

Was Mechanization De-Skilling?

The Origins of Task-Biased Technical Change

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Abstract: Did nineteenth century technology reduce demand for skilled workers in contrast to modern technology? I obtain direct evidence on human capital investments and the returns to skill by using micro-data on individual weavers and an engineering production function. Weavers learned substantially on the job. While mechanization eliminated some tasks and the associated skills, it increased returns to skill on the remaining tasks. Technical change was task-biased, much as with computer technology. As more tasks were automated, weavers' human capital increased substantially. Although technology increased the demand for skill like today, weavers' wages eventually increased and inequality decreased, contrary to current trends.

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Introduction

There is a broad consensus among economists that modern technological advance favors more highly skilled workers, that recent technical change is “skill-biased.”¹ But it is also widely believed that the very opposite was true during the nineteenth century when, it is held, technological change replaced skilled artisans with unskilled factory workers.² Clearly, this difference poses a puzzle that might reveal something important about the interaction between technology and investments in skill, including the effect of technological change on wages and on wage inequality.

However, despite the apparent consensus about de-skilling, the actual evidence supporting this hypothesis is limited, as I elaborate below. First, much of the theoretical support involves different notions of “skill;” researchers have used education, occupational status, or the organization of production as indicators of skill rather than a rigorous measure of human capital. Second, the case study evidence does not uniformly support the de-skilling hypothesis. Moreover, broader empirical studies have used only indirect measures of human capital such as industry, occupation or establishment wages (Field 1980, James and Skinner 1985, Atack et al. 2004).

In this paper, I conduct a formal statistical test of the de-skilling hypothesis using direct estimates of worker human capital at different levels of mechanization. I do this for one important technology, cotton weaving, during the nineteenth century, using detailed micro-data on workers and a detailed engineering production function. Over the course of the century, mechanization progressively

1 See, for example, Katz and Autor (1999) and Acemoglu (2002b).

2 Victorian social critics such as John Ruskin, Thomas Carlyle and William Morris argued that the new technologies were de-skilling by “turning...almost all handicraftsmen into machines” (Morris 1883) and so they advocated returning to craft production. Similar themes were echoed by sociologists concerned with work satisfaction and, following Braverman (1974), by labor historians and others concerned with labor alienation and worker control. See Marglin (1974), Montgomery (1979), Brody (1980), Stone (1974), and Gordon et al. (1982). Rodgers (1978) and Goldin and Sokoloff (1982) suggest that mechanization was profitable to manufacturers because it allowed them to replace skilled craftsmen with unskilled workers. Acemoglu (1998, 2002a, 2007) formally models de-skilling as a response to the relatively low supply of educated workers. Goldin and Katz (1998, 2008) see de-skilling arising from a transition from artisan workshops to the factory. Empirical research examining the de-skilling hypothesis includes Field (1980), James and Skinner (1985), Atack et al. (2004) and a number of case studies, which I discuss below.

automated more tasks, reducing the amount of labor required to produce a yard of cloth to one-fiftieth of the amount at the beginning of the century. Considering this change, I ask three questions:

1. Did the progressive mechanization of weaving reduce the human capital investment made in the weavers? If the de-skilling hypothesis is correct, then progressive automation should have been associated with decreased human capital investments in these ordinary production workers. To test this, I estimate technology-specific investments in human capital using data on weaver productivity. Weavers in the factories had minimal formal training, lasting only two or three weeks. But they had very significant learning on the job, as shown by the learning curves in Figure 1. These data are for three cohorts of new hires at the Lawrence Company in Lowell, Massachusetts and they show the yards of cloth each weaver produced per hour by the month on the job. Over the course of a year or so, these weavers increased their output per hour dramatically, more than doubling their labor productivity as they acquired new skills. As I discuss below, it is possible to infer human capital investments from these learning curves. Performing formal statistical tests, I find that later cohorts did indeed have greater human capital, rejecting the de-skilling hypothesis.

2. How, specifically, did technology change the skill premium for human capital investment? A naïve view holds that greater mechanization should require less human capital: because more tasks are automated, new hires would need to learn fewer tasks. Hence they would require less human capital. Thus the rejection of the de-skilling hypothesis might seem surprising.

However, a closer look explains this apparent paradox: greater automation dramatically increased the returns to skill on the *remaining* tasks. This is because the productivity of the machinery depended on the portion of time it was actively used to produce cloth. Looms had to be stopped so that weavers could perform necessary tasks and fix errors. Profits depended on the weaver getting to the loom and performing these tasks quickly and reliably. With greater automation, the output per weaver increased,

so the time to perform these tasks cost more in terms of lost output. Conversely, the returns to weaver skill on these tasks were greater. Because tasks are complementary, automating some tasks increases the returns to skill on the remaining tasks. To explore this formally, I use an engineering production function for cotton weaving that has been tested for nineteenth century mills and which incorporates changing levels of mechanization (Bessen 2011). I show that the marginal returns to skill increased sharply with greater automation.

3. What effect did this have on wages and on wage inequality? I show that weavers' real wages increased both absolutely and relatively to unskilled wages, that is, their skill premium increased. However, most of this increase happened only after a delay of several decades, perhaps because it took time for a labor market to develop for weavers with technology-specific skills. Initially, the skills were firm-specific, which, in theory, means that employers initially paid for most of the human capital investment and reaped most of the returns. Thus, the increase in wages supports the view that weaving involved significant human capital and this human capital increased over time, however, the picture is complicated by the role of employers' investments in firm-specific human capital.

Of course, the effect of automation on overall mean wages for women depends on two offsetting factors: while weavers' wages increased, fewer skilled weavers were needed to produce a given quantity of cloth. Depending on which of these factors dominated, the mean wage for women could have increased or decreased. I perform some simple calculations to show that the net effect was to increase the mean wage for women. Furthermore, because women were paid less than the mean wage for all workers, this reduced overall wage inequality.

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In my analysis, the effect of mechanization is two-sided: while automation eliminated some tasks, reducing the labor required to produce a yard of cloth, it also increased the incentives to invest in the skills of workers performing the remaining tasks. Technical change was thus "task-biased." This

two-sided effect is quite similar to some recent research on the effects of computer technology on labor markets. David Autor et al. (2003) find that computers also have a task-biased effect on skill: while computers eliminate some jobs performing routine tasks, they increase demand for other jobs involving non-routine skills. Thus the interaction between technology and skills might have more continuity between the nineteenth century and now than is generally recognized.

Literature Review

Case Studies

Despite the general impression that nineteenth century technology was de-skilling, case studies find a mixed pattern: technology eliminated skilled workers in some jobs but in other jobs, new skills were required, consistent with the task-biased technical change hypothesis. Chin et al. (2006) find that the introduction of steam power to merchant shipping reduced the skill requirements of some jobs, but increased it for others (see also Mitch 2004 who considers the skills of both the seamen and the shipbuilders in the transition to steam). In the rubber tire industry, mechanization mainly reduced the numbers of unskilled workers who conveyed materials within the plant, having little effect on skilled workers (Nelson 1987, p. 335). In canning, mechanization allowed skilled cooks in canneries to be replaced by lesser skilled workers, but many unskilled jobs were also mechanized (Brown and Philips 1986). And there are clear counterexamples where new technology created new occupations that required substantial skills, such as the mule spinner (Lazonick 1979). Similarly, employers thought that the Linotype machine would allow unskilled workers to replace skilled hand compositors. Instead, many hand compositors found their skill and knowledge to be an advantage in the new skilled occupation of Linotype operator (Barnett 1904, 1925, p. 130). A similar story applies to the introduction of the semi-automatic bottle machine (Barnett 1925). In iron and steel making, Stone (1974) asserts that mechanization removed skill differences, reducing workers to a homogeneous

unskilled level. But Elbaum and Wilkinson (1979) and Meyer (2005) show that pay levels within the steel and iron industry became *more* varied after mechanization, not less. Jardini (1995) finds that Bessemer production workers earned substantially more than the iron puddlers in earlier craft production. And although a number of historians have described interchangeable parts as a means of using machines to replace skilled machinists with unskilled operatives, Gordon (1988) shows that the technique depended very much on the skills of “artificers” and these skills took considerable time and effort to develop.

Several of the case studies suggest that workers in mechanized jobs sometimes received higher wages than craft workers for reasons similar to those in my model. Barnett (1925, p. 130) attributes the higher wages of Linotype operators to the high overhead costs (presumably capital cost) associated with the machinery. Chen et al. (2006) attribute the higher pay of able-bodied seamen to the critical nature of their skills when the steam engines failed. Jardini (1995, p. 297) and Elbaum and Wilkinson (1979) argue that the costliness of errors in high throughput production justified higher wages for steelworkers in automated plants.

Thus the case study literature does not provide clear support for the de-skilling hypothesis, but seems, instead, more consistent with a model of task-biased technical change.

Conceptual Review

Nevertheless, my empirical findings are at odds with the conventional wisdom, so it is helpful to look at how my conceptual framework differs from the previous literature.

First, there is substantial literature outside of economics, some of it quite old, that uses a different notion of skill. The idea that mechanization was de-skilling has been advanced since the early nineteenth century, but, as Dickens (1842) noted, much of the low assessment of the skills of women factory workers had more to do with prejudices about social class and gender, rather than any accurate portrayal of the women. The Arts and Crafts Movement argued that industrial technology, through the

division of labor, did not allow workers the same human potential as handicraft work. Similar themes were echoed by sociologists concerned with work satisfaction and, following Braverman (1974), by labor historians and others concerned with labor alienation and worker control.³ These notions of skill are clearly different from human capital and are, perhaps, less helpful in understanding the effect of technology on wages and wage inequality.

Second, as Atack et al. (2004) note, much of the broader empirical research on de-skilling has used indirect evidence. Some scholars have identified broad occupational and industrial categories with skill. James and Skinner (1985) classify workers as skilled if they worked in an industry that had a high level of mechanization relative to Britain (with exceptions for cotton textiles, boots and shoes). However, this procedure is not helpful for independently analyzing the effect of mechanization on skill. Field (1980) also uses broad industry and occupational categories, but these do not translate unambiguously into skill levels, especially since he recognizes that workers learn on the job.

Some scholars have used establishment type and size to study de-skilling. Following the nineteenth century critics, some scholars have identified de-skilling with the transition from artisan workshops to the factory. Craft artisans were typically apprenticed and thus had a long period of formal training, usually seven years. Factory production workers, on the other hand, typically had very short periods of formal training. But of course, factory workers learn on the job as demonstrated by learning curves such as those in Figure 1. Learning-by-doing has been observed in a wide range of industries, including nineteenth century technologies.⁴ Moreover, the magnitude of the human capital investment associated with on-the-job learning depends on the cost of learning as well as the duration. Because of

3 See Marglin (1974), Montgomery (1979), Brody (1980), Stone (1974), and Gordon et al. (1982). Hirshhorn (1984) and Nuwer (1988) view the change as one in the *type* of skill, e.g., from “manipulative skills” to “diagnostic skills”.

4 See Thompson (2010) for an overall review. David (1975), Lazonick and Brush (1985), Bessen (2003) and Leunig (2004) show learning curves in textile production. Although plant level learning does not necessarily imply human capital acquisition by individual production workers, plant level learning is associated with higher production wages, steeper increases in production wages with experience, education, unionization, and the permanence of employment attachments (Bessen 1997).

the high levels of throughput in the factory, the forgone output for factory workers could be quite large. Bessen (2003) shows, in fact, that factory weavers had human capital investments that were comparable to those of some craftsmen.

Goldin and Katz (1998) build a formal model where the transition from artisan workshop to factory is associated with de-skilling. Using this model, Atack et al. (2004) analyze wage levels at establishments of different sizes, positing that small establishments had the older artisan technology, while large establishments had the new technology.

This paper, in contrast, looks at the effect of progressive automation within one company where the goods produced and the workforce were fairly similar over many decades. This is important because it controls for possibly conflating factors. Comparisons between artisan shops and factories can be misleading regarding skills for several reasons. First, new technology was often used in small shops as well as factories (Scranton 1984), so the correspondence between establishment size and technology is not exact.

Second, the transition from artisan workshop to factory is not at all representative of the changes in the organization of production during the early decades of the Industrial Revolution. During the early decades, the factory replaced *household* production more than it replaced workshop production. Zevin (1971, p. 136) estimates that less than one seventh of the cotton cloth produced from New England yarn in 1815 was woven in manufacturing establishments; by 1824, it was all produced in factories.⁵ Other household goods such as shoes, hats and apparel were also produced largely at home initially and then later at the factory. Production of these household goods accounted for most of the factories employing over 100 workers in the 1850 Census.⁶ This means that the relevant comparison of skills should be between women working at home and those working in factories. But it is not obvious that

⁵ The factories also replaced British imports of coarse cotton cloths.

⁶ The following industries account for 58% of establishments with over 100 employees in the 1850 Census sample (Atack and Bateman 1999): textiles, apparel, footwear, household furniture, meat and dairy products. These goods had been produced previously largely within households.

home weavers were more skilled than factory weavers. Indeed, during the early years, many factory weavers likely had previous experience at home and they could have gained further skills in the factory. Goldin and Sokoloff (1982) find that women's wages *increased* substantially relative to male wages during the first half of the nineteenth century, a change that contemporaries attributed to their greater productivity in manufacturing.⁷

Third, comparing wages between small and large establishments might be misleading because the small shops often produced different, higher quality products, requiring different skills. While the factories could only produce coarse cloth initially, small weaving shops in Rhode Island and Philadelphia specialized in fancier weaves (Mohanty 1989, p. 203, Ware 1931, p. 17). However, the de-skilling hypothesis concerns skills levels involved in producing the *same* goods.

Fourth, the artisan crafts largely restricted employment to adult males while the factories employed women and children also. But factors other than skill affected the relative wages of these two labor supplies. For example, women's wages were likely influenced by the limited alternative employment opportunities available to them. Nickless (1979) argues that it is inappropriate to use gender as a proxy for skill, based on an analysis of textile wages. In this paper, I avoid all of these comparison problems by measuring human capital directly rather than relying on wage comparisons. Nevertheless, I find that weavers' wages increased in a controlled comparison.

The de-skilling hypothesis is also supported by theoretical arguments about the cost-savings associated with replacing skilled labor. Rodgers (1978) and Goldin and Sokoloff (1982) suggest that mechanization would be profitable to manufacturers if it allowed them to replace skilled craftsmen with unskilled workers. However, this argument ignores the much larger role that on-the-job learning appears to play in enabling greater productivity with mechanization. The gains from mechanization

⁷ Goldin and Sokoloff cite several examples including Albert Gallatin who wrote in 1831 that "female labor employed in manufactures appears from the rate of their wages to be more productive than if applied to the ordinary occupation of women."

typically far exceeded any gains possible from the elimination of workers' skill premia. For example, labor productivity in cotton weaving grew fifty-fold over the nineteenth century. To the extent that this automation was enabled by greater worker skills, as I argue, any benefits from eliminating the premia paid to workers with preexisting skills was clearly orders of magnitude smaller, e.g., typically only thirty to fifty percent.⁸ Although there are clear examples where mechanization allowed skilled workers to be replaced by unskilled workers,⁹ my model considers the role of worker skills in enabling greater labor productivity even for workers who entered the mills without formal training.

In a similar vein, Acemoglu (1998, 2002a, 2007) formally models de-skilling as a response to a relatively low supply of educated workers. However, these models only account for the preexisting skills of workers. On-the-job training is also a response to the limited education of the labor supply, especially for technology-specific skills. For cotton weaving, it appears to be the more important response.

Finally, the task complementarity in my model is similar to the capital-skill complementarity that is central to the analysis of Goldin and Katz (1998), in which more capital-intensive production requires more skilled employees to install, maintain and and repair the equipment. In their view, this complementarity was *not* important in the early factories, but it did increase the demand for skilled workers in later waves of automation.¹⁰ In my analysis, automation increased the returns to skill among ordinary production workers, not just among maintenance and repair workers, and the increased demand for skill occurred even in the early factories. This is important because it suggests that technology affected skills of many more workers than those few primarily performing maintenance and repair.¹¹

8 Margo (2000) finds skill premia of 32% for carpenters and 43% for masons relative to teamsters.

9 For example, Brown and Philips (1986) present data showing that a tomato cannery reduced labor costs 36% from 1865 to 1894 by reducing wages in skilled jobs. But mechanization also dramatically increased processing speeds, generating an additional 65% reduction in labor costs largely among unskilled workers over the same time period.

10 Feldman and van der Beek (2011) find evidence of capital-skill complementarity for mechanics in early mills.

11 There were relatively few maintenance and repair workers in the textile mills and such workers make up only a small

Human Capital Estimates

Data

To explore changes in human capital, I use data obtained from the records of the Lawrence Company, which had several mills in Lowell, Massachusetts. The company's payroll ledgers contain monthly output and wages of individual weavers. The data from 1833 through 1855 are for the Upper Weave Room of Mill No. 2 and were originally developed by Lazonick and Brush (1985, see also Bessen 2003). The data for 1883-4 are for the entire company. It was necessary to expand the sample during the latter period in order to obtain a sufficiently large sample of new hires without previous experience.¹² Nevertheless, the weavers in both samples largely produced very similar types of coarse cloth, the majority producing one or two standard cloths.¹³

New hires without experience were initially paid on an hourly or day rate for a couple of weeks while they were trained. After training, they were paid by the piece. I identified inexperienced hires as regular weavers who had not appeared previously in the payroll ledger and who were paid time wages initially.¹⁴

Testing the de-skilling hypothesis

In theory (Becker 1993), human capital can be measured as forgone output, that is, the difference between the actual output of the trainee and the greater output an experienced worker could produce

part of the workforce today. In Montgomery (1840), there were three mechanics (plus 4 overseers) in a mill with over 160 employees. In 1998, mechanics, repairers and installers accounted for only 4.4% of manufacturing employment and 6.4% of blue-collar employment in manufacturing. See also Griliches (1969) who finds some support for capital-skill complementarity.

- 12 During 1883-4, not only was employee turnover lower than in the earlier samples, but most newly hired weavers then had previous experience.
- 13 Workers were paid different piece rates for different types of cloth. Following Lazonick and Brush, I use the different piece rates to obtain a measure of output in "standardized yards" by weighting the number of pieces produced by a factor proportional to the piece-rate for that cloth. This weighting assumes that skilled weavers received the same pay for comparable effort and hours across the different types of cloth. For example, a cloth that took twice as long to produce per piece would have a piece-rate twice as large. The rates were normalized using the total number of yards recorded in the company's cloth book.
- 14 A small number of experienced weavers were hired to train new weavers and to assist other weavers and they were paid time wages. I distinguish these workers from inexperienced weavers by their total time on day wages (more than 72 days) in the first sample and by their rate of pay (more than 6 cents an hour) in the second sample.

given the same resources as the trainee.¹⁵ Forgone output captures the opportunity cost of dedicating those resources to the trainee. Figure 2 shows this using learning curves like those in Figure 1, a gray curve for an early cohort, the black for a later one. The later cohort has a higher plateau, representing the greater productivity of experienced weavers using more advanced technology. The human capital investment for this later curve is represented by the shaded area between the learning curve (solid black line) and a horizontal dashed line asymptotic to the curve.¹⁶ Since the learning curves have a roughly similar shapes, the amount of forgone output increases more or less directly with the height of the learning curve—the gap between initial and asymptotic productivity. From Figure 1, note that the height of the learning curves increases with the date of the cohort, suggesting that later cohorts had *greater* human capital investments in on-the-job learning. This can be measured and tested.

Table 1 shows the means of output per weaver-hour, measured in yards of cloth per hour, for different cohorts of weavers each at two different points in time. The top panel shows the output per weaver for inexperienced hires; the bottom panel shows output per weaver for comparable samples of experienced workers. The first cohort begins December 1833, when Mill No. 2 first started production, and ends May 1836, after which the payroll records are missing for two years (the mill was shut down because of depressed markets for most of this time). The second cohort begins April of 1842, when the weavers began operating three or more looms each, and ends December 1855, when the Lazonick-Brush sample ends. The third cohort begins April 1883 and ends December 1884. I chose 1883 for a post-bellum sample because an equipment inventory is available for that year. Below I will refer to these cohorts by the first year in each cohort. Each of these cohorts had a greater degree of mechanization than the previous one. Experienced weavers in the first cohort operated two looms; in

15 Note that the growth in output per weaver-hour in the learning curves could partially reflect greater effort as in Lazonick and Brush (1985). To the extent that it does, I include effort in the measure of human capital.

16 This simple formulation does not take into account differences in hours worked and turnover. For more complete calculations with similar results, see Bessen (2003). This formulation has the advantage of permitting straightforward statistical tests.

the second cohort, they operated three or four looms; in the last cohort, they operated five looms each. If the de-skilling hypothesis is correct, then each successive cohort should have a smaller human capital investment and the height of the learning curve should be smaller.

The first two columns of the table compare the output per weaver hour at two times. For inexperienced hires, the first column captures their mean output for the first month that the weavers were on piece rate.¹⁷ The second column captures the mean output per weaver-hour for observations of the same weavers nine through twelve months later. The bottom panel shows mean outputs per weaver-hour for experienced weavers over a comparable time lag.

Comparing columns one and two shows that new weavers increased their labor productivity dramatically over the first nine to twelve months after formal training as was apparent in Figure 1. This is evidence of learning on-the-job. Note that the values of output per weaver-hour for inexperienced workers in column two are still below the values for experienced workers reported in the lower panel of the table. This suggests that weavers continued to improve their skills after twelve months on the job, especially for the last two cohorts.

Column three takes the difference between the first two columns to measure the weavers' improvement over the first nine to twelve months. The differences are significant at the one percent level using a t-test with Satterthwaite's calculation for the degrees of freedom for comparing means with unequal variances (1946). Note that the change in output per weaver-hour over the first nine to twelve months is larger with the later cohorts, contrary to the de-skilling hypothesis. Also, this finding corresponds with estimates in Bessen (2003) that weavers' human capital increased from \$47.39 in the 1830s to \$161.62 in the 1840s and 1850s.

It is possible, however, that the changes in output per weaver-hour observed for inexperienced workers could be influenced by other factors that increased the labor productivity of all workers, not

¹⁷ If the weavers were paid on time for a portion of the month, the output is measured only for that portion when they were paid on piece rate.

just those of new hires. For example, the quality of the cotton inputs or of the technology might have improved, thus increasing the output per weaver-hour for all weavers. In particular, we know that experienced weavers in 1842 worked three looms, while many experienced weavers in 1855 worked four looms. This growth in capital per worker would have increased the labor productivity of all workers, including new hires. To control for such changes, I use a “difference-in-differences” approach. The bottom panel of column three reports the changes in labor productivity for cohorts of experienced weavers corresponding to the cohorts of inexperienced weavers in the top panel. These values should capture the effect of any changes in output per weaver-hour arising from factors that affected both experienced and inexperienced weavers. Column four takes the changes in output per weaver-hour for inexperienced workers reported in the top panel of column three and subtracts the changes in output per weaver-hour for experienced weavers reported in the bottom panel. That is, these values represent the growth in output per weaver-hour for inexperienced weavers adjusted for any changes in overall labor productivity. Again, the values are all highly significant.

Column 4 represents the height of the learning curves in terms of yards per weaver-hour. While forgone output can be measured in quantity (yards), it may be more meaningful to convert it into real dollars. Column 5 converts these values to real cost per weaver-hour by multiplying the figures in column 4 by estimated costs per yard for weaving.¹⁸

Even after adjusting for these other factors, the change in output per weaver-hour for new hires is substantially larger for the later cohorts. The height of the learning curve is six times greater in 1883 than in the 1833 cohort. But is this growth statistically significant? Column 6 shows the result of one-tailed t-tests of the hypotheses that the gain in output per weaver-hour for the 1842 and 1883 cohorts is less than or equal than the productivity gain of the 1833 cohort. These hypotheses are rejected at the one percent level of significance. Column 7 tests whether the productivity gain from learning in the

¹⁸ Estimated at 1.4, 1.0 and 1.1 cents per yard in 1860 dollars respectively, based on cost figures from Layer (1955), McGouldrick (1968) and Montgomery (1840), calculations available from author.

1883 cohort was less than the gain for the 1842 cohort.¹⁹ This, too, is rejected at a high level of significance. Thus the de-skilling hypothesis is formally rejected in these data. Instead, human capital investment seems to have increased substantially with the degree of mechanization.

Perhaps some other factor could explain the growing height of the learning curves. It is possible that later cohorts had less formal training, in effect, substituting on-the-job learning for formal training. If this were the case, then perhaps the greater height of the learning curve in later cohorts might simply reflect the greater degree of learning that occurred on the job. However, the actual number of days that inexperienced weavers were paid time wages did not vary much across the cohorts. Inexperienced hires spent 12.1 days on day wages in the 1833 cohort, 13.7 days in the 1842 cohort and 13.8 days in the 1883 cohort.²⁰ In other words, the amount of formal training did not change significantly across the cohorts.

Another possibility is that output quality changed. I have not adjusted the measure of output for the quality of the cloth. If quality decreased in later years, then the estimates of output forgone might be overstated. Lazonick and Brush (1985, p. 63) report that the same standard cloth was produced in Mill No. 2 in 1855 as in 1833. Also, the descriptions in the cloth ledgers from 1883 appear to describe cloths quite similar to those produced earlier. If there were major changes in the quality of output, this should be evident in the price of the cloth. The real price received per yard by the Lawrence Company fell from a mean of 7.3 cents per yard from 1842 through 1855 to 6.3 cents per yard for 1883 through 1884 in 1860 dollars (Layer 1951). Of course, a variety of other factors might influence output prices. But given the small magnitude of the price change, output quality cannot account for any of the increase in the height of the learning curves from the 1883 cohort to the 1842 cohort and it is unlikely to account for much of the increase from the 1842 cohort to the 1883 cohort.

¹⁹ Using the cost data in column 5, the probability that the cost gap is smaller in 1883 than in 1842 is 0.002, than in 1833 is 0.000 and the probability that the gap is smaller in 1842 than in 1833 is 0.083.

²⁰ Of course, the work day was shorter during the later cohorts. However, I estimate the hours spent in training as 146, 166, and 138 for the 1833, 1842 and 1883 cohorts, respectively.

Another possible explanation is that labor quality deteriorated so that the mills would need to provide more training to new hires in later cohorts.²¹ In fact, the 1833 cohort had a higher level of literacy than the later cohorts. In the 1833 cohort, 95 percent of weavers could sign their names in the payroll register; in the 1842 cohort, only 76 percent could (in 1883 weavers no longer signed the payroll register when they were paid). Perhaps literate workers learned more rapidly, thus requiring less human capital investment on the job. However, when I repeat the test in Table 1 excluding illiterate workers, the increase in the height of the learning curve is even greater between the 1833 and 1842 cohorts.²² Thus literacy rates cannot explain the different performance between these two cohorts and it is unlikely to explain the greater height of the 1883 cohort because literacy probably did not decline much more after 1855.

In summary, the changes in the quality of inputs and outputs and the amount of formal training seem unlikely to explain the very large change in the height of the learning curves over the fifty year period studied. Instead, human capital investment appears to have increased with mechanization.

Technology and skill

Mechanization of weaving

This finding might seem counter-intuitive because the weaver in 1883 actually performed *fewer tasks* than the weaver of 1833. One might suppose that learning fewer tasks required less human capital, not more. Unraveling this apparent paradox requires a closer look at the technology.

Table 2 shows the major tasks performed by a handloom weaver and compares these to the tasks performed on later looms. Gradually, over the course of the nineteenth century, more tasks were either partially or fully automated. One big difference between 1883 and 1833 was an invention called the

21 Of course, if the quality of new hires increased over time, then this would have reduced the training requirements so that the growing height of the learning curves in Table 1 understates the growth in human capital investment.

22 The adjusted changes in weaver productivity (column 4) were 0.89 (0.25) and 2.73 (0.54) for the 1833 and 1842 cohorts respectively. The one-tailed t-test rejects the de-skilling hypothesis with a probability of 0.001.

weft fork which, along with the friction brake, automatically stopped the loom when either the weft broke or the shuttle ran out of weft yarn. This meant that the weaver no longer had to manually stop the loom and perform the time-consuming task of backing the loom up to the point where the error occurred. The later looms also streamlined the tasks of adjusting warp tension and replacing the warp.²³

Thus the 1883 weaver did indeed perform fewer tasks. However, a look at the engineering production function suggests that the returns to human capital investment were also much greater for the 1883 weaver. The tasks listed in Table 2 are key to determining the productivity of labor. For a skilled weaver, each task would require a certain amount of time to complete and each task would occur with with a certain frequency on average. Each yard of cloth produced would therefore require a certain amount of the weaver's time for each task (the duration of the task times the frequency divided by the speed of the loom). Weavers handling multiple looms also required time to monitor the looms watching for errors. Sample values of these required times are listed in the last column of Table 2 for skilled weavers producing coarse cloth circa 1820.

To formalize this notion for production involving N different tasks, let T_i , $i = 1, \dots, N$, be the mean time required to perform task i per unit of output (yard of cloth in this case). Let T_0 be the mean monitoring time required per unit of output. Then the output per worker hour, y , is

$$(1) \quad y = \frac{1}{\sum_{i=0}^N T_i} .$$

This equation, combined with an equation determining the number of machines per worker, provides an engineering production function that can be matched rather closely with the actual performance at benchmark mills (Bessen 2011). The values of T_i and T_0 depend on the particular cloth,

²³ As discussed in Bessen (2011), the later weavers also achieved greater throughput because they were more efficient at monitoring the looms (task 0), thanks to greater skill and effort.

the conditions at the mill, the state of technology and the skills of the workers. T_0 also depends on the number of looms per weaver and captures the trade-off between labor and capital.²⁴

Tasks and skills

The weaver's output per hour is thus directly related to the weaver's proficiency at performing the N tasks, among other things. The substantial growth in weaver productivity over the first year or so of employment shown in Figure 1 and Table 1 must correspond to substantial reductions in the T_i .

What accounts for this substantial learning? Part of this learning involved formal instruction, for example, on how to tie a weaver's knot. Part of the gain involved practicing manual operations to find faster movements, for example, to replace an empty shuttle quickly. Part of it involved learning technical knowledge through experimentation, such as learning how to adjust the tension on the warp so as to minimize broken threads. Part of it involved planning skills, such as coordinating work on multiple looms. Part of it might have involved learning how to make subtle alterations to the machinery, for example, to keep the shuttle from flying out. Part of it simply involved getting used to the noisy, complicated environment of a weave room with leather drive belts spinning and looms clacking away.

While the weavers were learning these skills, they were producing less output than an experienced weaver would, given the same resources. This opportunity cost gave rise to a de facto human capital investment. To incorporate human capital into the production function in a simple way, let H_i represent the human capital invested in task i for a weaver, measured in forgone output. Suppose that the time requirement for each task is a function of this human capital,²⁵ such that

24 Actual values for benchmark mills and the full details of the engineering production function can be found in Bessen (2011) with somewhat different variables. To simplify the exposition here, T here corresponds to T/R in that paper and T_0 corresponds to W .

25 In a more sophisticated model, experience performing one task might improve performance on another task, so there would be a human capital production function. This added complexity would not change the insights I draw from the model here, so I use the simpler version.

$T_i \equiv T_i(H_i)$, $i=0,1,\dots,N$ and

$$(2) \quad \frac{\partial T_i(H_i)}{\partial H_i} < 0, \quad \frac{\partial^2 T_i(H_i)}{\partial H_i^2} > 0 .$$

That is, there are diminishing returns to investment in human capital.

The firm should choose the level of human capital investment so as to maximize profits. The benefits of greater skill are offset against the costs of human capital,

$$p \sum_{i=0}^N H_i ,$$

where p is the output price and H is measured in forgone output. Assume that the human capital investment is amortized over L time periods, ignoring discounting. Then the flow of profits per worker-hour with a two factor production function is

$$(3) \quad \pi = p y - p y k - w - \frac{p}{L} \sum_{i=0}^N H_i, \quad y = \frac{1}{\sum_{i=0}^N T_i(H_i)}$$

where k is capital's share of value added (one minus the wage bill divided by the value added) and w is the unskilled hourly wage. This assumes competitive labor markets so that the mill either pays for the human capital directly or it pays indirectly in the form of a wage premium above the unskilled wage.

For those tasks that do not affect k ,²⁶ the first order maximizing condition for the i th task is

$$(4) \quad -V \frac{\partial T_i(H_i)}{\partial H_i} - \frac{1}{L} = 0, \quad V \equiv (1-k)y^2$$

where V , the "skill premium," represents the value of a marginal increase of skill, that is, a marginal decrease in T_i . This equation shows that the returns to skill increase with the rate of output per worker.

To see this in an example, suppose that an experienced weaver could fix a warp end (thread) break in half a minute while a less experienced weaver took just six seconds longer. Also, suppose that

²⁶ As discussed in Bessen (2011), the tasks that affect k are those performed while the machine is stopped. For those tasks that do affect k , it is straightforward to show that the skill premium is even larger than the expression in (4), so this expression serves as a baseline value.

a warp end broke about every three yards of cloth woven on average. Then, using the average rates of output for experienced weavers from Table 1, the hypothetical inexperienced weaver would produce about 100 fewer yards of cloth than an experienced weaver would in a year (3,000 working hours) in 1833. But that same inexperienced weaver would produce over 600 fewer yards of cloth than the experienced weaver in 1883. So the payoff from obtaining the skill needed to fix the warp end break quickly would not be very large in 1833, but it would be substantial in 1883. In the later cohort, it would be worth making a significant investment in this particular skill; it might not have been worthwhile to invest much in this skill in 1833. The returns from investing in this skill would have been even smaller for an artisan weaver working a handloom: that weaver would have produced only three additional yards of cloth in a year by acquiring this greater skill. Thus although all three weavers performed the task of fixing warp end breaks, the later weavers might very well have performed this task faster and with greater reliability. In other words, although the mechanized weavers had fewer tasks to learn, there were strong incentives to provide them *deeper* skills. There were strong incentives to invest more heavily in learning the remaining tasks for the later cohorts.

Table 3 shows the increase in the returns to human capital across the three cohorts. The first column shows the gain in labor productivity for new hires and the second column shows the mean labor productivity of experienced weavers, both data from Table 1. The third column shows the skill premium, V . The seven-fold increase in the returns to skill might very well explain the apparent paradox of greater skills with fewer tasks—the greater investment in human capital for the remaining tasks could have more than offset the reduction in human capital associated with the elimination of some tasks. While the 1883 weavers no longer needed to learn how to back up the loom quickly, thanks to the weft fork, it would have paid for them to learn greater proficiency at some of the more complex remaining tasks such as monitoring and coordinating activity across multiple looms, fixing breaks and

adjusting warp tension.²⁷

Thus the mechanization of weaving appears to be an instance of “task-biased technical change.” The analysis of the engineering production function shows that automation eliminated some tasks, while it increased the returns to skill on other tasks.

Weavers' wages

Mechanization and wages

If mechanization increased weavers' skill, then mechanization should also be associated with higher wages, all else equal. Table 3 shows the mean wages, deflated to 1860 dollars, for experienced weavers in the three cohorts. Wages did, indeed, increase, although the proportional increase was much greater for the 1883 cohort (65 percent) than for the 1842 cohort (24 percent).

Figure 3 shows that this trend was general for weavers at all the mills in Lowell. The figure, based on Layan's (1955) estimates,²⁸ show that the hourly wages of weavers in Lowell increased modestly from the 1830s to the 1850s and then increased more sharply after the Civil War.

It is possible that these wage trends might have been influenced by general trends in the wages of women workers. Figure 3 also shows the wages for spinners. Most of the spinners in the Lowell mills were women working on throstle or ring spinning frames²⁹ and these jobs were widely seen as requiring less skill than weaving jobs. Leunig (2003) finds that ring spinners also exhibited learning curves, but their learning curves were substantially shallower than those of weavers, suggesting lower skill levels. Thus spinners' wages represents wages for less-skilled women and the gap between the two series represents the skill premium paid to weavers. This, too, grew modestly until the 1850s and then more

²⁷ Perhaps it is logical that simpler tasks tend to be automated first, because they are easier to automate as well as easier to learn.

²⁸ I applied Layan's index of the relative wages of weavers to the mean daily wages of all workers in the mills. I divided these figures by the mean hours and the consumer price index (Officer 2009).

²⁹ A small number of the spinners employed at Lowell were mule spinners who were male and were considered to be more highly skilled. But mule spinners comprised a very small percentage (Layan 1955, p. 51).

rapidly after the Civil War. The growing premium of weavers' wages to spinners' wages is shown in the fifth column of Table 3.

Why was growth in real wages and in the wage skill premium more rapid after the Civil War?

One possible explanation is that a thick market for skilled weavers emerged only slowly. This is supported by some evidence in the last column of Table 3 showing the percent of new hires in each cohort who had previous experience. During the early years, relatively few workers switched firms, there was only a small pool of locally resident experienced weavers to hire from and, consequently, the skills were effectively firm-specific (see Bessen 2003). This meant that employers paid for most of the investment in human capital and they also reaped most of the returns during the early decades.³⁰ Later, the evidence shows that a robust market for previously experienced weavers developed, so weavers could then make the human capital investments themselves (by earning below-market wages while they were learning) and be reasonably secure of earning a return on that investment. This interpretation also explains why weavers had such a small wage premium over spinners during the 1830s. Nevertheless, the results show that real wages increased along with human capital investment during the entire fifty year period studied.

The link between wages and mechanization is also shown by supplementary data on the use of steam captured in a special report in the 1880 Census on 83 cotton mills (Wright 1880). Some mills were run on water power, some on steam and some on a combination. Steam increased the output per weaver either by making it more economical to run the looms faster or because upgraded steam plants also included complementary improvements to the looms that reduced down time. The result was greater output per weaver-hour shown in column 1 of Table 4. Steam-powered mills had about thirty percent greater throughput than water-powered mills. In theory, this greater throughput should have been associated with greater skills and higher wages. The remainder of the table shows that this was, in

³⁰ Bessen (2003) estimates that employees paid only 19-25% of human capital investment for the first two cohorts.

fact, the case, both for weavers specifically and for the establishments as a whole. This result is consistent with Atack et al., who find steam is associated with greater labor productivity (2008) and also with higher wages (2004).

Mechanization and inequality

The relationship between technology and skill is widely implicated in recent growth in wage inequality. Because new technologies have increased the demand for some jobs while eliminating more routine jobs, the effect of technological change has been seen by some economists as polarizing (Autor et al. 2008, Goos and Manning 2007, Goos et al. 2009).

Mechanization had a similar double-edged effect: productivity gains eliminated the number of weavers needed to produce a given amount of output, but those remaining weavers would be paid more. Depending on which of these two effects dominated, mechanization could have either increased or decreased overall wages for women. Since women were paid less than men on average, an increase (decrease) in the mean wage for women would represent a decrease (increase) in overall inequality.

These changes can be analyzed as follows. The mean wage for women at time t can be written

$$(5) \quad s_t w_t + (1 - s_t) u_t = u_t \left(1 + s_t \frac{w_t - u_t}{u_t} \right)$$

where w is the skilled weavers' wage, u is women's unskilled wage, and s is the portion of working women workers who are skilled weavers. I assume that women who worked within households effectively earned the unskilled wage. Note that $s_t = D_t / y_t$ where D is the demand for cotton cloth per working woman and y is output per weaver, appropriately scaled.

Assuming a partial equilibrium model so that weaving technology does not significantly affect the unskilled wage, the effect of weaving on the mean wage is given by the second term within parentheses on the right. This term is the weavers' share of the workforce times their wage premium.

To the extent that technology increased the wage premium, it increased the mean wage of women; to the extent that technology decreased the share of weavers in the female workforce, it decreased the mean wage.

Mechanization of weaving at time 1 would have increased the mean wage from time 0 if

$$(6) \quad \frac{(w_1 - u_1)/u_1}{(w_0 - u_0)/u_0} > \frac{s_0}{s_1} \quad \text{or} \quad \frac{(w_1 - u_1)/u_1}{(w_0 - u_0)/u_0} > \frac{y_1 D_0}{y_0 D_1}$$

where y_i is the output per weaver, as above, and D_i is demand for cloth in appropriate units. Assuming that per capita demand for cloth did not decrease (prices decreased with increased productivity), a sufficient condition for mechanization to raise the mean wage for women is

$$(7) \quad \frac{(w_1 - u_1)/u_1}{(w_0 - u_0)/u_0} > \frac{y_1}{y_0} .$$

In words, the mean wage will increase if the relative skill premium of weavers increases proportionally more than the output per weaver-hour.³¹

Comparing the second and fifth columns of Table 3 shows that labor productivity increased by a bit over 60 percent from the 1833 to 1842 cohorts and again from the 1842 to 1883 cohorts. But the wage premium for weavers increased around 300 percent each time. Thus the effect of mechanization during the period studied was to increase the mean wage for women and so to decrease inequality.³² This trend is consistent with evidence on the increasing wages of women in New England manufacturing (Goldin and Sokoloff 1984).

Conclusion

Weaving on the power loom has been described as the epitome of de-skilled work (Rodgers 1978). But contrary to the conventional wisdom, progressive mechanization led to an increase in

31 In fact, estimates of the number of weavers relative to the population of working age women imply that demand for cotton cloth relative to the number of working age women increased substantially.

32 Of course, this also meant greater inequality between women workers.

weavers' human capital, not a decrease. Weavers acquired their skills differently than traditional craftsmen: they learned their skills mainly on the job, not in an apprenticeship or a classroom. And while mechanization reduced the amount of skilled labor required to produce a quantity of cloth, greater throughput sharply raised the incentives to invest in human capital on the remaining tasks and thus to deepen skills. Weavers' skills grew; their wages followed.

Economic historians have noted similar dynamics in steamships, steel and typesetting (Barnett 1904, Chin et al. 2006, Jardini 1995, Mitch 2004). This similarity might reflect a common underlying logic that is captured in the engineering production function. That logic is simple and quite general: if tasks are complementary, then automating some tasks raises the premium for performance on the other tasks. As long as skill enhances this performance, then automation will increase the returns to skill on these latter tasks. Under these conditions, technological change will be task-biased. Some tasks will require less labor (skilled or unskilled) while the demand for skill on other tasks will increase.

This pattern appears quite consistent with recent evidence (Autor et al. 2003) that computer technology substitutes for some tasks ("routine tasks") while it increases demand for others. This continuity might not be apparent because much of the recent discussion of wage inequality has focused on skills associated with formal education per se as opposed to learning on the job. Yet plenty of evidence suggests the continued importance of knowledge and skills learned on the job. For example, Abowd et al. (2002) find that formal education explains only a small part of human capital and Bresnahan and Greenstein (1996) find that computer technology depends on investments made by users in developing complementary knowledge and skills. This suggests that the future impact of computer technology on wage inequality might depend on which workers have opportunities to develop new forms of human capital.

Indeed, the weaving example shows that task-biased technical change does not necessarily increase wage inequality. Its effect depends on the number of jobs being eliminated, the number of

those experiencing increased demand and where their jobs fall on the wage distribution. Since women weavers were at the bottom of the total wage distribution, mechanization served to increase their average wage, thus reducing wage inequality. Rather than casting thousands of workers into poverty, it provided a means for many of them to acquire well-paying skills and so to rise above the pay of the unskilled.

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Table 1. Learning on the job by cohorts of weavers at the Lawrence Company

| | Mean T ₁ | Mean T ₂ | Difference T ₂ - T ₁ | Difference in differences New hires(T ₂ - T ₁) - experienced(T ₂ - T ₁) | Less than or equal to | | |
|---------------------------------------|-----------------------------|-----------------------------|---|---|----------------------------------|------------------------|------------------------|
| | Yards / weaver-hour 1 | Yards / weaver-hour 2 | Yards / weaver-hour 3 | Yards / weaver-hour 4 | Real cents / weaver-hour 5 | 1833-36 cohort 6 | 1842-55 cohort 7 |
| <u>Inexperienced New Hires</u> | | | | | | | |
| 1833-36 | 6.88 (0.07) | 7.91 (0.10) | 1.02 (0.13) | 0.88 (0.25) | 1.2 (0.4) | | |
| 1842-55 | 9.48 (0.22) | 12.14 (0.38) | 2.66 (0.44) | 2.25 (0.45) | 2.2 (0.4) | P = 0.004 | |
| 1883-4 | 13.63 (0.94) | 18.04 (0.23) | 4.41 (0.97) | 5.70 (1.13) | 6.2 (1.2) | P = 0.000 | P = 0.003 |
| <u>Experienced Weavers</u> | | | | | | | |
| 1833-36 | 8.10 (0.16) | 8.24 (0.15) | 0.14 (0.22) | | | | |
| 1842-55 | 13.08 (0.07) | 13.49 (0.07) | 0.41 (0.10) | | | | |
| 1883-4 | 22.13 (0.41) | 20.83 (0.40) | -1.29 (0.57) | | | | |

Notes: Standard errors in parentheses. Period T₁ is the first month on piece rate for new hires and a comparable month for experienced workers; T₂ is 9 to 12 months later (the mean of observations). Number of new hires are 166, 78, and 15 for 1833, 1842, and 1883 cohorts respectively; the number of experienced weavers are 103, 922 and 369, respectively. Column 5 represents the differences in column 4 in terms of hourly cost in 1860 dollars based on the estimated total cost of the weaving step. Column 6 reports the probability from a one-tailed t-test of the hypotheses that the given cohort has a difference in column 4 that is less than or equal to the difference for the 1833 cohort. Column 7 performs the test relative to the 1842 cohort.

Table 2. Major weaving tasks at different levels of mechanization

| Tasks | Handloom | Early power loom (~1820) | 1833 | 1883 | Weaver min. / yard T_i (~1820) |
|--|----------|-----------------------------------|------|------|---|
| <u>Preparatory tasks</u> | | | | | |
| Prepare warp | X | | | | |
| Dress warp | X | | | | |
| Spool weft | X | | | | |
| <u>Tasks performed while machine running (power loom)</u> | | | | | |
| Let off warp | X | | | | |
| Pick shuttle | X | | | | |
| Batten reed | X | | | | |
| Take up cloth | X | | | | |
| Adjust warp tension | X | X | X | Less | 0.28 |
| Replace empty bobbin | | X | X | X | 0.38 |
| Monitoring (T_0) | X | X | X | X | 10.3 |
| <u>Tasks performed while power loom stopped</u> | | | | | |
| Fix smashes (assisted by helpers) | | X | X | X | 0.05 |
| Adjust temples | X | X | | | 3.00 |
| Back up loom (when replacing empty shuttle or fixing broken weft before weft fork) | | X | X | | 1.60 |
| Replace empty shuttle | X | X | X | X | 0.38 |
| Fix broken weft | X | X | X | X | 0.10 |
| Fix broken warp end | X | X | X | X | 0.15 |
| Remove cloth, misc. cleaning | X | X | X | X | 0.07 |
| Replace warp. | X | X | X | Less | 0.25 |

Note: Weaver time estimates are for the time it would take a skilled weaver (circa 1900) to perform task per yard of standard coarse cloth (Bessen 2011).

Table 3. Summary data for cohorts

| | Change in productivity for inexperienced hires | Mean productivity for experienced weavers | Skill premium | Real hourly wage (experienced) | Weaver/ spinner wage premium | New hires with experience |
|----------------|---|---|------------------|--------------------------------------|------------------------------------|---------------------------------|
| | yards/ weaver-hour | yards/ weaver-hour | | cents/hour (1860 \$) | | |
| 1833-36 cohort | 0.9 | 8.2 | 40.1 | 4.2 | 1.9% | 18% |
| 1842-55 cohort | 2.3 | 13.3 | 106.3 | 5.2 | 7.9% | 65% |
| 1883-84 cohort | 5.7 | 21.7 | 300.9 | 8.6 | 30.4% | 87% |

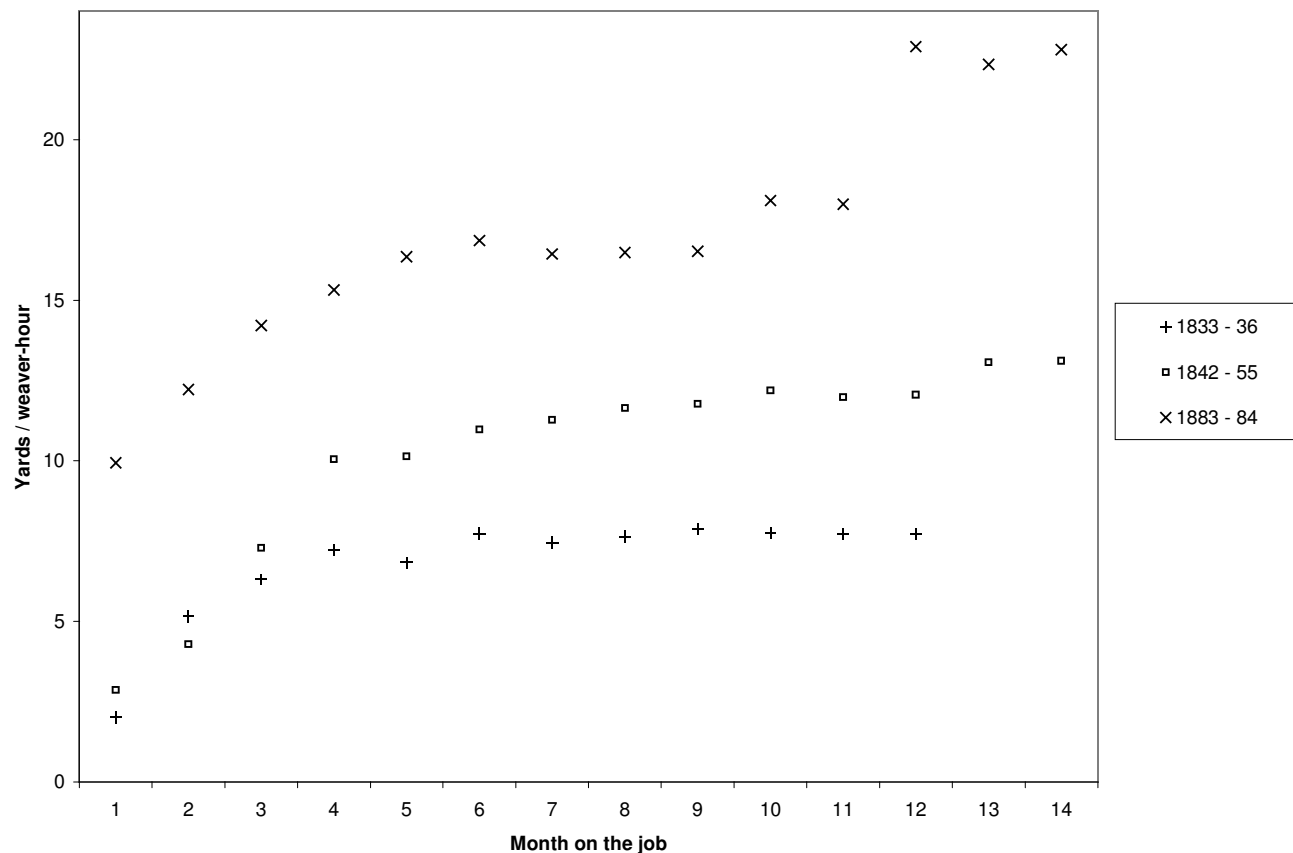
Note: The first two columns are from data in Table 1. The skill premium is calculated using labor shares calculated from Layer (1951). The real hourly wage is calculated from payroll data for experienced weavers deflated using the consumer price index. The premium of weavers' wages to spinners' wages are derived from Layer (1955), linearly interpolating data for five year periods.

Table 4. Steam power, productivity and wages

| Dependent variable | Ln (yards / weaver-hour) | Ln (weaver wage) | | Ln (establishment wage) | |
|-------------------------------|-----------------------------|------------------|-------------|-------------------------|--------------|
| | 1 | 2 | 3 | 4 | 5 |
| Steam only | 0.31 (.09)** | 0.20 (.07)** | 0.18 (.07)* | 0.18 (.06)** | 0.17 (.06)** |
| Water and steam | 0.18 (.06)** | 0.03 (.04) | 0.03 (.04) | 0.06 (.04) | 0.06 (.04) |
| Water only (omitted category) | | | | | |
| Looms/weaver | | | 0.03 (.03) | | 0.01 (.02) |
| Cloth type dummies | x | x | x | x | x |
| N | 83 | 82 | 82 | 76 | 76 |
| Adjusted R ² | .325 | .118 | .126 | .196 | .188 |

Note: OLS regression with robust standard errors in parentheses. One asterisk indicates statistical significance at the 5% level, two asterisks, at the 1% level. Sample from special report on factories in the 1880 census (Wright 1880) for cotton mills. Looms/weaver and weavers' wage taken as mid-point of range. Establishment wage calculated as weighted sum of weekly wages for men, women, and male and female children, weighted by the portion of the workforce comprised of each type.

Figure 1. Labor Productivity of New Hires at Lawrence Company



Note: The first two cohorts are means for balanced panels of 50 (1833-36) and 30 (1842-55) new hires at the Upper Weave Room of Mill No. 2. The 1883 cohort is an unbalanced panel of 15 new hires at all the mills of the Lawrence Company in Lowell. These samples exclude workers who had previous experience (identified by piece rate during their first month). In calculating yards per hour, workers on day rate were allocated the average productivity of all workers on day rate for the first two cohorts; for the 1883 cohort, I assumed that their actual productivity was such that their hourly earnings equaled the piece wages they would have earned.

Figure 2. Forgone output and height of the learning curve

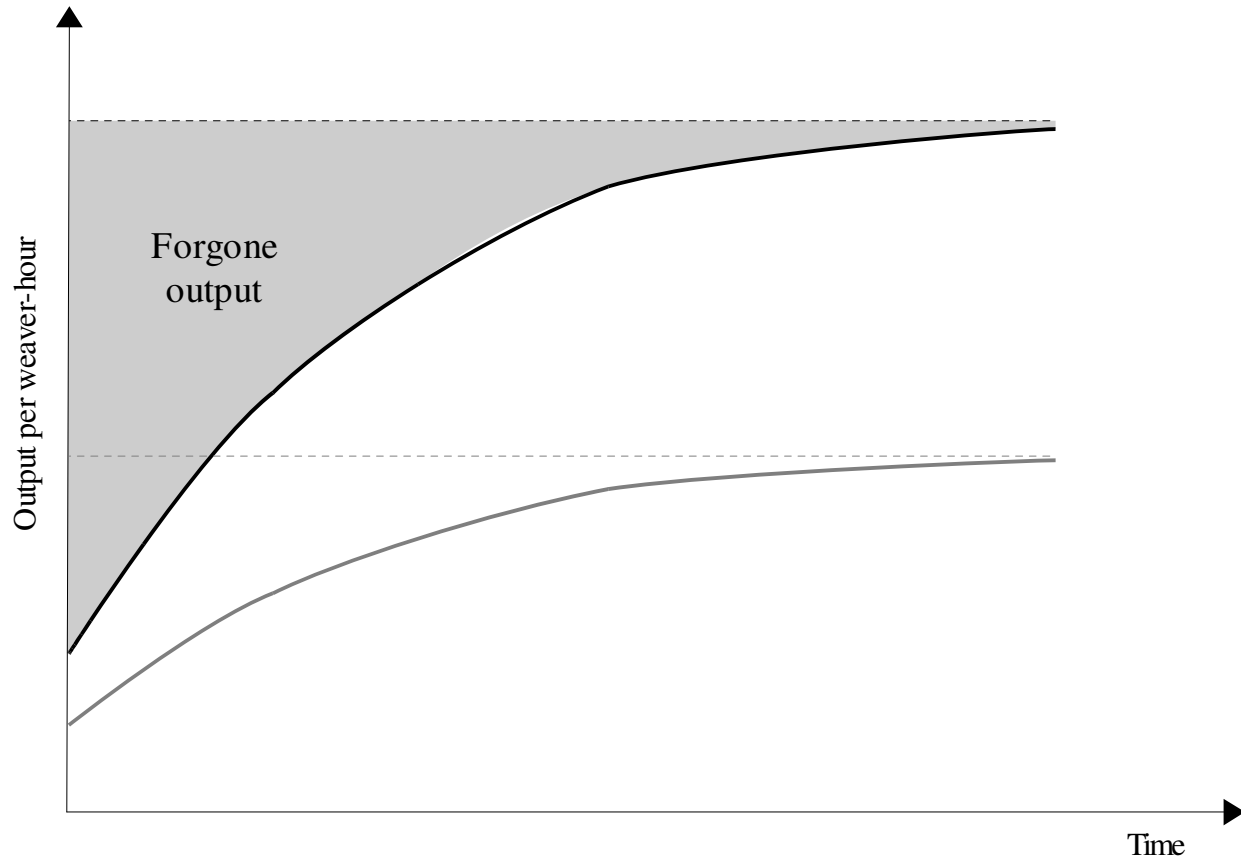
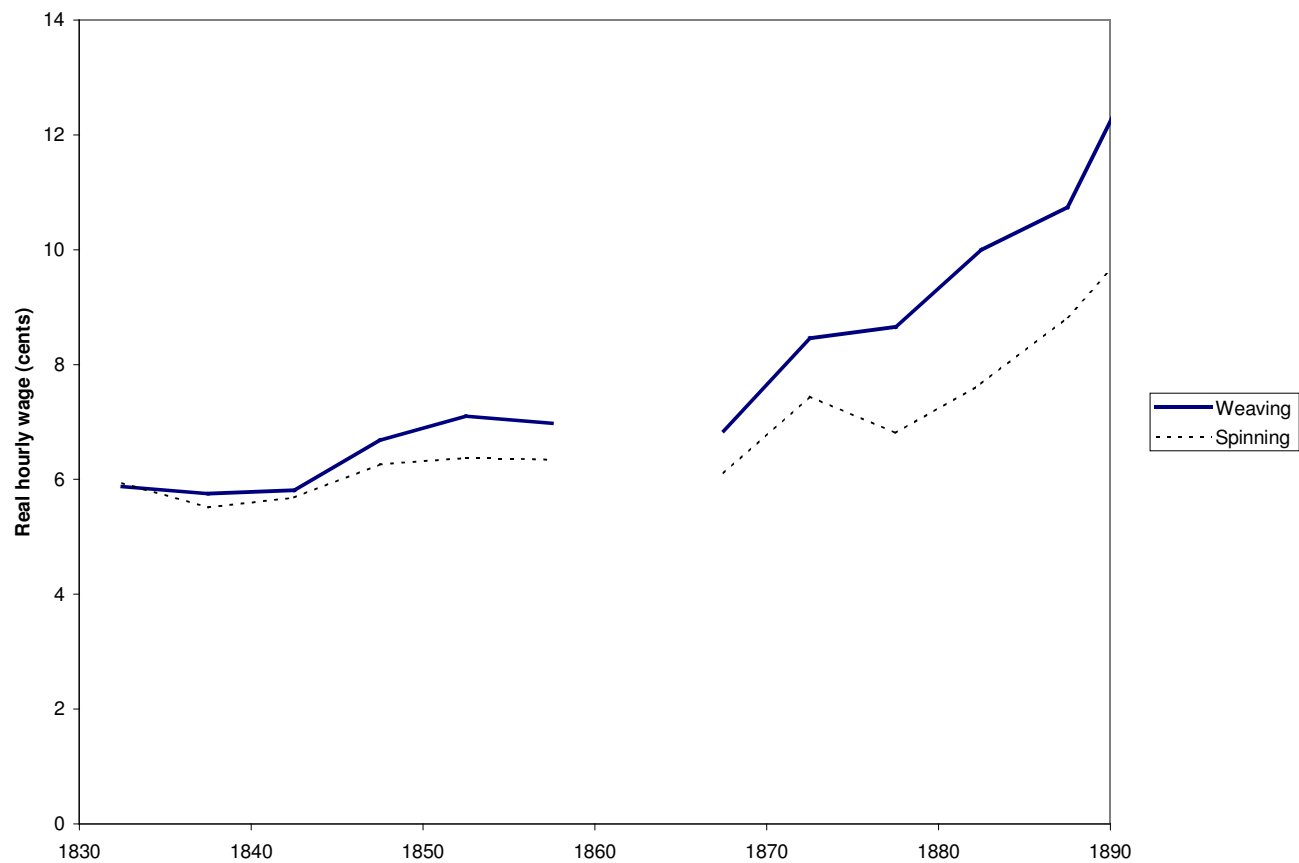


Figure 3. Real hourly wages for weavers and spinners in Lowell



Note: Based on Layer (1955) and deflated to 1860 dollars using the consumer price index (Officer 2009).