The Evolution of Work*

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Abstract

The division of labor first increased during industrialization, and then decreased again after 1970 as job roles have expanded. In this paper, we explain these trends in the organization of work through a simple model, making two minimal assumptions: (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. The model predicts capital-skill substitutability during industrialization and capital-skill complementarity in the maturing industrial economy: 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. Then, thanks to productivity growth, niche markets gradually expand, producers eventually move into customized production, and the division of labor decreases again. We test our model by exploiting the time-lags in the introduction of bar-coding in three-digit SIC manufacturing industries in the U.S.. 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.

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1 Introduction

> 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.
> *Frederick Taylor (1911, p. 21)*

Fredrick Taylor's principles of "scientific management" guided the organization of manufacturing work in the first half of the 20th century as workers performed a narrow set of tasks according to detailed job descriptions. However, in the last 50 years, departures from this Taylorist organization of 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 German or 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.

One possible, conventional explanation for changes in the organization of work is that there is a *direct complementarity* between work reorganization and recent technological progress (see Bresnahan, Brynjolfsson, and Hitt (2002) for the case of information technology). A large labor literature on skill-biased technological change builds on this hypothesis. It has examined the complementarity between technological progress and skilled labor, and its effects on the income distribution, such as Berman, Bound, and Grilliches (1994), Acemoglu (1998, 2002), Autor, Katz, and Krueger (1998), or Goldin and Katz (1998, 2007)[2].

However, evidence from case studies does not suggest that work reorganization is directly induced by technological change. For example, the Toyota production system did not require new types of machines but rather prescribed a rearrangement of standard machines on the shop floor (Womack, 1989). Instead, pressure to reorganize seems to have originated from the *demand side*, and in particular the demand for product customization. Osterman (1998) finds 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 varieties rather than price.

We propose a new model motivated by such demand side evidence that explains *both* the

[1]Osterman (1994, 2000) found in a representative sample of U.S. 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]See Katz and Autor (1999) and Acemoglu and Autor (2011) for a summary of the large body of the literature and recent refinements.

evolution of work organization *and* the skill premium from the beginning of the industrial period to modern times while making minimal assumptions about the direction of technological progress. We only assume that (a) machine production requires a minimum scale of production to cover the sunk cost of machinery; (b) every machine can only produce a single variety of a product at low marginal cost; (c) technological progress increases the productivity of machines and hence expands the size of the market. Larger market size in turn provides the scale to sustain more product varieties. For example, the most popular cars in 1920 and 2005 were the model T and Ford's F-series, respectively. Both sold a similar number of units (1.3 million versus 900,000). However, 60 percent of all cars sold were model T in 1920, while the F-series made up only 12 percent of sales in 2005.

The organization of work and the skill premium in our model are determined by the interaction between market size and demand. Consumers like the customization provided by larger market size. However, customization also gives rise to uncertainty about the composition of product demand because any specific variety is more likely to "flop:" for example, a retailer might know that one of 10 possible fashion styles will be successful this summer, but cannot perfectly predict the successful variety. Demand uncertainty in turn makes it necessary for firms to cross-train workers on several machines (equivalent to a broadening of job descriptions). This type of work organization favors skilled workers whom we assume to be more flexible than unskilled workers (who need to be re-trained for each new task).

As a result, the model we propose can explain the main patterns in the evolution of work organization and skill premia over time without assuming organization-biased or skill-biased technological change: In the pre-industrial era, machines are too inefficient to compete with artisans who produce custom-made products. Wage inequality is high as unskilled workers cannot customize products as efficiently as skilled workers. As machines improve, the market for uncustomized, standardized industrial goods becomes large enough to sustain machine producers. These firms hire cheap low-skilled workers who work on a single task and hence are not at a disadvantage compared to skilled workers. As machine production displaces artisans, wage inequality decreases together with the division of labor as more and more workers are assigned to a single task.

Piore and Sabel (1984) have pointed out that product standardization was a prerequisite for efficient mass production. For example, Ford' Model T was a highly standardized product that became widely used both as a family car and for business purposes.[3] Similarly, men's shirts became a commodity product and by the 1960s more than 70 percent of all shirts sold where white and had a standard cut (Abernathy, Dunlop, Hammond, and Weil, 1999). During industrialization technological progress is correlated with de-skilling and a decrease in the division of

[3]Landes (1969, p. 315) describes how U.S. 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.

labor despite the fact that technological change and worker skills are not direct substitutes.

However, as productivity of machines improves further, firms gradually start to increase product variety again. In the US, this process started in the 1960s as niche markets for customized varieties of basic products had become large enough to attract new entrants. For example, the increase in productivity allows consumers to purchase more shirts or a second or third car. Abernathy, Dunlop, Hammond, and Weil (1999) document product proliferation in the apparel sector where the proportion of standardized white shirts had decreased to 20 percent in 1986 (from 70 percent in the 1960s). Similarly, the number of different platforms in car manufacturing 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).

Such product proliferation increased uncertainty about the success of varieties. An intriguing indicator is the rise of mark-downs starting in the 1960s due to the greater need for clearing unwanted inventories: 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). Demand uncertainty also interferes with the strict division of labor in mass production plants. For example, Kelly (1982) surveys case studies of work reorganization in the 1960s and 1970s. Companies typically cited *line balancing* problems (uneven workloads under a stochastic demand mix) as the main motivation for abandoning traditional assembly line production.

During this post-industrial era of mass customization capital and skills become *complements*, again as predicted by our model: firms are implementing innovative organizations of work, such as "just in time" or "lean" production in order to deal with the increased uncertainty. Lean production plants often use the same machines as mass production plants but match them with a broader organization of work: 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. Skilled workers can more easily switch tasks and therefore there is an *increase* in wage inequality.

Our model has a number of additional applications. First of all, it provides a new channel for intra-industry trade to accelerate the rise of the New Economy by increasing the size of the market and hence product proliferation. Second, our model can be used to endogenize the path of technological progress in production technology and explain increased demand for retoolable multi-purpose machines. Third, we expose the special role played by information technology (IT) such as bar-codes in enabling the transition to the New Economy by allowing firms to react to demand shifts.

We provide strong evidence for our model using a new dataset on the introduction of bar-coding into U.S. firms. Essentially, bar-coding is an important enabling technology to respond to demand shifts which translates into demand for skilled, flexible workers, but does not change the production technology. We therefore regress the shares of workers of different levels of education in a given three-digit SIC industry on the share of firms that have adopted bar-coding while also controlling for investment in computers as in Autor, Katz, and Krueger (1998), the conventional measure of skill-biased technological change.

We find that an increase in bar-coding has a strong, statistically significant effect on labor demand at the center of the skill distribution. While the introduction of bar-coding has little effect on the highly skilled, it shifts demand away from high-school educated workers towards some-college educated workers. We thus observe our main effect exactly at the margin of unskilled, inflexible to skilled, flexible workers, consistent with our model. The effect of the adoption of bar-coding is robust and economically significant. In particular, it is approximately economically as significant as the change in investment in computers, the conventional measure of skill-biased technological change.

The balance of the paper is organized as follows. Section 2 introduces our model and derives the pattern of work organization and capital/skill complementarity over time. In section 3 we apply our theory to understand the implications for intra-industry trade, the trend towards multi-purpose machines and the role of IT. We empirically analyze the effect of information technology on the demand for skilled labor by looking at the use of bar-coding in 3-digit SIC industries in section 4. Section 5 concludes.

2 Theory

Our formal framework builds on the Dixit and Stiglitz (1977) model of monopolistic competition, but allows for a more elaborate demand and production system. Our goal is to develop a model that allows us to characterize the evolution of work during industrialization as well as during the rise of the New Economy. In the model, 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.

Consumer Demand

There is a continuum of products on the unit interval. Time is continuous and in each time period every product has m customizable features: any feature $1 \leq i \leq m$ can take values in the set $\{0, A_{i,t}, B_{i,t}, C_{i,t}\}$ where 0 means that the feature is uncustomized and $A_{i,t}$, $B_{i,t}$ or $C_{i,t}$ are three specific customizations at time t. We assume that features have to be customized sequentially: hence feature $i+1$ can only be customized if feature i has been customized as well. We call the 3^d varieties with exactly d customized features *partially customized* varieties. If $d = m$ we say that a variety is fully customized. The single variety without any customization is called the *generic variety*.

There is a mass 1 of consumers. Each consumer c has a preference vector $(\eta_{i,t}^c)$ over the features of a product at time t where $\eta_{i,t}^{c} \in \{A_{i,t}, B_{i,t}, C_{i,t}\}$. Preferences are only realized at time t according to the following distribution: (a) for each feature, one of the three possible realizations "flops" with equal probability and is drawn by no consumer; (b) each of the remaining two features is preferred by a consumer with equal probability and i.i.d across features. A product variety that contains any customized feature that does not fit her preference vector is a *mismatch* for the consumer. Hence, a variety is only matched to the consumer if every feature is either left uncustomized or has the correct customization. Therefore, any particular variety with d customized features flops with probability $1 - \left(\frac{2}{3}\right)^{d}$. Note, that generic varieties never flop while greater customization increases the probability that any given variety will flop. This specification captures the idea that product variety proliferation increases uncertainty about the mix of varieties demanded by consumers.

We assume that consumers derive no utility from consuming a mismatched variety. Hence, they will only purchase matched varieties at positive prices. Consumers have a CES utility function of the following form:

$$\begin{aligned}
\delta &: \text{discount factor} \\
x_d(s,t) &: \text{amount of matching variety of product } s \text{ with } d \text{ customized features at time } t \\
x(t) &= \left[\int_0^1 \left(\sum_{d=0}^{m} \mu^d x_d(s,t)\right)^{\rho} ds\right]^{\frac{1}{\rho}} \quad \text{such that} \qquad (1) \\
U &= \int_0^{\infty} x(t) \exp(-\delta t)\, dt
\end{aligned}$$

Following (Dixit and Stiglitz, 1977), we assume that goods are substitutes ($0 < \rho < 1$). We also assume that consumer 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 can then be derived as follows:[4]

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

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

Firms produce output in each time period t. We distinguish three phases in the production process: the *entry stage* at time $t.1$, the *preparation stage* at time $t.2$ and the production stage at time $t.3$. There are two types of firms, artisan firms and machine firms. There are also

[4] CES preferences are homothetic. Therefore, economic growth per se does not increase consumer's appetite for customized products. There is a "hierarchy of needs" literature which postulates that richer consumers prefer greater customization. However, the anthropological evidence does not support this hypothesis as Piore and Sabel (1984) point out.

Table 1: Entry, preparation and production stages in artisan and machine firms

	Artisan Firm	**Machine Firm**
Entry Stage	-hire worker	- hire workers - incumbent/ entrant play entry game
Preparation Stage	- prepare worker	- prepare workers - build machines
Production Stage	- demand realized - firm chooses price - switch workers - produce variety	- demand realized - firm chooses price - switch workers - produce variety

two types of workers - high skilled and low-skilled. We use the wage of high-skilled workers as numeraire in each time period and denote the wage of inflexible workers with ω.[5]

Artisan Firms

Each artisan firm hires a single worker during the entry stage $t.1$ (effectively, we can think of the worker running the firm as worker-owner). During the preparation stage the artisan firm assigns the worker to the production of one variety of a product. Demand uncertainty is realized in the production stage and the artisan firm can reassign the worker to another variety (the artisan firm will never want to produce varieties with flopped features). It also selects the price for its product.

Artisan technology is a constant returns to scale technology which can produce any product variety at any customization level: one unit of output of any variety requires c_A effective units of labor input. Competition between artisans will set the price of artisan products at c_A.

Workers

Each consumer/worker supplies one unit of labor inelastically. A share α of the workforce is flexible and provides one effective unit of labor at any task. The remaining share $1-\alpha$ of workers are inflexible. If they produce a variety that they have been assigned to, then during the preparation stage they provide one effective unit of labor. Otherwise, they provide only effective labor input of $a < 1$. We define the *division of labor index* for consumer/worker c as follows:

Definition 1 *The division of labor index $\Upsilon_c(t)$ is the probability that production worker c performs the production task that she has prepared for.*

Larger values of this index indicate a greater division of labor for worker c in the sense that the production task becomes more predictable.

[5]The relative wage of unskilled workers depends on t but we drop this index throughout for simplicity.

We will use the terms "flexibility" and "high-skilled" interchangeably. 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 figure out unfamiliar tasks autonomously (also see discussion in Section 2.3).[6]

Machine Firms

Each machine requires a sunk investment of $\alpha k(t)$ units of flexible labor and $(1-\alpha)k(t)$ units of inflexible labor. This Leontieff production for machines has the advantage that it leaves the ratio of flexible versus inflexible workers among production workers unchanged. Moreover, relative wages are completely pinned down by the substitutability of flexible vs. inflexible workers in the production sector.

Output can then be produced at (low) marginal effective labor input $c_M(t)$. Every machine can only produce a single variety. 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. Hence, the scale of production needed to break even does not change over time (except for changes in the relative wage of inflexible workers).

In every industry there is an incumbent firm and a single fringe competitor who play the following *entry game* during the entry stage: the incumbent firm (a) commits to a technology in the sense that they commit to the set of varieties that they are planning to produce and (b) hires workers. The single entrant observes the incumbent's technology choice and then decides whether to enter the industry or stay out. Entrants will never produce in equilibrium but they force incumbents to upgrade to more customized varieties over time as technology improves.

Machines are installed during the preparation stage and workers are assigned to varieties. Note, that machines are installed *before* demand uncertainty is realized while production commences afterwards. Therefore, any investment in a new machine for a variety with d customized features will fail with probability $1-\left(\frac{2}{3}\right)^d$. However, a firm can reassign production line workers to successful varieties. We assume that a machine producer either manufactures all product varieties of a certain degree of customization or none. This simplifying assumption makes total product demand (across varieties) for each firm deterministic.

Calibration of Model

The following condition is sufficient and necessary for our model to work for all α:

$$\mu < 3^{\frac{1-\rho}{\rho}} \tag{4}$$

Lemma 1 *Assume condition 4 holds and the incumbent produces partially customized varieties of degree d makes zero profit. Then any entrant that sells degree $d+1$ varieties at the same price*

[6] The degree of flexibility is also key in the model of task assignment by Holmes and Mitchell (2007).

will make negative profits.

According to (3) total demand increases by a factor of $\mu^{\frac{\rho}{1-\rho}}$ when adding one more customized feature. Since the number of varieties increases by a factor of 3, demand per variety changes by a factor of $\frac{1}{3}\mu^{\frac{\rho}{1-\rho}} < 1$. Since the entrant also faces potentially higher labor costs (due to greater task switching) she will certainly make negative profits.

The next three conditions are not essential for our results but they significantly simplify the analysis:

$$a\mu > \frac{1}{\rho} \tag{5}$$

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

$$k(0) > (1-\rho)\left(\mu^m \frac{c_M(0)}{c_A \rho}\right)^{-\frac{\rho}{1-\rho}} \tag{7}$$

Condition 5 ensures that machine producers of more customized varieties can price monopolistically without being constrained by competition from producers of less customized varieties. Conditions 6 guarantees that mass producers of the generic variety can compete with artisans on price at time $t = 0$. Otherwise, industrialization would start with partially customized varieties instead of generic varieties. Condition 7 ensures that demand at time 0 for industrial goods is insufficient to pay the fixed cost of a machine. Therefore, our economy at time 0 only has artisan production.

In the following, we analyze how the division of labor and income inequality evolve over time.

2.1 Industrialization, Taylorism and Capital-Skill Substitutability

At time 0, all workers are employed in artisan firms such that the relative wage of low-skilled artisans is:

$$\omega(m) = \left(\frac{2}{3}\right)^m + \left(1 - \left(\frac{2}{3}\right)^m\right) a \geq a \tag{8}$$

The division of labor in this pure artisan economy equals $\Upsilon_c(t) = \left(\frac{2}{3}\right)^m$ for all workers which is the lowest division of labor achievable in our model.

The marginal mass producer faces demand $x_{C0}(t)$ for her generic product variety:

$$x_{C0}(t) = \frac{E\rho}{c_M(t)\,\omega(m)} \left(\mu^m \frac{c_M(t)}{c_A \rho}\right)^{-\frac{\rho}{1-\rho}}, \tag{9}$$

where $E = \alpha + (1-\alpha)\omega(m)$ is the total income of consumers. Mass production will be unprofitable as long as revenues do not cover the fixed cost of a machine:

$$x_{C0}(t)\,(\underbrace{\frac{1}{\rho}c_M(t)-c_M(t)}_{\substack{\text{monopolistic}\\ \text{price markup}}})\omega(m) < \underbrace{k(t)\left[\alpha+(1-\alpha)\omega(m)\right]}_{\substack{\text{fixed cost: } \alpha \text{ units of flexible}\\ \text{labor}/(1-\alpha) \text{ units of inflexi-}\\ \text{ble labor)}}} \tag{10}$$

This can be rewritten as:

$$x_{C0}(t) < A\frac{\alpha+(1-\alpha)\omega(m)}{\omega(m)} \tag{11}$$

where $A=\frac{k(t)\rho}{c_M(t)(1-\rho)}$ is a constant as c_M and $k(t)$ decrease at the same rate. Due to condition 7 and equation 9 this inequality will hold at time 0. After time t_1^{C0}, the inequality no longer holds and mass production becomes competitive with artisan production.[7]

The next theorem describes the subsequent transition of the economy to complete mass production. All proofs are relegated to the Appendix.

Theorem 1 *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 time t_3^{C0} when 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}.*

Low-skilled mass production workers have division of labor index equal to $\Upsilon_c(t) = 1$ while skilled artisans continue to work in artisan firms with a low division of labor until they switch into mass production themselves. Therefore, low-skilled workers are the first to experience an increase in the division of labor.

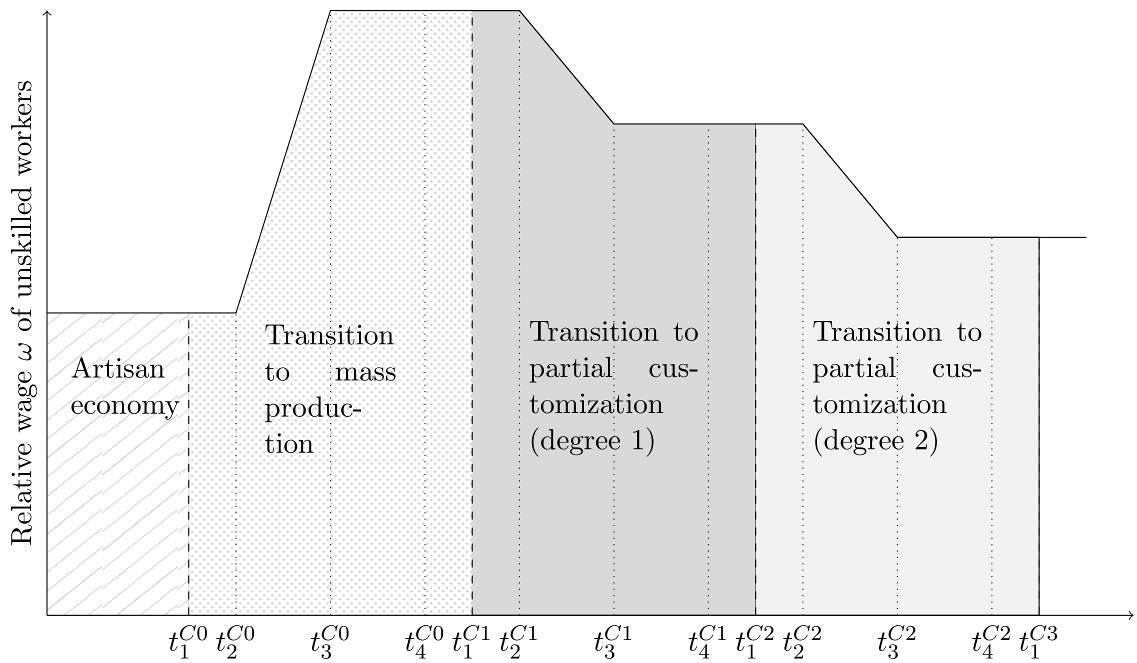
The transition is also illustrated in Figure 1. The important take-away is that capital (machines) and skills are *substitutes* during industrialization because flexible workers lose their comparative advantage in a mass production economy. The transition to mass production also gives rise to *Taylorism* where tasks become very predictable as demand uncertainty decreases due to a reduction in product varieties.

2.2 The Rise of the New Economy, Flexibility and Capital-Skill Complementarity

Continued productivity growth eventually makes producers of more customized products competitive again after time t_4^{C0}. Intuitively, the economy will go through m cycles of deepening customization. At the beginning of each cycle, all firms produce only varieties of degree $d-1$ and at the end of the cycle they have all switched to producing varieties of degree d. Within

[7]Note, that the left-hand side of inequality 7 is decreasing over time, while the right-hand side is increasing.

Figure 1: Evolution of income inequality



each cycle, the relative demand for flexible workers increases because more customized firms face greater demand uncertainty which pushes the relative of unskilled workers from $\omega(d-1)$ to $\omega(d)$. Theorem 2 summarizes the transition dynamics.

Theorem 2 *Flexible workers switch from firms producing less customized varieties of degree $d-1$ to producing more customized varieties of degree d after time t_1^{Cd} until all of them are employed in firms producing customized varieties at time t_2^{Cd}. From then on, the relative wage of flexible workers will start to increase until time t_3^{Cd} when the relative wage equals $\omega(d)$. Unskilled workers will then switch into more customizing firms until all workers are employed at such firms at time t_4^{Cd}.*

Flexible (high-skilled) workers are the first to switch into industries that produce more customized varieties and their division of labor decreases from $\Upsilon_c(t) = \left(\frac{2}{3}\right)^{d-1}$ to $\left(\frac{2}{3}\right)^{d}$. Eventually, after m transitions, the advanced machine economy resembles the artisan economy as the division of labor index approaches $\left(\frac{2}{3}\right)^{m}$ for all workers.

The first two transitions are shown in Figure 1. Capital and skills are *complements* during the rise of the New Economy because flexible workers regain their comparative advantage as customization progresses. Work tasks become less predictable as demand uncertainty increases due to proliferating product varieties.

2.3 Discussion

Our model can explain the 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.[8]

Skill and Flexibility. Our model equates the concepts of "skill" and "flexibility." 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.

Demand for flexibility has again increased in 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 U.S. 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. Spitz-Oener (2006) shows that occupations require more complex skills today than in 1979.

Capital-Skill Substitutability. 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 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.[9]

[8] See Atack, Bateman, and Margo (2004), Margo (2004), 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.

[9] 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.

3 Applications

Our model lends itself naturally to explain several related important economic phenomena. We describe these applications below.

3.1 Intra-Industry Trade

Our first applications relates to intra-industry trade, the organization of work and wage inequality. Trade with non-OECD countries has been explored as an explanation for the increase in wage inequality during the past 20 years. Since developing countries have relatively larger pools of unskilled labor, Heckscher-Ohlin models predict widening wage gaps in developed countries as a result of trade. However, Katz and Murphy (1992) and Berman, Bound, and Grilliches (1994), among others, have argued that changes in the volume of trade between OECD and non-OECD countries seem too small to explain the observed large shifts in the wage gap since the 1970s. Although total trade as a fraction of U.S. GDP more than doubled in the 1970s, most of this expansion affected trade with high-wage countries: the share of U.S. 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.[10] 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.

However, the rapid growth in *intra-OECD* trade since the 1960s is consistent with up-skilling in our model. Consider two identical economies in our model that have both undergone industrialization and are starting to move into customized machine production. Also assume that there is at least some overlap in consumer tastes (and therefore in successful varieties). Just like in other New Trade models, these two economies will trade to take advantage of economics of scale in machine production (see Krugman (1981), Dixit and Norman (1980) and Ethier (1982)). Trade induces a proliferation of product varieties which in turn increases wage inequality in our model by reducing the demand for inflexible unskilled labor. For example, Volkswagen's New Beetle was introduced in 1997 and exclusively assembled in Mexico from 1999 until 2010 for both the North American and the European markets. Direct supporting evidence comes from Osterman (1994) who found that firms are more likely to introduce innovative forms of work organization if they compete on international markets.

Consistent with this application of our model, we also observe evidence of increased product variety in imported goods. For example, Broda and Weinstein (2006) document a tremendous increase in product variety in U.S. import data over the last thirty years: The number of imported varieties has tripled between 1972 and 2001. During that period, the number of varieties imported to the U.S. increased from 74,667 and 7,731 goods, sourced from an average of 9.7 countries, to 259,215 varieties and 16,390 goods, sourced from an average of 15.8 countries.

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

3.2 Multi-Purpose Machines

Second, an application of our model is to rationalize the rise of multi-purpose machines in production. Historically, we see that engineers started to improve the *degree of control* of machines in the 1960s (see Bell (1972)). Up to the 1950s, the cost of re-tooling machines was so large that new car models required extensive shut-downs and/or building of entirely new factories. In contrast, modern numerically-controlled (NC) and computer-numerically-controlled (CNC) machines can be easily re-programmed to produce a variety of parts.

A natural extension of our model demonstrates how demand for such multi-purpose machines emerges endogenously with the rise of the New Economy. Recall, that a firm in an industry has to install 3^d special-purpose machines to produce 2^d successful varieties. Now assume, that it has the opportunity to buy a multi-purpose machine at a cost of $Ak(t)$ (compared to $k(t)$ for a special-purpose machine). A multi-purpose machine can be re-programmed ex-post to produce any variety.

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. Formally, the crossover-point is reached as soon as:

$$d > \frac{\ln A}{\ln(1.5)} \tag{12}$$

Theorem 2 continues to characterize the evolution of work in this extended model.[11]

3.3 Information Technology (IT)

Finally, our model also provides an explanation for the rise of information technology. In this respect, we purposefully distinguish between multi-purpose machines that are used directly in production and *information-technology* that is used in logistics. In the artisan economy, the production and distribution operations are usually integrated. 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 often 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

[11] Condition 4 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:

$$\mu < 2^{\frac{1-\rho}{\rho}}. \tag{4*}$$

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 large and of low frequency.[12]

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).

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.

Information technologies such as bar-codes are crucial catalysts in our model for a decreased division of labor and greater demand for skills. Without enabling technologies such as bar-codes, product proliferation will still progress (albeit at a slower rate), but skilled workers will not enjoy an advantage because firms lack the means to respond to demand uncertainty. 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).

It is instructive to compare the impact of information technologies with the previously discussed adoption of multi-purpose machines. Whereas the latter merely complement the rise of the New Economy, IT is a pre-requisite for 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.

An interesting, related paper in this context is Evans and Harrigan (2005). They argue, following Abernathy, Dunlop, Hammond, and Weil (1999), that technologies such as bar-codes and EDIs are key to flexible production in the apparel industry. They then build a model predicting that apparel production in very volatile segments of the apparel market should locate to close-by sites of production as these new information technologies spread. Indeed, they find evidence for this prediction by looking at production location and wage patterns of the apparel

[12] 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)).

sector in Asia and the Caribbean.

4 Empirical Evidence

In this section, we use a unique dataset on bar-coding to test the prediction of our model that organizational change induced by demand uncertainty and increased product customization has lead to increased relative demand for flexible workers. We find that the role of organizational change in explaining the relative demand for skilled labor is of the same magnitude as the role of technology upgrading for explaining labor demand shifts such as in Autor, Katz, and Krueger (1998).

4.1 Empirical Methodology

To test our model, we exploit the role of information technology as a catalyst for changes in the organization of work. 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. Only once sales data have been recorded with the help of bar-coding, can such information be processed and impact the production process. Therefore, firms which introduce bar-coding will be subject to more precise, but also more frequent demand updates. Hence, they will re-organize their production preferring to employ flexible workers in production. This increases their demand for more skilled, flexible workers.

To formally test this hypothesis, we have borrowed and extended the regression specification from Autor, Katz, and Krueger (1998). We thus estimate the following specification:

$$\Delta E_{it} = \alpha + \beta \Delta C_{it} + \gamma \Delta B_{it} + \eta_i + \epsilon_{it} \tag{13}$$

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 regress the annual changes in the educational share of the workforce in three-digit SIC industries on annual changes in the share of the total work force using computers at work and on annual changes in the sectoral percentage of bar-code-adopting firms. By including both bar-coding adoption and computer use on the right-hand side at the same time, we are able to 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.

Our empirical analysis thus adds an important, complementary dimension to the existing analyses of skill-biased technological change such as Autor, Katz, and Krueger (1998). We estimate our specification for firms in the manufacturing sector (SIC codes 200-399) and also for all industries. The reason is that we expect our model to apply particularly well to manufacturing industries, guided by the findings of an analysis of bar-coding and textile manufacturing by Abernathy, Dunlop, Hammond, and Weil (1999) or Evans and Harrigan (2005).

Finally, we address potential endogeneity in our setup as a robustness check. While, historically, large firms such as Walmart exogenously imposed on their suppliers the adoption of bar-coding, thus alleviating the econometric concern of endogeneity, we address potential endogeneity using an instrumental-variable strategy based on lagged levels of bar-coding adoption as instruments. The intuition behind the decision to use this instrument is that past sectoral rates of bar-coding adoption should be correlated with the current adoption growth rates following the logic of a simple growth model of gradual technology diffusion. At the same time, past adoption rates should not be correlated with future innovations in the error term. An F-statistic of 84.96 (396.47) in the first stage regression for the manufacturing (all) sectors suggests validity of the instrument.[13]

4.2 Data

First, to construct our dataset, we follow the methodology in Autor, Katz, and Krueger (1998), and compute 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.[14]

Second, we extract and merge data from two sources to create an industry-level dataset for the introduction of bar-coding. First, we obtain 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

[13] We have also used, as an alternative instrument, lagged changes in bar-coding adoption rates, with the same qualitative effect.

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

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 adoption in that year.

Since the UCC did not collect industry classification information, we use data from the 1999 American Business Disc (ABD) to add Standard Industrial Classification (SIC) codes to our data. The 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. We match the UCC to the ABD data so that we can determine in which industry firms were operating which introduce bar-coding. We consider only firms of employment size 10 or bigger. Appendix C describes in detail the algorithm we use 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). 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 are large companies.[15]

We then aggregate the matched data up to three-digit SIC industries. We calculate the share of bar-coding firms in a given year 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.

4.3 Results: Bar-Coding and Skill-Upgrading

Here, we present evidence for our model: the adoption of an innovative, flexible organization of work, proxied for by the introduction of bar-coding, is strongly associated with increased relative demand for flexible workers. We find that the adoption of bar-coding mainly affects the center of the skill distribution and is economically highly significant. In particular, this finding holds up when we also control for computerization, the conventional measure of skill-biased technological change.

First, we replicate the evidence for changes in the relative demand for skilled labor due to skill-biased technological change. We do so by estimating our regression specification with the change in computer use as the only explanatory variable and for manufacturing industries only. This is exactly the approach in Autor, Katz, and Krueger (1998). Table 3 shows our results. Our results are close to the results reported in their paper.

Next, we add our new measure of annualized percentage changes in bar-coding firms in each

[15] As Gabaix (2011) shows both theoretically and empirically, large firms play an important role in explaining aggregate productivity movements. This suggests that our analysis including many large firms captures an important subset of firms.

three-digit industry (manufacturing firms and all firms respectively) to the regression. We find strong, significant evidence that the adoption of bar-coding is positively associated with increased relative demand for skilled labor. We summarize this result in Table 4 for manufacturing and Table 5 for all sectors. Controlling for possible industry fixed effects in the rate at which different industries adopt bar-coding, we find that a one percentage point 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 was 22.44 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 economic 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 demand requires greater flexibility. We observe our main effect exactly at the margin of unskilled to skilled, or inflexible to flexible workers.

Finally, while our findings may already be robust to concerns of endogeneity due to historic reasons,[16] they are econometrically robust when using lagged bar-coding as an instrumental variable. We find that the adoption of bar-coding still affects the center of the skill distribution as shown in Table 6. The coefficient on high-school graduates remains negative and significant, the coefficient on some college educated workers remains positive but is now statistically insignificant. The main change now is that the coefficient on high-school graduates is much larger with an estimate of -5.211 for manufacturing sectors. A one percentage point increase in the share of bar-coding firms now decreases the share of high-school employment by 5.2 percentage points. At the same time, the coefficients on computer remain largely unchanged and are statistically not significantly different from the previous estimates.

5 Conclusion

Our model builds on the large body of empirical labor research exploring the relationship between technological progress, work organization and skill requirements. This literature convincingly

[16] Historically, large firms such as Walmart exogenously imposed on their suppliers the adoption of bar-coding. This somewhat alleviates the econometric concern of endogeneity.

demonstrates that these phenomena have been complements since the 1970s. Most of the literature assumes a direct complementarity between technological progress and the demand for skills. However, this approach raises the question why technology was substituting skilled labor during industrialization.

The contribution of our model is to explain the historical U-shaped evolution of work organization and skill demand from artisan economy to New Economy while making minimal assumptions about technology. We only assume that machines carry a fixed cost and hence industrial production is subject to increasing returns. Capital is neither a direct substitute nor complement to work organization or skills in our model – instead the effects of technological progress on the labor market are mediated through the product demand. Our model suggest 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 U.S. 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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6 Tables

Table 2: Number of UCC to ABD Matches for Different Company Size (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: † : 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: 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: † : 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 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. We include three-digit SIC fixed effects to 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: 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	32.50%	14.40%	26.60%	29.70%
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. We include three-digit SIC fixed effects to control for potentially industry-specific rates of change in the adoption of bar-coding and computerization. Regressions are weighted as in Table 3.

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

	College	Some College	HS Grad	Less than HS
Δcomputer use	**0.098**	**0.133**	**-0.162**	-0.070
	(0.040)†	(0.054)†	(0.076)†	(0.046)
Δbar-coding	1.088	2.525	**-5.211**	1.598
	(1.063)	(1.432)	(2.006)*	(1.214)
R^2	-6.90%	-2.60%	-4.17%	-6.70%
n	203	203	203	203
F-statistic	84.96			

Significance levels: † : 10% $*$: 5%

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. We include three-digit SIC fixed effects to control for potentially industry-specific rates of change in the adoption of bar-coding and computerization. Regressions are weighted as in Table 3. The instrument used is the two-year sectoral lagged level of the percentage of firms having adopted bar-coding. We report the F-statistic from the first stage.

A APPENDIX: Proof of Theorem 1

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:

$$\begin{aligned} p(t) &= \frac{c_M(t)\,\omega}{\rho}\left[y + (1-y)\left(\mu^m \frac{c_M(t)\,\omega}{c_A\rho}\right)^{\frac{\rho}{1-\rho}}\right]^{\frac{\rho-1}{\rho}} && (14) \\ x_{C0}(t) &= \frac{E\rho}{c_M(t)\,\omega}\frac{1}{y + (1-y)\left(\mu^m \frac{c_M(t)\omega}{c_A\rho}\right)^{\frac{\rho}{1-\rho}}} && (15) \\ x_A(t) &= x_{C0}(t)\,(\mu^m)^{\frac{\rho}{1-\rho}}\left(\frac{c_M(t)\,\omega}{c_A\rho}\right)^{\frac{1}{1-\rho}}. && (16) \end{aligned}$$

During industrialization machine producers are indifferent between entering mass production or staying out. Therefore, they have to make zero profits inequality 11 becomes an equality

$$x_{C0}(t) = A\frac{\alpha + (1-\alpha)\omega(m)}{\omega}.$$

where ω is the relative wage of low-skilled workers. At the onset of industrialization, the demand for high-skilled workers in the artisan industry exceeds supply and the low-skilled wage is simply $\omega(m)$, the same as in the artisan economy. This zero profit condition together with equation 15 provides us to pin down the share y of industrializing sectors:

$$A = \frac{\rho}{c_M(t)}\frac{1}{y + (1-y)\left(\mu^m \frac{c_M(t)\omega}{c_A\rho}\right)^{\frac{\rho}{1-\rho}}}. \tag{17}$$

Due to condition 6 the left hand side of this expression is decreasing in y and $c_M(t)$. Hence technological progress promotes industrialization.[17]

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.[18] Instead, the wage levels of both groups will gradually equalize. During this process the zero profit condition 17 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 rewritten as:

$$c_M(t)^{\rho}\,\omega = D\left(\frac{y}{1-y}\right)^{1-\rho}. \tag{18}$$

[17] 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.

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

where $D = \left(\frac{\alpha}{1-\alpha}\right)^{1-\rho} \frac{1}{\rho} \left(\frac{c_A}{\mu^m}\right)^{\rho}$.

If we define an auxiliary variable $z = c_M \omega$ we can rewrite the two conditions 17 and 18 in reduced form as

$$A = f(c_M, y, z) \tag{17a}$$

$$D = g(c_M, y, z), \tag{18a}$$

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

$$\frac{dy}{dc_M} = \frac{\frac{\partial g}{\partial c_M}\frac{\partial f}{\partial z} - \frac{\partial g}{\partial z}\frac{\partial f}{\partial c_M}}{\frac{\partial g}{\partial z}\frac{\partial f}{\partial y} - \frac{\partial g}{\partial y}\frac{\partial f}{\partial z}} < 0. \tag{19}$$

The relative wages of low-skilled workers will in deed increase as one can immediately see from equation 18.

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. 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.

B APPENDIX: Proof of Theorem 2

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:

$$p(t) = \frac{c_M(t)\,\omega}{\rho}\left[1 - y + y(\mu\omega)^{\frac{\rho}{1-\rho}}\right]^{\frac{\rho-1}{\rho}} \tag{20}$$

$$x_{C0}(t) = \frac{E\rho}{c_M(t)\,\omega}\frac{1}{1 - y + y(\mu\omega)^{\frac{\rho}{1-\rho}}} \tag{21}$$

$$x_{C1}(t) = x_{C0}(t)\frac{\mu^{\frac{\rho}{1-\rho}}}{3}\omega^{\frac{1}{1-\rho}}. \tag{22}$$

During transition entrants have to make zero profits so that

$$x_{C1}(t) = A\frac{\alpha + (1-\alpha)\,\omega}{\omega}.$$

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:

$$\Pi = (1-y)\left[x_{C0}(t)\,c_M(t)\,\omega\frac{1-\rho}{\rho} - k(t)\left[\alpha + (1-\alpha)\,\omega\right]\right] \tag{23}$$

$$= (1-y)\left[\alpha + (1-\alpha)\,\omega\right]k(t)\left[\frac{1}{\frac{(\mu\omega)^{\frac{\rho}{1-\rho}}}{3}} - 1\right]. \tag{24}$$

We can then rewrite total consumer income as:

$$E = [\alpha + (1-\alpha)\,\omega]\left[1 + (1-y)\,k\,(t)\left[\frac{1}{\frac{(\mu\omega)^{\frac{\rho}{1-\rho}}}{3}} - 1\right]\right] \tag{25}$$

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

$$A = \frac{\rho}{3\mu}\frac{\frac{z}{c_M(t)} + (1-y)\frac{k(t)}{c_M(t)}(3-z)}{1-y+yz} \tag{26}$$

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

$$A = f\,(c_M, y, z)\,. \tag{26a}$$

with $\frac{\partial f}{\partial c_M} < 0$, $\frac{\partial f}{\partial y} < 0$, $\frac{\partial f}{\partial z} > 0$.[19] 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 26 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:

$$\frac{yc_M\,(t)\,x_{C1}\,(t)}{(1-y)\,c_M\,(t)\,x_{C0}\,(t)} = \frac{\alpha}{1-\alpha}. \tag{27}$$

This condition can be written in reduced form as

$$F = g\,(y, z) \tag{27a}$$

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

Combining this condition with condition 27a 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 $\omega\,(1)$ 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}.

C APPENDIX: 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.

[19] The right hand side of expression 26a decreases in y. 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

$$\frac{1 + length(LCS)}{0.5 * (length(A) + length(B) + 2.001 - |length(A) - length(B)|).} \tag{28}$$

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[20].

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[21]. 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 of plural ss as a potential source

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

[21] 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 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.