor) and H and M are non-negative

integers. A block link is a mapping, designated H:M, between the hand (H) and machine (M)

blocks. The HML crosswalk provides the information to link together the specific machine and

hand operations required to perform what Wright termed the "equivalent" work to make the

product. Some hand operations could not be matched by the HML staff to any machine

operations because the operations were no longer performed under machine labor -- 1:0 block

links. Analogously, some machine blocks could not be matched to any hand blocks because the

machine operations were not performed under hand labor -- 0:1 block links. For all other block

links, H and M can take any integer value equal to or greater than one.

Table 1 shows the distribution of the block links in the regression sample that we use

along with some key sample statistics. There are no 0:1 or 1:0 block links in the regression

sample because the former represented hand operations that were no longer performed under

machine labor and the latter represented novel machine operations that were not performed under

hand labor.[13] The block links that are relevant for our regression analysis are those that overlapped between the two methods – 1:1, 1:M, H:1, and H:M -- as these are the operations that were matched by the HML crosswalk. By the HML's construction, the intermediate output of these block-links was the same under both hand and machine labor and is therefore held fixed in the productivity comparison. We report the mean fractions using steam, water, or mechanized (that is, used steam and/or water) for each block link type under machine labor. These are "one-touch" or extensive margin estimates – that is, if any activity within the machine block used inanimate power, we code the block link as "mechanized".[14]

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[13] In the sample of units studied in this paper there were 329 1:0 block links – hand operations no longer performed under machine labor – and 3,275 0:1 block links – novel machine operations. Many of these 0:1 links were associated with "furnishing power"; others involved "inspection" (for quality control given that the product passed through many hands) and "overseeing." On average, the amount of labor time in machine production devoted in 0:1 block links exceeded that devoted in hand production to 1:0 block links (see Atack, Margo, and Rhode 2019). Including the 0:1 block links, 47.5 percent of machine labor blocks were mechanized, 7.7 percentage points less than in the regression sample (55.2 percent). See Atack, Margo, and Rhode (2019) for a discussion of novel (0:1) versus abandoned operations (1:0) in the transition from hand to machine labor, in the context of Acemoglu's and Restrepo's (2018) model of automation.

[14] The one-touch measure is analogous to measures of inanimate power use in the 1850-1870 manufacturing censuses, which recorded the type of power (for example, steam) at the establishment level, see Atack and Bateman (1999).

All told, there are 4,405 block links in regression sample. Table 1 shows the

distribution by block link type and select sample statistics. Approximately 78 percent of these

were singleton tasks under hand labor that the HML staff matched up to singleton tasks under

machine labor (1:1 block links) slightly less than half (48.4 percent) of which were mechanized

under machine labor. The remaining quarter of the regression sample block links were more

complex, reflecting operations in which some task reorganization took place under machine

labor compared with hand labor (1:M, H:1, or H:M block links). Three-quarters (n = 743) of the

more complex block links (n =993) were 1:M or H:M, in which a one or more hand operations

were mapped into M machine operations. Overall, these were the most mechanized (79.9

percent) block links.[15]

Although less common than 1:M or H:M block links, the H:1 links were also highly

mechanized (74 percent). All told, about 55 percent of the block links in the regression sample

were mechanized under machine labor. The final column of Table 1 shows the mean values of Δ

ln T, by block link type and overall (also shown in Figure1). As previously discussed, Δ *ln T* is

the log difference between hand and machine labor in the time to complete the operation

represented by the block link, and it is the dependent variable in our regression analysis. The

associated geometric means by block-link type are shown in brackets.[16]

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[15] The 80 percent figure is a weighted average of the mean mechanization rates of the 1:M and

H:M block links.

[16] On average, the mean value of Δ *ln T* was larger by -0.512 (s.e. = 0.061) for the more complex

blocks than the 1:1 block links. This difference, however, declines to -0.062 and is not

significant (s.e. = 0.055) in a regression of Δ *ln T* with unit fixed effects, without controlling for

Given that not much more than half of the machine labor block links were mechanized, if mechanization is to "account for" (see below) a large fraction of the mean (ln) productivity gap in the regression sample, then the direct impact of mechanization on productivity must necessarily be relatively large or the productivity differences for non-mechanized operations relatively small. The implications of this are addressed next through our empirical analysis of productivity differences at the operation level.

Productivity Differences at the Operation Block Level: The Role of Mechanization

In this section we perform regression analyses of $\Delta \ln T$ using the sample of 4,405 block links that are matched between hand and machine labor through the HML crosswalk. We seek to measure the mean differential in the labor productivity gain between the mechanized (inanimately powered) and non-mechanized operations within the same production units. We present OLS estimates first followed by an instrumental variable analysis. The discussion in the text focuses on our base specification (equation 1, immediately below).[17]

<u>**OLS Estimation:**</u>

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mechanization. Most of the higher labor productivity of machine labor associated with the more complex block links is explained by their greater use in the production of certain goods for which machine labor had a greater productivity boost than average, compared with hand labor.

[17] We also conducted additional estimations to be sure that our substantive findings from the base specification were robust to changes in sample composition (such as 1:1 versus H:M), which they were. The robustness checks are reported in the online Appendix.

The regression specification is given by equation 1:

$$[Eq.\ 1]: \Delta \ln T\ (a,\ j) = \beta(j) + \gamma(a) + \lambda * Mechanized\ (a,j) + \varepsilon\ (a,j)$$

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 represented by the units were very different (such as circular saw blades vs. shoes) and there is no reason to believe that machine labor would be equally good at improving productivity across all manufactures, controlling for the extent of mechanization. Equally important, the *β(j)'s* control for any unit level differences between the hand and machine labor establishments that were the same for all block links within the unit, such as the total number of workers in machine vs. hand labor, the year(s) to which the data pertain, and so on. As the unit fixed effects soak up all unit level differences, we cannot include any unit level differences in [eq. 1].[18] Because of the complexities potentially introduced by multi-operation grouped tasks, which involve about a quarter of the blocks, our base specification also includes dummy variables for the block link types, γ(a).[19] In Table 2, we report the value of the coefficient λ for the single mechanization variable, *Mechanized*, which is

[18] In the next section we relax this restriction slightly by substituting four-digit SIC industry codes for the unit fixed effects. This allows us to include unit level variables in the regression.

[19] The values of *β(j)* and γ(a) from the various regressions estimated in this paper are not reported in the tables but are available on request. The left-out block-link dummy is 1:1. An F-test for the joint significance of the block link dummies for the OLS regression in Table 2 is well above the critical level (F = 29.7, significant at the 0.0001 level), indicating that the dummies belong in the regression. However, excluding the block link dummies has only a slight effect on the estimate of λ, reducing it to -1.006 (s.e = 0.065) from -1.037.

the "one-touch" measure of mechanization of a machine labor block introduced in the previous section. While "mechanized" means that either steam or waterpower was used somewhere in the block, the overwhelming majority used steam. The reason for the single mechanization variable will become clear shortly. The OLS estimate of λ is identified through the variation in *Mechanized* across block links within units. The fundamental premise of the HML study was that mechanization sped up production times, implying that λ should be negative.

Equation 1 provides the basis for a decomposition exercise *via* regression, familiar in modern economics (if not to Carroll Wright or his staff), which we perform in Table 2. The expected value of the dependent variable, E*(Δ ln T)*, equals a baseline effect that depends on the coefficient of the unit dummy and that of the relevant block link type, plus a uniform *Mechanization* effect (λ), for block links that were mechanized. Specifically, λ measures the average difference in (log) labor productivity between mechanized and non-mechanized operations, controlling for the unit fixed effects and block link dummies. The average difference in productivity reflects gains in technological efficiency (total factor productivity) and in capital per worker ("more" capital was embodied in the steam engine and other machines than in hand tools), but the regression does not tell us how much of the increase is due to efficiency versus higher capital intensity.[20]

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[20]While we know exactly which tools are used in each operation, we have no way of reliably aggregating capital at the block level and no information whatsoever regarding buildings or any capital employed outside of the immediate production activities. There may also be unmeasured differences in worker characteristics between mechanized and non-mechanized operations in

Table 2 shows the OLS estimate of λ, -1.037, which is precisely estimated (s.e. = 0.060). Taking the exponent of λ, subtracting from one, and multiplying by 100 percent computes the (approximate) additional percentage reduction in production time above baseline from mechanization -- 65 percent [= (1- (exp (-1.037))) x 100 percent]. This is a substantial, and statistically significant gain in average labor productivity – clearly, mechanization mattered. The table also shows the percent of the mean productivity gap accounted for ("explained") by mechanization, which is the estimate of λ multiplied by the mean value of *Mechanized*, divided by the mean value of $\Delta \, ln \, T$. The percent explained is 32.5 percent [= ((-1.037 x 0.552)/-1.761) x 100 percent], or about one-third. By construction, the remaining gap (67.5 percent) is accounted for collectively by the coefficients of the unit level and block link dummies.[21]

Instrumental Variables Estimation

Up to this point, we imagine that Carroll Wright would be both pleased and puzzled by our results. Pleased – because we have been able to compute the average difference in

machine labor versus hand labor. However, for the reasons discussed in footnote 23, we believe these to be minor.

[21] Evaluated at the sample means of the distribution of block links across units and across block link types, the unit level coefficients account for 69.5 percent of the mean value of $\Delta \, ln \, T$. Thus, the portion of the mean gap in productivity that is not accounted for by mechanization is attributed entirely (and then) to the unit fixed effects. Below, we modify the regression analysis to explore how much of this variation can be attributable to measurable factors at the unit level, such as the division of labor and production scale.

production times between hand and machine labor in the HML data, a calculation that he wanted

to make but which eluded him and his staff. Moreover, this average difference is large,

consistent with the study's professed aim and what Wright expected.   But also puzzled –

because Wright surely would believe that mechanization should account for a larger portion of

the mean productivity gap than it evidently did. As we noted, Wright acknowledged that many

machine labor operations were performed by hand, but he thought that, "in the main" these were

"simple and unimportant" (United States. Department of Labor. 1899, 1: 11). Clearly, this was

not the case.

However, before pressing forward to investigate what else besides mechanization might

have mattered, it is worth pausing to ask if the OLS estimate of λ is affected by endogeneity bias.

The HML study was observational; the staff did not randomly assign steam power to machine

labor operations -- they would not have known what this meant. Someone, presumably an owner

or manager, made the decision to mechanize (or not) the operations in the survey's machine

labor establishments.

One standard source of OLS bias, measurement error in the independent variable of

interest, *Mechanized*, is almost certainly not present, due to our use of the "one touch" measure

and the exceptionally careful data collection by the HML staff.[22] Omitted variables are a second

source of bias; however, we believe that the most likely omitted variables, those of worker

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[22] Measurement error would have been more likely, in our opinion, if the staff had attempted to

collect data on horsepower. All that the one touch measure requires, however, is that the staff

accurately noted the presence of inanimate power in the establishment and its use somewhere in

performance of a task.

characteristics, are unlikely to be a major problem in the study.[23] However, a third source,

reverse causality, cannot be readily dismissed.

In our view, the most likely source of reverse causality would create a negative

correlation between *Mechanized* and the error term, ε. This would happen if the owner and/or

manager of the machine labor establishment were more likely to mechanize an operation if the

expected time savings were large, and the expected time savings were positively correlated with

ε.[24] In this case, the OLS estimate of λ would be biased upwards in absolute value, thus

overstating the casual impact of mechanization.

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[23] In our opinion, the most likely source of omitted variable bias would be omitted worker

characteristics that affected productivity. Here, the evidence is limited but telling. We can

estimate eq. 1 with and without indicators for the differences between machine and hand labor

using the fraction of workers who were male and the fraction of children age 14 and under (this

is all that can be measured consistently using the age information recorded in the report). Use of

male labor is associated with higher productivity (shorter production time) and child labor with

lower productivity (longer production time) but the inclusion of both variables has virtually no

effect on the OLS coefficient of *Mechanization*. Details can be found in the online appendix.

[24] If the HML study were a true "before" (hand labor) vs. "after" (machine labor) panel of the

same establishments, reverse causality would be very likely.   The HML study, however, is not a

panel; the owner or manager of the machine labor establishment would not have known the

operation times in the matched hand labor establishment (recall that many of the hand labor

observations are from decades before the 1890s). However, this does not rule out *a priori* that

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To address reverse causality, we need an instrumental variable (IV) for *Mechanized* at the block link level, a difficult problem. Our identification strategy makes use of certain information in the textual descriptions of production operations. These descriptions, which are very brief, appear in the "General Table – Production by Hand and Machine Methods" in the column titled "Work Done," organized by unit number and production method, in Volume 2 of the HML study.

Specifically, we extracted all unique occurrences of gerunds appearing in the "Work Done" columns.[25] In general, the first word in the description of work is almost always a gerund, which describes the principal action taking place in the operation, so we call this the "principal gerund."[26]

To understand the conceptual basis for our gerund IV, it is useful to step back and view the problem through the lens of Acemoglu's and Restrepo's (2018) model of automation. In their model, production activities are arrayed on the unit interval, in order of labor's comparative

the error term in the regression is correlated with the expected time savings, which surely was an important factor in the decision to mechanize. We are grateful to a referee for this point.

[25] Any standardized way to define production activities could be used to generate an instrumental variable. We use gerunds because these are the words the HML used to describe the task operations and they represent actions/activity. A gerund is an English verb to which "-ing" has been appended. These function as a noun in grammatical context.

[26] Additional gerunds, if present, are always closely related to the main activity described by the principal gerund – the principal gerund is, in other words, the textual equivalent of a sufficient statistic.

advantage over capital (automation) in performing them. Initially, technology is primitive, and it is impossible to automate any production activities. Over time, however, scientific and engineering knowledge advances and it becomes technologically feasible to automate a subset of activities, starting from the left bracket of the unit interval to some point in it, T*. The activities that, in fact, are automated, [0, T], T < T*, depend on the relative cost of labor and capital. The Acemoglu-Restrepo model provides an important clue to make progress on our identification problem -- if an historical indicator of T* can be constructed that varies exogenously across production operations, this becomes a candidate instrumental variable.

To implement this approach, a member of our research term with expertise 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.[27] Based solely on the expert's knowledge of the history, activities described by the gerunds where the expert believed there was some technical feasibility of mechanization worldwide by the end of the nineteenth century were sorted into one bin (bin #1), while those for which there was very little or none were sorted into the other (bin #0). Once the sorting was completed, we used the results for the principal gerunds in the hand blocks in the regression sample to construct the IV (see below).

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[27]The list of gerunds was produced from a digitized version of the HML text. Because some gerunds can describe very different activities depending on a single letter – for example, "striping" vs. "stripping" – in a very few cases the expert was forced to consult the printed version of the HML study to be sure that the distinction was also present in the original text and not somehow garbled in the digitization, but the expert did not contemplate the text preceding or following the gerund in question.

Table 3 shows the distribution of the five most common principal gerunds for the hand

blocks in the 1:1 and 1:M block links in the regression sample, grouped by bin #0 (little or no

technical feasibility of mechanization) versus bin #1 (some technical feasibility).   The five most

common activities judged to have little or no feasibility of mechanization were "making",

"putting", "overseeing", "finishing", and "marking."   For each, human judgement played a

substantial role, and the requirements of the activity were idiosyncratic.   Conversely, the five

most common activities judged to have some feasibility of mechanization were "cutting",

"sewing", "smoothing", "stitching", and "conveying". These are all activities for which the

activity was repetitive, and for which special-purpose machinery was invented, often early in the

nineteenth century.[28]

For the 1:1 and 1:M block links there is a one-to-mapping from the two bins to our IV,

which is the "one-touch" analog 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 in the construction of the IV because when H > 1 there may be more than one

principal gerund.[29]   MECHABLE, in other words, is our measure of T*, representing exogenous

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[28]Some additional examples of gerunds involving repetitive activities and for which special-

purpose machinery was available by the late nineteenth century are "boring," for which

Wilkinson's boring machine (first patented in 1774), could be used; and "turning", for which

Blanchard's lathe (first patented in 1819), could be used. The complete gerund distributions

grouped by bin type underlying Table 3 are available from the authors on request.

[29] In the intermediate step we construct a weighted average of technical feasibility of

mechanization for each principal gerund in the H operations in the hand block, where the weight

shifts in the likelihood of mechanization. Note that, because we have one instrument, we can only have one endogenous variable (*Mechanized*).

For the exclusion restriction to hold, it must the case that MECHABLE affects productivity solely by exogenously shifting the likelihood of use of inanimate power, as required by the Acemoglu and Restrepo framework. This would be violated, for example, if the expert used additional information about the unit to classify the gerund into bins but, as noted above, only the list of gerunds was used. The exclusion restriction might also be violated if MECHABLE affected unmeasured worker characteristics directly; however, as noted above, we believe there is little evidence of omitted variables bias of this type.[30]

Table 4 shows the results for the IV estimation of Eq. 1. The first stage coefficient of *MECHABLE*, 0.316 (s.e. = 0.020), is positive (as it should be) and the associated Kleibergen-Paap F-statistic (240.7) indicates that the instrument is very strong (p-value = 0.00001).[31] The

is the share of time devoted to the operation in the overall time in the hand block. If the weighted average exceeds zero, MECHABLE = 1 for the overall block link.

[30] The exclusion restriction would be violated if the HML staff selected gerunds for the hand descriptions of activities that were mechanized under machine such that our expert would then classify them into bin #1 125-odd years in the future. Our reading of the HML protocols, however, indicates that the staff took great care to describe operations exactly as they occurred in practice, making this very unlikely.

[31] Aside from a successful first stage (see Table 4), one test of the plausibility of *MECHABLE* as an indicator of T* is that there should be very few "Always Takers" (Angrist and Pischke 2009) – operations that were mechanized under machine labor whose principal gerund was sorted into

2SLS estimate of λ, -0.749, is negative and significant (s.e. = 0.165) but about 28 percent smaller in magnitude than the OLS estimate, consistent with the presence of upward OLS bias due to reverse causality.[32] If we repeat the decomposition exercise using the 2SLS estimate, the percent explained by mechanization is about 24 percent, compared with 33 percent for OLS.

Like all such instrumental variable estimates, ours is a local average treatment effect (LATE) which, theoretically, could be smaller in magnitude than the population average treatment effect (ATE). This does not seem likely to us, however, given the aims of the HML study which sought to characterize the behavior of the "most advanced" of machine labor establishments.

Productivity Differences: The Role of Division of Labor, Quantity Production, and Other Factors

In answering the questions posed by Carroll Wright, our analysis of the HML data has uncovered a curious and unexpected puzzle. While mechanization clearly raised productivity at the production operation level, most of the superior productivity of machine labor on average

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bin #0 (little or no technical feasibility). In a two-by-two crosstab of *Mechanized* and *MECHABLE,* just 5 percent [= (219/4,405) x 100 percent] of mechanized machine labor operations have Mechanized = 1 and MECHABLE = 0, suggesting there were very few "Always Takers".

[32] Note, however, that the 95 percent confidence interval around the 2SLS estimate of λ (-0.4261, -1.071) includes the OLS estimate so, technically, we cannot reject the hypothesis that the 2SLS and OLS estimates are the same.

cannot be explained <u>directly</u> by the greater mechanization of machine labor. But, if that is the case, what accounts for the unexplained portion, particularly that captured by the unit fixed effects?

The published study grouped the units in Volume 1 by broad product categories. However, the HML product descriptions were very detailed, often to the point where the separately reported units were producing goods that were literally the same (such as "Vicuna worsted single-breasted vests, notched collars, breast measure 37 inches, length 26 inches" by Units 214 and 215 (United States. Department of Labor. 1899, 1: 38)) or very similar. Using these detailed descriptions of the goods produced, we found that we could map the HML units into 70+ four-digit SIC codes. These allow us to estimate equation 2, which is a slightly more parsimonious version of our base specification, where the SIC codes substitute for the unit fixed effects:

$$[Eq.\ 2]:\ \Delta\ ln\ T\ (a,\ j) = \eta(s) + \gamma(a) + \lambda*Mechanized\ (a,j) + X(j)*\gamma + \varepsilon\ (a,j)$$

The $\eta(s)$ are coefficients of the 4-digit SIC fixed effects. Because eq. 2 does not include unit fixed effects, we can add continuous or dummy variables, $X(j)$, at the unit level – for example, measures of the division of labor or scale. However, because the unit variables of interest are not available for all units in the original regression sample, the sample size for eq. 2, about 3,900 block-links, is smaller than the sample size in Table 1.[33] Coefficients of the unit level variables are identified by variation across units within the 4-digit SIC codes.

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[33]The main reason for the smaller sample is that for some hand units the HML staff found it necessary to blend data from different years (see, for example, United States. Department of Labor. 1899, 1: 174). As a result, the year of observation is not precisely defined for these units, and so they are excluded from the regression sample for Table 5. We also lose some observations

OLS estimates of λ and β and the associated percent explained calculations are shown in Table 5. It is highly reassuring that the point estimate of λ, -1.072, is the same to the third decimal point to that obtained using the eq. 1 specification with the Table 5 sample, indicating that the combination of the 4-digit SIC dummies and particular unit level variables shown in Table 3 does almost as well as capturing the salient variation in the data.[34]

Three "returns to scale" variables are included in the regression – two measures of the division of labor, and a "quantity production" dummy.[35] We know that Wright considered a high degree of division of labor to be an essential feature of machine labor methods. Indeed, as we previously pointed out, in describing machine production, Wright notes "matters are so arranged that every workman has his particular work to perform, generally but a small portion of that which goes to the completion of the article to be produced" (United States. Department of Labor. 1899, 1: 11). Since Adam Smith, economists have claimed that division of labor would raise labor productivity, as workers are allocated to production tasks based on their comparative advantage

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because of missing data on average daily hours or because we lack sufficient information to compute one of the measures of division of labor: the percent of tasks performed by the average worker.

[34] See the notes to Table 5. We say "almost as well" because the adjusted-R square with 4-digit SIC codes (0.411) accounts for about 81 percent as much of the variance compared with the eq.1 specification for the same sample (adjusted R-square = 0.510).

[35] We cannot measure the division of labor at the block link level for all observations in the regression sample because to do so we would need the names of the individual workers which, as previously noted, were not included in the published study.

and by saving on the set-up costs of switching tools between tasks. However, the various nineteenth century American censuses of manufacturing never attempted to measure the division of labor directly, and its presence (and potential impact on productivity) in census data can only be inferred from variation across establishments in the number of workers. To our knowledge, the HML study is the only data source for nineteenth century US manufacturing for which direct measures of the division of labor can be constructed.[36]

The first division of labor variable is the difference between machine and hand labor in the fraction of operations performed by the average worker. Holding constant the number of operations to be performed, if the average worker performs a greater share of total operations, there was less division of labor; conversely, if the share of operations performed by the average worker declines, the division of labor increases.[37] Assuming that an increase in the division of labor raises productivity, therefore, the coefficient of this variable should be positive – if the average worker performs a larger share of total operations, it will take more labor time to do so.

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[36] Sokoloff (1984) identifies division of labor through scale effects on labor productivity in production function estimation using establishment level data from the 1820 and 1850 manufacturing censuses of manufacturing. Margo (2015) shows that the scale coefficient is highly non-robust to measurement problems in the labor input in the 1850 data.

[37] We compute the share of operations performed by the average worker using the following formula: ([$\sum$ (#workers assigned to operation i) /(total number of different workers)]/(number of operations), see Atack, Margo, and Rhode (2017). This formula takes account of the possibility that some operations may overlap across workers (that is, are shared, in addition to operations performed alone).

The second division of labor variable is the difference in the logarithm of the number of operations performed in manufacturing the unit by machine versus hand. Holding constant the fraction of tasks performed by the average worker, an increase in the number of tasks will imply a greater division of labor – hence, its coefficient should be negative.[38] As can be seen in Table 5, the signs of both coefficients are as expected and are highly significant. The mean values of both variables are also as expected, indicating a greater degree of division of labor under machine production than under hand.

The third scale variable, *Volume Production*, measures the difference between machine and hand labor using a dummy variable indicating whether the actual machine or hand quantity produced exceeded a critical cutoff level where substantial scale economies might have kicked in. While the ideal cutoff should be guided by historical examples and discussion, the relevant literature provides no operational guidance.[39] The threshold we adopted was the quantity

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[38] If the fraction of operations performed by the average worker is held fixed, an increase in the number of tasks performed necessarily implies dividing up the operations among more workers – more division of labor.

[39] Here we have in mind the distinction made by Philip Scranton (1997) between "flow production"—bulk and mass production—as opposed to custom and batch production. However, the only occasion Scranton attaches a concrete number to any of these modes (other than the limiting case of "custom" as one of a kind), is that Brown and Sharpe's contract production of as many as 33,000 Willcox and Gibbs sewing machines a year (over 1,000 per day) represented "bulk" rather than "mass" production (Scranton 1997, p. 29). Similarly, Hounshell (1984) does not attach any quantity number to "mass production".

associated with the 75th percentile of the machine labor distribution, 1,500. Quantity production

clearly was more common under machine labor, as indicated by the positive mean value (0.139)

of the dummy variable. If quantity production did raise productivity, the coefficient of the dummy

variable should be negative – which it is, -0.297, and highly significant (s.e. = 0.084).

The HML staff also collected data on average daily hours. Over the nineteenth century,

there was a downward trend in average daily hours; on average, daily hours were shorter in the

machine labor establishments, although the mean difference was slight. There is some evidence

that shorter hours in nineteenth century manufacturing were associated with increases in labor

productivity (Atack and Bateman 1992; Atack, Bateman and Margo 2003; Goldmark and

Brandeis 1912). To test for this, we included the difference in the log of average daily hours

between machine and hand labor. This variable has a positive and significant coefficient, 1.49

(s.e. = 0.55). which is consistent with shorter daily hours being associated with higher labor

productivity.

As previously mentioned, the HML staff attempted to assess the quality differences in

goods produced by the machine and hand units in the surveyed establishments. For the most

part, they concluded there was either no meaningful difference or a difference in favor of the

machine labor version of the good. That said, if the hand product were of better quality, we

would expect that the hand operations would take longer to perform, increasing the apparent

productivity advantage of machine labor. To test this, we include a unit-level dummy, *Hand*

Better, in the regression; as can be seen, the coefficient is negative, -0.291, although it is

imprecisely estimated (s.e = 0.205).

We include the difference in the observation year between machine and hand labor in the

regression. This difference is almost always positive, and the mean is 27, indicating that, on

average, the hand labor data were older than the machine labor data by 27 years. The coefficient of this variable is negative, -0.006, and significant (s.e. = 0.002), indicating that the older the hand labor data was relative to machine labor, the greater the productivity advantage of the latter, other factors held constant. This pattern makes sense because earlier hand labor establishments were likely closer to the "old-fashioned" methods that Wright had in mind for the study, and thus less productive compared with the "most advanced" machine labor establishments in the 1890s.

Of course, we cannot and do not claim that the coefficients of these unit level variables reflect causal impacts, and we have no way of instrumenting them individually. Still, the mere fact that we can include these measures at all in the regression goes far beyond what is possible with other nineteenth century data. Further, each of the coefficients has its expected sign suggesting that it is still useful to compute their explanatory power ("percent explained") at the sample mean values. These are shown in the last column of Table 5. Of the various unit level variables, the three scale variables account for 18.7 percent of the mean productivity gap in concert, of which the two pertaining to the division of labor are the most important, accounting for 16.3 percent by themselves, equal to almost half of the explanatory power of mechanization alone. Machine establishments operated for fewer hours per day compared with hand, and this difference, too, contributed to the overall productivity advantage, albeit modest (2.6 percent). All told, the unit level variables account for 31.3 percent of the mean value of $\Delta \ ln \ T$, about nine-

tenths (= 31.3/34.6) of that explained by mechanization in the eq. 2 specification (34.6 percent).[40]

Concluding Remarks

Economic historians have long been interested in quantifying the sources of labor productivity growth during the historical Industrial Revolution. One common approach is growth accounting, attributing some portion of productivity growth to greater use of capital per worker, including that associated with inanimate power (see also Atack, Bateman and Margo 2005). The results of such analyses (Crafts 2004; Crafts 2004; Crafts and Mills 2004) generally find a relatively modest role for inanimate power and in that sense are broadly consistent with our findings. But a growth accounting exercise, no matter how well executed, can only reveal whether inanimate power mattered within the confines of the growth accounting framework. This requires assumptions about output elasticities or else time-series estimation of the same, with inherent limitations. In the American case, another approach is to use establishment level data from the 1850-80 censuses of manufacturing (Atack and Bateman 1999) to estimate the extent of economies of scale in a production function framework (see, for example, Margo 2015) but the literature has yet to reach consensus on this because of serious econometric problems that may never be fully resolved.[41] By contrast, the HML data are vastly more informative than any

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[40] Mirroring the earlier results in the paper, if we estimate eq. 2 using 2SLS, the percent explained by mechanization declines to 23 percent while that of the unit level variables is 34 percent (20 percent for the three scale variables).

[41] Using establishment level manufacturing data from the 1850-80 censuses, Atack, Bateman, and Margo (2008) show that use of inanimate power significantly increased value added per

of the census data, allowing us to pinpoint exactly which operations were affected by use of inanimate power and to develop and apply an identification strategy to explore endogeneity. Albeit with less rigor, we can also measure the effects of other key factors, including the division of labor, which is otherwise impossible for the period on any systematic basis.

Our OLS and 2SLS analyses of the HML operations data reveals that "mechanization" clearly did "take command"; it is likely that no other single factor was more important quantitatively in advancing productivity growth in the transition from hand to machine labor. At the same time, however, our results establish (solidly, in our view) that mechanization accounts for less than a majority of the large average productivity difference between machine and hand labor which, therefore, must be due to other factors. Our expanded analysis of the HML data in the final section of the paper is more speculative, but we believe it justifies a fresh effort to investigate the role of these other factors in raising labor productivity in nineteenth century manufacturing.

In particular, the HML study suggests that division of labor, volume production, and improvements in the work environment within factories such as shorter daily hours are worthy of closer scrutiny. Of these, the role of division of labor may deserve the most attention. 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 critical factor (Atack, Haines and Margo 2011). The transportation revolution increased market access and in so doing, made a larger scale of operation more profitable – as the saying (from Adam Smith)

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worker but, unlike the HML data, the census data do not identify which operations were affected, nor is it possible to control for differences in the output mix across establishments.

goes, "the division of labor is limited by the extent of market". As the division of labor

increased, workers became more specialized in production, and the "average worker" was a

convex combination of individuals performing different operations according to comparative

advantage, more productive than a single artisan performing all tasks from start to finish.

Compared with such artisans, the typical nineteenth century factory operative had much less to

learn on the job, lowering the costs of supplying labor to manufacturing. Although advances in

technology and emerging complementarity with capital increased the skill demands on factory

workers, this calculus remained the same until well into the twentieth century when the forces of

automation eventually caught up, making operatives highly vulnerable to displacement by

machinery (Acemoglu and Restrepo 2018; Goldin and Katz 1998).

Table 1: Distribution and Sample Statistics by Block-Link Type: Regression Sample

Block Link Type (**H**and:**M**achine)	Number of Block Links	Mean Fraction Steam, Machine Labor	Mean Fraction Water, Machine Labor	Mean Fraction Mechanized, Machine Labor	Mean Value, $\Delta \ln T$
1:1	3,412	0.460	0.025	0.484	-1.646 [0.193]
1:M, M > 1	619	0.732	0.055	0.784	-1.920 [0.147]
H:1, H > 1	250	0.704	0.052	0.744	-2.729 [0.065]
H:M, H, M> 1	124	0.815	0.073	0.879	-2.189 [0.112]
Total, Regression Sample	4,405	0.522	0.032	0.552	-1.761 [0.172]

Source: computed from digitized HML study (United States. Department of Labor. 1899).

Notes: Block links are defined as follow -- 1:1: a single hand labor operation is mapped to a single machine labor operation; 1:M, M> 1: a single hand labor operation is mapped to a block of M machine operations, M> 1; H:1, H> 1: A block of H (>1) hand operations is mapped to a single machine labor operation; H:M: A block of H hand labor operations is mapped to a block

of M machine labor operations, H and M > 1.   Mechanized = 1 if machine block used steam or waterpower or both; see text. NA: not applicable. Figures in brackets are geometric means of Δ *ln T* (for example, 0.172 = exp (-1.761) for the regression sample in the final row).

Table 2: OLS Regression and Decomposition Analysis of Δ *Ln T*

Variable	Coefficient	Mean Value of Independent Variable	Percent Explained of Mean Value of Δ *Ln T*
Mechanized	-1.037	0.552	32.5%
	(0.060)		
Adjusted R-Square	0.499		

Source: see Table 1. Notes: The decomposition ("Percent Explained of Mean Value of Δ *Ln T*") is computed by multiplying the regression coefficient of *Mechanized* (-1.037) by the mean value of *Mechanized* (0.552) and dividing the product (-0.572) by the mean value of Δ *ln T* (-1.761) = (-1.037 x 0.552)/(-1.761) = 0.325, or 32.5 percent. The sample size for the regression is 4.,405 block links. The regression also includes dummy variables for block link types and for units (see the text). Standard errors are clustered at the unit level. Sample means are from Table 1.

Table 3: The Top-Five Activities (Principal Gerunds) in Hand Production, 1:1 and 1:M Block-Links in the Regression Sample: Bin #0 versus Bin #1

Bin #0	Number	Bin #1	Number
Making	156	Cutting	597
Overseeing	141	Sewing	136
Putting	121	Smoothing	77
Finishing	38	Stitching	76
Marking	34	Conveying	73
Total count in Bin #0	690	Total count in Bin #1	2,968

Source: see Table 1. 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.

Table 4: 2SLS Regression and Decomposition Analysis of Δ *Ln T*

Variable	Coefficient	Mean Value of Independent Variable	Percent Explained of Mean Value of Δ Ln T
First stage, *MECHABLE*	0.316 (0.020)	0.820	
Kleibergen-Paap F-Statistic	240.7		
2SLS, *Mechanized*	-0.749 (0.165)	0.552	23.5%

Notes: The decomposition ("Percent Explained of Mean Value of Δ Ln T") is computed by multiplying the 2SLS regression coefficient of *Mechanized* (-0.749) by the mean value of *Mechanized* (0.552) and dividing the product (-0.413) by the mean value of Δ ln T (-1.761) = (-0.413)/(-1.761) = 0.235, or 23.5 percent. The sample size is 4,405 block links. The first stage and 2SLS regressions also includes dummy variables for block link types and for units (see the text). The Kleibergen-Paap F-statistic refers to the instrumental variable *MECHABLE.* Standard errors are clustered at the unit level. Sample means of Δ *ln T* and *Mechanized* are from Table 1.

Table 5: OLS Regression of Δ *Ln T* with 4-Digit SIC Code Dummies

Variable	Coefficient	Mean Value of Independent Variable	Percent Explained at Sample Mean of Δ *Ln T*
Mechanized	-1.072 (0.057)	0.553	34.6%
Unit Level Difference, Machine – Hand Labor:			
Ln (# of Operations)	-0.222 (0.085)	0.472	6.1
Fraction of Operations Performed by the Average Worker	0.442 (0.121)	-0.397	10.2
Volume Production	-0.297 (0.084)	0.139	2.4
Ln (Daily Hours of Operation)	1.489 (0.545)	-0.030	2.6
Hand Better	-0.291 (0.205)	0.030	0.5
Observation Year	-0.006 (0.002)	27.0	9.5
Percent Explained, Unit Level Variables			31.3
Percent Explained, Unit Level + Percent Mechanized			65.9
Adjusted R-Square	0.411		

Source: see Table 1 Notes: Sample size is 3,876 block links because of missing data on some

unit level variables (see text). Mean value of Δ ln T for this sample is -1.713. Regression

includes 4-digit SIC code dummies and block link dummies (coefficients not reported).

Coefficient of *Mechanized* = -1.072 (s.e. = 0.064) if eq. 1 specification is estimated instead.

Volume Production is the difference between two dummy variables, (Volume_Machine –

Volume_Hand). Volume_Machine (Volume_Hand) = 1 if actual quantity>1,500; 0 otherwise.

Hand Better = 1 if HML staff judged the product made by the hand labor establishment to be of

better quality than the machine labor establishment. Standard errors are clustered at the unit

level.

Figure 1: Distribution of Log Change in Labor Time between Machine and Hand Production Operations
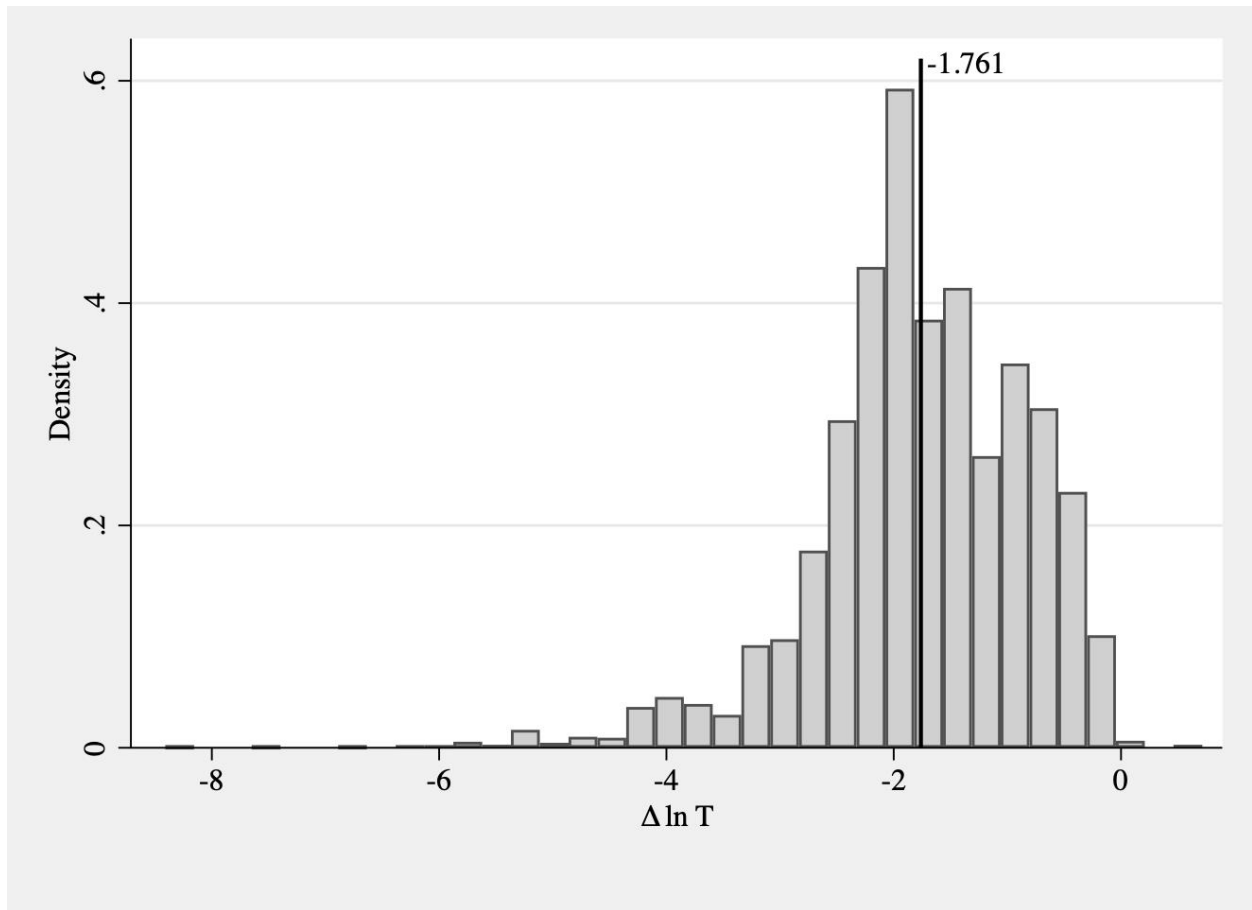
Source: computed from digitized HML study (United States. Department of Labor. 1899).

Notes: Figure uses data for regression sample (see Table 1). $\Delta \ln T$: machine – hand difference in log T, T = time to complete the operation (n = 4,405). The histogram displays unit level averages of $\Delta \ln T$, weighted by the number of observations in the unit. The dark line is at the overall sample mean across all units, -1.761.

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Online Appendix

This is the online Appendix for our paper, 'Mechanization Takes Command'? Inanimate Power and Labor Productivity in Late Nineteenth Century American Manufacturing". It contains additional details on calculations in the paper and on the robustness checks that we performed.

Coverage of the HLM Study

Online Appendix Table 1 shows the distribution of the HML study units in the regression sample (see Table 1 in the paper) by two-digit standard industrial classification (SIC) code compared with establishments shares in manufacturing in 1899 available for most of the codes. Except for two industry groups (Petroleum and Coal Products, Rubber and Plastic Products), the HML study included units in all industry codes of that time although not in proportion to the establishment shares in the 1900 census – that is, the HML units were a broad, but not representative, sample of manufactured products of the time. Appendix Table 1 also shows the mean values of $\Delta\ ln\ T$ by SIC codes. Larger negative values of $\Delta\ ln\ T$ indicate greater productivity change. Sectors that were important in the First Industrial Revolution, such as Textiles (SIC 22) and Primary Metals (33) show notably large mean values of $\Delta\ ln\ T$.

Estimating the Share of Value Added in Establishments using Inanimate Power: 1904

In footnote 9 of the paper, we report that 94 percent of manufacturing value-added was produced in establishments using inanimate power. This was computed as follows. According to the 1910 Census of Manufactures {United States. Bureau of the Census., 1913 #6972, 332}, there were 216,180 establishments, 134,481 of which (62 percent) used inanimate power, almost entirely by steam (95 percent). The Census also reported {United States. Bureau of the Census.,

1913 #6972, 180} the distribution of establishments across five value of product categories.

There were 81,699 non-powered establishments in 1904. If we assume that all of these were small in terms of output, the non-powered establishments then account for all of the establishments in the first category ($< \$5,000$) plus approximately 15 percent of the second ($\$5,000$-$20,000$). Together, this implies that the non-powered establishments produced 2.8 percent of aggregate value-added (see online Appendix Table 2). We believe 2.8 percent is too small, because some small establishments used power and some large establishments did not. We have made a conservative adjustment by doubling the share to 5.6 percent, implying that 94.4 percent [$= 100 - 5.6$] of manufacturing value added in 1904 was produced in establishments using power.

While this estimate is very rough, it is arguably in the ballpark of the true figure. For example, computing the share of value-added produced in establishments using inanimate power in 1850 and 1870 using the national samples of establishments discussed in Atack and Bateman {, 1999 #2} produces estimates of 57.3 percent and 71.1 percent.   A linear projection of this upward trend in the value-added share between 1850 and 1870 shows an increase of 6.9 percentage points per decade implying that 91.8 percent of value added was produced in powered establishments in 1900, just slightly below our estimate for 1904.

OLS Estimates of λ: With and Without Controls for Worker Gender and Age

The HML study reported some information on worker gender and age. This information is sufficient to measure the differences between machine and hand labor in the fraction of workers who were male, Δ *Male*, and the fraction of child workers ages 14 and under, Δ *Child14*, at the block line level. Using the regression sample, we re-estimated equation 1, including these two additional variables. The coefficient of Δ *Male* is negative and significant, -0.177 (s.e. =

0.080), indicating that production times were lower for male workers. The coefficient of Δ *Child14* is positive, 0.381 (s.e. = 0.361), indicating that children took longer to complete the operation, although the impact is not statistically significant. Importantly, including both variables has virtually no effect on the estimated coefficient (λ) of *Mechanization*, -1.036 (s.e. = 0.060) compared with the base specification (λ = -1.037), suggesting that endogeneity bias due to omitted worker characteristics is probably a minor concern in the HML study.

Robustness Checks: OLS and IV estimates of λ for Different Subsamples

Our regression analysis yields three substantive findings. First, the OLS and 2SLS coefficients of *Mechanization* (λ) are negative and statistically significant. Second, there is some evidence of reverse causality in so far as the 2SLS estimate of the coefficient is smaller in absolute value than the OLS estimate. Third, the percent explained by mechanization of the mean value of Δ *ln T*, the dependent variable, is approximately 33 percent for OLS and somewhat less for 2SLS.

We tested the robustness of these findings by estimating equation 1 (OLS and 2SLS) for various sub-samples: a) 1-1 versus non-1:1 block links, b) restricting to observations from the 1890s only, c) units for which the machine labor version good was deemed to be of "superior quality" to the hand labor good, d) units for which the reverse was true (hand labor superior to machine labor or no difference, including no opinion). Results are shown in online Appendix Table 3. Except in row 4 of the table, all regressions include unit fixed effects. For the subsample comprised of the H:1, 1:M, and H:M block links (row 3) we were unable to obtain 2SLS results that converged with unit fixed effects and substituted 4-digit SIC codes instead for both OLS and 2SLS.

The OLS estimates range from -0.937 to -1.086, which we view as broadly similar to the overall coefficient (-1.037).   The 2SLS coefficients are not as precisely estimated but, like the main results reported in the paper, all are smaller in absolute value than the corresponding OLS coefficients. Using the OLS coefficients, the percent explained ranges from 28.5 to 33.3 percent, again not very different from the base specification for the overall regression sample (32.5 percent). Consequently, we conclude that our substantive findings are robust to various sub-samples of the overall regression sample.

Online Appendix Table 1

Distribution by Two-Digit SIC Code: HML Units and Manufacturing Establishments in 1899

SIC	SIC Industry	Percent of HML Units	Mean Value, Δ ln T	Percent of 1899 Establishments
20	Food and Kindred	6.4	-1.244	NA
21	Tobacco	1.3	-1.102	7.3
22	Textile	8.2	-2.748	2.9
23	Apparel	8.3	-1.222	6.2
24	Lumber and Wood	10.2	-2.056	15.9
25	Furniture	7.4	-1.920	1.3
26	Paper	4.0	-1.420	0.9
27	Printing	8.2	-1.817	11.9
28	Chemical	0.5	-1.776	3.7
29	Petroleum and Coal	0	NA	0.2
30	Rubber and Plastic	0	NA	0.1
31	Leather	5.4	-1.796	2.8
32	Stone, Clay, and Glass	5.8	-0.995	5.7
33	Primary Metal	2.5	-2.709	NA
34	Fabricated Metal	10.3	-2.167	NA
35	Industrial Machinery	0.9	-2.411	NA
36	Electric Equipment	0.2	-0.698	0.3
37	Transportation	8.3	-2.226	NA
38	Instruments	0.2	-2.588	0.5

39	Miscellaneous	11.8	-1.392	NA

Notes: Columns 3 and 4 are computed from HML study {United States. Department of Labor., 1899 #1437} and pertain to the regression sample in the paper (see Table 1). There are 551 units in the regression sample. The overall mean of Δ ln T is -1.761 (Table 1). Column 5 is the share of establishments in 1899 in the SIC category, computed from {United States. Bureau of the Census., 1975 #1405, 669-80}. The denominator is total establishments in 1899 (204,734) excluding hand and neighborhood industries {United States. Bureau of the Census., 1975 #1405, 666, series P-1}. NA: 1899 establishment count not available for the SIC code.

Online Appendix Table 2

Manufacturing Establishments in 1904, Distributed by Value of Product

Value of Product:	Total	<$5k	$5-20k	$20-100k	$100-1000k	$1000k+
Establishments	216,180	71,147	72,791	48,096	22,246	1,900
Wage-earners	5,468,383	106,353	419,466	1,027,047	2,515,064	1,400,453
Value of Product ($k)	14,793,903	176,128	751,048	2,129,258	6,109,013	5,628,456
Value Added ($k)	6,293,695	114,781	424,130	1,090,271	2,782,642	1,881,870
Percentage shares						
Establishments	100.0	32.9	33.7	22.2	10.3	0.9
Wage-earners	100.0	1.9	7.7	18.8	46.0	25.6
Value of Product	100.0	1.2	5.1	14.4	41.3	38.0
Value Added	100.0	1.8	6.7	17.3	44.2	29.9

Source: {United States. Bureau of the Census., 1913 #6972, 180}

Online Appendix Table 3

Subsample Estimates of the Coefficient of Mechanization, and Percent Explained: OLS and 2SLS

Row Number	Sub-Sample	N	Mean Value, Mechanized	Mean Value, $\Delta \ln T$	OLS	Percent Explained	2SLS	Percent Explained
1	Base (Table 2))	4,405	0.552	-1.761	-1.037 (0.060)	32.5	-0.749 (0.165)	23.5
2	1:1 Block Links	3,412	0.484	-1.646	-1.086 (0.069)	31.9	-0.744 (0.193)	21.9
3	1:M, H:1, H:M Block Links	993	0.785	-2.157	-0.915 (0.141)	33.3	-0.859 (0.347)	31.3
4	Only 1890s Observations	998	0.460	-1.513	-0.937 (0.107)	28.5	-0.899 (0.365)	27.3
5	Hand Product Better Quality or No Quality Difference	1,621	0.472	-1.630	-1.125 (0.106)	32.6	-0.816 (0.362)	23.7
6	Machine Product of Better Quality	2,784	0.598	-1.837	-0.986 (0.070)	32.1	-0.788 (0.166)	25.7

Source: see Table 1. Notes: Hand quality Better or No Difference: includes units where no opinion on quality differences was expressed by the HML staff. All regressions, except row 4 include unit fixed effects; row 4 substitutes SIC fixed effects (see online Appendix text). Standard errors, shown in parentheses, are clustered at the unit level. Rows 1, 4, 5, and 6 include the full set of block-link dummies (1:1 is the left-out dummy). Row 3 includes block link dummies for H:1 and H:M (M:1 is the excluded dummy).