Employment relationships and the labor market during technology takeoffs

a revised dissertation proposal[1]

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The research questions and approaches

During a technology takeoff, what effects are visible in the data on employment relationships and labor markets? In particular, can we find evidence for the hypothesis that there is bidding for certain types of employees which raises income inequality among workers overall during a technology takeoff?

By *technology takeoff* we mean the response of firms and entrepreneurs to a new technology, analogous to a gold rush. When technologies of production are evolving, the contributions of different types of workers may vary more than when technology is stable, because some skills, talents, or experiences may suddenly be in short supply. This dissertation explores that conjecture from many angles. Can this effect be seen in data on earnings? Can we model an intuitively plausible mechanism by which it would be brought about? And is there a useful contrast between this proposition and the view built into much of the research literature, that information technology imparts a skill bias, expanding inequalities more permanently?

This document proposes a dissertation made up of several approaches to these problems. The first chapter models the skill and ability differences that could drive the effects described, and in two chapters we look for evidence of temporary earnings dispersion during technology takeoffs.

Relevant literature and the key hypothesis

Many economists have thought that new production technologies may bring about temporary income inequality. Kuznets (1955) made the observation, later dubbed the Kuznets curve, that societies transitioning from low-paid agriculture to relatively high-paid manufacturing would have greater income inequality during the transition than before or afterward, simply because some workers be in each category. He thought this could be a general truth about industrialization. Williamson (1985) claimed to have found a similar curve in the British nineteenth century on a nationwide level. Feinstein (1988), using similar data, disputes the claim.

In the recent period the issue has come up regarding computers and their possible causal force in raising income inequality in the United States since about 1970. Perhaps the most convincing and thorough work in this class has been Autor, Katz, and Krueger (1997). They show that in industries and sectors with more computers, more employee computer usage, and more computer investment as a fraction of investment, wage inequality increased more than in other industries. Their findings suggest that 30 to 50 percent of the increase in income inequality since 1970 could be attributed to computer technology. Like previous authors they find that the changes in incomes are principally a result of changes in demand for labor not its supply.

[1] Thanks for their many useful comments to Christopher Taber, Joseph Ferrie, Thomas M. Geraghty, Paulo Santiago, and other seminar participants at Northwestern University.

Greenwood and Yorukoglu (1996) shows a model in which adjustment to new technologies may be so uncertain and take so long that it produces a temporary dispersion in the distribution of wages. They model the labor choices of a firm that faces a dynamic optimization problem of continuing production, as it must also bring in new equipment embodying new technologies. The firm can hire from a potential work force of heterogeneous workers who vary both in skills useful in immediate production and in their ability to creatively adapt the new technology to productive use. These talents are assumed to be correlated with one another.

During the period of learning-by-doing about the new technology, the firm responds to its environment by investing increasingly in the new capital stock, and investing the time of its workers into learning about the new macroinvention and adapting it through microinventions to productive use. This investment requires some sacrifice of immediate production and therefore leads to lower measured labor productivity. Because the true productivity of the workers who are quickest or most able to adapt to the changing environment, taking into account their contributions to future production, has risen relative to the contribution of the others, wages become more unequal during the adoption period. Once the new technology is well understood and incorporated into the production process, the model predicts that the wage distribution contracts again.

With a similar assumption – that workers vary in the cost of learning a new technology, but the skills they need are well defined – the model of Caselli (1997) generates greater inequality across industries in capital per worker as well as in worker pay, an effect that is shown to exist in U.S. macroeconomic data.

There is formal evidence of the difference in learning between workers. Bartel and Lichtenberg (1987) explore a particular postulate along these lines -- that “when a new product or process has been recently introduced, there is ‘more (remaining) to be learned’ about the technology, and there is a greater premium on the superior ‘signal-extraction’ capability of educated labor.” They report empirical results in which the introduction of new technology (proxied for by the introduction of new equipment) correlates with relative demand for educated workers, and that this difference is seen more strongly in R&D-intensive industries.

The literature on income inequality is vast and sprawling. It is the ideas in Greenwood and Yorukoglu (1996), Caselli (1997), and Autor, Katz, and Krueger (1997) that are developed further here. The core idea is that when the technology of production is changing, worker contributions to production (either “marginal product of labor” or “present discounted job surplus”) are more dispersed than when the technology is stable. Aside from discussing the general observations about employment in technology takeoffs, this dissertation will explore the conjectures (1) that this particular effect is seen in historical examples, and (2) that it happens because workers can make contributions to the technology or production function of employers.

Chapter one: a model of wages and employment during technology takeoffs built around talent and skill heterogeneity

Consider an invention or discovery in a scientific laboratory, barely understood at the beginning, which evolves and appears in widespread routine applications forty years later. Let us call this process a **technology takeoff**. There are repeated technology takeoffs of this kind in the West since the Industrial Revolution which start with a **macroinvention** in the language of

Mokyr (1990)[2]. Microinventions adapt the discovery to productive use. They realize the potential complementarities between the macroinvention and current production technology. The changes consist of both changes in process within a production organization (learning by doing) and changes in the kinds of outputs of production organizations (ease of use or design improvements).

The motivating examples for this thesis are new industries or drastic changes arising from new technologies: the U.S. steel industry in the 1870s, the telephone industry starting in the 1890s, the automobile business of the early twentieth century (before the assembly line), and the microprocessor-driven businesses since 1971.

Greenwood and Yorukoglu (1996) suggest with tantalizing but incomplete evidence that both the industrial revolution in the U.S. and the period since 1974 have been characterized by these three observations -- high capital investment, lowered measured labor productivity, and wage dispersion (usually discussed in terms of income inequality). Possibly the causes are similar – new technologies are described as significant in both periods. Greenwood and Yorukoglu conjecture that new information technology causes them to arise in the recent period. Labor market issues such as search and matching frictions, employment contracts, and unemployment are not modeled there; the effects are seen in decisions about plant closures and capital decisions.

There are other models incorporating technological change. A Solow growth model with a production function like $Y_t=A_tL^sK^{1-s}$ allows one to explore some similar issues. So does a model with simple labor-augmenting technological change: $Y_t=(A_tL)^sK^{1-s}$. A skill-biased technological change model can have the form: $Y_t=(A_tL_{skilled})^s\ L_{unskilled}{}^rK^{1-r-s}$. (Such a function is discussed in a simple form in Hamermesh (1993) and is the main driver of the model in Krusell, Ohanian, Rios-Rull, and Violante (1996).) In vintage capital models, high complementarity of new production capital with skilled labor can drive effects on wages. All of these may have missed a major component of the effects of information technology change, and possibly of most technology change – the economic value of learning and adaptation by the work force. Greenwood-Yorukoglu (1996) hits this nail on the head, but it does not model the labor market, as this chapter will.

Here the goal is to model micro mechanisms of technological change by which heterogeneity of workers could be especially important during a period of change. One such mechanism would be an increased value to preexisting skills or education. The mechanism to be explored here is that there is instead an increased value to learning and adaptation capabilities. (In the literature this is sometimes called a skill, as in "skill to adapt" but this phrasing is avoided here because it stretches the core idea of skill.) In this model some workers – "high types" – help the firm learn by changing their employer's cost function, and others – "low types" – cannot. In times of technological change this produces wage dispersion in the model because the high types contribute more and receive a compensation premium.

By trying out the mechanism in different model environments (e.g., with a matching function; with uncertainty of various kinds; with firm capital and debt decisions; with national borders or industrial sectors) we can explore whether the "learning" mechanism would be intuitively plausible, useful, and would generate some of the stylized observations of these periods of technological takeoffs. We can contrast the theoretical effects of differences in learning

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[2] The language of "General Purpose Technologies" recently used by Bresnahan and Trajtenberg could substitute for macroinvention here.

("ability") to the effects of differences in preexisting skills. In the models the firm can see the learning ability of workers before bidding for them.

Greenwood and Yorukoglu's model did not have the property that a worker's success in learning and adaptation would contribute to the employer's technology, but this is an effect that could be important and is a property that is often visible in engineering professions.[3] That assumption will be explored here.

One might also argue that in a technology takeoff the decisions made by firms reflect partly a panic not a rational information calculation. Perhaps the players do not understand the game they are in, or they do not agree on it so their choices are not properly described as an equilibrium. Or perhaps players speculate in the product or labor markets in ways analogous to fads or speculative bubbles in asset pricing theories. Or perhaps they take their expectations from industry leaders, theorists, and consultants, and do not compute from their own information. This is more likely in the case of celebrated technologies such as Bessemer steel and the microprocessor. Or perhaps they are not maximizing profits as formulated here, but instead satisficing profit requirements to pursue some other objective such as appearing to keep up with the latest methods. In this model, however, the players all have a correct understanding of the game environment and they maximize only present discounted profits and income subject to their information constraints.

In this model, two different events are compressed into one. The appearance of an invention in a laboratory is not enough. The invention must be publicized, and more importantly production must be technologically feasible and potentially profitable. In the model, the event labeled a macroinvention is actually the simultaneous correct realization by a class of entrepreneurs that the macroinvention will eventually lower costs. In the case of Bessemer steel's adoption in the U.S. the achievement of feasibility was years after the main inventions had occurred. But in the model, time zero identifies the point at which the entrepreneurs recognize feasibility.

The product market is made up of one homogeneous good. Total revenue for the industry is normalized to 1 every period, although quantities vary over time in the model, and therefore price does. (Much of the modeling will be designed to screen out any effects of changing demand or of industry structure.) Let there be three periods indexed by t=0, t=1, and t=2. Within each period there is a matching stage, when firms and workers are matched together in a Pareto-efficient way, and then a production stage when product is made, sales occur, wages are paid, and employment contracts are made for the next period.

In the model we imagine a shock at time zero. An announcement is made that starting in time two, there will be an improvement in the best practice technology, and all the necessary information to use it will be common knowledge at that time. To get the information earlier requires having a certain kind of observant or insightful employee. Firms want to get the information early -- in period one -- because it will lower their costs and therefore raise their profits

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[3] Management consultants may have the same property. Management consulting firms often seem to bid for employees on the basis of perceived ability, not perceived skills. They offer the service of rapid learning and analysis, and may have especially good opportunities during times of technological change. In other words, they may be high types in the language of the model. One of the first management consultants, the legendary Frederick Taylor, first worked as a steel patternmaker and left that work in 1878. Growth in management consulting is characteristic of the technologically turbulent times considered in both empirical chapters of this thesis.

in period one. There are M firms and M+1 possible workers. Fraction h of possible workers are of the high type, and the other (1-h)(M+1) are not. Within the model then there will be temporary wage dispersion.

It will be necessary to consider the time order of the stages within each period in order to calculate the value functions.

Stage 1: Any macroinvention is announced; this includes the revelation of types, and the termination of any previous period of technological uncertainty that would end this period.
Stage 2: Unemployed workers apply to firms for jobs.
Stage 3: Each firm makes a wage offer to one worker.
Stage 4: Each worker chooses among the firms that made offers to him.
Stage 5: Production and wage payment occur.

The goal here is to model a firm's dynamic response to a macroinvention that affects its long run supply curve for a product.

Imagine an industry producing a homogenous product at a perfectly competitive price. Each firm is made up of a production technology, which it owns, and one worker it employs at a wage. A firm is thus identical to a job match.[4] All workers are equally productive. Firms may in principle vary in the quality of their technology, but we begin by considering the case where all technology is public information. The industry faces potential competition, and its firms behave perfectly competitively in the product market. There may be many firms, but they behave as if there were one competitive one.

An **equilibrium** here is the collection of strategies followed by (i) producing firms, (ii) employed workers, (iii) unemployed workers. We use the Nash equilibrium concept in which all actors behave exactly as they would if they knew the strategies of the others. Each class of player will maximize a value function. Firms choose what wage to offer current workers and potential workers, and when to shut down. In the structure described here, no firms would choose to exit.

In equilibrium in each period all M firms will produce and one worker will be unemployed. All wage contracts split the surplus of the job match (defined to be the present discounted value of the job match, over the outside options of the two parties), with positive fraction β of the surplus going to the worker, and positive fraction (1-β) going to the firm.[5] All firms and workers are equally productive, producing quantity q each period. In the absence of any macroinvention, all wages are the same; that is, there is no wage dispersion.

Imagine now the history of this firm starting at t=0 and moving forward a few periods, where workers and firms alike discount future periods in the same way. We will characterize a

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[4] The model's results are not intended to be sensitive to this narrow specification of a firm; if a firm had many employees, job roles, and employee types, the same basic results regarding wage dispersion should occur. I have not shown this.

[5] In the model β is exogenous and for simplicity does not vary across types of workers. This simplifies bargaining away to a Nash Bargaining Solution outcome without modeling any bargaining game. Similar structures are used in some macroeconomic models (e.g. the Mortensen-Pissarides series), and have been estimated on a few occasions. Values of β in the range of .3 to .5 fit the post-1970 macro data in the industrialized countries for which it has been measured. Whether β is similar for various types of workers in empirical estimation is not known to me. If not, the model might adapt to that finding by adjusting the outside options of the worker types.

history by $\{p_t, Q_t, w^h_t, w^l_t\}$, where $Q_t=Mq_t$ is constant, and $p_t=1/Q_t$ for all t. w^h_t and w^l_t will be the high and low wage offers the firm makes to different workers. At this point there is no difference between workers, so $w^h_t=w^l_t$ for all t.

Consider now what happens when there is a kind of technology shock called a **macroinvention** which harbors the promise of higher future productivity but does not make higher production possible immediately. A macroinvention is an information event at t=0 characterized by $\{q'/q, h, \pi, d\}$, which changes expected long run productivity but not the immediate production of any firm. q'/q is the new highest possible productivity. h is a fraction of workers who are of a high type; the remainder are of the low type with respect to this technology. A high type worker is capable of making the critical insight or **microinvention** necessary to bring the firm up to the new maximum productivity. π is the probability that a given high type worker does so in a single period of production. d is the duration of the period of technological immaturity; that is, after d periods the ideal application of the macroinvention becomes common knowledge. So the asymmetry of information between players disappears at that time, and no difference in forecasted production between high and low types remains.[6]

This paper does not take a stand on what makes a worker a high type. It might be education, skill, tenure at this firm, talent, or creativity. It might be experience working in some other firm, industry, job, or location. It could have been an attribute of the job match, not the worker alone, but the current model is designed around its being a worker attribute because this is easier to explain. The point is that some job matches have the high type; others do not; and hiring a different worker may bring a different high/low type attribute to the match. The technology of production may also be broadly interpreted: perhaps during a period when an invention like the microprocessor makes new hardware possible, engineers may be the high types. During a period of deregulation, managers with financial sophistication may be the high types.[7]

I have not derived the following results, but they are intuitively plausible. Each would be in a variant of the simplest model, with some assumptions changed. It is hoped that these results can be compared to general observations of technological takeoffs.

- Wage dispersion appears temporarily in the model during the technological takeoff because some workers can make special learning contributions.
- Short run profits and measured labor productivity are lower at the beginning the technological takeoff because the employers are investing in the future through the learning process. The employers expect a payoff to their investment in the medium run, before the technology becomes common knowledge.
- If some firms can tell which workers may be able to make useful contributions during the period of uncertainty, they are more likely to get profit rents than those firms which

[6] If low types could leave the industry during the period of technological immaturity for jobs paying the same amount as they used to make in another industry, they probably would. Their only outside option here is unemployment. A more realistic framing with the same outcome might involve search costs, long training times, or long run benefits from staying within this industry as it matures technologically. If in historical instances workers flowed out of industries adopting new and uncertain technologies, there would be value in modeling the outside option in greater detail, but this is not generally observed.

[7] Similar predictions would arise from a model in which the firms were completely in error about who was a high type in productive terms. The signal distinguishing high from low types might be constructed externally, not a result of calculation. For example it might be believe that males or whites or the ones with college degrees were high types, and this would produce wage dispersion that was hard to distinguish from the one described in the model. It may be useful to explore these models but it is not proposed to do so in this chapter.

cannot; but some firms of both types survive in general. (This is meant to give us a sense of properties that the entrepreneur must have, technical or otherwise.)

- If high type workers are distributed between countries, but the new technology is in one country and not the other, the technological takeoff will cause immigration of certain types of people.
- If education or training can change, or seem to change, a worker from a low type to a high type, the technological takeoff will induce an increase in costly worker retraining. In other words, a useful education will be more likely to be purchased (by either workers or employers), but so will one that just improves a signal of the worker's type (though workers, not employers, would pay for that).
- If capital investments into the new firms are necessary, investors prefer to get equity rather than debt for the same cash infusion, because the variance of possible returns is so great.
- With a standard choice of utility functions over consumption and leisure, it will be optimal for the joint firm-worker pair to extend working hours during the technology takeoff for the high types but not for the low types.

If these results can be derived, I can make the case that they fit observations of technology takeoffs historically. I expect to be able to show a key difference between the fixed-skill-bias hypothesis and the learning-or-adaptability-bias hypothesis – firms successfully bidding for high types will have earn greater rents in the long run if they hire a person who contributes to their own capital stock than if they must bid for skill in each period.

The idea, again, is that during a period when the new technology is immature, the production process requires insight, creativity, and adaptation. We can think of this as a period when there are a hundred steps in making steel, many of which are difficult. Some workers, learning or exploring as they go, can figure out how to make the new process more manageable. Job roles for these workers appear during the adoption period that pay them a bonus for those skills during the adoption period because firms are competing for medium term rents (although in the real world of technology takeoffs, only the winners even survive as firms except in niches). Twenty years later, when the process is well understood and the related technologies are working well, there are only twenty steps which use only off the shelf parts in a routine way. The temporary wage advantage to the talented employees or the ones in those special job roles has gone away.

The idea of productivity must be interpreted broadly. The employer values tons of steel made immediately, tons of steel to be made next year, and also changes in the steel-making process that the worker or job role may make possible that improve production or cost figures in the future, at an uncertain time and to an uncertain degree. Uncertainty or risk in the production process might induce the employer to pay more to workers who can reduce the risk. Or perhaps the value or scarcity of capital equipment drives the employer to allocate more of the profit in wages to induce the employee to behave in a trustworthy way.

A smoother generalization of the model, in continuous time rather than three discrete periods, should be able to produce the general results when firms face a partly-predictable technology gradient (that is, growth rate). When the gradient is expected to be high, firms respond to (a) prospects of high profits and (b) uncertainty by paying the high types more, and this produces wage dispersion. When the gradient is expected to be low, the premium for being a high type will drop, and there will be a contraction in the wage distribution.

Chapter two: The U.S. iron and steel industry during adoption of the Bessemer process, 1870-1880

This is a study of the wages of iron and steel workers at the time the Bessemer steel production process was introduced from England into the United States. Before 1870 relatively little steel was produced in the U.S. Following the introduction of the Bessemer production process, the mass U.S. market for such steel exploded from about one ton in 1867 to six million tons in 1886.

A critical timesaving design innovation made certain parts of the Bessemer converter removable so they could be replaced when the molten steel had damaged them. Alexander Holley introduced this in about 1870, and a race among steel firms began. Technological change was a dominant factor in this rapid growth. Steel was in great demand especially for the railroads then being built.

Scientific sophistication had not been important to the industry until then, but the Bessemer process made it relevant. For example, chemists had not previously been employed by the iron and steel business but became essential. Andrew Carnegie's firm employed the first known chemist in the industry in 1872.

Engineers who understood the process actively made innovations. Plants worked together to improve production methods even as they competed in the steel market. They advanced from the 1870 technology and by 1880 all Bessemer plants had similar designs and could make steel from an iron ingot in twenty minutes. The price of steel declined sharply during these years.

At this time employment was minimally regulated so any wage dispersion effects should be visible in the data. The natural years to study are 1870 to 1885. We stop at 1885 because afterward the rise of U.S. Steel and its mergers are likely to overwhelm the effects on wages of technological uncertainty. Weak evidence for a temporary increase in income inequality among the affected work force was presented in Meyer (1997), which addressed this topic. The proposed chapter will use more and stronger data.

2.1 Data

The data prepared for this study come from the Weeks Report, an 1884 addendum to the 1880 Census. The data have some weaknesses, but it was intended to be a large, unbiased survey and it is widely published although it has not been available in electronic form. A side benefit of tackling this project is that once parts of the Weeks report are in electronic form they can be published on the Internet and made available to other researchers.

This data could conceivably be extended by another survey of manufacturing workers from the 1880s and 1890s, usually called the Aldrich Report. More data could potentially come from the U.S. Bureau of Labor's Bulletin No. 18, *Wages in the United States and Europe, 1870 to 1898*. The form of the data is different in each survey, but a separate study of each could test for biases in these early data sets.

The hypotheses to be tested are that

(a) wage dispersion among production workers increased at the beginning of the takeoff, but not throughout the period, and
(b) this can be observed both between and within job categories, and

(c) the effect is greater among firms that are closer to the new process either in materials used or in technologies used.

Measures of economic distance will be useful to demonstrate (c). Such measures are discussed later in this document.

A typical data record from the Weeks Report follows.

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  Firm: Ashland Iron Company    City: Ashland       State: MD
Category: Iron blast-furnace  Coal technology: Anthracite
Year: 1875                    Source: Weeks 1880   page: 113   Record #: 6

    Manager, time unit: m             wage:
    Founder, time unit: d             wage:
    Keeper, time unit: d              wage: 1.675
    Keeper's helper, time unit: d     wage: 1.350
    Bottom-filler, time unit: d       wage: 1.350
    Top-filler, time unit: d          wage: 1.350
    Cinderman, time unit: d           wage: 1.350
    Blast engineer, time unit: w      wage: 9.975
    Common laborer, time unit: d      wage: 1.425
    Blacksmith, time unit: d          wage: 1.550
    Carpenter, time unit: d           wage:
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Note that not every job exists (or is reported) in every firm. The time units of pay vary, from days to weeks to months, and sometimes to tons of iron and other output units. For comparison of measures of inequality it will sometimes be necessary to convert to common units, and this will require judgement. In some cases a company may have multiple plants, and it may be useful to consider each plant as a separate productive unit.

The data set has been entered into spreadsheets. The spreadsheets have approximately 2900 plant-year observations, each of which, like the above, has several job categories and associated wages, and company and plant information such as:

(a) the plant's location;
(b) the company's industry: iron blast furnace, car-wheel foundry, stove foundry, general foundry, cutlery and hardware tools, machinery, rolling mill or nail factory, car-works, or carriage-works;
(c) a short description of its technology, e.g., whether it made steel as well as iron products, and for the blast furnaces some measure of the heat of the furnace (represented by the use of anthracite versus bituminous coal versus charcoal fuel);
(d) the company's name, in some cases, which could lead to information from other sources.

From these, a rough measure of technological or economic distance from the Bessemer process can be constructed.

2.2 Econometrics

The theory suggests that a firm's technology type and product type should predict its proximity to the technological frontier and therefore the wage dispersion within the firm. Levy and Murnane (1992) catalog measures of inequality or dispersion. They discuss the Gini coefficient, the variance of the natural log of earnings (VLN), the coefficient of variation, and the Theil Entropy Index. Choice of measure can matter, even in the sense that in special cases certain changes in distributions are evaluated as dispersions by some measures and contractions by others. For this historical period it is standard to use ratios of wages of highly skilled workers to those of less skilled workers, which can summarize and simplify the data for collections of occupations.

A possible regression equation for the firms in this data set is, for firm i in year t:

$$WAGEDISPERSION_{it} = a + bFIRMTECHNOLOGY_{it} + gYEARDUMMIES + dOTHERPREDICTORS + e$$

The hypothesis predicts that the coefficients on the early years are positive and the coefficients on the later years are negative. Firm's technology can be measured in the case of a blast furnace by the temperature, proxied by the kind of fuel it used, and by whether the material made or used was iron or steel. Other predictors can include relevant union actions, such as strikes within the state in the previous year. The measure of wage dispersion can vary from regression to regression, and could be either between job categories or within them. The theory predicts $\alpha > 0$, $\beta > 0$ (where higher FIRMTECHNOLOGY represents the use of a hotter furnace or steel not iron.[8] Advanced technology (e.g., the use of bituminous coal, or the production of steel items like rails) should positively predict wage dispersion between the job categories in the early years.

The data set does not have the wages of individuals in it but it is possible to regress wage dispersion within job categories nationwide as well, by looking at the same job title across firms and across industries.

Here the goal is only to establish basic evidence for or against this hypothesis: the *switch to an immature technology of production brings about temporary wage dispersion in the work force*. If this hypothesis is true, it represents a useful platform for further discussion of technology and the work force – for which technologies is it true, and in what contexts? Does productivity variation cause that wage dispersion?

Tests of this hypothesis cannot establish the mechanism proposed, that the wage dispersion arises from productivity differences, or that learning speeds are involved. Other systematic causes of the wage inequality are possible, other than those listed, that are linked to productivity. Perhaps when a new technology is being brought in, senior or especially talented workers have an advantage in positioning themselves within the firm to higher-paid positions, but they are not actually more productive. Perhaps there is a shortage of skilled workers but it is because the training is slow, not because their abilities or job roles are special. Perhaps increased capital stock (not the technology) is complementary to human capital of some kind (as is often supposed in discussions of the rise in U.S. income inequality over the last twenty years), and organized worker opposition eventually resists and reverses it.

2.3 Context

[8] FIRMTECHNOLOGY is permitted in the specification to change over time, but the Weeks report reports only the technology as of about 1880, which will be usable as a proxy. The technologies measured (like fuel type) were not very flexible. The type of fuel was a prerequisite to large fixed capital decisions such as the type of furnace. Unless other evidence is available, the relative position of firms technologically will be assumed to be the same over the sample period as they are in the Weeks report. There is also the problem that the firm's technology and wage dispersion are in principle jointly chosen. If one believed that the observed wage dispersion was very likely to affect the choice of technology, or that they were both strongly affected by other factors, this specification would be inappropriate and hard to interpret. In the evidence, variation in wage dispersion is not large whereas differences in technology are large and presumably mostly exogenous to wage dispersion.

Many confounding issues affect interpretations of the data. Meyer (1997) has an extended discussion of these. In short, they can be accounted for and do not seem to be the cause of the slight rise and fall in income inequality in the relevant worker populations observed in that paper:

(a) The 1873 depression coincided with the start of a rise in wage inequality in iron-related industries measured in Meyer (1997). In other industries, however, wage inequality generally declined during the depression, suggesting the depression did not drive higher inequality in the iron and steel businesses. No major wars, which have independent effects on income inequality, affect the U.S. in this period.
(b) If demand for steel were sometimes substantially below capacity, that would soften any bidding for workers. But it appears that the firms were always constrained by their production capacity. Some evidence is provided by the import figures. Despite the massive expansion of North American production, imports of iron and steel exceeded exports every year from 1870 through 1883. Imports came principally from Great Britain.
(c) Similarly the labor market could in principle have been buffeted by strategic behavior by firms selling steel but this will be presumed not to be the case. In Meyer (1997) a case was made against both increases in plant scale and competitive actions in the steel product market causing the increase in wage inequality before 1885.
(d) Working hours each day declined over the period and prices changed with inflation and deflation. Because the measures studied are those of inequality between contemporaneous wages only, they should not be sensitive to such trends and will not be adjusted for them.

The absence of other institutions such as a minimum wage law, collective bargaining by unions, and unemployment insurance meant that many of the smoothing effects that today’s work force expects were not present. For example, Allen (1987) documents that wage differences across industries vary from year to year ten times as much before 1890 as after World War II. Workers were not protected from shocks to productivity or demand. Employee compensation was simpler than now -- insurance benefits and pensions were minimal or nonexistent. Some fraction of pay came in the form of bonuses or benefits (like lodging) but the Weeks report attempted to convert that to money in the data. Bonuses were often proportional to pay in any case and would not affect the within-firm pay ratios studied here.

There were many strikes and walkouts however. Maybe if any wage equalization came about, it was in response to labor action. Meyer (1997) did not consider this possibility but Prof. Joseph Ferrie has given me a substantial database of labor actions of the period (from Currie and Ferrie (1995)) and I will use their presence in the previous year as an explanatory variable to distinguish this hypothesis from the learning hypothesis.

Meyer (1997) explored many of the right issues but its data were too sketchy and irrelevant to make a convincing case, it did not take labor actions into account, and it could not explain why the effect seen among Pennsylvania workers was not seen in the Illinois workforce which was also at the technological frontier. This chapter can be stronger, since it will have more cross section wage evidence, better accounting for actual production technology of the time, and data to argue for or against the proposition that trade unions reduced the wage gap.

Chapter three: Engineers versus others since the invention of the microprocessor

This chapter is a study of compensation of engineers since the invention of the microprocessor, roughly parallel to the Bessemer steel chapter. The microprocessor is one of the defining inventions of the information technology revolution. If in some basic sense information technology for the brain is really unlike industrial technologies for the hands, we might find in a series of studies that the information technologies impart permanent wage dispersion whereas the industrial technologies imparted only temporary wage dispersion. We cannot know from these two studies alone whether that is the case.

3.1 Data

The Current Population Survey done by the Census Bureau has enough electrical engineers in its annual data set to make it possible to test the proposition that a wave of inequality went through the occupational category "electrical and electronic engineers" and then through other categories of engineers. There are over 100 electrical engineers surveyed each year, and their industry or other category of employer is known for each one. The data set used in preliminary studies is from the Mare-Winship standardized collection of CPS data, expanded to 1992 by Christine Collins at NBER. The data set covers 1968 to 1992, and could be expanded to include later years and possibly earlier ones.

It will be straightforward to expand this data set, or to examine various hypotheses in similar data sets from the decennial Census. Such data sets have 5% of the engineers in the entire population and will be more representative than the Current Population Survey (CPS). There also exist specialized data sets of information on engineers. I have access to some data from at least two. The Institute of Electrical and Electronic Engineers (IEEE), an international association, conducts a detailed compensation survey which includes detail on the engineering content of the work, the education, and career experience of U.S. electrical engineers. This data would be ideal, but the data actually accessible only start in 1993. With effort, it may be possible to get access to additional years of this data. SESTAT is a generally accessible NSF survey of scientists and engineers with data on compensation, education, and career experience of the engineers. That data does not start until 1993 or 1995, but overall has 100,000 scientists and engineers, and so may be useful for confirming or disconfirming the CPS evidence.

3.2 Econometrics

As in chapter two, the hypothesis to be tested is that compensation will become temporarily more dispersed, both between and within job categories, according to their "distance" from the microprocessor. "Distance" has no single measure, but engineers working on computers should be affected more than engineers working on electric power distribution, and engineers working in regions or for firms that are investing in the new technology should be affected more than those that do not. Subfields of engineering include electrical, chemical, and mechanical; electrical engineers should be affected more than the others.

The Greenwood-Yorukoglu proposition can be interpreted here as the hypothesis that a macroinvention in 1971 produces wage dispersion in the nearby occupations sooner and to a greater extent than in the distant occupations. Let p_i be a positive index of closeness of occupation i to the major invention; that is, let it be near zero for remote occupations and highly positive for electrical engineers. Let $CV_{i,t}$ be the measured coefficient of variation of salaries of engineers in subfield i in year t after the invention -- or, in another specification, the mean squared residual after known factors like education have been taken into account. Thus:

$$CV_{i,t} = a + bp_i + cp_i^2 + dt + et^2 + fp_it + gp_it^2 + \text{errors}$$

If the G-Y hypothesis were strongly true and nothing else were going on in the data, b, d, and f would be positive and c, e, and g negative. That is, the rise and fall would be steeper for the nearby occupations, the rise would precede the fall, and proximity would accelerate the rise and fall. This may well turn out to be a clumsy or inappropriate specification, but it represents a start an empirical investigation. This method cannot distinguish the learning ability hypothesis from the unobserved fixed skills hypothesis econometrically.

A better specification that can be derived from basic statistical assumptions about steady rates at which events occur is below:

$$CV_{it} = a_i + p_i*\exp(-btp_i)*[1-\exp(-ct)]$$

In that equation the first exponential expression represents the declining frequency of contexts in which the invention that appeared at t=0 is new, and the second expression represents the general diffusion of the invention to all useful contexts over time. The lag at which the dependent variable reaches its peak ("modal lag") is 1/b and the modal height is approximately c/b. This is an early and simplified form of such an econometric specification. It is similar to one in Jaffe and Trajtenberg (1998) used to model the spread of knowledge in the context of patent citations.

The regressions above are designed to explain some of the wage inequality within occupations. It would also be possible to measure income inequality within industries in the CPS, but the data set does not have enough information about employers to measure income inequality within firms. It would also be possible to compare the distributions of observed electrical engineering salaries to the one predicted by the respondents' ages, education, and previous occupations. The regression can be applied to other occupational groups besides engineers too.

3.3 Context

Employment relationships are more complicated institutions now than they were in the Bessemer steel period. Compensation to the engineers of the modern period includes benefits, stock options, bonuses, and so forth. To some extent these are recorded in the data set. The CPS has information on both wage-and-salary income and self-employment income. The categories of outside income they do ask about include dividends, interest, and rental income. I do not believe I can get evidence from the CPS on stock option income or bonuses, but perhaps if I ask the CPS experts they will have advice. Understanding these issues may really require looking at other databases. Specialized engineers also receive implicit payoffs from proximity to a new technology insofar as demand may be especially high for them in the future, or they may get the opportunity to start their own firms or become managers or executives. If income dispersion takes the form of expanded promotion opportunities for the engineers, it is difficult but possible to measure that by looking at the category of people in the CPS who self-describe as having been engineers in the previous year and see how their choices evolve over the decades.

The first microprocessor was designed at Intel in 1969. It was licensed exclusively to one relatively obscure customer at first, and was not an immediate success as a product. By the end of 1971, Intel was making two kinds of microprocessors, and was advertising them for general sale. By then Intel had competition -- Texas Instruments was also selling a microprocessor. By 1974 packaged personal computer kits were on sale. The measures of economic distance will not be sensitive to the exact year of the critical event, and the continuity of the events makes it artificial to pick one. For comparability to the model in chapter one, we can state it thus: for purpose of this study, all industry events after 1971 are taken to be endogenous to the appearance of competition in the microprocessor market.

The actual work roles of electrical and other kinds of engineers, technicians, and software specialists will need to be made clear in this chapter. Furthermore there is the issue of how occupations are documented by the Census and the CPS. The Census does not offer a list of occupations to the survey recipient, but simply a blank space to identify an occupation. The Census Bureau then publishes a book of the answers given (approximately 23,000 in the 1970 Census) and how they were grouped into the standard categories to be used here. That list tells us about 30 more precise job titles, and a more complete understanding will have to come from other data sets and documentation about these careers.

Wage inequality by job title has a strong prospect of being economically structural – since it is work and production for which the employee is actually paid. Contrast this with the common studies of inequality by demographic characteristics such as sex and race which are important as measures of performance, but which rarely lead to simple economic, structural, understanding.

It is also common to study wage inequality as predicted by the highest formal educational level of the workers.[9] Although that approach is widely respected and cited – and examples will be cited here – it suggests the assumption that the worker is paid for his education. That is a weak link in such studies, since the economically important properties of an education -- like knowledge, skills, and signals – are not well identified. We do not know what the employee knows, or what skills he has, or what ability rank is suggested by his education, and if we did we would not know which of these the employer pays for in a given employment relationship. This is avoided by focusing on the employee's job content, since it is firmly associated with the employee's productive activity. That gives us a better chance at finding coherent and robust explanations. So this approach may well represent a better – but rarely used – approach than previous analyses of inequality.

3.4 Measures of economic distance

The data on each worker includes the industry of the respondent, and this will be useful to construct a measure of the worker's proximity to the new technology. Measurement of an industry's technological proximity to new technology or to information technology in particular can be defined in many ways:

(1) By the degree to which electrical engineers (or other engineers) are employed in those industries. A long run time average of the fraction of industry employment who are engineers could be a predictor, but like other measures it is endogenous to the response to the macroinvention.
(2) By whether the industry's products fell in quality-adjusted price, which is endogenous and also may have been forecast. The measure is feasible for most industries since the CPS and Census categories for industry are listed with the closest SIC match.
(3) By whether the industry uses inputs that are related to the microprocessor according to input/output tables.
(4) By the age of plant and equipment in the industry and the fraction of industry investment that goes into research and development, as in Bartel and Lichtenberg (1987).

[9] E.g. Autor, Katz, and Krueger (1997), Juhn, Murphy, and Pierce (1993), and Katz and Murphy (1992).

(5) By the measures of computer use within each industry used by Krueger (1993) and Autor, Katz, and Krueger (1996). They use results of CPS surveys in 1984 and 1989 on whether the respondent used a computer at work. That survey result could be used directly in the wage dispersion regressions in this thesis, or it could be used to measure the technological proximity of every industry to the microprocessor invention. (The desktop computer is not the only application of the microprocessor, however; 80% of microprocessors are not in personal computers, and this fraction has stayed steady over time; the studies cited are about the office computer, not the microprocessor.)

(6) Jaffe (1986) and Jaffe's unpublished dissertation constructed 21 "technological clusters" of firms in 1972 and 1978 according to the patent class (a substantive categorization of technologies) in which they received most of their patents. Jaffe (1986) also has a measure of proximity of firms in technology space. This work could be extended, I believe, to define an index of proximity to the microprocessor. One way would be to simply rank firms on the basis of their technological proximity to Intel (the canonical firm, which invented the microprocessor and has led production since), or Fairchild Semiconductor (Intel's parent) using Jaffe's measure. Then one might average scores of firms in an industry to get a score of proximity of each industry to the invention. That index of industry proximity could then be a regressor in my wage dispersion equations. I do not know at this point that this procedure is feasible from the evidence that is actually available.

Because readers may be doubtful that any particular choice of index of economic distance is reasonable, it will be necessary to show the effects as predicted by more than one.

In the Bessemer steel case, possible measures of proximity to the Bessemer steel invention could come from the degree to which an industry is a user of iron and steel, as measured by the Bateman-Atack-Weiss data from the Census of Manufacturers.

3.5 The evidence so far

Examination of the data on the engineers so far shows several things. The number of engineers in most fields (aerospace, chemical, civil, industrial, mechanical, mining, metallurgical, and not-elsewhere-classified) shows no trend, or a slow trend up. But in fields that seem closely linked to information technology, the number rises rapidly – doubling over the course of the data set for electrical engineers and technicians, and more than doubling for the two software categories, programmers and system analysts. Average wage and salary income falls then rises for the information technology categories over the course of the 24 year period, but the other engineering categories stay steady. Why would this happen? Possibly because the new entrants to these expanding fields are inexperienced, or possibly because they accept lower salaries in the near run in order to get a job in an expanding field.

Average age, hours worked, and the age distribution of the workers in each of the engineering fields do not seem to vary much over the period of the data set, which suggests that the growth in population for the information technology engineers occurs relatively smoothly. Possibly this occurs because they are trained at specialized institutions, which could only expand gradually.

The coefficient of variation of income within each occupation group is the statistic where one would look for early evidence of the Greenwood-Yorukoglu hypothesis. Among most engineering categories, the coefficient of variation is not trended up or down. Among the software categories, there is a slight drift up from 1972-1992. The Greenwood-Yorukoglu hypothesis could be confirmed if incomes of electrical engineers grew much faster than those of electrical engineering technicians – one might interpret this as a separation of high and low types between occupational categories. Early evidence does not show this.

Regressions of the incomes of engineers on explanatory variables find routine results. Overall an engineer in this data set receives 2.6% more income per year of education. Unfortunately the measure of education in the data accounts for any post graduate education, no matter how long, as one year past college. These engineers receive on average 1.8% more income per year of experience (measured roughly, but in the standard way, as age minus years of education minus five). With those variables taken into account, those who report having the same occupation in the previous year receive 47.5% more income than those who don't. Presumably those who didn't have the same occupation in the previous year are less experienced.

If we examine the squares of the residuals after that regression is used to predict incomes of an engineer, we find that for the information technology occupations, the squared residuals rise noticeably after about 1983. They rise only slightly for the other engineering categories. This could well be a Greenwood-Yorukoglu effect. If we were looking at a panel data set, this would represent volatility (an ARCH effect). Since it is a repeated cross section, we are seeing a kind of variability that might be called dispersion *given an employee's attributes*. That is, the salary income is less well predicted by the regression after 1983. A natural next step is to see if regressors such as years of education or experience or distance from the new technology predict the appearance of this effect. It could also be predicted by region, since the new technology arose in the western part of the U.S., and would have had its major effects on labor markets there. I have not taken these steps. If the predictions work for engineers I will try to apply them to other employee categories.

There is the possibility that the payoffs to those in the information technology sector come in the form of enhanced future opportunities. Because the CPS records the respondent's occupation in the previous year, I can study who transitions into and out of these occupations.

Further research

The methods attempted in chapter three are meant to be portable to other times and places of technology takeoff. The framing of this dissertation assumes that the information content of an invention affects whether the wage dispersion occurs. One example is insufficient to show such a general phenomenon, and the steel case is not a high information-content one. It could well be that the microprocessor-related inventions show the phenomenon but the steel one does not, even if the general hypothesis is true.

If the methods succeed in illuminating anything about technological changes, they could be applied using Census data to the advent of the telephone, the automobile, and electrification. Another possible study would use the Census of Manufacturers database collected by Bateman, Weiss, and Atack for the census years 1850-1880. Power sources evolved over this period toward the use of steam and later electricity. That database includes for each firm its SIC code, capital invested, type of power source, and average wages for certain kinds of employees (male and female in 1850 and 1860, all employees taken together in 1870, and skilled and unskilled in 1880). One could therefore get a measure of the dispersion of average wages per firm across the industry in these rough categories, and see if it was affected by the early use of new power sources.

Appendix A: Occupational categories in the Census and CPS data

The Current Population Survey (CPS) referred to in chapter 3 uses Census definitions of occupation. These change over time, so there is a problem comparing some occupational categories. Most engineering categories have the same titles in all decades, but the software ones evolved substantially. Here is a list of the how the categorized were standardized for the study in chapter 3.

Job title from CPS/Census	**Standardized occupation code**	1968-71 code (from 1960 census)	1972-81 code (from 1970 census)	1982-1992 code (from 1980 census)
Occupations close to the invention:				
Electrical and electronic engineers	**1**	083	012	55
Computer programmers (note 1)	**2**		003	229
Electrical and electronic engineering technicians	**4**	190	153	213
Computer systems analysts (and scientists, for 1980s) (note 2)	**5**		004	64
Occupations less close:				
Aerospace engineers	**20**	080	006	44
Metallurgical and materials engineers	**21**	090	015	45
Mining engineers	**22**	091	020	46
Chemical engineers	**24**	081	010	48
Civil engineers	**25**	082	011	53
Industrial engineers	**26**	084	013	56
Mechanical engineers	**27**	085	014	57
Engineers not-elsewhere-classified	**28**	093	023	59

Note 1: No form of computer programmer is in the 1960 list of occupations. The Census Bureau's list of how they classified self-reported occupations tells us that computer programmers would have been put in the category "professional, technical, and kindred workers (not elsewhere classified)" which is very broad and cannot be used as a close substitute here. So the computer programmer data starts in 1972.

Note 2: There is no computer systems analyst category in the 1960 Census. In the 1970 Census it is a standalone category, but in 1980 it becomes a broader category that includes computer scientists (who were categorized elsewhere in 1970). There are relatively few computer scientists, however – systems analysts are much more common. So this category is somewhat risky for cross-decade comparisons, but within-decade comparisons should be fine.

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