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THE EVOLUTION OF WORK

Markus Mobius
Raphael Schoenle

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ABSTRACT

The division of labor first increased during industrialization and then decreased again after 1970 as job roles have expanded. We explain these trends in the organization of work through a simple model where (a) machines require standardization to exploit economies of scale and (b) more customized products are subject to trends and fashions which make production tasks less predictable and a strict division of labor impractical. At the onset of industrialization, the market supports only a small number of generic varieties which can be mass-produced under a strict division of labor. Thanks to productivity growth, niche markets gradually expand, producers eventually move into customized production and the division of labor decreases again. The model predicts capital-skill substitutability during industrialization and capital skill complementarity in the maturing industrial economy. Moreover, conventional calculations of the factor content of trade underestimate the impact of globalization because they do not take into account changes in product market competition induced by trade. We test our model by exploiting the time-lags in the introduction of bar-coding in three-digit SIC manufacturing industries in the US. We find that both increases in investments in computers and bar-coding have led to skill-upgrading. However, consistent with our model bar-coding has affected mainly the center of the skill distribution by shifting demand away from the high-school educated to the less-than-college educated.

Markus Mobius
Harvard University
Department of Economics
Littauer 327
Cambridge, MA 02138
and NBER
mobius@fas.harvard.edu

Raphael Schoenle
Princeton University
Department of Economics
Fisher Hall
Princeton, NJ 08544-1021
schoenle@princeton.edu

1 Introduction

During the first two thirds of the 20th century the organization of manufacturing work relied on a sharp division of labor where workers performed a narrow set of tasks according to detailed job descriptions. The principles of job design in the mass production economy were outlined by Frederick Taylor 1911, p. 21 in his theory of "scientific management":

> Under our system a workers is told just what he is to do and how he is to do it. Any 'improvement' he makes upon the orders given to him is fatal to his success.

In the last 30 years departures from this *Taylorist* organization of manufacturing work have become increasingly common. Job roles are expanding both horizontally through job rotation and the merging of narrow job descriptions into broad job classifications, and vertically by introducing flat hierarchies and autonomous work teams.[1]

In many ways these innovative forms of work organization in the *New Economy* resemble those of a much earlier era, namely the pre-industrial artisan economy where skilled craftsmen worked on a product from start to finish. The technologies used by the carriage maker of the 19th century and the team worker in a Japanese transplant car factory might differ enormously. However, in terms of their work experience they have far more in common with each other than with an assembly line worker in Ford's Model T plant in the 1920s.

How can we explain this pattern in the organization of work over time? A formal framework helps to clarify the question. The organization of work Ω and the skill mix S are inputs in the firm's production function $F(\Omega, S, E)$ while the set of technological and market environment is described by the parameters $E = \{\tau, P\}$ where τ denotes the productivity of machines and P denotes the degree of customization in product markets.[2] We are interested in the mechanism which translates changes in firms' environment into new forms of work organization.

A large part of the empirical labor literature has ignored the organization of work and instead focused on the relationship between technological progress and the demand for skills over time such as the recently observed "skill-biased technological change". Can an analogous hypothesis of "organization-biased" technological change explain the decreasing division of

[1] Osterman (1994, 1998) found in a representative sample of US establishments that 23.8 percent of companies had job rotation in place in 1992 with at least half of all production workers involved while 39.8 percent of companies organized their workforce in teams. By 1997 the use of job rotation had more than doubled to 56.4 percent. Pil and MacDuffie (1996) analyzed a matched sample of assembly plants as part of the International Motor Vehicle Project and reported that 15.7 percent of employees were involved in teams in 1989 but 46.3 percent in 1996.

[2] A growing body of empirical evidence suggests that the organization of work is a choice variables of firms. Industry studies show that the *same* technology can be combined with widely different forms of work organization. Wilkinson (1983) and Giordano (1992) analyzed the adoption of computer numerically controlled metal cutting machines in the engineering industry. They can be either programmed by engineers in a central planning department or by machine operators themselves. In the apparel industry sewing machine technology has remained essentially unchanged for the last 30 years as a growing number of companies have introduced team assembly since the late 1980s (Abernathy, Dunlop, Hammond, and Weil, 1999).

labor in the New Economy? Evidence from case studies on work reorganization suggests that the answer is no.[3] The introduction of innovative forms of work organization does generally not require a new type of production technology, but rather emphasizes the need to use existing technology in a new way. Instead, pressure to reorganize seems to come mainly from the demand side. Osterman (1998) found that the best predictors for the adoption of innovative work systems are the intensity of product market competition and a company's decision to compete on the basis of quality and product variety rather than price. The importance of the product market for the organization of work was first noticed by Piore and Sabel (1984) who argued that stable product markets were a prerequisite for the mass production economy.

Building on this early work we develop a formal model which allows us to explain the evolution of work from artisan production, over mass production to the New Economy. We start from the premise that technology determines the degree of variety or *customization* in product markets. Greater product variety implies a less predictable product demand mix because producers become subject to unanticipated trends and fashions. Uncertainty about the composition of demand in return makes production tasks less predictable and favors a flexible organization of work with a weak division of labor. In contrast, if products are standardized production tasks are perfectly predictable and the division of labor is low. Because of its significance for the rest of the paper we restate this link between the degree of customization and work organization as a separate principle:

Taylor's Principle: *The division of labor is determined by the extent of standardization in the product market.*

In our model it is technology which ultimately determines the organization of work with the product market P acting as the transmission mechanism. In other words, firms in our model face a production function of the form $F(\Omega, S, P(\tau))$ and there is no direct effect of technology on the organization of work.

This set-up allows us to explain changes in the organizational of work by making minimal assumptions about the characteristics of the underlying production technology. The artisan economy used general purpose tools and a constant returns to scale technology. A customer could describe the specifications of a good exactly to the artisan who produced diverse output. The degree of customization was therefore high and independent of the extent of the market. The lack of standardization limited the division of labor in artisan production and skilled craftsmen performed most of the intermediate production steps themselves.

[3]Formally, technical change is organization-biased if $\frac{\partial^2 F}{\partial\Omega\partial\tau} > 0$. Bresnahan, Brynjolfsson, and Hitt (2002) find evidence for complementarity between information technology and work reorganization. We do not regard such 'IT-enabled organizational change' as a form of organization-biased technological change because the set of computer users in a company is typically distinct from the set of workers who are involved in work reorganization.

The machine economy uses dedicated special purpose equipment to produce identical items at low marginal costs. Production exhibits increasing returns to scale and the degree of customization depends positively on the size of the market. At the onset of industrialization machine production could only support a small number of product varieties. Therefore, US manufacturers began to actively pursue the standardization of product markets towards the end of the 19th century.[4] These efforts made the output mix predictable during the mass production era, and allowed companies to assign workers to narrowly defined tasks.

The mass production economy started to reach its limits in the 1960s when niche markets for more customized varieties of a basic product had become large enough to attract new entrants. Product proliferation[5] in the mature machine economy offers consumers a similar degree of customization as the early artisan economy but also gives rise to uncertainty about the mix of varieties.[6] Producers are implementing innovative production system, frequently referred to as Just in Time or Lean Production system, in order to deal with the greater uncertainty about the composition of product demand.[7] Job classifications in these systems are typically broader than in mass production facilities. The Toyota production system, for example, groups machines in cells on the shop floor instead of separating them by function. Workers are no longer assigned to a particular machine but to a cell.

A simple extension of our model can provide a non-technological explanation for shifts in the relative demand for skilled labor over time. We assume that skilled workers are more flexible than unskilled workers in the sense that they have a higher average productivity when performing more than one task. High-skilled workers then enjoy a comparative advantage over low-skilled workers in the artisan and the New Economy but demand for flexible labor decreases during the mass production era when production tasks are very predictable. Technological progress and the relative demand for skilled labor are therefore negatively correlated during industrialization but increasingly positively correlated during the rise of the New Economy. Our model generations the historic pattern of capital/skill complementarity which has been reported

[4]Landes (1969, p. 315) describes how US metal working companies were the first to adopt uniform shapes and sizes, and imposed them by fiat on manufacturing clients and consumers from the 1880s on. When Henry Ford started to mass produce his Model T he famously declared that customers could have their car in any color they wanted as long as it was black.

[5]Abernathy, Dunlop, Hammond, and Weil (1999) document product proliferation in the apparel sector. For example, men's shirts were a commodity product up to the 1960s when more than 70 percent of all shirts were white and had a standard cut. That proportion had decreased to 20 percent in 1986. Similarly, in car manufacturing the number of different platforms used as structural under-bodies for product families such as the Oldsmobile increased from 24 in 1955 to 69 in 1973 and 91 in 1986 (Womack, 1989, table 7).

[6]The increase in demand uncertainty and the subsequent need to clear unwanted inventories has led to a significant change in pricing practice for consumer goods starting in the late 1960s as more products were sold at mark-down. The dollar value of total mark-downs (on all merchandise sold in department stores) as a percentage of sales increased from 5.2 percent in 1955, to 6.1 percent in 1965, 8.9 percent in 1975, and 16.1 percent in 1984 (Pashigian and Bowen, 1991).

[7]Kelly (1982) surveys case studies of work reorganization in the 1960s and 1970s in mass production plants. Companies typically cited *line balancing* problems (uneven workloads under a stochastic demand mix) as the main motivation for abandoning traditional assembly line production.

for the US economy by Goldin and Katz (1998). But unlike the literature on skill-biased technological change, we do not have to make any special assumptions about the direction of technological change during different time periods because our model does not assume any direct effect of technological change on skills (e.g. $\frac{\partial^2 F}{\partial S \partial \tau} = 0$).

An analysis of the impact of globalization on labor markets provides another application of our theory. Trade between similar countries accelerates the rise of the New Economy as it increases the size of the market and therefore promotes product proliferation. We demonstrate that conventional calculations based on the factor content of trade underestimate the effects of trade on wage inequality because they do not take into account changes in product market competition induced by trade.

Finally, the model can be used to endogenize the path of technological progress. During the last 30 years new control technologies became available which gave rise to re-toolable multi-purpose machines on the production side, and information technologies such as bar codes and point of sale information processing on the distribution side. The demand for control arises naturally in our model as the machine economy matures and the demand mix becomes less predictable. The theory also implies that multi-purpose machines and information technology have different feedback effects on the organization of work and on skill requirements.

We use the time-lags in introducing bar codes in three-digit SIC industries in the US to test our theory. Industries where bar-coding is more wide-spread can respond more effectively to changes in consumer demand which increases the demand for skilled workers. To distinguish the effects of investments in bar-coding from investments in computers in general we regress the demand for skilled workers on both bar-coding and IT investments. We find that an increase in bar-coding has an independent effect on labor demand at the centre of the skill distribution. Bar-coding shifts demand away from high-school educated workers towards less-than-college-educated workers but has little effect on the highly skilled.

Taylor's principle is the central assumption of our model and closely resembles the famous insight by Smith (1776) that the division of labor is determined by the extent of the market. At the onset of industrialization both principles coincide as improved means of transportation create mass markets for standardized goods. However, the traditional theory cannot explain the observed decrease of the division of labor in the New Economy. Modification of the basic Smithian model can at best explain a slowdown in the division of labor, for example, by introducing coordination costs (as in Becker and Murphy (1992)). This paper is also related to recent work by Thesmar and Thoenig (2000) who interpret product market instability as a high rate of creative destruction in a model of Schumpeterian growth. Globalization and an increase in the supply of skilled labor after 1960 can increase that rate. Skilled workers leave production for research which increases the skill premium.

The balance of the paper is organized as follows. Section 2 introduces the basic model and derives the pattern of work organization over time. Section 3 demonstrates how the model can generate capital/skill substitutability during industrialization and accelerating capital/skill complementarity as the machine economy matures. Sections 4 and 5 discuss implications of international trade and endogenizes technological progress. Section 6 presents our empirical results on bar-coding and the demand for skills. Section 7 concludes.

2 The Basic Model

Our formal framework builds on the now standard Dixit and Stiglitz (1977) model of monopolistic competition, but allows for a more elaborate demand and production system. Consumers do not simply purchase products but can choose between different varieties, or degrees of customization of each product. On the production side there are both monopolistic machine producers, and perfectly competitive artisans. This extension allows us to characterize the evolution of work during industrialization as well as during the rise of the New Economy.

2.1 Product Varieties

There is a continuum of consumers $C = [0, 1]$ who buy products on the unit interval $P = [0, 1]$. Each product has m customizable *features* $\Xi = \{\xi_1, \xi_2, .., \xi_m\}$. At any point t in continuous time each consumer $c \in C$ has a preference profile $(\xi_1 (c, t), \xi_2 (c, t), .., \xi_m (c, t))$ over all features.

Consumers' preferences for each feature ξ_i are distributed according to an i.i.d. process with mass function $g_{i,t}$ and support $\{A_{i,t}, B_{i,t}, C_{i,t}\}$. Each of these three values corresponds to a 'trend' or 'fashion'. While producers know the set of possible trends in advance they cannot perfectly predict which trends will materialize. Formally, the mass function $g_{i,t}$ can take the form $\left(\frac{1}{2}, \frac{1}{2}, 0\right)$, $\left(\frac{1}{2}, 0, \frac{1}{2}\right)$ or $\left(0, \frac{1}{2}, \frac{1}{2}\right)$ with equal probability, e.g. only two of the three possible trends turn out to be successful and each prospective trend fails with probability $\frac{1}{3}$.

Producers can either customize a feature ξ_i with the three possible trends $A_{i,t}$, $B_{i,t}$ and $C_{i,t}$ or they can leave it uncustomized (indicated by the value U). A product with a profile of customized features is called a *variety* and is said to have degree of customization d if exactly d features are customized. For the sake of simplicity we assume that features can only be customized sequentially, i.e. feature ξ_i can only be customized after ξ_{i-1} has been customized.[8] The single variety without any customization is called the *generic* variety and there are 3^m *fully customized* varieties. In total, the set V of varieties for each product category $s \in P$ has size $\frac{1}{2}\left(3^{m+1} - 1\right)$.

2.2 Consumer Demand

A consumer prefers varieties which have a greater number of customized features matching her preference profile. However, she will attach no value at all to a variety with unwanted

[8]For example, in the case $m = 3$ the three varieties with degree of customization $d = 1$ are $(A_{1,t}, U, U)$, $(B_{1,t}, U, U)$ and $(C_{1,t}, U, U)$.

customized features. A variety with degree of customization d is said to 'flop' if any of the d targeted trends is unsuccessful. Hence the generic variety is not subject to trends while a partially customized variety flops with probability

$$1-\left(\frac{2}{3}\right)^{d}$$

which increases in the degree of customization d.

This specification embodies the idea that product proliferation increases uncertainty about the mix of varieties demanded by consumers.[9] Products with few customized features may be uninspiring but demand for them is fairly predictable. Taste shifts will hardly matter because they occur mainly within the targeted consumer groups. Varieties become more vulnerable to trends as they are designed to target smaller niche markets. Taste shifts will occur between rather than within targeted consumer groups which gives rise to endogenous demand uncertainty.

At any point in time a consumer can buy a quantity $x_d(s,t)$ of some variety with d customized features matching her preference profile.[10] Consumers have a CES utility function of the following form:

$$\begin{aligned} U &= \int_0^\infty x(t)\exp(-\delta t)\,dt, \text{where} \\ x(t) &= \left[\int_0^1\left(\sum_{d=0}^{m}\mu^d x_d(s,t)\right)^{\rho} ds\right]^{\frac{1}{\rho}} \qquad (1) \end{aligned}$$

Good are substitutes ($0<\rho<1$) and consumers prefer varieties with a greater degree of customization ($\mu>1$).

We will show that in equilibrium all consumers buy product varieties in industry s with the same degree of customization $d(s,t)$ at price $p(s,t)$. The aggregate price level $p(t)$ and the total demand for all varieties of product $s\in P$ can then be derived as follows:

$$p(t) = \left[\int_0^1\left(\frac{p(s,t)}{\mu^d(s,t)}\right)^{\frac{\rho}{\rho-1}}\right]^{\frac{\rho-1}{\rho}} \qquad (2)$$

$$x(s,t) = x(t)\left[\mu^{d(s,t)}\right]^{\frac{\rho}{1-\rho}}\left(\frac{p(s,t)}{p(t)}\right)^{-\frac{1}{1-\rho}} \qquad (3)$$

Remark: A consumer's preference for more customized products is independent of her income because the demand function is homothetic. A bigger market alone is therefore insufficient

[9]The total demand for all varieties in a product class $s\in[0,1]$ will be stable in the model.

[10]In equilibrium not all varieties might be available to consumers.

for greater market segmentation.[11] In our model, the level of customization depends on the interaction between production technology and market size.

2.3 Artisan Production

Each consumer/worker supplies one unit of labor inelastically. There are three stages of production, namely the *entry stage* at time $t.0$, the *implementation stage* at time $t.1$ and the *production stage* at time $t.2$.[12] Table 1 illustrates the sequence of actions taken at each stage. At the entry stage workers have to decide whether they want to become self-employed artisans or industrial workers in a competitive labor market. Plants purchase machines needed for manufacturing during the implementation stage and artisans/ production workers are assigned to preliminary production tasks. The tastes of consumers, however, are only revealed at the production stage when artisans and plants finally decide which varieties should be produced. We assume that the manufacturing process differs for each product variety in both artisan and industrial production: the set of possible production tasks in industry $s \in P$ is therefore indexed by the set of varieties V.

Artisans use a constant returns to scale production technology based on general purpose tools which can be costlessly acquired during the implementation stage. Artisan technology is completely flexible, i.e. it can be used to produce any variety. One unit of output requires c_A units of artisan labor. Artisans decide in the production phase which variety to produce and sell their products in a competitive market.

In order to discuss the organization of work we introduce the following *organizational index*.

Definition 1 *The organizational index $\Upsilon(s,t)$ measures the probability that in the production stage a production worker/ artisan performs the task she has been assigned to in the implementation phase.*

By measuring the attachment of a worker (artisan) to a task the organizational index captures the extent of the division of labor in industry s. The index reflects Taylor's principle that the division of labor is determined by the extent of standardization. If the degree of customization is low there is little demand uncertainty. This makes production tasks predictable and the organizational index assumes a value close to 1. In contrast, under full customization a worker has to anticipate a large variety of potential tasks. The low degree of division of labor is reflected in an organizational index close to 0.

[11] There is a literature on the 'hierarchy of needs' which essentially assumes that poor people want basic products while rich consumers want more customized varieties. However, the anthropological evidence does not support this hypothesis as Piore and Sabel (1984) point out.

[12] The sequential timing of these three stages would be better captured by a discrete time version of our model in which producers would plan at time $t-1$ and produce at time t. For the sake of simplicity we have 'merged' all phases into period t. The basic intuition of the model is unaffected by this assumption.

Table 1: Entry, implementation and production stage in artisan and machine production

	Artisan Production	**Machine Production**
Entry Stage		- incumbent/ entrant play entry game
Implementation Stage		- hire workers - build machines
	- production workers prepare for task	- production workers prepare for task
Production Stage		- switch workers
	- produce variety	- produce variety

Clearly, artisans will always produce fully customized products because artisan technology can produce any variety at the same cost. The artisan economy therefore exhibits a low degree of division of labor and the organizational index takes the value $\Upsilon(s,t) = \left(\frac{2}{3}\right)^m$.

2.4 Machine Production

Machine technology relies on dedicated equipment to produce large quantities of identical goods at low marginal costs. However, efficiency comes at the cost of inflexibility. We make the (extreme) assumption that each product variety requires an extra machine which has to be installed during the implementation stage. A labor input of $k(t)$ is needed to develop and install this machine.[13] Each unit of output requires an additional labor input of $c_M(t)$ during the production stage.[14] We assume that due to general technological progress both the fixed cost $k(t)$ and the marginal cost $c_M(t)$ decrease at the same rate θ. This specification implies that the ratio of the average cost of producing x_1 and x_2 units does not change over time while productivity improves. For simplicity, we also assume that a machine producer either manufactures all varieties of a certain degree of customization or none.[15]

As in the standard Dixit and Stiglitz (1977) model we would expect a firm to sell its output at a mark-up of $\frac{1}{\rho}$ over marginal production costs. However, the firm might face competition

[13] We define a 'machine' fairly broadly. We assume that it consists of all sunk investments which a firm has to make before it can begin the large-scale production of a new variety. In the automobile industry, for example, a company has to commission expensive design studies and prototypes before it can install any physical equipment. This final step does not necessarily involve the construction of a green-field plant because the body of a new car model can be produced on existing pressing machines after re-tooling.

[14] Machine technology exhibits increasing returns to scale because the average cost of a unit of output decreases with the scale of production.

[15] This assumption is not essential. It simplifies the set-up because the total demand for each product is deterministic even though the product mix is uncertain. Companies which produce all varieties of a certain degree of customization can then reassign production workers internally rather than 'trade' them in a secondary labor market.

from the producer of less customized varieties. The following condition ensures that such lower quality varieties will never succeed because consumers value customized features sufficiently:[16]

$$\mu > \frac{1}{\rho} \tag{4}$$

In each industry there is an incumbent and free entry of firms. Shares in the incumbent are equally owned by consumers. Incumbent and entrants play the following game during the entry period. The incumbent has a first-mover advantage and commits to producing all varieties of degree of customization d_I *unless* an entrant decides to enter the market with more customized varieties. The entrant observes the design decision of the incumbent and commits with probability y to produce varieties with degree of customization $d_I + 1$ in which case the incumbent drops his production plans.[17]

In the implementation stage the winner of the entry game hires workers from a competitive labor market and builds machines. Consumer tastes are realized at the production stage and producers can react to the news by assigning production workers to different tasks. The total demand in each sector is deterministic and a company can therefore reassign production workers internally when it responds to the realization of trends. However, the investment into a machine is sunk even if the corresponding variety is never produced.

One further condition ensures that incumbents would not always want to produce fully customized varieties. A necessary condition is that producers face a decrease in the expected demand for each variety. Since the total demand for a product increases by a factor $\mu^{\frac{\rho}{1-\rho}}$ by adding one more customized feature (see expression 3) and the number of varieties increases by a factor of 3 the condition can be calculated as:

$$\frac{\mu^{\frac{\rho}{1-\rho}}}{3} < 1 \tag{5}$$

Condition 5 expresses the tradeoff between customization and increasing returns. In each industry incumbents have to commit to a degree of customization such that entry generates either no profits or entrants are just indifferent between entering and staying out.

The organizational index can be calculated as

$$\Upsilon(s,t) = \left(\frac{2}{3}\right)^{d(s,t)}.$$

Although the producer who survived the entry game invests in machines to produce all $3^{d(s,t)}$

[16] If the competitor prices its variety at marginal cost the up-market producer can charge consumers a price up to $c_M \mu$ before they defect to the less customized variety. But profits are maximized at a price of $\frac{c_M}{\rho}$ which is *below* that limit.

[17] Note, that it would not make sense for the entrant to produce the same varieties as the incumbent. Bertrand competition would erode all potential profits. It will also become clear that the entrant would not want to enter with a more customized variety.

potential varieties only the $2^{d(s,t)}$ successful ones will be produced. An industry is said to engage in *mass production* if it produces only the generic variety, i.e. $d(s,t) = 0$. In this case the division of labor is high since there is no demand uncertainty. If niche markets are large enough an industry can offer fully customized products and the organization of work resembles that under artisan production.

2.5 Characterizing the Dynamics

In the remainder of this section we derive the evolution of the economy over time. We assume that time starts at $t = 0$ and calibrate the model such that all workers are artisans initially. We then show that the economy goes through two basic transitions. During industrialization machines gradually replace artisan technology. However, product markets are still small and the nascent machine economy can only support mass-produced generic varieties. The weak division of labor under artisan production therefore gives way to a strict Taylorist work organization. At later stages of development product markets fragment as companies target increasingly narrow niches. A New Economy emerges which eventually offers the same degree of customization as the artisan economy. Although vastly more productive the work organization in the New Economy is the same as under artisan production. The era of mass production appears as an intermediate stage in economic development when increasing returns constrain the depth of customization in the machine economy.

We assume that machine producers of generic varieties have sufficiently low marginal costs to compete from the start with any artisan:

$$\mu^m \frac{c_m(0)}{\rho} < c_A \tag{6}$$

The marginal mass producer faces the following demand for her generic product variety:

$$x_{C0}(t) = \frac{E\rho}{c_M(t)\,\omega} \left(\mu^m \frac{c_M(t)}{c_A \rho} \right)^{-\frac{\rho}{1-\rho}}, \tag{7}$$

where $E = 1$ is the total income of consumers once we take the wage as the numeraire. Mass production will be unprofitable as long as the level of demand for the generic variety does not justify the expense of building a dedicated machine:[18]

$$x_{C0}(t) < \frac{k(t)}{c_M(t)} \frac{\rho}{1-\rho} = A \tag{8}$$

If machines are sufficiently expensive (i.e. the fixed cost of a machine is sufficiently large relative to the marginal cost) this condition will be fulfilled at time $t = 0$ and mass producers

[18] Note, that $\frac{k(t)}{c_M(t)}$ is constant over time because both the fixed and the marginal cost decrease at the same rate.

will stay out of the market.

However, over time the output of the marginal mass producer increases as machines continue to improve due to technological progress. Eventually, entry occurs as soon as $x_{C0}\left(t_1^{C0}\right) = A$ which marks the onset of *industrialization*. From then on artisans in more and more industries will become displaced as mass production spreads through the economy.

Theorem 1 *The share y of industrialized sectors increases until the entire economy has industrialized at time t_4^{CO}. The division of labor becomes stricter as the organizational index increases from $\Upsilon\left(s, t_1^{C0}\right) = \left(\frac{2}{3}\right)^m$ to $\Upsilon\left(s, t_4^{C0}\right) = 1$.*

Proof: see appendix A $(a = 1)$

In the mass production economy the marginal producer of a variety with one customized feature faces demand $x_{C1}(t)$ which can be calculated as:

$$x_{C1}(t) = \frac{\mu^{\frac{\rho}{1-\rho}}}{3} \frac{E\rho}{c_M(t)} \tag{9}$$

Initially, customized production is unprofitable because the volume of demand does not cover the fixed cost of investing into a machine:

$$x_{C1}(t) < A \tag{10}$$

As technology improves the niche markets for customized varieties eventually become large enough to attract entrants at time t_1^{C1} when $X_{C1}\left(t_1^{C1}\right) = A$. From then on customized production spreads and mass markets dissolve until mass production is completely replaced. Now a new cycle starts and the economy moves to the next stage of customization in an analogous fashion.

Theorem 2 *At time $t_1^{C(d+1)}$ producers of variety d start to face entry from competitors who offer varieties with degree of customization $d+1$. The probability y of entry is increasing over time until the entire economy has moved to producing varieties with degree of customization $d+1$ at time $t_4^{C(d+1)}$. During each cycle the division of labor becomes less strict as the organizational index decreases from $\Upsilon\left(s, t_1^{C0}\right) = \left(\frac{2}{3}\right)^d$ to $\Upsilon\left(s, t_4^{C0}\right) = \left(\frac{2}{3}\right)^{d+1}$.*

Proof: see appendix B $(a = 1)$

3 The Emergence of Capital Skill Complementarity

In section 2 we demonstrated how a model based on Taylor's principle can explain the evolution of work organization. Another important aspect in the evolution of work is the changing relative demand for skilled labor. A simple extension of our model can map the results on the organization of work into predictions about the relative demand for skilled labor. We first outline the main idea and discuss some of the related literature before introducing the formal model.

3.1 Skills, Flexibility and the Organization of Work

The main facts to be explained are a decrease in the demand for skilled labor during industrialization in the 19th century followed by a gradual increase in relative demand during the first two-thirds of the 20th century and an acceleration of this trend since the 1970s.[19] Our model replicates this pattern if we add the assumption that skilled workers are more *flexible* than unskilled workers. We call a worker flexible if her productivity does not depend on the production task to be performed while inflexible workers achieve high productivity only for the subset of production tasks with which they are familiar. There are strong theoretical reasons to believe that skill and flexibility are correlated: skilled workers have either acquired customary knowledge of a number of tasks through experience, or they have an abstract understanding of the entire production process and can therefore deduce the work content of unfamiliar tasks autonomously.

Flexible workers enjoy no comparative advantage when the division of labor is high because inflexible workers can prepare for the production task which they are likely to perform. This "cost of labor" argument was first made by Babbage (1835, p. 175-176) who realized that the increasing division of labor under industrialization eroded the position of the skilled worker:

> ...the master manufacturer by dividing the work to be executed into different processes, each requiring different degrees of skill or force, can purchase exactly that precise quantity of both which is necessary for each process; whereas if the whole work were executed by one workman, that person must possess sufficient skill to perform the most difficult, and the sufficient strength to execute the most laborious, of the operations into which the art is divided.

Flexibility has again become an important quality in the rise of the New Economy. Caroli and Reenen (2001) analyze a sample of British and French firms and find that organizational change decreases the demand for unskilled labor. Direct evidence about the positive effect of innovative forms of work organization on skill requirements in the US has been collected by Capelli and Rogovsky (1994). Case studies by Murnane, Levy, and Autor (1999) and Zell (1997) also demonstrate that companies which undergo organizational change provide better training and apply a more discriminating selection process.

An outside observer who would try to interpret changes in the demand for skilled labor over time might conclude that capital and skills were substitutes during industrialization but

[19] See Goldin and Katz (1995, 1998), and Goldin and Margo (1992) for pre-1960s evidence, and Bound and Johnson (1992), Berman, Bound, and Grilliches (1994), and Katz and Murphy (1992) for evidence on acceleration.

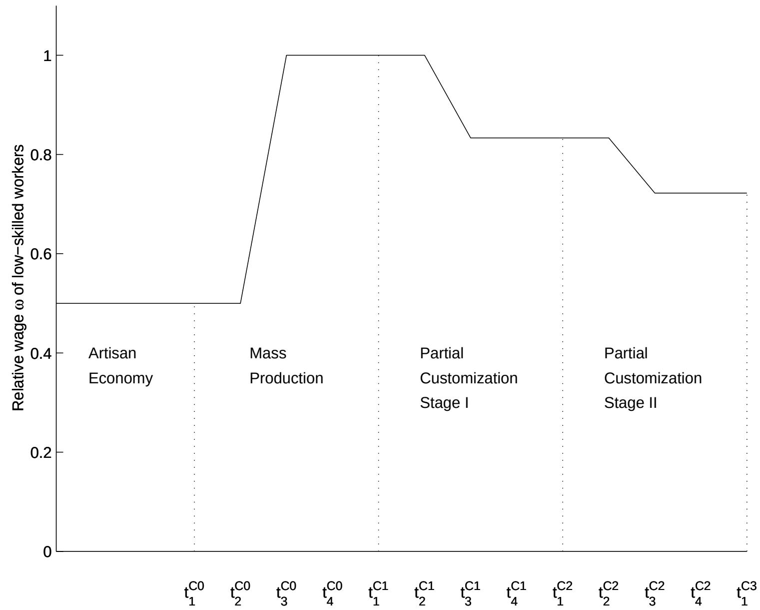

Figure 1: Evolution of income inequality in the extended model

that they increasingly complement each other as the machine economy matures. We want to emphasize that this interpretation would be wrong in the context of our model: there is no direct complementarity between skills and technology. Instead technological change affects skill requirements only indirectly with the product market acting as transmission mechanism. In particular, we do not have to invoke skill-biased technological change to explain the recent increase in the demand for skills as most of the labor literature does.[20]

3.2 Extending the Basic Model

We assume that there are two types of workers: a share α of the workforce is flexible and provides a full unit of labor at any task. The remaining share $1-\alpha$ of workers are inflexible. They can *prepare* for exactly one production task in the implementation phase (see table 1). If they perform this particular task in the production phase they are as productive as skilled workers. However, at any other task they only provide a labor input of $a < 1$.

We assume that the productivity advantage of flexible workers is not too large:

$$a > \frac{1}{\mu} \tag{11}$$

[20]Bartel and Lichtenberg (1987), and Galor and Tsiddon (1997) argue that capital-skill complementarity arises because skilled workers are better in implementing new technologies. Acemoglu (1998) suggests that technology complements skills not by nature but by design and demonstrates how an increase in the supply of skilled workers can induce directed technological change.

Condition 11 ensures that both flexible and inflexible artisans will always produce fully customized varieties. Income inequality in the economy is completely characterized by the relative wage ω of inflexible artisans/ workers. In the artisan economy the relative wage can be calculated as:[21]

$$\omega = w(m) = \left(\frac{2}{3}\right)^m + \left(1 - \left(\frac{2}{3}\right)^m\right) a \tag{12}$$

Condition 4 in the basic model ensured that machine producers of more customized varieties do not face competition from less customizing producers. This condition has to be modified because competitors can use cheap inflexible workers in production:[22]

$$\mu a > \frac{1}{\rho} \tag{13}$$

Furthermore, we now assume that of the $k(t)$ units of labor required for installing a machine, $\alpha k(t)$ workers have to be skilled and $(1-\alpha)k(t)$ workers unskilled. Assuming a Leontief production function for machines makes the model particularly easy to solve.

The organization of work follows the same dynamics in the extended model as in the basic model. However, the division of labor will now determine the relative wage of unskilled workers which in return influences the tradeoff between more and less customized production.

As before, the marginal mass producer will not enter as long as the market for generic varieties is small (note, that $\omega = w(m)$ and that the marginal mass producer only uses cheap unskilled labor):

$$x_{C0}(t) < \frac{k(t)}{c_M(t)} \frac{\rho}{1-\rho} \frac{\alpha + (1-\alpha)\omega}{\omega} = A \frac{\alpha + (1-\alpha)\omega}{\omega} \tag{14}$$

After entry at time t_1^{C0} the following theorem describes the process of industrialization in the extended model.

Theorem 3 *Inflexible workers gradually switch into mass production until all of them are employed in industry at time t_2^{C0}. From then on the relative wage of inflexible workers will start to increase until unskilled workers earn the same wage as artisans ($\omega = 1$). The remaining artisans will become production workers subsequently such that all workers are employed in mass production at time t_4^{C0}.*

Proof: see appendix A

Figure 1 describes the path of income inequality during industrialization. Initially, flexible workers will continue as artisans because they do not have a productivity advantage over un-

[21] A slight complication arises from the fact that inflexible artisans face income uncertainty because they can only prepare for a task successfully with probability $\left(\frac{2}{3}\right)^m$. We assume that workers have access to perfect income insurance in order to avoid this complication.

[22] The relative wage of low-skilled workers is $\omega = a$ in the worst case. Note, that condition 13 implies condition 11.

skilled workers in standardized mass production. As machine technology becomes increasingly productive the relative demand for artisans decreases once all low ability workers moved into manufacturing. This process erodes the relative wage of artisans and eventually equalizes it. From then on skilled artisans are willing to move into manufacturing until mass production has spread across all sectors.

Mass producers will initially face no entry because the niche markets for more customized varieties are too small (note, that $\omega = 1$ and that the marginal producer therefore only uses flexible labor):

$$x_{C1}(t) < A[\alpha + (1-\alpha)\omega] = A \tag{15}$$

Eventually, niche markets become large enough to attract entrants at time t_1^{C1}. The next theorem describes the subsequent emergence of the New Economy as a series of cycles in which producers customize more and more features of their products and upskill their labor force in the process.

Theorem 4 *The relative wage of unskilled workers at time t_1^{Cd} is $w(d-1)$. Flexible workers will gradually switch into producing goods with depth of customization d until all of them are employed in the more sophisticated industries at time t_2^{Cd}. From then on the relative wage of unskilled workers will start to decrease until it has reached the level $w(d)$ and firms in the more sophisticated industry are indifferent between employing flexible or unskilled production workers at time t_3^{Cd}. Unskilled workers will start to move into the more sophisticated industries until the entire economy only produces goods with level of customization d at time t_4^{Cd}.*

Proof: see appendix B

Figure 1 illustrates the rise in inequality as the New Economy emerges. The wage of inflexible workers has to fall once all flexible production workers have moved into the more sophisticated sectors and demand for flexible labor outstrips supply. This process continues until the relative wage reflects the comparative advantage of flexible workers under less predictable manufacturing conditions.

4 The Impact of Globalization

Unlike in standard Heckscher-Ohlin models, trade between *similar* countries (i.e. intra-OECD trade) can increase the returns to skills in our model. This contrasts with the prevailing view that globalization did not greatly affect the distribution of income in the US because it only focuses on the factor content of trade but ignores changes in product market competition induced by trade.

In our model two identical countries trade with each other to take advantage of increased market size and scale economies in machine production.[23] This motivation to trade has been explored by the New Trade literature in order to explain phenomena such as intra-industry trade (see Krugman (1981), Dixit and Norman (1980) and Ethier (1982)). Our model adds to this list the possibility that trade between equals promotes a more flexible organization of work and an increase in the demand for skilled labor. The opening of the US economy to world trade, in particular trade with OECD countries, could therefore have accelerated the rise of the New Economy.

Attempts to quantify the impact of globalization on wage inequality in the US based on the factor contents of trade focus only on trade with less developed countries which have a relatively large pool of unskilled workers matters. However, the volume of such trade seems too small to have a sizable effect on the US wage distribution as Katz and Murphy (1992) and Berman, Bound, and Grilliches (1994) showed. Although total trade as a fraction of GDP more than doubled in the 1970s most of this expansion affected trade with high-wage countries. The share of US manufacturing imports from low-wage countries in manufacturing value-added only increased from 5.7 percent in 1960 to 5.1 percent in 1978 and 10.9 percent in 1990.[24] In contrast, imports from high-wage countries increased from 0.8 percent in 1960 to 13.2 percent in 1978 and 19.8 percent in 1990.

Krugman (2000) concluded that we should think of the OECD as one large closed economy and dismiss trade with LDCs as a significant force behind the widening income distribution in the US. However, it would be wrong to put forward pervasive skill-biased technological change as the only logical explanation. Our model predicts the transition from mass production towards New Economy to occur in all mature economies even in the absence of biased technological progress.[25] Intra-OECD trade might well have accelerated this transition and even triggered it in some industries. Direct empirical support for this view comes from Osterman (1994) who found that firms are more likely to introduce innovative forms of work organization if they compete on international markets.

[23]It is not necessary that consumers in both countries have the same tastes, i.e. follow the same trends. As long as there is some overlap between preferences trade will increase the average degree of customization. This condition is likely to hold as a simple example demonstrates: Volkswagen's New Beetle is manufactured in Mexico for both the North American and the European markets.

[24]Low-wage countries are those with a monthly wage less than or equal to 50 percent of the US monthly wage. See table 3 in Sachs and Shatz (1994).

[25]When comparing the rate of up-skilling amongst advanced nations Berman, Bound, and Machin (1998) found similar cross-industry patterns. While they interpreted these results as evidence for pervasive skill-biased technological change the data is also consistent with our model if the degree of uncertainty about the demand mix in each industry is correlated amongst countries.

5 Technological Progress and the Emergence of Control

The path of technological progress has changed systematically in the last 30 years by providing a greater degree of *control*.[26] Up to the 1950s machines were so specialized that the cost of retooling was enormous. Starting in the 1960s control technologies gradually improved. This gave rise to *multi-purpose machines* (i.e. numerically controlled and computer numerically controlled machines) which are directly used in manufacturing, and *information technology* which is mainly used to coordinate the distribution of goods (i.e. bar codes, point of sale information). Starting with Milgrom and Roberts (1990) comparative statics comparisons based on the level of control have become a standard exercise in a literature which relies on supermodular production functions to explain the clustering of business practices such as outsourcing, lean production and integrated and process development.

In this section we demonstrate how improvements in control arise naturally in our model. It is intuitively obvious that the demand for flexible technology should increase as the economy matures and the demand mix becomes less predictable. However, the precise mechanism differs for multi-purpose machines on the one hand, and information technology on the other hand. The former complement the rise of the New Economy but are not essential since the production system can usually be made more productive by using existing technology differently (such as grouping machines in cells rather than by function). In contrast, information technology not only complements the rise of the New Economy but also enables it because it gives companies the ability to administer demand uncertainty effectively. By distinguishing between these different types of new technologies our model can make sense of the empirical findings of Doms, Dunne, and Troske (1997) who found that the use of information technologies are correlated with workers' skills both in the cross-section and the time series while the use of multi-purpose machines is correlated with skill requirements only in the cross-section. The model also explains the correlation reported by Bresnahan, Brynjolfsson, and Hitt (2002) between the adoption of information technology and the use of innovative forms of work organization.

5.1 Multi-Purpose Machines

In our model dedicated *special-purpose machines* become an increasingly risky investment as the economy matures. If an industry offers varieties with a degree of customization d such a machine will be obsolete with probability $\left(\frac{2}{3}\right)^d$ after consumer trends have realized. Capacity utilization (the ratio of expected to maximum volume of production) will therefore decrease rapidly as industries offer more customized varieties.

[26] Bell (1972) suggested a useful classification of technological progress. He argued that up the 1950s technological innovation strived to improve labor productivity through advances in the *transformation* of workpieces (i.e. mechanical looms, pressing machines) and their *transfer* between work stations (assembly lines, pumps). Engineers began to address the control dimension only in the 1960s.

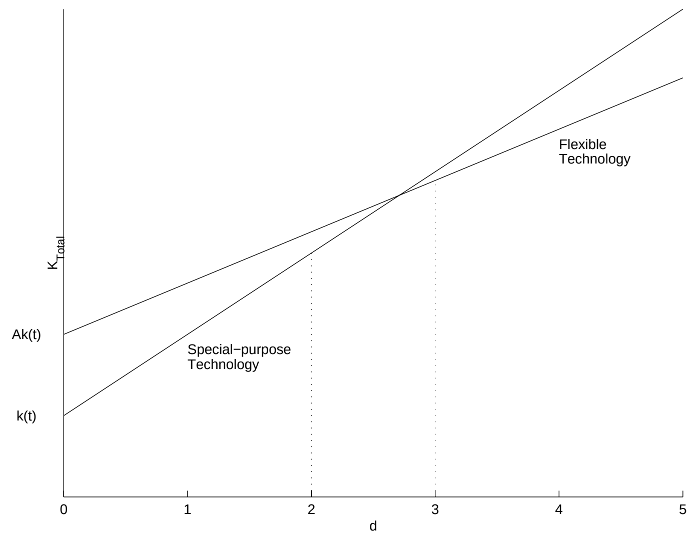

Figure 2: Comparison of the total fixed cost of flexible and special-purpose machines for different degrees of customization (on log-scale with $A = 2$): flexible equipment is more cost effective at a degree of customization $d \geq 3$

A natural extension of the model gives companies the option to install *multi-purpose machines*. We continue to assume that producers can build special-purpose machines which require a total labor input of $k(t)$ workers and which have to be scrapped if the respective variety flops. Alternatively they can install flexible machines which can be re-tooled exactly once at the production stage and which can produce any variety with degree of customization d.[27] Although flexible machines will always be fully utilized their versatility comes at a price. We assume that multi-purpose tools are more expensive than standard machines and require a total labor input of $Ak(t)$ with $A > 1$.

Under mass production there will be no demand for flexible technology because the specifications of a product are entirely predictable. Multi-purpose machines only become valuable once the economy starts to offer varieties with a greater degree of customization d and uncertainty about the product demand mix increases. It is easy to show that multi-purpose equipment become more cost-effective than standard machines once the capacity utilization rate of special-purpose machines has dropped sufficiently:

$$\left(\frac{2}{3}\right)^{d} < \frac{1}{A} \tag{16}$$

There exists a critical depth of customization d^* such that firms will choose flexible technology over special-purpose machines for all $d \geq d^*$ (see figure 2). Theorem 4 continues to characterize

[27]This condition can be relaxed. Assuming a single opportunity to re-tool assures that even flexible machines cannot produce two distinct varieties at the same time.

the evolution of work even in the extended model.[28]

What can we learn from this richer set-up? First of all, production technology with a greater degree of control emerges endogenously in our model as an increasingly unpredictable demand mix erodes the cost advantage of special purpose machines. Second, the option to install multi-purpose machines will induce machine producers to offer more customized varieties sooner. Greater control therefore accelerates the rise of the New Economy.

Third, the model can shed light on the puzzling observation by Doms, Dunne, and Troske (1997) that the use of advanced manufacturing techniques (in particular, multi-purpose machines) explains some of the cross-sectional variations in the demand for skilled labor but little of the time-series variation. This can be seen by introducing some heterogeneity into the model. We assume that not all varieties are equally predictable because one of the two successful trends for each of the m features is known to producers at the implementation stage. This reduces the degree of demand uncertainty for all varieties which incorporate one or more known trends.[29] Skilled, flexible workers and multi-purpose machines are then utilized in the production of 'risky' varieties with few known trends while 'safe' varieties are produced by unskilled workers on special-purpose equipment. However, the demand for more flexible workers will increase in both risky and relatively safe industries because of continuing market fragmentation. Controlling for multi-purpose machines in a time series regression will then only pick up the difference in the rate of up-skilling between adopters and non-adopters which is not clearly signed.

5.2 Information Technology

In the artisan economy the production and distribution operations are usually integrated. Customers can walk into an artisan shop and describe the exact specifications of a variety. The craft economy therefore never produces 'flops'. In contrast, economies of scale lead to the concentration of production in the machine economy and goods reach customers only after they have traversed an elaborate distribution system. Goods are no longer made to order and producers bear the risk of accumulating inventories of 'flopped' varieties. As long as industry produces standardized varieties this risk is small because the demand mix is predictable. The main logistical challenge of the mass production system is to create and efficiently supply mass markets for machine produced goods rather than to track consumer tastes. Mass retailers such as department stores and mail-order houses placed orders well in advance and shipments were

[28] Condition 5 has to be strengthened in order to make sure that firms do not suddenly start to produce fully customized products when they switch to flexible technology:

$$\frac{\mu^{\frac{\rho}{1-\rho}}}{2} < 1 \tag{5*}$$

[29] We continue to assume that machine producers either manufacture all varieties of a certain degree of customization or none.

large and of low frequency.[30]

This system started to run into problems in the late 1960s as a result of ever greater product proliferation. The demand mix became less predictable and retailers found it more difficult to match their inventories to consumers' tastes. They held an increasing number of 'flops' in their inventories which had to be marked down for sale. The dollar value of mark-downs (of all merchandise sold in department stores) almost tripled from 6.1 percent in 1965 to 16.1 percent in 1984 (Pashigian and Bowen, 1991).

The problems of mass retailing in the maturing machine economy can be easily analyzed in our model. Producers cannot adjust the mix of varieties because demand information is only revealed to them *after* they have manufactured all 3^d varieties. Hence, a variety has to be marked down with probability $1-\left(\frac{2}{3}\right)^d$. Product markets continue to fragment over time but at a slower rate than in the standard model.[31] However, the organization of work remains the same as under mass production because firms cannot switch workers between production lines for lack of information. Flexible workers do not enjoy a comparative advantage over unskilled workers and earn the same wage.

In order to respond to fashions and market trends in time, the distribution system has to collect, process and relay information about the demand mix back to suppliers. The development of bar codes, scanners and electronic data interchange (EDI) are a rational response of the distribution system to the increased uncertainty in the product market. In the late 1970s a new breed of lean retailers began to take advantage of these information technologies in an attempt to improve inventory management. Wal-Mart, for example, no longer *pushes* inventories to consumers through promotions and other discounts. Instead, the company lets customers *pull* their orders: Wal-Mart collects point of sale information from its various stores in real time which is used to rapidly replenish 'hits' and discontinue 'flops' without holding a large stock of inventory.

The adoption of information technology has a number of testable implications in our model. First of all, firms now find it profitable to implement a more flexible organization of work which allows them to adapt their output mix rapidly. Organizational change in return increases the demand for flexible workers and the skill premium. Second, there is an increase in the degree of customization because producers no longer manufacture unprofitable 'flops'. Empirical support for the implied complementarity between firms' adoption of information technologies, greater customization and innovative forms of work organization includes Bresnahan, Brynjolfsson, and Hitt (2002).

[30] In the apparel market, for example, these transactions typically occurred eight to ten months before the beginning of each season (see Abernathy, Dunlop, Hammond, and Weil (1999)).

[31] Customizing one more feature will increase the effective unit labor input for each *successful* variety by 50 percent because producers take the risk of mark downs into account. Formally, it can be calculated as $\left(\frac{3}{2}\right)^d c_M(t)$. Therefore, the expected demand for each more customized variety decreases by a factor $\frac{\left(\frac{2}{3}\mu\right)^{\frac{\rho}{1-\rho}}}{3}$ which exceeds the contraction of demand in the standard model.

It is instructive to compare the impact of information technologies with the previously discussed adoption of flexible equipment. Whereas multi-purpose machines merely complement the rise of the New Economy, information technology acts as the catalyst which enables it. This is consistent with the findings of Berman, Bound, and Grilliches (1994), and Autor, Katz, and Krueger (1998) that investments in information technology on the industry level explain some of the time series variation in the demand for skilled workers even though the adoption of multi-purpose machines does not.

6 Empirical Results

We can exploit the role of information technology as a catalyst for changes in the organization of work by using it to test our theory. We expect that different industries will introduce bar-coding at different rates depending on the specific volatility of demand faced in that industry as well as due to the random emergence of large retailers such as Walmart or Home Depot in the 1980s and 1990s which forced their suppliers to introduce bar codes.

Our empirical analysis builds on Autor, Katz, and Krueger (1998) who regress annual changes in the educational shares of the workforce in three-digit SIC industries on annual changes in the share of the total work force using computers at work. We replicate their analysis but also control for annual changes in the percentage of barcode-adopting firms in the industry. Thus, we differentiate between skill-biased technological change through increased computer use and skill-enhancing changes in the organization of work driven by the increased ability of firms to react to more volatile consumer demand.

Formally, we estimate the following regressions:

$$\Delta E_{it} = \alpha + \beta \Delta C_{it} + \gamma \Delta B_{it} + \eta_i + \epsilon_{it} \tag{17}$$

where

ΔE_{it} : change in education percentage share in three-digit SIC industry i in year t

ΔC_{it} : change in percentage share of computer use in industry i in year t

ΔB_{it} : change in percentage share of bar-coding firms in industry i in year t

η_i : fixed effect for industry i

ϵ_{it} : i.i.d. error term

We report results both for manufacturing firms (SIC codes 200-399) and all industries because we expect that our model should apply particularly well to manufacturing industries.

6.1 Data

We exactly follow Autor, Katz, and Krueger (1998) and construct education shares for the college, less-than-college, high-school and less-than-high-school educated in three-digit SIC industries for the years 1979, 1984, 1989, 1993 and 1997 from the NBER merged outgoing rotation group files of the Current Population Survey (CPS). We construct shares of the work force using computers at work from the October 1984, 1989, 1993 and 1997 October CPS.[32]

We extract and merge data from two sources to create an industry-level dataset for the introduction of bar-coding. First, we obtain the bar-coding data from the Uniform Code Council (UCC) database. The UCC data contains the names and addresses of all firms which applied for a UCC bar code between 1971 and 1998. The UCC only assigns the UCC Company Prefix which constitutes the set of digits on a UCC bar code. The trailing digits are assigned privately by the manufacturer who only has to apply for another prefix if she has already used up all trailing digits. Obtaining a company prefix is therefore a prerequisite for bar-coding and we will use the percentage share of companies in the industry which have applied by a certain year for at least one UCC company prefix as our measure of bar-coding in that year.

UCC did not collect Standard Industrial Classification (SIC) information for the companies which applied for a prefix. In order to add SIC codes we therefore use data from the 1999 American Business Disc (ABD). ABD is a directory of all firms in the US with more than 5 employees and uses the 1987 SIC revision at the four-digit level. By matching the UCC to the ABD data we can determine when firms introduced bar-coding and in which industry the respective firms were operating. We consider only firms of employment size 10 or bigger.

Appendix C describes in detail the algorithm we used to match up the UCC and ABD data. The merged data set contains only unique matches. We obtain 50,631 matches out of 211,752 matchable UCC companies (excluding multiple UCC to ABD matches).

ABD also collects information about the size of companies in its directory. Table 2 shows a break-down of the number of matched UCC firms by firm size, relative to the number of firms in the corresponding category of the ABD data. Most of our matches were large companies.

We then aggregate the matched data up to three-digit SIC industries. We calculate the share of bar-coding firms in year XX of size larger than or equal to ten as the number of UCC-to-ABD matched firms of size larger than or equal to ten which had applied for a UCC Company Prefix by that year divided by the total number of firms in that 3-digit industry of size larger than or equal to ten in the ABD data in 1998.

Since the October CPS asked about computer use only in the years 1984, 1989, 1993 and 1997, we also calculate annualized changes (multiplied times 100) in the share of bar-coding firms only for the year groups 1984-1989, 1989-1993 and 1993-1997.

[32] The CPS asks whether a worker uses a computer keyboard at work.

6.2 Results

Table 3 replicates the regressions in table V of Autor, Katz, and Krueger (1998) for manufacturing industries only.[33] Our results for manufacturing are close to the result reported in their paper.

In tables 4 and 6 we add our new measure of annualized percentage changes in bar-coding firms in each three-digit industry (manufacturing firms and all firms respectively). Controlling for possible industry fixed effects in the rate at which different industries adopt bar-coding, we find that a one percent increase in the share of bar-coding firms decreases the share of high-school employment by about 1.2 to 1.3 percentage points and increases the share of less-than-college employment by about 1 to 1.2 percentage points. The estimated coefficients on percentage changes in computer use remain mostly unchanged from table 3. Interestingly, the effects of bar-coding for the high-school and the less-than-college educated are almost ten times as large the as the effects of computerization. This difference in the magnitudes of the coefficients on bar-coding and computer use reflects the difference in the absolute levels of each variable. On average, 1.06 percent (2.38 percent) of all (manufacturing) firms engaged in bar-coding in 1984, while computer use was22.44 percent (33.90 percent) in all (manufacturing) industries in 1984. These percentages increased to 4.31 percent (8.96 percent) in 1997, and 43.06 percent (46.90 percent) in 1997, respectively. Therefore, the actual impact of changes in use of bar-coding and computers is of the same magnitude.

Unlike computerization, which also raises the demand for college educated workers in an industry, bar-coding mainly affects the center of the skill distribution. This is consistent with our model which predicts that the demand for skilled production workers increases as more volatile consumer demand requires greater flexibility. However, we do not find that effects of bar-codes on manufacturing industries are stronger than the effects in all three-digit industries.

We test for the appropriateness of a fixed- versus a random-effects specification using a Hausman test for both the manufacturing industries sample and the full sample. The test rejects the null hypothesis that the random-effects specification is consistent at the five percent significance level two out of 4 times in the case of all industries, and one out of 4 times in the case of manufacturing.[34]

7 Conclusion

Our model builds on the wave of recent empirical research which explored the relationship between technological progress and the transformation of the workplace. This literature con-

[33] Including the mean education level from 1974 has only a small effect on the estimated coefficients. We can also replicate the regressions in Autor, Katz, and Krueger (1998) using data for all 3-digit industries.

[34] For manufacturing industries the p-values of the Hausman test for higschool-, less-than-highschool-, some-college- and college-educated workers are .3519, .0096, .0887, .6109 respectively. For the full sample the corresponding p-values are .6787, .1278, .0899 and .1289 respectively.

vincingly demonstrated that new technologies, workplace reorganization and skill requirements have been complements since the 1970s.

However, the typical paper in this literature follows a methodology which makes it problematic to infer organization-biased and skill-biased technological change from this evidence. It assumes a reduced form production function of the form $F(\Omega, S, \tau)$, throws in controls for the various dimensions of technological progress and estimates the strength of the complementarities. Since the transmission mechanism from technology to the demand for skills is not modeled it is perhaps unsurprising that cross-partial between technology and skills was negative during the industrial revolution when unskilled machine operators replaced skilled artisans and became positive after 1970.

In contrast, we explicitly model the transmission of technological progress through the product market environment in which firms operate. This set-up allows us to explain the historic U-shaped evolution of work organization from artisan to New Economy. Moreover, we can derive the impact of distinct technological innovations on the demand for skilled workers within a unified framework. The model promotes the view that the era of mass production was a transitory phenomenon, a period in which the scale economies embodied in machine production limited the degree of product customization.

We test our model by exploiting the time lags in the introduction of bar-coding in three-digit SIC US manufacturing industries. We find that both increases in investments in computers and bar-coding have led to skill upgrading. Unlike investment in computers, however, the adoption of bar-coding is associated with shifts in the middle of the skill distribution, away from high-school graduates towards less-than-college graduates. This is consistent with our model since the ability to better respond to demand changes will mainly affect the organization of work at the margin of unskilled to skilled.

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Table 2: Number of UCC to ABD matches for different company sizes (using size classification in ABD data set)

	Manufacturing Firms		All Firms	
Firm size	# of Matches	Share of ABD firms	# of Matches	Share of ABD firms
10,000+	87	22 %	178	14 %
5,000+	68	19 %	127	10 %
1,000+	398	16 %	652	7 %
500+	447	12 %	681	5 %
250+	967	12 %	1,418	4 %
100+	2,434	10 %	3,883	3 %
50+	2,247	8 %	4,246	3 %
20+	3,473	6 %	8,042	1 %
10+	2,653	4 %	7,337	1 %
All firms	17,226		47,696	

Details of the matching procedure are discussed in appendix C.

Table 3: OLS First Difference Estimates of the Relationship between Computerization and Educational Upgrading in Three-Digit Manufacturing Industries between 1979 and 1993. Dependent Variable defined as 100*(Annual Change in Employment Share)

	College	Some College	HS Grad	Less than HS
Δcomputer use	**.127**	**.089**	**-.311**	**.095**
	(.052)*	(.042)*	(.081)**	(.054)†
Intercept	.184	.407	.429	-1.020
	(.106)*	(.087)**	(.166)*	(.111)**
R^2	.079	.059	.174	.0415
n	73	73	73	73

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Standard errors are shown in parentheses. Industries are restricted to manufacturing industries only (SIC codes 200-399). ΔComputer use is 100 times the annualized change in industry computer use frequency between 1984 and 1993 as reported in the October 1984 and 1993 CPS. Changes in educational shares are measured as 100 times the annual change in the share of industry workers in each educational category as reported in the 1979 and 1993 Merged Outgoing Rotation Groups of the CPS. Industries are coded as 191 consistent CICs, spanning the standard 1970, 1980, and 1990 CICs. All regressions are weighted by the product over the sum of the industry's share of total employment in each of the two years used in constructing the dependent variable. See the Data Appendix in Autor, Katz, and Krueger (1998) for further details.

Table 4: Fixed-Effects Regression Estimates of the Relationship between Computerization, Bar-Coding and Educational Upgrading in Three-Digit Manufacturing Industries between 1984 and 1997. Dependent Variable defined as 100*(Annual Change in Employment Share)

	College	Some College	HS Grad	Less than HS
Δcomputer use	**.083**	**.114**	**-.111**	**-.086**
	(.036)*	(.049)*	(.059)†	(.042)*
Δbar-coding	-.101	**.990**	**-1.16**	.268
	(.305)	(.413)*	(.495)*	(.349)
Intercept	-.283	.074	.121	-.478
	(.158)	(.214)	(.257)	(.181)**
R^2	.224	.142	.197	.213
n	203	203	203	203

Significance levels: $\dagger$: 10% $*$: 5% $**$: 1%

Standard errors are shown in parentheses. Industries include all industries. Δbar-coding is 100 times the annualized change in industry bar-coding use frequency of year groups 1984-1989, 1989-1993, 1993-1997. Bar-coding data are obtained from the merger of the UCC and ABD dataset described in appendix C. Changes in educational shares and Δcomputer use are constructed as in table 3 but for year groups 1984-1989, 1989-1993, 1993-1997. Fixed effects control for potentially industry-specific rates of change in the adoption of bar-coding and computerization. Regressions are weighted as in table 3.

Table 5: Random-Effects Regression Estimates of the Relationship between Computerization, Bar-Coding and Educational Upgrading in Three-Digit Manufacturing Industries between 1984 and 1997. Dependent Variable defined as 100*(Annual Change in Employment Share)

	College	Some College	HS Grad	Less than HS
Δcomputer use	**.114**	**.096**	**-.132**	**-.078**
	(.029)**	(.038)*	(.047)*	(.034)*
Δbar-coding	.113	.245	**-.422**	.064
	(.141)	(.186)	(.228)†	(.165)
Mean ed 1974	.051	.034	-.093	.008
	(.028)†	(.037)	(.045)*	(.033)
Intercept	-5.91	-3.64	10.89	-1.35
	(3.33)†	(4.40)	(5.39)*	(3.90)
R^2	.087	.037	.060	.028
n	203	203	203	203

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Standard errors are shown in parentheses. Industries include all industries. Δbar-coding is 100 times the annualized change in industry bar-coding use frequency of year groups 1984-1989, 1989-1993, 1993-1997. Bar-coding data are obtained from the merger of the UCC and ABD dataset described in appendix C. Changes in educational shares and Δcomputer use are constructed as in table 3 but for year groups 1984-1989, 1989-1993, 1993-1997. Lagged industry education means are drawn from the 1974 May CPS. Regressions are weighted as in table 3.

Table 6: Fixed-Effects Regression Estimates of the Relationship between Computerization, Bar-Coding and Educational Upgrading in all Three-Digit Industries between 1984 and 1997. Dependent Variable defined as 100*(Annual Change in Employment Share)

	College	Some College	HS Grad	Less than HS
Δcomputer use	**.038**	**.123**	**-.106**	**-.056**
	(.016)*	(.032)**	(.029)**	(.018)**
Δbar-coding	-.120	**1.16**	**-1.34**	.302
	(.319)	(.565)*	(.492)**	(.317)
Intercept	.242	.281	.300	-.224
	(.062)**	(.105)**	(.096)**	(.062)**
R^2	.325	.144	.266	.297
n	497	497	497	497

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Standard errors are shown in parentheses. Industries include all industries. Δbar-coding is 100 times the annualized change in industry bar-coding use frequency of year groups 1984-1989, 1989-1993, 1993-1997. Bar-coding data are obtained from the merger of the UCC and ABD dataset described in appendix C. Changes in educational shares and Δcomputer use are constructed as in table 3 but for year groups 1984-1989, 1989-1993, 1993-1997. Fixed effects control for potentially industry-specific rates of change in the adoption of bar-coding and computerization. Regressions are weighted as in table 3.

Table 7: Random-Effects Regression Estimates of the Relationship between Computerization, Bar-Coding and Educational Upgrading in all Three-Digit Industries between 1984 and 1997. Dependent Variable defined as 100*(Annual Change in Employment Share)

	College	Some College	HS Grad	Less than HS
Δcomputer use	**.038**	**.103**	**-.074**	**-.055**
	(.015)**	(.024)**	(.022)**	(.015)**
Δbar-coding	.158	.348	-.121	-.014
	(.130)	(.244)	(.168)	(.184)
Mean ed 1974	.007	.003	-.013	.006
	(.005)	(.009)	-(.006)*	(.008)
Intercept	-.689	.107	1.13	-.964
	(.568)	(1.12)	(.708)	(.971)
R^2	.025	.030	.041	.020
n	497	497	497	497

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

Standard errors are shown in parentheses. Industries include all industries. Δbar-coding is 100 times the annualized change in industry bar-coding use frequency of year groups 1984-1989, 1989-1993, 1993-1997. Bar-coding data are obtained from the merger of the UCC and ABD dataset described in appendix C. Changes in educational shares and Δcomputer use are constructed as in table 3 but for year groups 1984-1989, 1989-1993, 1993-1997. Lagged industry education means are drawn from the 1974 May CPS. Regressions are weighted as in table 3.

A Proof of Theorems 1 and 3

For the proof of theorem 1 simply set $a = 1$, e.g. all workers are of high-ability. We assume that a share y of the economy utilizes mass production. The price level $p(t)$ in the economy and the demand $x_A(t)$ for artisan goods and $x_{C0}(t)$ for industrial goods can be derived from equations 2 and 3:

$$p(t) = \frac{c_M(t)\,\omega}{\rho}\left[y + (1-y)\left(\mu^m \frac{c_M(t)\,\omega}{c_A \rho}\right)^{\frac{\rho}{1-\rho}}\right]^{\frac{\rho-1}{\rho}} \tag{18}$$

$$x_{C0}(t) = \frac{E\rho}{c_M(t)\,\omega}\frac{1}{y + (1-y)\left(\mu^m \frac{c_M(t)\omega}{c_A\rho}\right)^{\frac{\rho}{1-\rho}}} \tag{19}$$

$$x_A(t) = x_{C0}(t)\,(\mu^m)^{\frac{\rho}{1-\rho}}\left(\frac{c_M(t)\,\omega}{c_A\rho}\right)^{\frac{1}{1-\rho}} \tag{20}$$

During industrialization machine producers are indifferent between entering mass production or staying out. Therefore, they have to make zero profits and condition 14 holds:

$$x_{C0}(t) = A\frac{E}{\omega}$$

At the onset of industrialization the demand for high-skilled workers in the artisan industry exceeds supply and the wage differential is $w(m)$, the same as in the artisan economy. The zero profit condition will then determine the share of industrializing sectors:

$$A = \frac{\rho}{c_M(t)}\frac{1}{y + (1-y)\left(\mu^m \frac{c_M(t)\omega}{c_A\rho}\right)^{\frac{\rho}{1-\rho}}} \tag{21}$$

Due to condition 6 the left hand side of this expression is decreasing in y and $c_M(t)$. Hence technological progress promotes industrialization.[35]

At some time t_2^{C0} all low-skilled workers switched to industrial production while the demand for artisans continues to decrease. However, artisans will not enter industry yet because they would have to accept the wages of low-skilled workers.[36] Instead, the wage levels of both groups will gradually equalize. During this process the zero profit condition 21 continues to hold. Furthermore, the ratio of high-skilled artisans and low-skilled industrial production workers equals the relative share of both groups:

$$\frac{(1-y)\,c_A x_A(t)}{y\,c_M(t)\,x_{C0}(t)} = \frac{\alpha}{1-\alpha}$$

This condition can be simplified:

$$c_M(t)^\rho\,\omega = \left(\frac{\alpha}{1-\alpha}\right)^{1-\rho}\frac{1}{\rho}\left(\frac{c_A}{\mu^m}\right)^{\rho}\left(\frac{y}{1-y}\right)^{1-\rho} = D\left(\frac{y}{1-y}\right)^{1-\rho} \tag{22}$$

[35] Note, that the entry decisions of mass producers are strategic substitutes. Every new entrant lowers the demand faced by other mass producers because goods are substitutes. This guarantees uniqueness of the equilibrium.

[36] High-skilled workers do not enjoy a comparative advantage in producing generic goods because the division of labor is high.

If we define an auxiliary variable $z = c_M\omega$ we can rewrite the two conditions 21 and 22 in reduced form as

$$A = f(c_M, y, z) \tag{21a}$$
$$D = g(c_M, y, z), \tag{22a}$$

with $\frac{\partial f}{\partial c_M} < 0$, $\frac{\partial f}{\partial y} < 0$, $\frac{\partial f}{\partial z} < 0$, $\frac{\partial g}{\partial c_M} < 0$, $\frac{\partial g}{\partial y} < 0$, $\frac{\partial g}{\partial z} > 0$.

We can then deduce that industrialization proceeds during wage equalization as

$$\frac{d\,y}{d\,c_M} = \frac{\frac{\partial g}{\partial c_M}\frac{\partial f}{\partial z} - \frac{\partial g}{\partial z}\frac{\partial f}{\partial c_M}}{\frac{\partial g}{\partial z}\frac{\partial f}{\partial y} - \frac{\partial g}{\partial y}\frac{\partial f}{\partial z}} < 0 \tag{23}$$

The relative wages of low-skilled workers will in deed increase as one can immediately see from equation 22.

At time t_3^{C0} the wages of workers will have equalized. High-skilled workers are now indifferent between staying on as artisans or becoming industrial production workers. They will gradually switch into mass production until the entire economy has industrialized at time t_4^{C0}.

It is important to note that throughout the process of industrialization no machine producer would wish to customize a variety. Due to condition 5 her revenue from the production of the variety would be less than the revenue of a mass producer but her cost of producing a dedicated machine would be the same. As mass producers just break even customized varieties would be unprofitable. QED

B Proof of Theorems 2 and 4

For the proof of theorem 2 simply set $a = 1$, e.g. all workers are of high-ability. Without loss of generality we concentrate on the demise of mass production. In a share y of sectors incumbent mass producers face entry by firms which offer more customized varieties. The price level $p(t)$ in the economy and the expected demand $x_{C0}(t)$ for generic goods and $x_{C1}(t)$ for varieties with degree of customization $d = 1$ can be derived from equations 2 and 3:

$$p(t) = \frac{c_M(t)\,\omega}{\rho}\left[1 - y + y(\mu\omega)^{\frac{\rho}{1-\rho}}\right]^{\frac{\rho-1}{\rho}} \tag{24}$$
$$x_{C0}(t) = \frac{E\rho}{c_M(t)\,\omega}\frac{1}{1 - y + y(\mu\omega)^{\frac{\rho}{1-\rho}}} \tag{25}$$
$$x_{C1}(t) = x_{C0}(t)\frac{\mu^{\frac{\rho}{1-\rho}}}{3}\omega^{\frac{1}{1-\rho}} \tag{26}$$

During transition entrants have to make zero profits and condition 15 holds:

$$x_{C1}(t) = A\left[\alpha + (1-\alpha)\,\omega\right]$$

The income of consumers consists of labor income and profits made by incumbent mass producers, e.g. $E = \alpha + (1-\alpha)\,\omega + \Pi$. Profits can be derived as follows:

$$\Pi = (1-y)\left[x_{C0}(t)\,c_M(t)\,\omega\frac{1-\rho}{\rho} - k(t)\left[\alpha + (1-\alpha)\,\omega\right]\right] \tag{27}$$
$$= (1-y)\left[\alpha + (1-\alpha)\,\omega\right]k(t)\left[\frac{1}{\frac{(\mu\omega)^{\frac{\rho}{1-\rho}}}{3}} - 1\right] \tag{28}$$

We can then rewrite total consumer income as:

$$E = [\alpha + (1-\alpha)\,\omega]\left[1 + (1-y)\,k\,(t)\left[\frac{1}{\frac{(\mu\omega)^{\frac{\rho}{1-\rho}}}{3}} - 1\right]\right] \tag{29}$$

After time t_1^{C1} the supply of high-skilled workers exceeds demand in the mass production economy and wages are equal for both types of workers. The zero profit condition determines the share of sectors y with customized production and can be expressed as

$$A = \frac{\rho}{3}\frac{\frac{z}{c_M(t)} + (1-y)\frac{k(t)}{c_M(t)}(3-z)}{1-y+yz} \tag{30}$$

with the help of the auxiliary variable $z = (\mu\omega)^{\frac{\rho}{1-\rho}}$. This condition can be written in reduced form as

$$A = f\,(c_M, y, z) \tag{30a}$$

with $\frac{\partial f}{\partial c_M} < 0$, $\frac{\partial f}{\partial y} < 0$, $\frac{\partial f}{\partial z} > 0$.[37] Because z is fixed ($\omega = 1$) technological progress implies an increase in the share y of customized sectors in the economy.

At some time t_2^{C1} all high-skilled production workers are employed in the customized sectors and the labor market tightens as a result. The relative wage of high-skilled workers then has to increase. During this process the zero profit condition 30 continues to hold. Furthermore, the ratio of high-skilled production workers in the customized sectors and low-skilled mass production workers equals the relative share of both groups:

$$\frac{yc_M\,(t)\,x_{C1}\,(t)}{(1-y)\,c_M\,(t)\,x_{C0}\,(t)} = \frac{\alpha}{1-\alpha} \tag{31}$$

This condition can be written in reduced form as

$$F = g\,(y, z) \tag{31a}$$

with $\frac{\partial g}{\partial y} > 0$ and $\frac{\partial g}{\partial z} > 0$.

Combining this condition with condition 31a we can deduce that the share of customized sectors will continue to increase during the process of wage widening.

At time t_3^{C1} relative wages have reached the level $w\,(1)$ and reflect the productivity difference between low-skilled and high-skilled workers in the customized industries. Low-skilled workers will gradually leave mass production until the entire economy produces varieties with degree of customization $d = 1$ at time t_4^{C1}. QED

C Matching UCC and ABD Data

To merge the UCC and ABD data, we developed a simple matching algorithm. The algorithm is based on the firm-level information available. This information includes the firms name, address, city and zip code.

[37] The right hand side of expression 30a decreases in y because of condition 11. The derivative of the expression with respect to z has the same sign as $1-(1-y)\,k\,(t) - 3yk\,(t)$ which is the mass of production workers in the economy and therefore positive.

Before the actual matching, we cleaned the data carefully. This involved standardizing alternate spellings of common words and stripping redundant punctuation and spacing in order to ensure that company names, city names, and addresses would match despite alternate spellings or wordings. For cities, for example, we converted "St" into "Saint", "Mt" into "Mount" etc. Different word lists and heuristics were used for company names, city names, and addresses respectively. Our code contains a complete list of the conversions and is available from the authors. Moreover, we added leading zeroes to zip codes that are 3, 4, 7 or 8 digits to make them either 5 digits or 9 digits long.

After these transformations, we find matches between the two databases by comparing selected fields through a string similarity algorithm. The matching works through comparisons of the same items of a record in both data sets, for example company name in the UCC data and company name in the ABD data. To be a match, each piece of a records information across the two databases had to attain a specified similarity score, potentially different across pieces of information. We calculate the similarity score between strings A and B as follows. First, the Longest Common Subsequence (LCS) is calculated for the two strings. This is the longest possible sequence constructed by deleting zero or more characters from A, and deleting zero or more characters from B, to produce the same sequence. Then we calculate the similarity score by the formula

$$\frac{1 + length(LCS)}{0.5 * (length(A) + length(B) + 2.001 - |length(A) - length(B)|)} \tag{32}$$

This formula calculates the ratio of the length of LCS to the total length of A and B, with additional factors to ensure that the score is never zero and to compensate for one string being longer than the other[38].

To obtain the highest possible number of matches, we varied the degrees of similarity required in several rounds of matching. At the same time, we sped up the matching process by hashing either company name, or zip code, or the first three to five letters of a zip code combined with company names. In the first round of matching, we required perfect matches (similarity score of 1) for all pieces of a records information. Then, we relaxed the requirement on the address to attain a similarity score of at least 0.9, and then of at least 0.7. As a forth step, we imposed 0.7 fuzziness on address and city information, besides perfect similarity on all other items. As a next step, we additionally required at least four digits of the zip code to match with the remaining requirements unchanged. At round six of matching, we again required perfect matching for all items, except state and address, which we ignored. As a variant, we kept ignoring the address, required the company name and state to match perfectly, and imposed a minimum similarity of 0.7 on city and zip code. At round eight, we switched from hashing company names to hashing by the first five of zip plus each word of the company name, removing hash keys that got more than some number of UCC members[39]. We used a cutoff hash of 15 and required city and state to match perfectly, address to attain a similarity score of at least 0.9 and of 0.7 for company names. As a variant, we had the same requirements but imposed 0.85 fuzziness on company names, 0.7 on address, and took account

[38] In a situation where we are comparing a short name of a company to a long name of the same company, for example.

[39] In addition, we controlled for high-frequency words that can occur in company names. We excluded words from company names that occurred more than 350 times in the UCC data on company names, such as "The" or "Incorporated". The list of words was taken from a frequency count.

of plural ss as a potential source of matching information differences. Finally, we hashed by the first three of zip plus each word of the company name, removing hash keys that got more than some number of UCC members. Again, we controlled for high frequency words in the company names. We used a cutoff hash of 15 and required city and state to match perfectly, address to attain a similarity score of at least 0.9 and of 0.7 for company names. Whenever we identified a match for a record in a matching round, we flagged the UCC record as matched and saved the ABD and UCC information in a new file. As we varied the similarity scores required, we only considered UCC records that had not been matched yet.

The algorithm was implemented in Perl and code is available from the authors.