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ABSTRACT

During the nineteenth century, the US manufacturing sector shifted away from the “hand labor” mode of production, characteristic of artisan shops, to the “machine labor” of the factory. This was the focus of an extremely detailed but extraordinarily complex study by the Commissioner of Labor published in 1899 that has until now defied systematic analysis. Here, we explore the overall productivity gains associated with these changes in production methods and the specific, causal role of inanimate power. Under the machine labor mode, the time necessary to complete production tasks declined by 85 percent, a remarkable gain in labor productivity. We also present OLS and IV estimates of the effects of using inanimate power, such as steam, at the production operation level Our IV is based on the gerunds describing the various production activities. Treating our IV estimates as causal, about one-third of the higher productivity of machine labor is attributed to greater use of inanimate power per se.

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1. Introduction

During the nineteenth century, the manufacturing sector in the United States underwent substantial growth and development, as evidenced by increases in the sector's share of the labor force, in capital intensity, and in labor productivity (Broadberry 1998, Atack, Bateman et al. 2005). Even more fundamentally, the entire character of manufacturing changed. At the start of the century, most manufacturing had taken place in small, dispersed artisan shops where the proprietor, perhaps with a few assistants fashioned goods using simple hand tools. With the exception of a few industries, such as saw and flour milling, virtually nothing in the production process was "mechanized" – in particular, there were no machines using inanimate power that mimicked human actions.[1] However, as the century progressed, manufacturing shifted away from the "hand labor" characteristic of artisan shops to the "machine labor" of the factory where many production tasks were mechanized. Specialized machines were invented that were able to duplicate certain human actions and thus displaced some human labor in the production process. At the same time, these machines created a demand for labor to build, install, maintain, and operate them. Many also required an inanimate source of power. Initially, water provided that power but by the end of the nineteenth century steam power was the dominant motive source.

In this paper, we use a unique and extraordinarily detailed study from the late nineteenth century – the US Department of Labor's 1899 Hand and Machine Labor Study (HML study) which appeared as the Commissioner's 13th Annual Report – to explore the overall gains in

[1] Throughout the paper we are equating "mechanization" with the use of steam or water power (or equivalently, that inanimate power refers to steam or water) We are aware that there were machines in the nineteenth century that were driven by muscle power (e.g., treadle sewing machines) or which used wind power or were driven by horses, or used stored energy (e.g., spring driven clocks). However, use of steam or water power is dominant in the HML study, as it was in industry more generally at the time. We borrow the quote in the title from Giedion (1948).

productivity associated with the transition from hand to machine labor and the specific, causal role of inanimate power. (United States. Department of Labor. 1899). This study was prompted by the observation of radical changes in production methods and the widespread perception of its dramatic impact on labor. Agents for the Department collected information at the production task or "operation" level, as the HML study called it. This information included whether or not the operation used inanimate power, the tool or machine employed, and crucially for us, the amount of time that it took to complete the task. The Department selected 600+ highly specific products for study and collected data from paired "units" (e.g. establishments) making the same product using old-fashioned methods – hand labor – and another using "machine labor.". Agents took great care to track and match the transformation of raw materials to finished product across the two production units such that it was possible to calculate exactly how much time and labor cost were "saved" by machine production in any particular operation that occurred in both types of production; and, overall, for any particular good.

Well known in its time, and later recognized by scholars as a potential gold mine for the unprecedented detail, the HML study nevertheless languished for decades. The structure of the published report – two volumes with hundreds of detailed, highly complex tables, all verso-recto (printed across the left and right pages of the opened book), with many of them occupying several pages – made it a popular source of anecdotal information for specific products, but its complexity overwhelmed statisticians intent on providing summary figures. Carroll D. Wright, US Commissioner of Labor and the study's director, described the dilemma in a magazine article published in 1900. "This report," Wright stated, "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" (Wright 1900). The invention of modern computers, and even the Cliometrics revolution, did nothing to change Wright's lament. Too big and too messy, the HML study remained on the scholarly "to do" list until very recently.

Now, more than a century after publication of the original report, advances in computing and econometrics have finally made it possible to provide the kind of overall summary and detailed analyses that Wright and his team of agents were unable to deliver. Here, we use a digitized version of the HML study to explore two questions. The first is the "aggregation" question that Wright posed—on average, how much more productive was machine labor than hand labor? We frame our answer in terms of labor time saved, the measure of productivity used by the HML staff and the only one for which data were provided. The second is the "question of machinery" to use Wright's phrase—how much of the productivity gain associated with machine labor can be attributed to use of inanimate power *per se*, which we refer to as "mechanization."

We attack these questions in steps. The first, necessary to address either question, is to use the HML's detailed compilation and crosswalk of production tasks across hand and machine labor to define a unit of observation and aggregate the relevant data to this level. We call this unit of observation a production "block," which is a collection of one or more individual production tasks performed under hand or machine labor. Some production blocks are unique to hand labor; these are tasks that cannot be linked to machine labor because they were no longer performed. Other blocks are unique to machine labor; these are tasks that were novel, not previously performed by hand labor. Blocks that are found in both hand and machine labor begin with the same input and finish with the same output—that is to say the stage of completion for the product in blocks that were matched is the same. Our empirical analysis focuses on these common blocks because, by construction, the underlying activities performed in these blocks were the same in both hand and machine labor except that, under machine labor, an inanimately powered machine might be used to accomplish one or more tasks. There are approximately 5,800 such blocks; these comprise the data that we use for our empirical analysis.

To answer the first question, we focus on the difference between machine and hand labor in the average amount of time that it took to complete the blocks in the regression sample. As discussed in section 4, we calculate that, on average, machine labor could perform an equivalent production block a little more than six times quicker than could hand labor, that is, cut production time by about 85 percent. This calculation, we reiterate, though seemingly so simple, was not possible either at the time of the original study or until very recently, given the complexity of the data and the computational difficulties of analyzing them.

To answer the second question, we begin by estimating OLS regressions in which the dependent variable is the difference between machine and hand labor in the log of the time spent in the production block. The relevant independent variables are the differences in two variables, the percentage of tasks in the block using steam power and the percentage using water. We also estimate regressions in which inanimate power use is captured by a combined measure, the difference in percent mechanized (be that by steam or water). If inanimate power made machine labor more productive, we expect the coefficients of these variables to be negative – it took less time to complete the relevant tasks under machine labor compared with hand labor when inanimate power was used in the former compared with the latter. The OLS coefficients, indeed, are negative, relatively large, and statistically significant. Evaluated at the sample means of the differences between machine and hand labor, the OLS coefficients imply that greater use of inanimate power accounts for 20-28 percent of the higher average productivity of machine labor relative to hand labor, depending on the regression specification.

Although meticulously and exhaustively conducted for the time, the HML study was observational, not a randomized control trial. As such, we cannot claim that our OLS results are causal. Instead, to measure the causal effect, we need an instrumental variable for the difference between machine and hand labor in the use of inanimate power at the level of the operation block. Our primary solution makes use of gerunds that appear in text descriptions of the hand labor operations in the relevant block. A gerund is an active English verb that has "-ing" appended at the end, allowing it to function grammatically as a noun – "drilling," for example.

We assign each unique gerund a 1-4 rating from low to high, based on an assessment of whether the underlying production activity could be mechanized ca. 1890, given the economy-wide state of knowledge of science and engineering. Some human activities – for example, those involving broad, repetitive movements of the arm – were understood well enough to be replicated by an inanimately-powered machine using cams, cranks, and so on – think of sewing machines or duplicating lathes. Activities like "dipping" were, in principle, even simpler, being purely mechanical. The treatment of metal to achieve specific properties (like tempering or annealing) could, with experience, be reduced to a matter of the proper amount of time under specific conditions. All such activities lent themselves to mechanization and automation (Giedion 1948, Hounshell 1984). However, there remained activities (especially those requiring fine adjustments, depending on touch, or ones that required mental judgement in the moment) which were impossible to mechanize in the nineteenth century – like "fitting," "inspecting" and "finishing" each require a judgment call – an <u>opinion</u> that could only be rendered by a human. Such activities still pose a technological challenge today.

We collapse the four ranks into a 0 -1 dummy, in which “one” represents the highest rank (= 4). This dummy is aggregated to the block where, in percent form, it becomes our base instrumental variable. Because we have a single instrument, we can only have one endogenous variable. For this purpose, we use the difference between machine and hand labor in the mechanization dummy (=1 if steam or waterpower is used) previously described.

The first stage regression is successful, finding a strong, positive, and highly significant relationship between our instrument and the difference in mechanization – if, by the end of the nineteenth century, the hand activity could be mechanized, the greater the likelihood that it was in machine labor, relative to hand labor. The 2SLS coefficient is negative, highly significant, and slightly larger in absolute value than the coefficient from the OLS specification. Using the IV coefficients and again evaluating at the sample means, we attribute 30-33 percent, of the higher productivity of machine labor to greater use of inanimate power. This is our main finding. However, while clearly numerically and economically significant, the greater use of inanimate power under machine labor does not account for the majority of its productivity advantage of over hand labor.

In Section 7 we conduct an extensive series of robustness checks of our main finding on the explanatory power of mechanization. While there is some variation in the magnitude of the coefficients and their associated explanatory power, in all cases we find that mechanization accounts for less than half, and usually much less, of the higher average productivity of machine labor.

The principal contributions of this paper are, first, to resuscitate an extraordinary and long-neglected data source on manufacturing processes in the late nineteenth century United States and, second, to use the data to answer questions posed at the time which the study was not able to answer regarding the overall productivity gains of machine labor and the role played by inanimate power *per se*. In the concluding section, we discuss factors other than mechanization that may have contributed to these productivity gains, such an increase in the division of labor.

2. Inanimate Power and the Development of Manufacturing in Nineteenth Century America

Scholars of historical industrialization have long studied the sources of labor productivity growth in manufacturing during the so-called "First Industrial Revolution." These sources include, among others, pure total factor productivity growth (learning-by-doing), increases in capital per worker, and an increased division of labor reflected in growth in average establishment size. Although these various sources can be listed and described independently, in reality they are interrelated. New capital goods embody new technology, such as the steam engine, and the diffusion of new technology will therefore be correlated with changes in capital intensity. A new technology may also prompt changes in organization of work on the shop floor and the speed with which a particular part is produced, leading to changes in the scale of production (see, for example, Devine 1983, Hounshell 1984). Indeed, aspects of the HML study resemble the time-and-motion studies that would become associated with Frederick Winslow Taylor (Taylor 1911, Taylor 1911) and other advocates of "scientific management" who became prominent early in the twentieth century (for example, Gilbreth and Kent 1911, Gantt 1913, Gantt 1919).

Central to the narrative of industrialization in nineteenth century America has been the diffusion of water and steam power (Temin 1966, Hunter 1979, Atack, Bateman et al. 1980, Hunter 1985). Much of the previous literature approaches the issue from the cost side – that is, reductions in the real cost of inanimate power prompted establishments to substitute it for hand or animal power. This shift was initially towards waterpower and later to steam power, with the shift to steam being especially important. Steam was inherently more reliable than water, because it was not so dependent on nature; where "nature" refers to the weather and topography. By contrast, steam was "footloose"—a steam-powered establishment could locate anywhere that fuel—especially and increasingly coal—was deliverable (Chandler 1977, Kim 2005). In particular, production could be located and concentrated in cities, near thicker labor and product markets. Moreover, steam power was also scalable – an establishment could add more steam engines of a given size or it could pair a larger size engine with multiple boilers – whereas the marginal cost of water power eventually rose steeply due to the difficulties and cost of expanding capacity at any given site (Hunter 1985). Indeed, many water-powered establishments had to install steam engines as their power demands grew.

The evidence for the United States suggests that the pace of diffusion of inanimate power was steady over the nineteenth century, especially if one adjusts for establishment size as measured by the number of workers. According to Atack, Bateman, and Margo (2008, p. 189) around 44 percent of workers in manufacturing were employed in establishments using inanimate power, mostly water (80 percent) in 1850. The shift towards steam accelerated during the second half of the nineteenth century, particularly in larger establishments as the cost of steam power plummeted (Atack 1979, Atack, Bateman et al. 2008).

Although scholars have studied the factors associated with the diffusion of inanimate power, there has been relatively little attention paid to measuring the impact of inanimate power on labor productivity directly. The closest paper to the present one is by Atack, Bateman, and Margo (2008). They used establishment level data from the 1850-1880 manuscript Censuses of Manufactures (CoM), which provide information on outputs and inputs, including use of machinery powered by steam and water. In their analysis, output is real value added per worker, which is regressed on dummies for steam and waterpower, and interactions between power and establishment size. Their basic finding is both water and steam power significantly increased labor productivity. However, whereas the effect of waterpower was largely independent of establishment size, the effect of steam power was greater overall than waterpower, and especially so in larger rather than in smaller establishments.[2] There are several differences between that analysis and ours here. First, the data are obviously very different – in particular, the measure of output is value added per worker in the CoM versus the time associated with making a given quantity of a specific good in the HML study. Second, the CoM data contain no information whatsoever on production operations; if an establishment reported using steam power, it is simply unknown if it did so for most production operations, or only a few—and the HML study reveals wide variations in the number of task that were powered from product to product. Third, while Atack, Bateman, and Margo's regression specification is highly flexible with extensive controls, for example, for establishment size, industry, and geography, no attempt is made to address the endogeneity of power use. Consequently, one cannot claim that the effects in their

[2] Appendix A (see also footnote 8) reports on an accounting exercise using the CoM data to apportion the role of mechanization in labor productivity in manufacturing from 1850 to 1880.

paper are causal. By contrast, as discussed later in this paper, we develop an instrument variable strategy using text information in the HML study to address endogeneity bias.

3. The Hand and Machine Labor Study

In 1894, Congress requested that the US Commissioner of Labor investigate the impact of the on-going transition from "hand" to "machine" labor in commodity production (United States. Congress 1894). Although the title of the resultant study was "Hand and Machine Labor," Commissioner of Labor Carroll D. Wright cautioned in his introductory remarks that the words were not used in their strictest sense, but rather to broadly 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." Similarly, some tasks in machine production continued to be performed by hand using these same simple tools, including for 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 to the production process (United States. Department of Labor. 1899, p. 11). The report took the Department more than five years to assemble and publish in the form of a complex set of tables prefaced by some introductory text and discussion, spreading across two volumes and almost 1,600 pages. We have digitized the data tables and converted them into a format that makes them amenable to standard econometric analysis and are in the process of encoding various qualitative and textual data (Gentzkow, Kelly et al. 2019). We have also used various words in the discussions to characterize different aspects of the products, like their quality.

The tables describe in great detail each step in the production process for paired establishments using these different production methods to make a highly specific and carefully defined product.[3] In composing these tables, trained agents collected data either through direct observation or from written records, usually for two establishments using hand methods and two using machine methods. The data were then scrutinized and compared for inconsistencies, missing data, and inaccuracies, with agents following up when necessary to resolve ambiguities, before selecting the "the better and more complete one" of each mode of production of the specific product for presentation (United States. Department of Labor. 1899, v1, p. 13). 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. We discuss this further below.

For machine production, the vast majority of the observations pertain to activities conducted in the mid-to-late 1890s (i.e. between 1894 and 1898). For a few products, the HML staff were unable to find matching hand production from the same year nearby, presumably because the relevant establishments were no longer in existence—itself *prima facie* evidence of competitive market forces between different modes of production. In such cases, the agents

[3] For example, "men's medium grade, calf, welt, lace shoes, single soles, soft box toes" (Unit 71) where 7 adjectives are used to describe the product. Some descriptions are simpler: "cane-seat maple chairs, Grecian pattern" (unit 326) or "No 7 horseshoe nails, 125 per pound" (unit 472). In just a few cases, there were minor variations in the product description between hand and machine-made products, for example, Unit 135 "Velvet carpet." In the handmade carpet, there were 780 worsted ends, 522 linen ends, and 790 cotton ends whereas the machine-made product had 216 worsted ends, 432 cotton ends, and 648 jute ends (United States. Department of Labor. 1899).

assiduously sought out historical records or, in a handful of cases, located hand production establishments overseas that they deemed similar to those that no longer survived in the United States. All machine production data, however, were taken from US establishments.

In Volume One, the following was reported for matched pairs of establishments 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 Volume Two, the following information was reported for each mode of producing the product: a brief description of the operation in the order in which it was performed; a list of tools or machines used in the operation; the type of motive power if used; the number of workers assigned to that operation; worker characteristics, such as their gender and occupation title; the time spent on the task; and the labor cost of each employee engaged in the operation along with any miscellaneous comments.

For example, the machine production of key-wound watch movements (unit 204) was broken down into 881 operations. Operations were listed in their production order under both hand and machine production and the tasks themselves were linked across the two methods from machine production back to hand production, sub-dividing machine tasks where and if necessary and creating composite hand tasks when there was no analog between the two such that the nature of the output at each stage was the same. We elaborate upon this below. In the hand production method for key-wound watch movements, for example, 347 tasks are identified—considerably fewer than in machine production of the same good. Most importantly for this paper, we know the length of time it took for each step to be completed and the source of power employed.

Overall, there are 672 paired units in the HML study of which 27 in agriculture, 10 in mining and quarrying, and 9 in transportation, leaving 626 paired units producing manufactures. It is upon these manufactures which we focus. Further, we drop 15 units where the hand production establishment was located outside the United States, leaving 611 (domestic) units matched pairs of manufacturing operations from which we construct the sample of production operations for our empirical analysis.

Before turning to our analysis and findings, we highlight five limitations of the HML data. First, although a wide range of goods and industries were 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 the production of the product (and its supervision). No information was collected on capital in forms other than equipment. Consequently, any analysis of productivity, including ours, must rely on the sole measure provided by the study—the amount of time that it took to complete an operation. 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.[4] Fourth, while in an ideal study design, literally none of the hand labor operations would have used inanimate power, this ideal was not achieved – although as will be seen below, the fraction of hand operations that made use of steam or water was

[4] Nor can the information not reported in the published volumes be recovered because a Joint Select Committee of Congress approved the destruction of the underlying records on March 12, 1906 (U.S. Congress. House. 1906). The National Archives Record Group 257 does, however, retain a blank copy of the survey form that the agents used.

extremely low. Finally, 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 in the rescaled production may not reflect how producers, especially hand producers, would have operated at that specific (usually substantially larger) scale under more realistic time-cost considerations.

4. Operation Blocks and Block Links

The fundamental objective of the HML study was to enable comparisons to be made between hand and machine labor, either at the product (what the HML study termed the "unit") level or at the operation level (that is, production activities) where both the input to and output from the process was the same. To do this, the HML staff took a series of steps. First, they ordered the machine operations within each unit from start to finish, giving each a consecutive number, which was listed in a column labelled "Operation number." For example, the production of a 14-tooth steel garden rake by machine labor (unit #30, volume 2, p. 480) took 16 operations; the first, operation #1, was "cutting iron into pieces" using shears while the last, operation #16, was "inspecting rakes and overseeing the establishment." The staff did the same for the hand labor operations, except that in the "Operation number" column, there could be letters, numbers, or combinations of both where the numbers matched up with those from machine production. It is these entries in the hand labor "Operation number" column that provide a "crosswalk" between the hand and machine operations.

To understand this better, it is useful to introduce the concepts of an operation "block" and operation "block link," although the HML study did not actually use these terms. An operation block is a collection of operations of size H (for hand labor) or M (for machine labor), where H and M are integers equal to or greater than one. A "block link" is a mapping between the hand and machine blocks. Some hand operations could not be matched to any machine operations because the operations were archaic or "old" – that is, was no longer performed under machine labor. We refer to these as 1:0 block links. Analogously, some machine blocks could not be matched to any hand blocks because the machine operations were novel – that is, were not performed under hand labor. We call these 0:1 block links. All other block links are designated H:M, where H and M are both equal to, or greater than, one although not necessarily equal to each other.

The H:M block links are key to our analysis, because by differencing between hand and machine labor within these links we eliminate a "block-product" fixed effect (see below). That is, when we difference within such links, we are making comparisons between hand and machine labor such that the underlying production activities are held constant and the product at the conclusion of that stage or activity was the same, except for the possibility that the machine operations might be mechanized to a greater extent than the hand operations; hence, by differencing, we get rid of the fixed effect. Note, however, that, we cannot make the same argument for the "old" (1:0) or "new" (0:1) links because, by definition, the operation content for these links did not overlap.[5] As such, the 1:0 and 0:1 links are excluded from our regression analysis. Overall, there are 5,777 block links in our regression sample.

[5] We could aggregate the 1:0 and 0:1 blocks to the unit level, and then difference between labor types. However, these differences would be perfectly correlated with the product fixed effects that we include in the regression and thus would be uninformative.

Table 1 shows the distribution of 1:0, 0:1, and most common H:M links from the perspective of hand labor (Panel A) or machine labor (Panel B). In each panel, we also report the mean fraction using steam, water, or "mechanized" (that is, used steam and/or water). The overall means are equally weighted averages across the producing units. For hand labor, there were a total of 6,208 operation blocks. Of these, 431, or just 6.9 percent, were 1:0 links, that is, hand operations that were not practiced under machine labor.

For machine labor, there were a total of 10,017 blocks – significantly more than the number of hand labor blocks. This difference primarily reflects a large number of machine operations – 4,240 or 42.3 percent – that were 0:1 links that is, had no counterpart under hand labor (such as tending to the power source).[6] On average, 56 percent of the machine blocks that overlapped with the hand blocks (labelled "regression sample" in Table 1) were mechanized, the vast majority of which (96 percent) used steam power alone. Interestingly, the degree of mechanization was greater for those blocks in which some subdivision of operations took place in the transition from hand to machine labor (1:M blocks) or, alternatively, consolidation (H:1). In our main empirical analysis, we will pool the data across the relevant block links but include block link dummies as a control. In our robustness checks, we will allow the effects of power to differ between the 1:1 and non-1:1 block links.

[6] Collectively the share of total time devoted to 0:1 links (15.8 percent) among machine labor blocks exceeded the share of time devoted to 1:0 links among hand labor blocks; see Atack, and Margo, and Rhode (2019, Table 1, p. 59).

5. Empirical Analysis

We use the block level data for operations as described in the previous section, as the basis for our analysis of the effects of mechanization on labor productivity. To derive our base regression specification, we start with the following equation:

$$\text{Ln } T(i,j,k) = \alpha(i,k) + \beta(j,k) + \gamma(i,j) + \lambda^*(\text{Steam} = 1|i,j,k) + \theta^*(\text{Water} = 1|i,j,k) + \varepsilon(i,j,k)$$

The index i refers to the block; the index j, to the type of labor (j = hand or machine); and the index k, to the specific product, what the HML staff called the "unit" (in our case, k = 1,…,611). Ln T(i,j,k) is the log of the amount of time that it takes to complete the operation block for labor type j in unit k; and ε is the error term.

The parameter α(i, k) is a block product fixed effect; that is, it is indexed for block 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 blocks might take proportionately longer than others for a given product, these relative differences are the same under both machine and hand labor. In effect, the block-product fixed effects control for the underlying mix of production tasks in the block, which is specific to the product, but not the labor type. Because α is not dependent on labor type j, the fixed effects disappear when we difference the data between machine and hand labor (see below).

The parameter β(j,k) is a labor type-product fixed effect; it is indexed by j and k but not by i. When we difference between hand and machine labor this results in a set of product fixed effects, $\Delta\ \beta$. The inclusion of the $\Delta\beta$ fixed effects follows directly from the underlying design of the HML study, which sought to compare the productivity of hand and machine labor, in production units that were in close geographic and temporal proximity, for literally the same good. Because the study was conducted after the transition to machine labor had already commenced, it was relatively straightforward to identify machine labor units with data from the 1890s and located in the "principal geographic centers" where production of the specific goods took place. Agents had more difficulty in collecting the hand labor data, and in some cases had to rely on information from earlier in the century or, in a few cases, from overseas. We do not know the locations of the units within the US because of the department's efforts to anonymize the data, but foreign observations are identified and, as previously noted, excluded from our analysis.

What did the HML study mean by the "same" good? In practice, agents looked for close similarities in the 4F's – physical form, function, fit and finish – durability, ease of repair, and other indicators of quality. Form and function were easy to discern – a circular saw blade is a circular saw blade, and so on – as were fit and finish. Other aspects of quality could be debated; to their everlasting credit, the DOL agents recognized this and discussed quality differences in the text accompanying the study tables. We have extracted the relevant text and classified the data into three quality groups: goods for which the machine product was deemed "better", goods for which the hand product was better, and goods for which there was no perceived difference. In the regression sample studied in this paper, 60 percent of the machine-made goods were deemed to be of superior quality, 34 percent were classified as no difference in quality, and the hand product was claimed to be superior in just six percent of the goods.

The upshot of the above discussion is that it is crucial, on conceptual grounds, to include product fixed effects in the differenced specification of the regression. These fixed effects are perfectly correlated with fixed features of the data, such as the location of the units; the year to which the data pertain; and quality differences. While we are not interested in this paper in the coefficients of the fixed effects per se, our robustness analysis (section 6) explores whether, for example, differences in product quality or whether the data come from the 1890s or some earlier period affect any of our substantive conclusions. Lastly, the parameter $\gamma(i,j)$ is a block-labor type fixed effect; when we difference the data this results in a set of block-link type fixed effects, $\Delta \gamma$. These dummies allow for the possibility that the productivity gains associated with the transition to machine labor varied across block link types, after controlled for use of inanimate power.

Our main interest is in the parameters λ and θ which are the log effects of steam and water. If use of steam or proportionately reduces the amount of time that it took to complete a block, then $\lambda < 0$ and $\theta < 0$.

To estimate this regression, we need to compute differences between machine and hand labor within units for all variables measured at the block level. For the 1:1 links, we can do this directly because for every machine operation there is an exact counterpart operation under hand labor. For the other block links, it is necessary to compute averages or totals at the block level before taking the differences. In the case of the motive power variables on the right-hand side, this involves computing the proportion of operations in the block that use a particular power source, so we refer to these variables, for example, as “Fraction Steam” or “Fraction Water” as appropriate.

After differencing, we have:

$$\Delta \ln T = \Delta\beta + \Delta\,\gamma + \lambda^{*}\,\Delta\,(\text{Steam} = 1) + \theta^{*}\,\Delta\,(\text{Water} = 1) + \Delta\,\varepsilon$$

Our first approach is to estimate this regression using OLS. To interpret the power coefficients as casual effects in this specification, we would have to assume that changes in inanimate power use at the block link level were uncorrelated with the error term, $\Delta\,\varepsilon$. Below we relax this assumption when we develop our instrumental variable strategy.

Column 1 of Panel A in Table 2 reports the equation as specified above along with those from alternative right-hand side specifications. Instead of reporting on the effects of steam and water separately, we can collapse the power variables, Δ Fraction Steam and Δ Fraction Water, into a single variable, Δ Fraction Mechanized. This variant, reported in column 3 of Panel A, is used as our baseline when we turn to the IV analysis below. Substantively, however, the change to a joint single power variable has very little impact because the vast majority of changes in power in the HLMS involve the adoption of steam. One can also include the log of the time to complete the hand labor block as a right-hand side variable. This specification is analogous to including a lagged dependent variable in a panel regression. As such, we anticipate that the coefficient of this "lagged" variable will likely be negative, and that the magnitude of the power coefficients will be reduced. The effects of including this variable are reported in columns 2 and 4 of Panel A.

The power coefficients are uniformly negative and highly significant, indicating that mechanization reduced the amount of time to complete the operation block and, therefore, raised labor productivity. The marginal effect of steam in this regard was much larger than water, indicating the superiority of steam as a source of power. Collapsing the power dummies into a single mechanization variable only slightly reduces the magnitude of the power coefficient as one might expect because most inanimate power in machine labor involved steam. Including the log of the time spent in the hand task reduces the magnitude of the power coefficients, although they remain relatively large and statistically significant.

In Panel B of Table 2 we use the OLS coefficients and the mean values to compute the "percent explained" of the average productivity difference between hand and machine labor by mechanization. As shown in Panel B, the average productivity gain, in log terms, was -1.90. If we take the exponent, we get exp [-1.90] = 0.15, that is to say the average machine block took just 15 percent of the time to complete that its counterpart under hand labor took – that is, machine labor was 6-7 times as productive as hand labor, using the HML study metric. For tasks that were common to both machine and hand production, this answers Wright's first question.[7]

One possible answer to Wright's second question of how much of this impressive productivity gain can be attributed to mechanization appears in the bottom two rows of Panel B. In the penultimate row, we show the predicted change in the dependent variable based on the regression coefficients applied to the mean values of the mechanization variables. In the last row, we divide the predicted change by the mean value of the dependent variable. According to this calculation, between 20 and 28 percent of the gains in productivity can be attributed to mechanization.[8]

[7] This slightly overstates the productivity advantage of inanimate power because the HML study recorded the labor time of workers "furnishing power" (e.g. operating the steam engine) as a new operation (0:1 block link). However, these activities took up only a tiny fraction of the total time of new activities (the mean time share was 2.6 percent), indicating that any overstatement of the productivity gains is minimal.

[8] As previously mentioned, Atack, Bateman, and Margo (2008) use nineteenth century CoM data to explore the impact of inanimate power on labor productivity using OLS regression. They also present a "percent explained" calculation (p. 195) but this holds capital per worker constant and allows for interactions with establishment size,

Our OLS estimates suggest that mechanization clearly was a quantitatively important factor behind the greater productivity of machine labor, but by itself does not account for close to a majority of the gains in productivity. However, the HML did not conduct a randomized control trial in which use of inanimate power was experimentally assigned. Rather, use of inanimate power was endogenous. To correct for endogeneity and recover the causal effect of mechanization, we need an instrumental variable.

6. Instrumental Variable Analysis: Gerunds

In this section we present our instrumental variable strategy for measuring the casual effect of mechanization. This strategy makes use of text descriptions of production operations. The descriptions 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.

We begin by first extracting all occurrences of gerunds appearing in the "Work Done" columns for both hand and machine labor. A gerund is an English verb to which "-ing" has been appended and functions as a noun in grammatical context. For example, consider the gerund "reading," derived from the verb "read". In the sentence, "I enjoy reading," "reading" is a

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which is not the case for our calculation. In the Appendix, we use the sample analyzed by Atack, Bateman, and Margo to estimate an OLS regression that does not include capital per worker as a control and excludes the relevant interaction effect. As discussed in Appendix A, in our preferred HML specification for comparison purposes, the percent explained of the growth in labor productivity between 1850 and 1880 due to increases in inanimate power is slightly more than 30 percent in the CoM, compared with 28 percent in the HML study. Thus while the data and analysis are very different, the explanatory power is similar. Again, however, we stress that neither the analysis in this section nor in Atack, Bateman, and Margo (2008) is causal.

gerund, a noun that describes an action. Gerunds are active. All gerunds end in "-ing" but not all words ending in "-ing" are gerunds. For example, in the sentence "I am reading a book," "reading" is not a gerund, but rather the present participle.

Our extraction produces a list of approximately 23,000 occurrences of gerunds. Some of these are used frequently, such as "cutting," which appears 14 times in the descriptions of the work performed in the hand production of men's medium grade shoes (Unit 71). The same term appears in 22 of the 173 distinct operations for the machine production of the same product. Indeed, cutting was the single most common gerund and was used in describing approximately 2,400 tasks, involving organic materials like leather, paper and textiles as well as metals. Some gerunds are very similar to one another such as "counterboring" and "countersinking," "cleaning" and "cleansing," and "joining" and "jointing."[9] Despite similarities, however, each unique gerund, a little more than 600 in total, is treated as a different production activity.[10]

The text descriptions are very brief. For example, in the "Work Done" column for hand operations in unit #28, in which the product was a pitchfork with 12-inch tines, the first operation is "Cutting out blanks for forks". The gerund here is "cutting" and observe that it is literally the first word in the description. In fact, the first word in a description is almost always a gerund, which describes the principal action taking place in the operation, so we call this the "principal gerund". This principal gerund is the only gerund in most descriptions, although there are rare instances in which up to five gerunds appear. However, additional gerunds, if present, are

[9]There is a small distinction between counterboring and countersinking in that a bore is straight-sided whereas the sink is tapered. In each case, though the objective is to let a screw or bolt sit at or below the surface.
[10] We also paid special attention to certain gerunds—for example, "striping" and "stripping," which look very similar to one another but are not—the one we think of as adding material; the other, of removing material. In these cases, the original text was carefully checked to verify that they were not a product of mistaken transcription or a result of type-setting or spelling errors in the assembly of the text. We concluded that they were not.

always closely related to the main activity described by the principal gerund – the principal gerund is, in other words, the text equivalent of a sufficient statistic.

We use the principal gerund to construct an instrumental variable that measures the technical feasibility of mechanization by the end of the nineteenth century. Some activities — like cutting, drilling, boring and turning—achieved technical feasibility much earlier using successful devices like Wilkinson's boring machine (patented 1774) or Blanchard's lathe (patented 1819). Other activities still defy mechanization today as they involve too much idiosyncratic decision-making or complexity, such as "overseeing," "examining," "finishing," "inspecting," "assembling," and "repairing," or require attention and judgment—like "assisting," "examining," "fitting," "gauging." and "beaming" warp.[11] The principal gerunds used in the construction of the instrument are those that occur in the text descriptions of hand labor tasks represented in the block links – 1:1, 1:M, N:1, and N:M – making up the regression sample.

Specifically, each principal gerund is ranked based on an expert assessment. The assessment was performed by one member of our research team (Atack) who was given the list of gerunds and asked to rank them without consulting the HML study. The ranking is from one – little or no technical feasibility of mechanization – to four – high technical feasibility of mechanization. For example, activities like annealing, boring, drilling, or turning are viewed as involving purely technical issues that had already been solved and were ranked high. Some of these issues were mechanical, as in boring or drilling and involved experiential or experimental decisions like determining the "right" metal for the bit and best speed for the parts being worked.

[11] "Beaming warp" refers to the tensioning of warps on a weaving frame which have to be tensioned "just-so"—tightly but not so tightly that they will break if subjected to a little extra pressure from say the weft. This will vary with humidity, the type (and possibly the batch) of thread used for the warp and relied upon operator experience and expertise.

Activities like annealing and tempering, however, once the metallurgical issues were resolved, were simply time dependent. Other tasks, like grinding and trimming, could be mechanized but may have required some product redesign so the item would register properly or required some minimal active oversight of the operation. These activities were ranked medium-high (rank = 3). Activities like "fitting," "forging," "gluing," and "cementing" required (and often still require) more idiosyncratic judgement and were assigned a medium-low ranking (rank = 2). Fit, for example, is often determined by how much resistance is involved in putting the parts together and how much "wiggle" remains once they are in place, issues that are difficult to teach (except by experience) or measure. Lastly, there were those activities, like "assisting," "overseeing," "examining," "finishing," and "assembling" where human judgement was essential because the requirements differ from case to case. These have a low potential for mechanization (rank = 1).

This four-way classification was then used to construct a dummy variable, MECHABLE, assigned a value of 1 if and only if the potential for mechanization had been judged "high," (rank = 4) otherwise zero. MECHABLE is constructed for the principal gerund(s) appearing in the hand operation text descriptions and then aggregated to the appropriate block level, producing the variable "Fraction MECHABLE". If the block link is 1:1 or 1:M, there will be one principal gerund in the hand labor block, so "Fraction MECHABLE" will be 0 or 1. If the block link is N:1 or N:M, "Fraction MECHABLE" will be 0, 1 or a number in between (e.g. 0.33). Because we only have one instrument, we can only have one endogenous variable, which (from the previous section) is Δ (Fraction Mechanized), the difference in mechanization between hand and machine labor in the block link. Our first stage, therefore, is a regression of Δ (Fraction Mechanized), the endogenous variable, on "Fraction MECHABLE," the instrument. This regression also includes the product and block type fixed effects.

As shown in Table 3, the first stage works well – the coefficient is positive and highly significant, indicating that if, on average, the activities in a hand labor block were judged as having a high potential to be mechanized, a higher than average share of the tasks in the block were, in fact, mechanized under machine labor. The 2SLS coefficients (also shown in Table 3) are negative, highly significant, and slighter larger in magnitude than the OLS coefficients. One possible explanation for the apparent downward bias in the OLS results is unobserved worker quality – specifically, that the machine worker was less able than the hand worker, doing the same operation. Correcting for this bias would increase the magnitude of the 2SLS coefficient relative to its OLS counterpart, which is what we observe.

We use the 2SLS coefficients reported in Table 3 in conjunction with the mean values of the dependent variable and the change in fraction mechanized to compute the percent explained of the change in labor productivity. Because the 2SLS coefficients are a bit larger in magnitude, we now attribute somewhat more of the change in labor productivity to mechanization, ranging between 31 and 33 percent depending on the regression specification. As before, therefore, mechanization was clearly important to raising labor productivity in manufacturing but on its own it still does not account for the majority of the gap in productivity between hand and machine labor.

Because our IV is based on expert assessment, it is natural to be suspicious of it because such assessments can vary across experts. For example, one expert might assign a ranking of "4" to an activity while another might assign a "3". In the next section we test the robustness of our IV results by, first, using a broader definition of MECHABLE (=1 if the rank is 3 or 4, 0 otherwise) which is less dependent, by construction, on which activities are given the highest rank. We also report results using a "Leave-One-Out" instrument that makes use of the information on gerunds but which that does not require expert assessment at all. In both cases, the substantive findings remain unchanged.

7. Robustness Checks

In this section we conduct a number of robustness checks. Our main goal is to determine if the 2SLS coefficients remain negative and significant and if the percent explained by mechanization remains fairly consistent with our base analysis and, in particular, is it always less than a majority (50 percent) of the difference in average productivity between hand and machine labor. We report the 2SLS coefficients from the robustness checks in Table 4.

We begin with two robustness checks involving our instrument. In the first check, we alter the instrument so that it equals one if the rank is either three – indicating a fairly high likelihood that the process could be successfully mechanized – or four, instead of just four. We call this version of the instrument, MECHBROAD. We then aggregate this to the block level, estimate the first stage, and then the second stage. As can be seen, the 2SLS coefficient of percent mechanized is negative and statistically significant, and the percent explained is about the same as when we use our base instrument.

Next, we continue to make use of the information on gerunds, but instead of expert assessment of the likelihood of mechanization, we construct a "leave-one-out" or "jackknife" instrument that makes use of actual mechanization in machine production (Angrist, Imbens et al. 1999). Any expert assessment, ranking, no matter how well informed, is still subjective and could be systematically biased; the "leave-one-out" instrument, which uses actual mechanization, guards against this. The construction of the leave-one-out instrument is described in Appendix B. As can be seen, using this instrument yields slightly larger 2SLS coefficients, but the percent explained is very similar to our original instrument.

Having established the robustness of our instrumental variable strategy, we explore other "cuts" of the sample to see if our main findings on explanatory power hold up. For example, our base analyses treat each block link observation equally. An alternative is to weight observations by the total number of operations in that block – for example, if an observation is a 1:M block, the weight is 1 + M. As can be seen in Table 4, weighting in this manner reduces the coefficient magnitudes very slightly, but these remain highly negative and significant.

In Tables 2 and 3 we pooled the data across block link types to estimate the OLS and IV regressions. Some pooling is necessary because the sample sizes are too small to perform the estimation separately by block type. However, we can split the analysis between the 1:1 and non-1:1 block links and see if the relevant coefficients differ across the types. As can be seen in Table 4, we find some evidence that the power coefficients differed in size between the 1:1 and non-1:1 links, but any such difference largely disappears once we control for the log of time spent in the hand labor block as a right hand side variable.

We noticed that a relatively large fraction (14 percent) of observations in the regression sample come from the small number (five) of units. These all made watches or clocks (units 201-205) and were part of the famed "American System" of manufactures, which emphasized mechanization, division of labor, and widespread use of interchangeable parts (Hounshell 1984, pp. 51-61). It is reasonable, therefore, to wonder if our base results primarily reflect the impact of this industry. However, dropping watches and clocks from the sample, if anything, strengthens the effects of mechanization.

Earlier in the paper we indicated that the HML staff tried to collect data from hand and machine labor units that were in close physical and temporal proximity and, as much as possible, for the same quality of good. To the extent that this strategy failed, whatever differences of this type existed are controlled for, on average, by including product fixed effects in the regression specification. However, it is possible that the treatment effect of mechanization differed, for example, if the machine labor product was considered superior in quality to that produced by hand, or if we restrict the analysis to goods for which the agents were able to obtain contemporaneous observations. In all of these checks, we continue to find a negative, and statistically significant 2SLS coefficient, whether or not we control for the log of the time spent in the hand labor block. In no case, moreover, does the explanatory power of mechanization rise as high as 50 percent and the largest effect occurs for products in which the machine product was deemed superior in quality.

Our regression specification treats each production block as an independent observation. However, it is possible to imagine spillover effects of machine production—the use of mechanized equipment in one operation might, down the line, reduce the amount of time needed in a subsequent hand labor operation. Remarkably, the HML staff anticipated this objection and mentioned it when deemed relevant in Volume Two. For example, in the text pertaining to unit #150 in machine production, which made carriages and wagons: the text notes "the previous operations on machines were done so perfectly that but little was left to be done by hand whereas in the hand work the forging and welding were done so roughly as to leave a considerable amount of work … of leveling and truing"). We have extracted such text and identified the relevant units. If these are then excluded from the regression sample, the percent explained is essentially unchanged.

8. Discussion and Concluding Remarks

It has long been an article of faith among economic historians that the use of inanimate power was a critical factor in the secular increase in labor productivity in American manufacturing. We have used a unique and extraordinarily detailed late nineteenth century data set, the Department of Labor's *Hand and Machine Labor* study, to analyze the effects of mechanization. Specifically, we present OLS and IV estimates of the "treatment effects" of mechanization at the production operation level. Treating our IV estimates as causal, then around one third of the higher degree of labor productivity in machine production is attributed to mechanization *per se*.

The vast majority of instances of mechanization in the HML study pertain to steam power and thus our findings broadly support modern scholars, both economic historians and economists, who argue that the steam engine was the first great "general purpose technology" (GPT), and that historical automation, particularly in its productivity effects, bears many similarities to automation today. At the same time, mechanization, by itself, cannot account for the majority between hand and machine labor in the HML study.

If mechanization alone does not explain the higher level of machine labor productivity, what other factors might? One likely factor is an enhanced division of labor. Ever since Adam Smith, economists have known that division of labor, by itself, could raise labor productivity, as workers are allocated to production tasks based on their comparative advantage and by saving on the set-up costs of shifting tools between tasks.

To incorporate the division of labor directly into the empirical analysis in this paper, we would need to be able to measure it at the level of the operation block. This would be feasible if we could recover the full assignment of the individual workers to production operations which, in turn, would be straightforward to do if the names of the workers had been reported in the published study. Names were collected in the original survey but, as we noted earlier in the paper, these were not published and the original forms with this information were destroyed (U.S. Congress. House. 1906).

While we cannot measure the division of labor at the operation block level, we can measure it at the production unit level. We explored the ramifications of this in an earlier paper (Atack, Margo et al. 2017) in two ways. First, we showed that, on average the division of labor was far higher in machine labor units than hand labor units. Second, we used OLS to estimate a regression equation similar to the base specification in this paper in which the dependent variable was the logarithm of the time taken to produce the product in its entirety, not just a specific operation block. In that regression, there were two observations per product, one pertaining to hand labor and the other to machine labor. In our base specification in the earlier paper, we included a dummy variable for hand labor, product fixed effects, and a log linear term in the number of workers. The coefficient of the dummy variable for hand labor is positive and highly significant, implying that hand production took longer over all to construct the finished product – that is, hand labor was less productive, on average. The coefficient of the log linear term in the number of workers, however, is negative, implying that larger establishments (in terms of the number of workers) were more productive.

Next, at the production unit level, we construct two measures of the average division of labor: the logarithm of the total number of operations performed in making the product, and the proportion of operations performed by the average worker. When we include these variables in the regression, their coefficients imply that an increase in the division of labor is associated with higher labor productivity. Moreover, including these variables eliminates the negative coefficient on the log-linear term in the number of workers. This is consistent with division of labor being an additional factor behind the productivity advantage of machine labor.

We do not at present have an instrumental variable for the unit-level division of labor measures and so caution should be exercised before giving the results just described a causal interpretation. That said, it seems extremely unlikely that mechanization-cum-division of labor can fully explain the productivity advantage of machine labor. This leaves open several other possibilities, none of which (unfortunately) can be explored with the HLM data. study.

For example, it is widely believed that the shift towards larger scale production led to innovations in managerial techniques (Chandler 1977). Although we know of no direct causal evidence, there is much in the way of anecdotal evidence that the innovations raised productivity on the shop floor. Advances in indoor lighting and climate control made factories more comfortable places to work, which could have raised labor productivity. Atack, Bateman, and Margo (2003) argue that decreases in the length of the working day and a more regular work year, both of which were concentrated in larger establishments, led to gains in productive efficiency. Improvements in financial markets and in access to transportation may have led to increases in labor productivity that favored machine labor over hand labor (Hilt 2015, Hornbeck and Rotemberg 2019).

9. Text Tables

Table 1: Block Links, Hand and Machine Labor Study

Panel A: Hand Labor

Block Link	Number of Links	Fraction Steam	Fraction Water	Fraction Mechanized
1:0	431	0.009	0.007	0.016
1:1	4,275	0.014	0.035	0.048
1:M, M > 1	897	0.029	0.009	0.038
N:M, N, M > 1	220	0.007	0.018	0.025
N:1, N> 1	385	0.008	0.139	0.146
Total	6,208	0.015	0.035	0.050
Total, Regression Sample	5,777	0.016 [0.014]	0.037 [0.037]	0.052 [0.051]

Notes to Panel A: computed from digitized version of Hand and Machine Study, see text and (United States. Department of Labor. 1899). Block links are defined as follows--1:0: hand labor operations that “disappeared” (have no counterpart) in the transition to machine labor; 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; N:M: A block of N hand labor operations is mapped to a block of M machine labor operations, N and M > 1; N:1, N> 1: A block of N (>1) hand operations is mapped to a single machine labor operation.

Regression sample excludes 1:0 observations by construction. Mechanized = 1 if operation used steam or water power or both. Two different computations of the Fraction Steam, etc. are presented. The first is computed in two steps: (1) within each block, fraction of operations that use steam or water (2) overall fraction is equal weighted average across units. The second, reported in brackets is also computed in two steps but step (1) differs between the two methods: (1) time-weighted average across within the block (2) overall figure is equal weighted average across units

Table 1, Panel B: Machine Labor

Block Links	Number of Links	Fraction Steam	Fraction Water	Fraction Mechanized
1:1	4,275	0.485	0.028	0.508
1:M, M> 1	897	0.621	0.037	0.625
N:M, N, M > 1	220	0.694	0.033	0.724
N:1, N> 1	385	0.738	0.034	0.770
0:1	4,240	0.363	0.012	0.372
Total	10,017	0.459	0.022	0.479
Total, Regression Sample	5,777	0.531 [0.529]	0.030 [0.030]	0.557 [0.555]

Notes to Panel B: computed from digitized version of Hand and Machine Study, see text and (United States. Department of Labor. 1899).

Block links are defined as follows--1:0: hand labor operations that "disappeared" (have no counterpart) in the transition to machine labor; 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; N:M: A block of N hand labor operations is mapped to a block of M machine labor operations, N and M > 1; N:1, N> 1: A block of N (>1) hand operations is mapped to a single machine labor operation.

Regression sample excludes 1:0 observations by construction. Mechanized = 1 if operation used steam or water power or both. Two different computations of the Fraction Steam, etc. are presented. The first is computed in two steps: (1) within each block, fraction of operations that use steam or water (2) overall fraction is equal weighted average across units. The second, reported in brackets is also computed in two steps but step (1) differs between the two methods: (1) time-weighted average across within the block (2) overall figure is equal weighted average across units

Table 2: The Productivity Effects of Inanimate Power in the Transition from Hand to Machine Labor: OLS Estimates and Percent Explained

Panel A: OLS Estimates, Productivity Effects of Inanimate Power

Dependent Variable	Δ Ln (Time spent in block)	Δ Ln (Time spent in block)	Δ Ln (Time spent in block)	Δ Ln (Time spent in block)
Ln (Time spent in hand labor block)		-0.38 (10.96)		-0.38 (11.20)
Δ Fraction Steam	-1.04 (19.27)	-0.76 (15.22)		
Δ Fraction Water	-0.35 (3.29)	-0.22 (2.24)		
Δ Fraction Mechanized			-0.99 (17.55)	-0.72 (14.93)
Adjusted R2	0.500	0.597	0.500	0.594

Note: sample consists of 1:1, 1:M, N:1 and N:M block links for which there was complete information on the relevant variables (N = 5,747). See Table 1 for source information.

Δ: difference between machine and hand labor. All regressions include product fixed effects and dummy variables for block type (the left-out dummy is 1:1). Standard errors are clustered at the product level. Absolute values of t-statistics are shown in parentheses

Table 2, Panel B: Percent Explained of Δ Ln (Time) by Δ Power

Regression includes Ln (Time spent in hand labor block)?	No	Yes	No	Yes
Mean Value of Dependent Variable	-1.90	-1.90	-1.90	-1.90
Mean Value of Δ Fraction Steam	0.52	0.52		
Mean Value of Δ Fraction Water	-0.007	-0.007		
Mean Value Δ Fraction Mechanized			0.51	0.51
Predicted Change in Mean Value of Dependent Variable	-0.54	-0.39	-0.51	-0.37
Percent Explained (Predicted Change/Mean Value of Dependent Variable) x 100 percent	28.4%	20.7%	26.6%	19.5%

Predicted change in mean value of dependent variable: computed by multiplying OLS coefficients of power use dummies (e.g. Δ (Steam = 1) by mean value of change in power use (e.g. Δ (Steam = 1). Example, column 1: -0.54 = (-1.04 x 0.52) + (- 0.35 x -0.007).

Table 3: Instrumental Variable Regressions

Dependent Variable	Δ Ln (Time spent in operation block)	Δ Ln (Time spent in operation block)
Includes Ln (Time spent in hand operation block)?	No	Yes
First Stage Coefficient	0.23 (11.27)	0.23 (11.78)
Mean Value of Instrument (Fraction MECHABLE)	0.62	0.62
2SLS:		
Δ Fraction Mechanized	-1.25 (7.10)	-1.18 (8.06)
Predicted Change in Dependent Variable	0.64	-0.60
Percent Explained	33.6%	31.7%

Instrument variable (Fraction MECHABLE) is based on gerunds in the text description of the hand operation; see text.

First stage coefficient: coefficient of instrument in a regression of Δ (Mechanized = 1) with product and block link type fixed effects, column 2; or product and block type fixed effects and ln (Time spent in hand labor block), column 3. Standard errors clustered at unit level. Absolute t-statistics shown in parentheses.

Percent Explained: predicted change in dependent variable using 2SLS coefficient and mean value of Δ Percent Mechanized, divided by mean value of dependent variable; see Table 2, Panel B.

Table 4: Robustness Checks, 2SLS Coefficients

Robustness Check	2SLS, Δ Fraction Mechanized	Percent Explained	2SLS, Δ Fraction Mechanized	Percent Explained
Include ln (time in hand block)	No	No	Yes	Yes
IV is Fraction MECHBROAD	-1.10 (6.87)	29.5%	-0.90 (6.18)	24.2%
IV is Leave-One-Out	-1.35 (15.49)	35.8%	-0.90 (6.18)	23.8%
Weighted, pooled sample	-1.15 (4.72)	29.9%	-1.11 (6.59)	28.7%
1:1 block links	-1.36 (8.26)	36.5%	-1.17 (7.48)	31.4%
Non-1:1 block links	-0.65 (1.01)	17.0%	-0.95 (3.01)	24.8%
Pooled sample, drop Watch/Clock units	-1.44 (10.18)	42.0%	-1.26 (9.27)	36.8%
Hand Good is Superior	-1.24 (3.00)	23.4%	-0.72 (1.69)	13.6%
Machine Good is Superior	-1.53	44.3%	-1.41	40.7%
No Difference in Quality	-0.64 (1.68)	15.2%	-0.64 (2.36)	15.2%
Observations from 1890s Only	-0.86 (2.40)	22.0%	-0.72 (3.28)	18.4%
Exclude Spillover Units	-1.25 (7.21)	33.2%	-1.11 (7.70)	29,4%

See text for definitions of MECHBROAD and Leave-One-Out IVs. Absolute values of t-statistics shown in parentheses. Weighted sample: observations are weighted by the number of underlying operations in the block link; for example, if the observation is a 1:M link, the weight is 1+ M.

10. Appendix A: Comparison with 1850-1880 Census of Manufactures

Atack, Bateman and Margo (2008) use establishment level data from the 1850-1880 censuses to study the impact of steam and water power on labor productivity. In this appendix, we estimate a variant of their base regression specification using these same data and compare those results with those from the HML study.

As we have previously stressed, the two data sources are very different – value added per worker in the CoM is nothing like the measure of the labor productivity in the HML study data – time spent in an operation or in fashioning a specific good from start to finish – although the measures are surely correlated. In the HML analysis, we are trying to explain, to a first approximation, contemporaneous differences in productivity between two types of labor regime whereas in the CoM analysis we are explaining overall changes in labor productivity over time. We can, as in the HML study, measure mechanization by steam and water power separately, and we can also do so with dummy variables, which is effectively what we are doing in our analysis of the HML operations level data.

The dependent variable in our analysis of the CoM data is the same as that used in Atack, Bateman, and Margo (2008), namely the log of value added per worker. The CoM provides no information about the allocation of labor in production and only the most rudimentary (if steadily improving) information about time. We pool the data across the four census years. The main independent variables are dummies for use of steam power and for water power. We also include flexible controls for establishment size; the fraction of workers who were female; a dummy for urban status; fixed effects for year, state, and 3-digit SIC code; and year-region and year-SIC interactions. Observations are weighted by the number of workers in the establishment, again following Atack, Bateman and Margo (2008).

Appendix A Table 5 shows the coefficients of the steam and water dummies, and the results of a percent explained calculation analogous to those in Tables 2-4. The power coefficients are positive and statistically significant; consistent with the findings reported in the original Atack, Bateman, and Margo (2008) paper, the marginal impact of steam power is larger than that of waterpower. If we use the coefficients in conjunction with the mean values of the power dummies in 1850 and 1880 to predict the change in labor productivity over the period, the predicted change is 0.076 log points, compared with an actual change in log real value added of 0.244 log points. Thus, shifts in power use, as revealed in the CoM data, account for approximately 31 percent of the rise in labor productivity in US manufacturing between 1850 and 1880. This is very similar to the percent explained in Table 3, Panel B, column 2, which is the preferred HML specification for comparison with the CoM analysis.   It is important to keep in mind, though, that our OLS analysis of the CoM is subject to the usual critique of endogeneity bias, which neither we nor Atack, Bateman, and Margo (2008) address.

Appendix A Table 5: Census of Manufactures Estimates and Percent Explained

Coefficient of Steam Dummy	0.242 (17.15))
Coefficient of Water Dummy	0.039 (2.13)
Adjusted R-Square	0.248
Δ Mean, 1850-1880 of:	
Ln (Real value added/worker)	0.244
Fraction Steam	0.373
Fraction Water	-0.159
Predicted Δ in ln (real value added/worker)	0.076
Percent Explained [= (row 8/row 5) x 100 percent]	31.1%

Rows 1, 2: coefficients from a regression analysis of ln (value added/worker) using the sample of establishments from the 1850-1880 censuses of manufacturing analyzed by Atack, Bateman, and Margo (2008). See text for discussion of regression specification. 1880 observations are reweighted to account for under-reporting in the original census; see Atack, Bateman, and Margo (2008). Nominal value added converted to real value added using the output price deflator in Atack, Bateman, and Margo (2008).

12. Appendix B: Construction of the Leave-One-Out Instrumental Variable

This appendix discusses the construction of the leave-one-out instrumental variable used as a robustness check in section 7. To fix ideas, let j index all of the block links in the regression sample. For any block link in the regression sample, we define the term, $g_j(m)$. If the block link is 1:1 or N:1, $g_j(m)$ is the principal gerund associated with the single machine operation in the block link. If the block link is 1:M, or N:M, $g_j(m)$ is the principal gerund associated with the last machine operation in the block (recall that the HML staff numbered the machine operations from start to finish for every product, so for any machine block we know in which order they were performed). Also, let m(j) be the Percent Mechanized of the machine operations in block link j.

Next, we identify all other machine blocks in the regression sample in which g(m) is the principal gerund of the machine block, as just described. We compute $M = \sum m(i)$, which sums over all block links in which g(m) is the principal machine gerund, including block link j. Let N be the number of block links in this sum. Our leave one out instrumental variable (LOOIV) is: LOOIV = (M – m)/(N – 1). This is the average Percent Mechanized in all block links in which g(m) is the principal gerund, except block link j ("leave one out").

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