

Federal Reserve Bank of Minneapolis
Research Department Staff Report

August 2000

The transition to a new economy*

Andrew Atkeson

Patrick J. Kehoe

ABSTRACT

During the Second Industrial Revolution, from 1860-1900, a large number of new technologies, including electricity, were invented. These inventions launched a transition to a new economy: a period on the order of seventy years of ongoing rapid technical change. Following this revolution, however, there was a delay of several decades before growth in both output and productivity rose to new higher levels. Historians hypothesize that this delay was due to the slow diffusion of the new technologies that were embodied in the design of new plants together with ongoing learning in plants after they had adopted the new technologies. Motivated by these hypotheses we build a quantitative model of this transition and show that it implies both slow diffusion and a delay in growth similar to that in the data.

*Atkeson and Kehoe thank the National Science Foundation. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System.

The period 1860-1900 is often called the Second Industrial Revolution due to the large number of new technologies that were invented at that time. These inventions heralded a new economy: a period on the order of seventy years of ongoing rapid technical change. In the transition to this new economy, however, there was a delay of several decades before growth in both output and productivity rose to new higher levels. We build a quantitative model of the transition to a new economy following the Second Industrial Revolution which is motivated by several of the hypotheses that historians have advanced to explain this delay.

Historians such as David (1990, 1991), Devine (1983), Rosenberg (1976), and Schurr and Netschert (1960) focus on the development of electricity in the Second Industrial Revolution as the driving force of the prolonged period of rapid technical change following this revolution. These historians hypothesize that the development of electricity did not have an immediate payoff in terms of higher growth in output and productivity because of two reasons. First, new technologies based on electricity diffused only slowly. Second, even after a new plant embodying the new technology was built there was an extended period of learning of how best to take advantage of that technology.

Several factors help account for the slow diffusion of electricity. As David (1990, 1991) and Devine (1983) explain, manufacturing plants needed to be completely redesigned in order to make good use of electricity. Indeed, David and Wright (1999) argue that "the slow pace of adoption prior to the 1920's was largely attributable to the unprofitability of replacing still serviceable manufacturing plants embodying production technologies adapted to the regime of mechanical power derived from water and steam." Rosenberg (1976), argues that ongoing technical change itself helps account for this slow diffusion: people anticipated ongoing improvements in the technology and thus chose to wait for further improvements

before adopting.

Several historians emphasize the importance of learning how best to use the new technologies resulting from the Second Industrial Revolution. Schurr et. al. (1960, 1990) discuss the process of learning following new applications of electricity to plant and machine design. They argue that the benefits of adopting electricity went far beyond the direct cost savings from reduced energy consumption. The electrification of plants opened opportunities for continual innovation in processes and procedures within an existing plant to improve overall productive efficiency. In practice, it took time for managers to learn how best to take advantage of these opportunities. Chandler (1992) emphasizes the importance of organization-specific learning of the management of the flow of inputs through the processes of production in the growth of new firms following the Second Industrial Revolution.

Motivated by these hypotheses we build a simple quantitative model of technology adoption and learning and show that it can account for both the slow diffusion of new technologies and a delay of several decades between a sustained increase in the pace of technical change and increased growth in both output and measured productivity. In our model new technologies are embodied in the design of new manufacturing plants as discussed in David (1991) and Devine (1983). The ongoing technical change discussed in Rosenberg (1976) is modelled as ongoing improvements in these designs. Finally, the process of learning within an existing plant, discussed by Schurr et. al. (1990) and Chandler (1992), is modelled as a stochastic process for the productivity with which that plant implements the technology embodied in its design. Thus, in the model, the decision to adopt new technology amounts to a decision to close existing manufacturing plants based on old technologies and replace them with new plants based on the current frontier technology and undergo the process of learning

to use that technology.

We quantify our model to capture the main patterns of industry evolution at the plant level in the U.S. economy. In the model, as in the data, the process of starting a new plant is turbulent and time-consuming. New plants tend to start small in terms of output and employment and fail often. Surviving plants tend to grow for up to twenty years. We model this evolution as resulting from a stochastic process for plant-specific productivity (as in Hopenhayn and Rogerson 1993). We quantify this process by observing that the size of plants is determined by their specific productivities. We choose the parameters of this stochastic process to replicate the patterns of birth, growth, and death of plants in the U.S. economy as discussed in Davis, Haltiwanger, and Schuh (1996).

We then ask what theory predicts about the transition to a new economy. We model the new economy as a once-and-for-all increase in the rate of improvement in the frontier technology embodied in the design for new plants. In this new economy new technologies diffuse only slowly, plants learn to use these technologies efficiently over time and there is a several decade long delay before the growth in output and productivity climb to their new steady state levels. We show that the path of diffusion of new technology in the model is similar to the path of diffusion of electric power in plants in the data from 1870-1940. We also show the trends in output and productivity generated by the model are similar to those in the data for the period 1870-1970.

Throughout the paper we focus on the transition to a new economy following the Second Industrial Revolution. Economists have argued that in the 1990's the U.S. economy is going through an Information Technology Revolution. We agree with David (1990) who argues that by understanding the transition following the Second Industrial Revolution we

may better understand the Solow productivity paradox of the last decade during which major inventions in information technology occurred with little apparent impact on the growth of output and productivity.

Our paper is related to several strands of literature. Our model of industry evolution and learning at the plant level is related to the models of Jovanovic (1982) and Hopenhayn and Rogerson (1993). The role of learning in the transition to a new economy is related to the role of learning in the theoretical models of general purpose technologies of Aghion and Howitt (1998) and Helpman and Trajtenberg (1998) and in the applied papers on the post-1974 productivity slowdown by Greenwood and Yorukoglu (1997) and Hornstein and Krusell (1996). The impact of an economy-wide transition on output growth is related to the some theories on transition of Eastern European countries following the collapse of communism. (See Atkeson and Kehoe 1993, Aghion and Blanchard 1994 and Brixiova and Kiyotaki 1996, Castanheira and Roland 1996.)

1. Growth and the Second Industrial Revolution

A great many of the new technologies that had a profound impact on living standards in the 20th century were invented in the period 1860-1900. These technologies include electricity, the internal combustion engine, petroleum and other chemicals, telephones and radios, and indoor plumbing. (See Gordon 2000a for a description.) While all of these inventions are undoubtedly important we follow David (1990, 1991), Devine (1983), Rosenberg (1976), and Schurr et. al. (1960, 1990) and focus on the new technologies based on electricity.

In this section we document the gradual replacement of water and steam power with electric power in U.S. manufacturing over the period 1870-1940 together with the gradual

increase in the growth of output and productivity in the U.S. over the period 1870-1970. We then report on three features of the historical data that motivate features in our model. First, the change to electric power led to major changes in factory design and machine organization that went hand in hand with electrification. Second, the process of improving efficiency through changes in factory design continued through at least the 1980's. Third, for each new factory design there was an extended process of learning how best to use the new design.

To document the slow diffusion of electricity, in Figure 1 we plot the fraction of mechanical power in manufacturing derived from water, steam and electricity in manufacturing in the period 1869-1939. (See Devine 1983.) Before 1900 more than 95% of mechanical power was derived from water and steam. Between 1900 and 1930 electricity use gradually replaced water and steam so that by 1930 over 75% of mechanical power was electric. In Figures 2 and 3 we plot output per hour and productivity as measured by the Solow residual over the period 1870-1970 using annual data from Gordon (2000b, Figure 3). We also show linear trends for the three periods, 1870-1900, 1900-1930, and 1950-1970. These periods were chosen to omit the Great Depression and World War II. The trend growth of output per hour in these three periods was 1 percent, 1.5 percent, and 2 percent respectively. The corresponding trend growth of the Solow residual for these periods was .6 percent, 1.2 percent, and 1.5 percent.

In light of the work of David (1990,1991) and Devine (1983), we interpret these periods as follows. In the period 1870-1900 the modern technology of electricity generation, distribution, and electric motors was developed. Figure 4, taken from Devine (1983), gives a chronology of the gradual development of the modern technology of electric power in manufacturing. Briefly, the two major developments were the shift in the architecture of factories to take advantage of electric motors (outlined in panel a) and the development of the tech-

nology of producing electricity in large centralized power plants and then shipping it over a distance to factories (outlined in panels b and d). In the period 1900-1930 this modern technology gradually diffused throughout the manufacturing sector. In the period 1930-1970 this modern technology was the dominant one in manufacturing.

A central element of the analysis of diffusion in David (1990, 1991) and Devine (1983) is that the adoption of the modern technology of electricity required a complete redesign of the manufacturing plant. In steam- and water-driven plants, power was distributed mechanically throughout the factory by a series of shafts and belts called a direct-drive system. In modern electric plants, power is distributed as electricity through wires to individual motors in what is called a unit-drive system.

Devine (1983, p350) describes the direct-drive system used in steam and water driven plants.

“Until late in the nineteenth century, production machines were connected by a direct mechanical link to the power sources that drove them. In most factories, a single centrally located prime mover, such as a water wheel or steam engine, turned iron or steel ‘line shafts’ via pulleys and leather belts. These line shafts—usually 3 inches in diameter—were suspended from the ceiling and extended the entire length of each floor of a factory, sometimes even continuing outside to deliver power to another building. Power was distributed between floors of large plants by belts running through holes in the ceiling... The line shafts turned, via pulleys and belts, ‘countershafts’—shorter ceiling-mounted shafts parallel to the line shafts. Production machinery was belted to the countershafts and was

arranged, of necessity, in rows parallel to the line shafts... The entire network of line shafts and countershafts rotated continuously-from the time the steam engine was started up in the morning until it was shut down at night-no matter how many machines were actually being used. If a line shaft or the steam engine broke down, production ceased in a whole room of machines or even in the entire factory until repairs were made."

Panel a of Figure 5 (from Devine 1983) illustrates this 'direct-drive' system of power.

The system of power gradually evolved to the unit drive system used in modern electricity-driven plants illustrated in panel d of Figure 5. In this system each machine is driven by its own electric motor and power for that motor is delivered through power lines from some potentially far off electric utility plant. Panels b and c show short-lived intermediate stages in this evolution referred to as electric-line drive and group drive.

As Devine (1983) describes, the unit drive system has a number of advantages over the direct drive system. One important advantage is that with the unit drive system plants could be designed and machinery in the plant could be arranged so as to minimize the handling of material according to the natural sequence of manufacturing operation, rather than according to physical placement of shafts as necessitated by the direct drive system. Moreover, once the shafts in the direct drive system became unnecessary, plants could also be designed to accommodate overhead electric cranes, which were thought to revolutionize material handling, and to have adequate ventilation, illumination and cleanliness.

As documented by Devine (1990) and Sonenblum (1990), the adoption of the unit drive system was only the beginning of a period of ongoing advances in the production process and

modes of organization of factories that are dependent on the uses of electricity. Moreover, these historians argue that, for each new advance in factory design, there was an extended period of learning to best use this design.

Sonenblum (1990) documents three stages of this ongoing technical change. In the first stage (1899-1920), new factory design evolves from the traditional line drive through the intermediate stages of the electric line shaft drive and the electric group drive to the electric unit drive. In the second stage (1920-1948), the attention in new factory design shifted to modifying the factory layout in order to speedup the throughput of materials. Machines were arranged so that materials moved smoothly from one operation to the next and assembly lines became more common. In the third stage, (1948-1985), new factories were designed to optimally use new servomechanisms that automatically controlled machine actions and numerically controlled machines. While these factory systems were developed in the 1940's and 1950's they began to spread only through the 1960's. They allowed factories to rely less on large inflexible assembly lines and to produce nonstandard products in small batches. Moos (1957) and Slesinger (1958) also discuss the changes in plant design driven by the development of automatically controlled machines and the learning required to take advantage of such plants. As Devine (1990) discusses, in the 1980's the evolution of factory design has evolved to accommodate new methods of computer-materials handling and computer-integrated manufacturing in which a computer controls whole groups of machines. Figure 6, from Devine (1990) gives a brief chronology.

Chandler (1992, p.84) discusses the type of built up organizational capabilities that resulted from firms learning to use the technologies developed in Second Industrial Revolution efficiently. He argues that the learned capabilities that resulted from solving problems

of scaling up the processes of production manifest themselves in firms production and distribution facilities. These learned capabilities were developed through trial and error, feedback and evaluation and were organization specific.

2. A model of technology diffusion

In this section we develop our quantitative model of technology diffusion. Motivated by the discussion in the previous section we incorporate three key elements into the model. First, new technologies are embodied in plants. Second, improvements in the technology for new plants is ongoing. Third, new plants must undergo an extended period of learning to use their technology most efficiently.

Our model economy is as follows. Time is discrete and is denoted by periods $t = 0, 1, 2, 3, \dots$. The economy has two types of agents: workers and managers. There exist a continuum of size 1 of workers and a continuum of size 1 of managers.

Workers are each endowed with one unit of labor per period, which they supply inelastically. Workers are also endowed with the initial stock of physical capital and ownership of the plants that exist in period 0. They have preferences over consumption given by $\sum_{t=0}^{\infty} \beta^t \log(c_{wt})$. Given sequences of wages and intertemporal prices $\{w_t, p_t\}_{t=0}^{\infty}$, initial capital holdings k_0 , and an initial value a_0 of the plants that exist in period 0, workers choose sequences of consumption $\{c_{wt}\}_{t=0}^{\infty}$ to maximize utility subject to the budget constraint

$$(1) \quad \sum_{t=0}^{\infty} p_t c_{wt} \leq \sum_{t=0}^{\infty} p_t w_t + k_0 + a_0.$$

Managers are endowed with one unit of managerial time in each period. Managers have preferences over consumption given by $\sum_{t=0}^{\infty} \beta^t \log(c_{mt})$. Given sequences of managerial wages and intertemporal prices $\{w_{mt}, p_t\}_{t=0}^{\infty}$, managers choose consumption $\{c_{mt}\}_{t=0}^{\infty}$ to maximize

utility subject to the budget constraint $\sum_{t=0}^{\infty} p_t c_{mt} \leq \sum_{t=0}^{\infty} p_t w_{mt}$. Notice that we have given all the initial assets to the workers. Since worker and manager utilities are identical and homothetic, aggregate variables do not depend on the initial allocation of assets.

Production in this economy is carried out in plants. In any period, a plant is characterized by its *specific productivity* A and its age s . To operate, a plant uses one unit of a manager's time, physical capital, and (workers') labor as variable inputs. If a plant with specific productivity A operates with one manager, capital k , and labor l , it produces output

$$(2) \quad y = zA^{1-\nu}F(k, l)^{\nu},$$

where the function F is linearly homogenous of degree 1 and the parameter $\nu \in (0, 1)$. The technology parameter z is common to all plants and grows at an exogenous rate. We call z *economy-wide productivity*. Following Lucas (1978, p.511), we call ν the *span of control* parameter of the plant's manager. The parameter ν may be interpreted more broadly as determining the degree of diminishing returns at the plant level. In what follows, we index plants by their specific productivity A and their age s . We refer to the pair (A, s) as the plant's organization-specific capital, or simply its *organization capital*. This pair summarizes the built-up expertise that distinguishes one organization from another.

The timing of events in period t is as follows. The decision whether to operate or not is made at the beginning of the period. Plants that do not operate produce nothing; the organization capital in these plants is lost permanently. Plants with organization capital (A, s) that do operate, in contrast, hire a manager, capital k_t , and labor l_t and produce output according to (2). At the end of the period, operating plants draw independent innovations ϵ to their specific productivity, with probabilities given by age-dependent distributions $\{\pi_s\}$. Thus, a

plant with organization capital (A, s) that operates in period t has stochastic organization capital $(A\epsilon, s + 1)$ at the beginning of period $t + 1$.

Consider the process by which a new plant enters the economy. Before a new plant can enter in period t , a manager must spend period $t - 1$ adopting a blueprint for constructing the plant that determines the plant's initial specific productivity τ_t . Blueprints adopted in period $t - 1$ embody the frontier of knowledge regarding the design of plants at that date. This frontier evolves exogenously, according to the sequence $\{\tau_t\}_{t=0}^{\infty}$. Thus, a plant built in $t - 1$ starts period t with initial specific productivity τ_t and organization capital $(A, s) = (\tau_t, 0)$.

We assume that capital and labor are freely mobile across plants in each period. Thus, for any plant that operates in period t , the decision how much capital and labor to hire is static. Given a wage rate for labor w_t , a rental rate for capital r_t , and a managerial wage w_{mt} , the operating plant chooses employment of capital and labor to maximize static returns:

$$(3) \quad \max_{k, l} z_t A^{1-\nu} F(k, l)^\nu - r_t k - w_t l - w_{mt}.$$

Define $d_t(A) = z_t A^{1-\nu} F(k_t(A), l_t(A))^\nu - r_t k_t(A) - w_t l_t(A)$, where $k_t(A)$ and $l_t(A)$ are the solutions to this problem. The static returns to the owner of a plant with organization capital (A, s) in t are given by $d_t(A) - w_{mt}$.

The decision whether or not to operate a plant is dynamic. This decision problem is described by the Bellman equation

$$(4) \quad V_t(A, s) = \max[0, V_t^c(A, s)]$$

$$V_t^c(A, s) = d_t(A) - w_{mt} + \frac{p_{t+1}}{p_t} \int_{\epsilon} V_{t+1}(A\epsilon, s + 1) \pi_{s+1}(d\epsilon),$$

where the sequences $\{\tau_t, w_t, r_t, w_{mt}, p_t\}_{t=0}^{\infty}$ are given. The value $V_t(A, s)$ is the expected discounted stream of returns to the owner of a plant with organization capital (A, s) . This

value is the maximum of the returns from closing the plant and those from operating it. The term $V_t^c(A, s)$, the expected discounted value of operating a plant of type (A, s) , consists of current returns $d_t(A) - w_{mt}$ and the discounted value of expected future returns $V_{t+1}(A, s)$. The plant operates only if the expected returns $V_t^c(A, s)$ from operating it are nonnegative.

The decision whether or not to hire a manager to prepare a blueprint for a new plant, is also dynamic. In period t , this decision is determined by the equation

$$(5) \quad V_t^0 = -w_{mt} + \frac{p_{t+1}}{p_t} V_{t+1}(\tau_{t+1}, 0).$$

The value V_t^0 is the expected stream of returns to the owner of a new plant, net of the cost w_{mt} of paying a manager to prepare the plans for the plant. Plans for new plants are prepared only if the expected returns from these plans, V_t^0 , are nonnegative.

Let μ_t denote the distribution in period t of organization capital across plants that might operate in that period, where $\mu_t(A, s)$ is the measure of plants of age s with productivity less than or equal to A . Let $\phi_t \geq 0$ denote the measure of managers preparing plans for new plants in t . Denote the measure of plants that operate in t by $\lambda_t(A, s)$. This measure is determined by μ_t and the sign of the function $V_t^c(A, s)$ according to

$$\lambda_t(A, s) = \int_0^A 1_{V^c}(a, s) \mu_t(da, s),$$

where $1_{V^c}(a, s) = 1$ if $V_t^c(a, s) \geq 0$ and 0 otherwise. For each plant that operates, an innovation to its specific productivity is drawn, and the distribution μ_{t+1} is determined from $\lambda_t, \phi_t, \{\pi_s\}$, and $\{\tau_t\}$ as follows:

$$(6) \quad \mu_{t+1}(A', s+1) = \int_A \pi_{s+1}(A'/A) \lambda_t(dA, s)$$

for $s \geq 0$ and

$$\mu_{t+1}(\tau_{t+1}, 0) = \phi_t.$$

Letting k_t denote the aggregate physical capital stock, the resource constraints for physical capital and labor are $\sum_s \int_A k_t(A) \lambda_t(dA, s) = k_t$ and $\sum_s \int_A l_t(A) \lambda_t(dA, s) = 1$. The resource constraint for aggregate output is $c_{wt} + c_{mt} + k_{t+1} = y_t + (1 - \delta)k_t$, where y_t is defined by $y_t = z_t \sum_s \int_A A^{1-\nu} F(k_t(A), l_t(A))^\nu \lambda_t(dA, s)$. The resource constraint for managers is

$$(7) \quad \phi_t + \sum_s \int_A \lambda_t(dA, s) = 1.$$

Managers are hired to prepare blueprints for new plants only if $V_t^0 \geq 0$. Since there is free entry into the business of starting new plants, in equilibrium we require $V_t^0 \leq 0$. We summarize this condition as $V_t^0 \phi_t = 0$. Also, in equilibrium, $a_0 = \sum_s \int_A V_0(A, s) \mu_0(dA, s)$ is the value of the worker's initial assets.

Given a sequence of frontier blueprints and economy-wide productivities $\{\tau_t, z_t\}$, initial endowments k_0 and a_0 , and an initial measure μ_0 , an *equilibrium* in this economy is a collection of sequences of consumption; aggregate capital $\{c_{mt}, c_{wt}, k_t\}$; allocations of capital and labor across plants $\{k_t(A), l_t(A)\}$; measures of operating plants, potentially operating plants, and managers preparing plans $\{\lambda_t, \mu_{t+1}, \phi_t\}$; value functions and operating decisions $\{d_t, V_t, V_t^c, V_t^0\}$; and prices $\{w_t, r_t, w_{mt}, p_t, \}$, all of which satisfy the above conditions.

3. Linking specific productivity and size

Now we link the level of specific productivity of a plant or a cohort of plants to the size of these units. We use this link to argue that the data imply that the specific productivity of a cohort of plants of a given age grows substantially as the cohort ages. We then show that

the model can be rewritten with size instead of specific productivity as a state variable. This alternative representation is convenient when we quantify the model.

We start with the data on employment by plants of different ages. Table 1 presents the share of manufacturing employment in plants of various age groups stated both as the share of workers employed by plants of that age group and the share employed by a one-year cohort within each group.¹ In the table, we see that as a cohort of plants ages from newborn to 20 years old, it employs a growing share of the labor force. In our model, these data imply that the aggregate of specific productivities across a cohort of plants is also growing for up to 20 years.

We develop the relationship between the employment share and the aggregate specific productivity of a cohort of plants by first deriving the relationship between the size and the specific productivity of a single plant and then aggregating across plants in the cohort. To that end, consider the allocation of capital and labor across plants at any point in time. Since capital and labor are freely mobile across plants, the problem of allocating these factors across plants in period t is static. For a given distribution λ_t of organization capital, it is convenient to define

$$(8) \quad n_t(A) = \left(\frac{A}{\bar{A}_t} \right)$$

as the *size* of a plant of type (A, s) in period t , where

$$(9) \quad \bar{A}_t = \sum_s \int_A A \lambda_t(dA, s)$$

is the aggregate of the specific productivities. The variable $n_t(A)$ measures the size of the plant in terms of its capital or labor or output, in that the equilibrium allocations are

$$(10) \quad k_t(A) = n_t(A)k_t, \quad l_t(A) = n_t(A)l_t, \quad \text{and} \quad y_t(A) = n_t(A)y_t,$$

where $y_t = z_t \bar{A}_t^{1-\nu} F(k_t, l_t)^\nu$ is aggregate output. To see this, note that since the production function F is linear-homogeneous of degree 1 and there is only one fixed factor, all operating plants in this economy use physical capital and labor in the same proportions. The proportions given are those that satisfy the resource constraints for capital and labor.

Now define the aggregate of the specific productivities of a cohort of plants of age s as $\bar{A}_t(s) = \int_A A \lambda_t(dA, s)$. Note from (8) that $\bar{A}_t(s)/\bar{A}_t = \int_A n_t(A) \lambda_t(dA, s)$. Using (10), we then have

PROPOSITION 1. *The aggregate of specific productivities in all plants of age s relative to that in all plants is the share of total employment in those plants, that is,*

$$(11) \quad \frac{\bar{A}_t(s)}{\bar{A}_t} = \int_A \frac{l_t(A)}{l_t} \lambda_t(dA, s).$$

Note for later that we use Proposition 1 in our data analysis when we identify the right side of (11) with the employment shares in Table 1 and use those shares to back out the relative productivities of cohorts of plants of different ages.

We now show that on a balanced growth path, for each plant we can replace the state variable specific productivity A with the state variable size n . To ensure that our model has a balanced growth path, we assume that $F(k, l)$ has the Cobb-Douglas form $k^\theta l^{1-\theta}$.² We define a *balanced growth path* in this economy as an equilibrium in which the following conditions hold: The quality of the best available blueprint τ_t and the productivity $\bar{A}_t$ grow at a constant rate $(1 + g_\tau)$, the economy-wide level of technology z_t grows at a constant rate $(1 + g_z)$, aggregate variables y_t, c_t, k_t, w_t , and w_{mt} grow at a rate $(1 + g)$, where $(1 + g) = [(1 + g_z)(1 + g_\tau)^{1-\nu}]^{1/(1-\nu\theta)}$; variables ϕ_t, V_t^0 , and r_t are constant; and the distributions of organization capital across plants satisfy $\mu_{t+1}(A, s) = \mu_t(A/(1 + g_\tau), s)$ and $\lambda_{t+1}(A, s) = \lambda_t(A/(1 + g_\tau), s)$ for all t, A, s ,

$V_{t+1}(A, s) = (1+g)V_t(A/(1+g_\tau), s)$, $d_{t+1}(A, s) = (1+g)d_t(A/(1+g_\tau), s)$, and $V_{t+1}^c(A, s) = (1+g)V_t^c(A/(1+g_\tau), s)$ for all t, A, s .

Along the balanced growth path we can recast our state variables as (n, s) instead of (A, s) as follows. Define the function $W(n, s) = V_0(A, s)/y_0(1-\nu)$, where $n = A/\bar{A}_0$. Define the function $W^c(n, s)$ from $V_0^c(A, s)$ in a similar way. Let $\omega_m = w_{m0}/y_0(1-\nu)$ and $\{\rho_s\}$ be the cumulative distribution functions of $\eta = \varepsilon/(1+g_\tau)(1+g_z)$ induced by $\{\pi_s\}$. We refer to $\{\rho_s\}$ as the steady-state distributions of shocks to plant size. Consider the Bellman equation

$$(12) \quad W(n, s) = \max[0, W^c(n, s)]$$

$$W^c(n, s) = n - \omega_m + \beta \int_{\eta} W(n\eta, s+1) \rho_{s+1}(d\eta)$$

where $\omega_m = \beta W(\tau_0/\bar{A}_0, 0)$. Since the value functions V_t and V_t^c that solve the original Bellman equation (4) along the steady-state path, the functions W and W^c defined above satisfy this second Bellman equation. The terms in this second Bellman equation have the same interpretation as those in (4) as descriptions of the returns to operating or closing a plant of size n and age s . The function $W^c(n, s)$ defines a rule for operating plants in that plants with $W^c(n, s) \geq 0$ operate and those with $W^c(n, s) < 0$ do not.

In the next section, we will use the micro data to quantify the shocks to plant size η . Note that since only the product $(1+g_\tau)(1+g_z)$ enters the definition of shocks to size η , the data on the size-age distribution of plants does not pin down the relative contribution to growth in the Solow residual of growth in the two types of technology: frontier and economy-wide.

4. Calibration and measurement

Now we calibration our model. We draw on steady-state observations from macro aggregates to determine the preference parameter β , the depreciation rate δ , the physical capital share $\nu\theta$, and the growth rate of aggregate total factor productivity which must be allocated between growth in the frontier technology and growth in the economy-wide technology. We use steady-state observations from micro data on manufacturing plants in the United States to choose the parameters affecting the shocks to size. The parameters of the model and their values are listed in Table 2.

The choice of the macro parameters is standard. The time period of the model is one year. Along a steady-state growth path,

$$\frac{c_{t+1}}{\beta c_t} = \frac{(1+g)}{\beta} = \frac{p_t}{p_{t+1}} = \nu\theta \frac{y_t}{k_t} + (1-\delta).$$

We use the data in Gordon (2000b) to compute the trend growth rate in output per hour from 1870-1900 to be $1+g = 1.01$. In our experiments we set this to be the growth rate in the original steady state. In our experiments we start the transition in 1885 but find that the growth of output per hour and the Solow residual stays roughly constant until 1900. We use the time period 1870-1900 to set the initial steady state growth rate because it downweights the relative importance of the large business cycle fluctuations in the 1870's.

We set the discount factor $\beta = .96$ and the depreciation rate $\delta = .08$. We set the physical capital/output ratio $k/y = 2.2$ and this equation thus implies a capital share of about $\nu\theta = .29$. The steady state growth rate of output per worker, $1+g$, is related to the growth of the Solow residual by $(1+g)^{1-\nu\theta}$ which using the above numbers is .7. The growth of the Solow residual can be decomposed as $(1+g)^{1-\nu\theta} = (1+g_z)(1+g_\tau)^{1-\nu}$. The steady

state is not affected by the decomposition of the Solow residual into these components while our transition experiments are affected by this decomposition. In our transition experiments we consider different decompositions of this Solow residual into the part due to growth in the frontier technology and the part due to the growth in economy-wide technology..

Consider the span of control parameter ν . Hundreds of studies have estimated production functions with micro data. These analyses incorporate a wide variety of assumptions about the form of the production technology and draw on cross-sectional, panel, and time series data from virtually every industry and developed country. Douglas (1948) and Walters (1963) survey many studies. Recent work along these lines has also been done by Baily, Hulten, and Campbell (1992), Bahk and Gort (1993), and Bartelsman and Dhrymes (1998). Atkeson, Khan, and Ohanian (1996) review this literature and present evidence, in the context of a model like ours, that $\nu = .85$ is a reasonable value for this parameter.

We parameterize the distributions of shocks to size as follows. We assume that these shocks to size have a lognormal distribution, so that $\log(\eta_s) \sim N(m_s, \sigma_s^2)$. We choose the means and standard deviations of these distributions to be smoothly declining functions of s . In particular, we set $m_s = \gamma_1 + \gamma_2(\frac{S-s}{S})^2$ for $s \leq S$ and $m_s = \gamma_1$ otherwise and $\sigma_s = \gamma_3 + \gamma_4(\frac{S-s}{S})^2$ for $s \leq S$ and $\sigma_s = \gamma_3$ otherwise. With this parameterization, the shocks to size for plants of age S or older are drawn from a single distribution. Thus, shocks to size are parameterized by $\{\gamma_i\}_{i=1}^4$ and age S .

We choose the parameters governing the shocks to size so that the model matches data on the fraction of the labor force employed in plants of different age groups, as well as job creation and job destruction in plants of different age groups from the 1988 panel of the U.S. Census Bureau's Longitudinal Research Database (the LRD). We chose the data from this

panel because it has the most extensive breakdown of age categories.

More formally, Davis, Haltiwanger, and Schuh (1996) define the following statistics. *Employment* in a plant in year t is $(l_t + l_{t-1})/2$, where l_t is the labor force in year t . *Job creation* in a plant in year t is $l_t - l_{t-1}$ if $l_t \geq l_{t-1}$ and zero otherwise. *Job destruction* in a plant in year t is $l_{t-1} - l_t$ if $l_t \leq l_{t-1}$ and zero otherwise. In Figs. 7A, 7B, and 7C, we report for each age category total employment, total job creation, and total job destruction for all plants in that category relative to the total employment in all plants.

We set the parameter $S = 100$ and choose the γ_i to minimize the sum of the squared errors between the statistics computed from the model and those in the data. The resulting model statistics are also plotted in Figs. 7A, 7B and 7C. For completeness, note that the implied statistics for the overall job creation and destruction rates are 8.3 and 8.4 for the data and 9.1 and 9.1 in the model. This difference between the overall job creation and destruction rates in the data and the model is not large in comparison to the fluctuation in these rates in annual data from 1972-1993. The standard deviation of the job creation and job destruction rates over this period are 2.0 and 2.7.

In our quantification of the process of plant-specific productivity we use data on industry evolution from 1988. In our model we interpret these data as being generated from the steady state of an economy that has undergone the transition to a new economy. In our model as we change the rate of growth of the frontier technology of new plants so does the steady-state pattern of industry evolution and the corresponding distribution of organization capital across plants. In our experiments we set the initial distribution of organization capital across plants to be equal to the steady state distribution implied by the rate of growth of the frontier technology in the original steady state. For each of our transition experiments we

report on these patterns.

In our model we have assumed there is a fixed number of plants. An alternative, pursued by Hopehayn and Rogerson (1993) is to assume there is a constant fixed cost in terms of consumption goods of starting a new plant. In this alternative model the number of plants grows over time. We have chosen our specification because it seems to be a good approximation to the data. Sands (1961) reports that from 1904-1947 the number of manufacturing plants in the United States grew by only 1/2 of one percent per year while output per manufacturing establishment grew by nearly 3 percent per year. Clearly, most of the growth of output in this period came from more output from each plant and only a small part from an increase in the number of plants.

5. Contrast with the learning-by-doing literature

In our model we have used the size of plants to quantify their productivity. Here we explore the different implications for labor productivity of learning by individuals and learning by plants. The early literature on learning-by-doing studied individuals performing specific tasks or groups of individuals performing a given number of tasks. (See the survey by Argote and Epple 1990.) This early literature shows that in a wide variety of tasks an individual's average productivity increases with the number of times that task is performed. Based on this literature one might think that the extent of learning in plants might show up as changes in the average productivity of labor in plants. In our model, however, even though there is differential learning across plants, at each date the average productivity of labor is constant across plants. We argue that this implication of our model is consistent with the data.

An individual who learns shows increases in labor productivity. An organization that learns grows by adding variable factors so as to keep labor productivity constant (at least with Cobb-Douglas production). Hence, the key variable to look at to determine the amount of organization-specific capital is not some measure of either labor or capital productivity but rather some measure of relative size.

To see this consider a simplified version of our model in which the output in plant number i at time t is given by

$$(13) \quad y_{it} = z_t A_{it}^{1-\nu} l_{it}^{\nu}.$$

where A_{it} may depend on the age of the plant. In equilibrium, each plant at each date t chooses labor l_{it} to maximize profits, which implies that

$$(14) \quad l_{it} = A_{it} \frac{l_t}{A_t}.$$

where $l_t = \sum_i l_{it}$ and $A_t = \sum_i A_{it}$. Hence, taking logs of (13) and substituting for A_{it} from (14) gives that, in equilibrium, labor productivity is given by

$$\frac{y_{it}}{l_{it}} = z_t (A_t/l_t)^{1-\nu}$$

and hence is constant across all plants regardless of their specific productivity A_{it} . If we extend the model to include capital then (10) implies $y_t(A)/l_t(A) = y_t/l_t$ and $y_t(A)/k_t(A) = y_t/k_t$. Hence our model predicts that both of these measures of average productivity are constant across plants.

We argue that data supports the view that plants accumulate a large amount of organization-specific capital as they age and that this capital is reflected in their size not in some measure of their average productivity. That plants grow in size with age is clear from

the data on the employment shares of plants of different ages presented in Davis, Haltiwanger and Schuh (1996) (at least for plants first 20 years of production). That these differences in organization specific capital are not reflected in average productivity of capital or labor is documented in Bartlesman and Dhrymes (1998). They report, for a large sample of manufacturing plants drawn from the LRD, a geometric weighted average of capital and labor productivity

$$\left(\frac{y_{it}}{k_{it}}\right)^{\alpha} \left(\frac{y_{it}}{l_{it}}\right)^{1-\alpha}$$

by age category and size decile as measured by the average size of employment over 1972-1986 where the weights are obtained from a regression of outputs on inputs. We report their figures for this measure by age categories and size deciles in Table 3. While they find variations in this measure across individual plants, Table 3 makes clear that there is no systematic relation between the mean productivity and either age or size. We think that this feature of the data is important in distinguishing our approach for measuring the specific productivity of plants from a good portion of the literature on learning-by-doing.

6. The new economy

In this section, we use our calibrated model of organization capital to simulate the transition to a new economy with a permanently higher rate of growth of technical change. We think of this simulation as a quantification of the hypotheses of David (1990, 1991), Devine (1983) and others for the transition following the Second Industrial Revolution. In the simulation the increase in technical change is driven by faster growth in the frontier technology for new plants. We think of this increased growth in the frontier technology of new plants as capturing the possibilities for new plant design based on electric power. We find

that the process of replacing old plants based on old blueprints with new plants is gradual. As a result there is a substantial delay before the increase in technical change is observed in faster growth of output and the Solow residual.

Consider the transition following an unexpected increase in the rate of growth of the frontier technology available to new plants. Specifically, consider an economy that is on a balanced growth path with steady growth in the frontier technology causing output to grow at 1 percent per year. In this economy, at the beginning of the period labelled 1885, agents learn that the growth rate of the frontier technology increases once and for all so that on the new balanced growth path output grows at 2 percent per year.

In Figure 8 we show the diffusion of the new technology in the model and in the data. For the model we graph the percentage of physical capital employed in plants with blueprints dated 1885 and later. For the data we graph the percentage of total horsepower in manufacturing establishments provided by electric motors. To make this comparison we are assuming in the model that plants built 1885 and later are driven by electric motors while those built previously are driven by steam and water power. The diffusion in the model is quite similar to that in the data.

In Figures 9 and 10 we show the model's implications for output per hour and the Solow residual during the transition from 1870 to 1970. As in the data, the growth in output per hour and the Solow residual in the model gradually accelerate. Over the period 1900-1930 the trend growth rate in output per hour is 1.3 percent in the model and 1.5 percent in the data, while the trend growth rate in the Solow residual is 1 percent in the model and 1.2 percent in the data. In the model the growth rate in output per hour reaches its new steady state of 2 percent by 1940 and the growth rate in the Solow residual reaches its new steady

state of 1.4 percent by 1935.

Overall, the model confirms the following hypothesis. When technical change is ongoing and embodied in plants and when plants must learn to use new technologies then an increase in the pace of technical change leads to a slow diffusion of new technologies and a slow transition to a new economy with higher growth in output and the Solow residual.

In our model new technologies are embodied in plants. This assumption is essential in generating the slow transition to a new economy. To see this consider an alternative transition driven entirely by an increase in the growth rate of the economy wide technology z . Suppose that at the beginning of the period 1900, agents learn that the growth rate of the economy-wide technology increases once and for all so that on the new balanced growth path output grows at 2% per year.

In this transition, the trend growth rate of output and the Solow residual over the period 1900-1930 is 1.9 percent per year and 1.4 percent per year. These are very close to the corresponding long run growth rates of 2 percent and 1.4 percent. Clearly, when the increase in technical change is not embodied in plants, there is little or no delay in the transition.

So far we have focused on the diffusion of technology and the transition paths for output per hour and the Solow residual. Our model also implies that the pattern of industry evolution in the original steady state differs from that in the new steady state if the growth rate of the frontier technology differs across these steady states. Thus, when all of the increase in the pace of technical change comes from economy-wide technical change there is no difference in the patterns of industry evolution across steady states. More interesting are the patterns when all of the increase in pace of technical change comes from the frontier technology. The main differences these patterns are as follows. In the original steady state

the overall rate of job creation is 7.1 percent while in the new steady state it is 9.0 percent. Also, the fraction of the labor force employed in plants 25 years and older is 86 percent in the original steady state while this fraction is 53 percent in the new steady state. Briefly, the slower pace of technical change in the original steady state means that plants die more slowly and the pace of industry evolution is somewhat slower.

Unfortunately, we have not found data on the pace of industry evolution from the turn of the century. It is worth noting, however, that there is some evidence from the recent data to support the idea that faster growth in technical change leads to higher rates of job reallocation. Davis, Haltiwanger and Schuh (1996 p.52) report that both net job creation and within-industry reallocation are higher in industries with higher productivity growth rates.

7. Conclusion

A sustained increase in the pace of technical change eventually leads to a new economy with higher growth in output and productivity. David and Devine, among others, argue that if new technologies are embodied in organizations and if organizations must learn to use new technologies efficiently then there will be a substantial delay in the transition to the new economy. We have formulated quantitative model of this hypothesis and have shown that it can account for the main features of the transition to a new economy following the Second Industrial Revolution.

David (1990) argues that this transition serves a useful historical parallel for understanding the recent paradox of the rapid technical change in information technologies together with the slow growth in output and productivity. In order to flesh out this parallel in a quantitative model one would have to deal with two key issues. First, where are the new tech-

nologies embodied. Second, how extensive is the period of learning after these technologies are adopted.

In our model of the Second Industrial Revolution we followed the historical literature in assuming that new technologies are embodied in the design of manufacturing plants. This assumption does not seem to be immediately applicable to the Information Technology Revolution. There is some evidence that organizations can use these technologies efficiently only after they have been substantially restructured and have undergone an extended period of learning. (See Brynjolfsson and Hitt 2000.) Perhaps our model could be adapted to analyze the Information Technology Revolution but the unit of analysis would probably shift to some level of organization other than plants.

Notes

¹Here and throughout the paper our microdata is taken from the Census Bureau's Longitudinal Research Database on U.S. manufacturing plants (LRD). This data is broken down by crude age categories. In Table 2 we use data from the 1988 panel obtained from the computer disk that accompanies Davis, Haltiwanger and Schuh (1996), also available from Haltiwanger's website: <http://www.bsos.umd.edu/econ/haltiwanger/>

²This assumption of Cobb-Douglas production is necessary for a steady-state growth path. Along a steady-state growth path, $\bar{A}$ grows at constant rate $(1 + g_\tau)$, the capital-labor ratio k grows at rate $(1 + g)$, and $(1 + g_\tau)f((1 + g)k) = (1 + g)f(k)$, where $f(k) = F(k, 1)$. Thus $f(k)$ is homogenous of degree $x = 1 - \frac{\log(1 + g_\tau)}{\log(1 + g)}$. Since $f(\lambda k) = \lambda^x f(k)$, then $f(k1) = k^x f(1)$, so f is a power function and thus F is Cobb-Douglas.

References

- Aghion, Philippe, and Howitt, Peter. 1992. A model of growth through creative destruction. *Econometrica*, 60, 323-51.
- Aghion, Philippe, and Blanchard Olivier J. 1994. On the speed of transition in central Europe. In NBER Macroeconomics Annual, edited by Fischer, Stanley, and Rotemberg, Julio, vol 9, Cambridge MA, MIT Press.
- Argote, Linda and Epple, Dennis. 1990. Learning curves in manufacturing. *Science* 247 (4845), 920-924.
- Atkeson, Andrew, and Kehoe, Patrick. 1993. Industry Evolution and Transition: The Role of Information Capital, Federal Reserve Bank of Minneapolis Staff Report: 162.
- Atkeson, Andrew, Khan, Aubhik, and Ohanian, Lee. 1996. Are data on industry evolution and gross job turnover relevant for macroeconomics? *Carnegie-Rochester Conference Series on Public Policy*, 44, 215-50.
- Bahk, Byong-Hong, and Gort, Michael. 1993. Decomposing learning by doing in new plants. *Journal of Political Economy* 101 (4), 561-83.
- Baily, Martin Neil, Hulten, Charles, and Campbell, David. 1992. Productivity dynamics in manufacturing plants. *Brookings Papers on Economic Activity; Microeconomics*; 187-249.
- Bartelsman, Eric J., and Dhrymes, Phoebus J. 1998. Productivity dynamics: U.S. manufacturing plants, 1972-1986. *Journal of Productivity Analysis*; 9(1), 5-34.
- Brixiova, Zuzana, and Kiyotaki, Nobuhiro. 1996. Private Sector Development in Transition Economies. Forthcoming in *Carnegie Rochester Conference Series on Public Policy*.

- Brynjolfsson, Erik, and Hitt, Lorin, M. 2000. Beyond computation: Information technology, organizational transformation and business performance. Mimeo Sloan School of Management, MIT.
- Castanheira, Michael, and Roland, Gerard. 1996. The optimal speed of transition: A general equilibrium analysis. Mimeo, Universite Libre de Bruxelles.
- David, Paul, A. 1990. The dynamo and the computer: An historical perspective on the modern productivity paradox, *American Economic Review*, 80 (2), 355-361.
- David, Paul, A. 1991. Computer and dynamo: The modern productivity paradox in a not-too distant mirror. *Technology and Productivity: The Challenge to Economic Policy*, OECD, Paris.
- David, Paul, A. and Wright, Gavin. 1999. General purpose technologies and surges in productivity: Historical reflections on the future of the ICT revolution. Stanford Economics working paper 99-026.
- Davis, Steve J., and Haltiwanger, John, and Schuh, Scott. 1996. Job creation and destruction. MIT Press, Cambridge MA.
- Devine, Warren, D. Jr. 1983. From shafts to wires: Historical perspective on electrification. *Journal of Economic History*, 43 (2), 347-372.
- Devine, Warren, D. Jr. 1990. Electricity in information management: The evolution of electronic control. In *Electricity in the American Economy*, edited by Schurr, Sam H.; Burwell, Calvin, C.; Devine, Warren D. Jr. and Soneblum, Sidney, New York: Greenwood Press.
- Dewatripont, Mathias and Gerard Roland. 1992. Economic reform and dynamic political constraints. *Review of Economic Studies*, 59, 703-30.

- Douglas, Paul H. 1948. Are there laws of production? *American Economic Review* 38 (1), 1-41.
- Gordon, Robert J. 2000a. Does the "New Economy" measure up to great inventions of the past? NBER working paper 7833, forthcoming *Journal of Economic Perspectives*.
- Gordon, Robert J. 2000b. Interpreting the "One big wave" in U.S. long-term productivity growth. NBER working paper 7752.
- Greenwood, Jeremy and Yorukoglu, Mehmet. 1997. "1974". *Carnegie Rochester Conference Series on Public Policy*, 46, 49-95.
- Helpman, Elhanan, and Trajtenberg. 1998. Diffusion of general purpose technologies. In *General purpose technologies and economic growth* edited by Helpman, Elhanan, Cambridge MA, MIT Press.
- Hopenhayn, Hugo, and Rogerson, Richard. 1993. Job turnover and policy evaluation: A general equilibrium analysis. *Journal of Political Economy* 101 (5), 915-38.
- Hornstein, Andreas and Krusell, Per. 1996. Can technology improvements cause productivity slowdowns? *NBER Macroeconomics Annual*. pp. 209-259.
- Jovanovic, Boyan. 1982. Selection and the evolution of industry. *Econometrica* 50 (3), 649-70.
- Krusell, Per and Rios-Rull, Jose Victor . 1996b. Vested interests in a positive theory of stagnation and growth. *Review of Economic Studies*, 63 (2), 301-30.
- Lucas, Robert E., Jr. 1978. On the size distribution of business firms. *The Bell Journal of Economics* 9, 508-23.
- Rosenberg, Nathan. 1976. On technological expectations. *Economic Journal* 86 (2), 523-535.
- Schurr, Sam H.; Netschert, Bruce C.; Eliasberg, Vera; Lerner, Joseph, and Landsberg, Hans

- H. 1960. *Energy in the American Economy*. Baltimore, MD, John Hopkins Press.
- Schurr, Sam H.; Burwell, Calvin, C.; Devine, Warren D. Jr.; Soneblum, Sidney. 1990. *Electricity in the American Economy: Agent of Technological Progress*, New York: Greenwood Press.
- Sonenblum, Sidney. 1990. Electrification and productivity growth in manufacturing. In *Electricity in the American Economy*, edited by Schurr, Sam H.; Burwell, Calvin, C.; Devine, Warren D. Jr. and Soneblum, Sidney, New York: Greenwood Press.
- Walters, A. A. 1963. Production and cost functions: an econometric survey. *Econometrica* 31 (1-2), 1-66.

Figure 1:
Sources of Mechanical Drive in Manufacturing Establishments 1869-1939
Source: Devine (1983 Table 3)

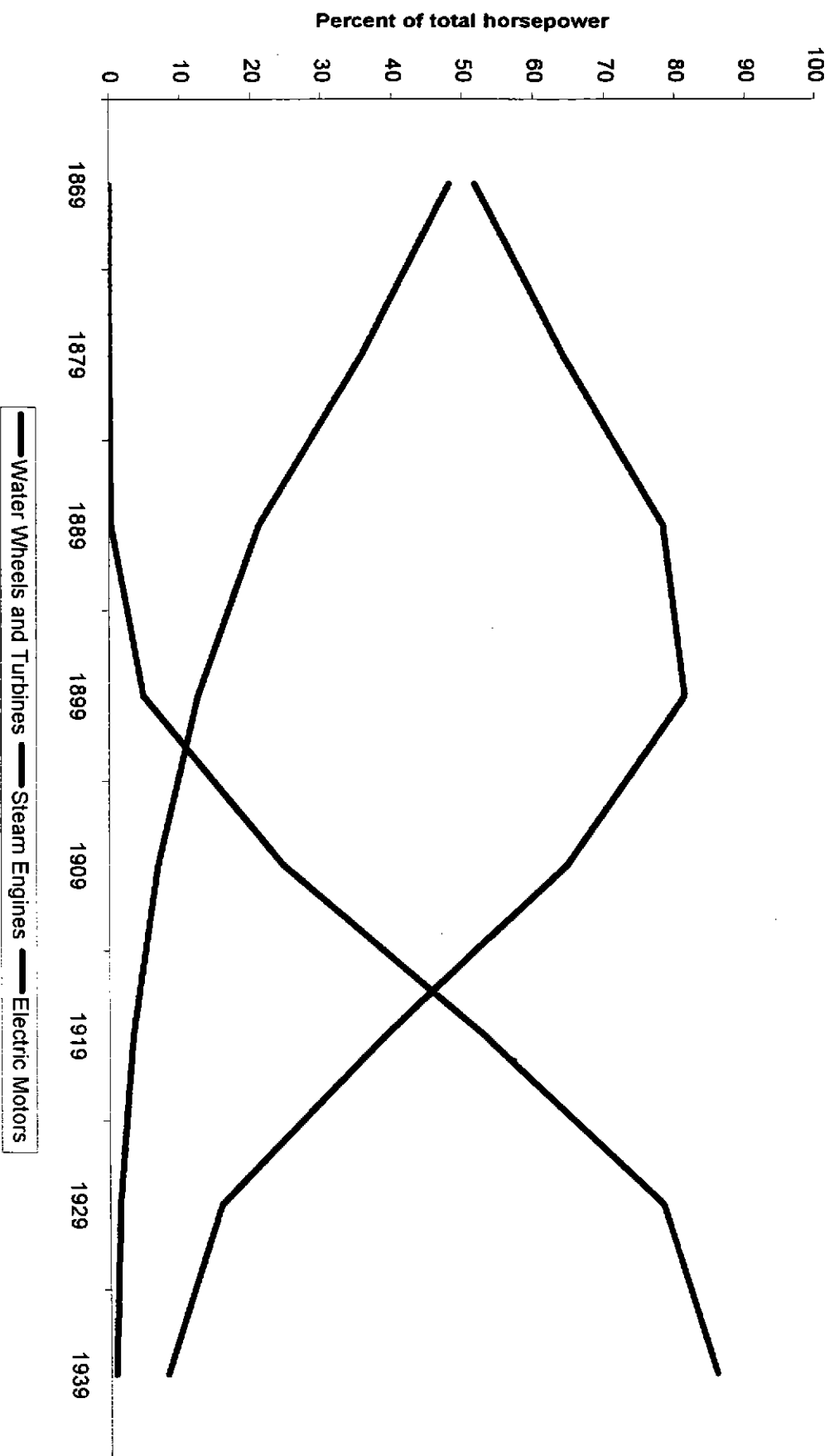


Figure 2:
Log of Output/Hour 1870-1970
Source: Gordon (2000b figure 3)

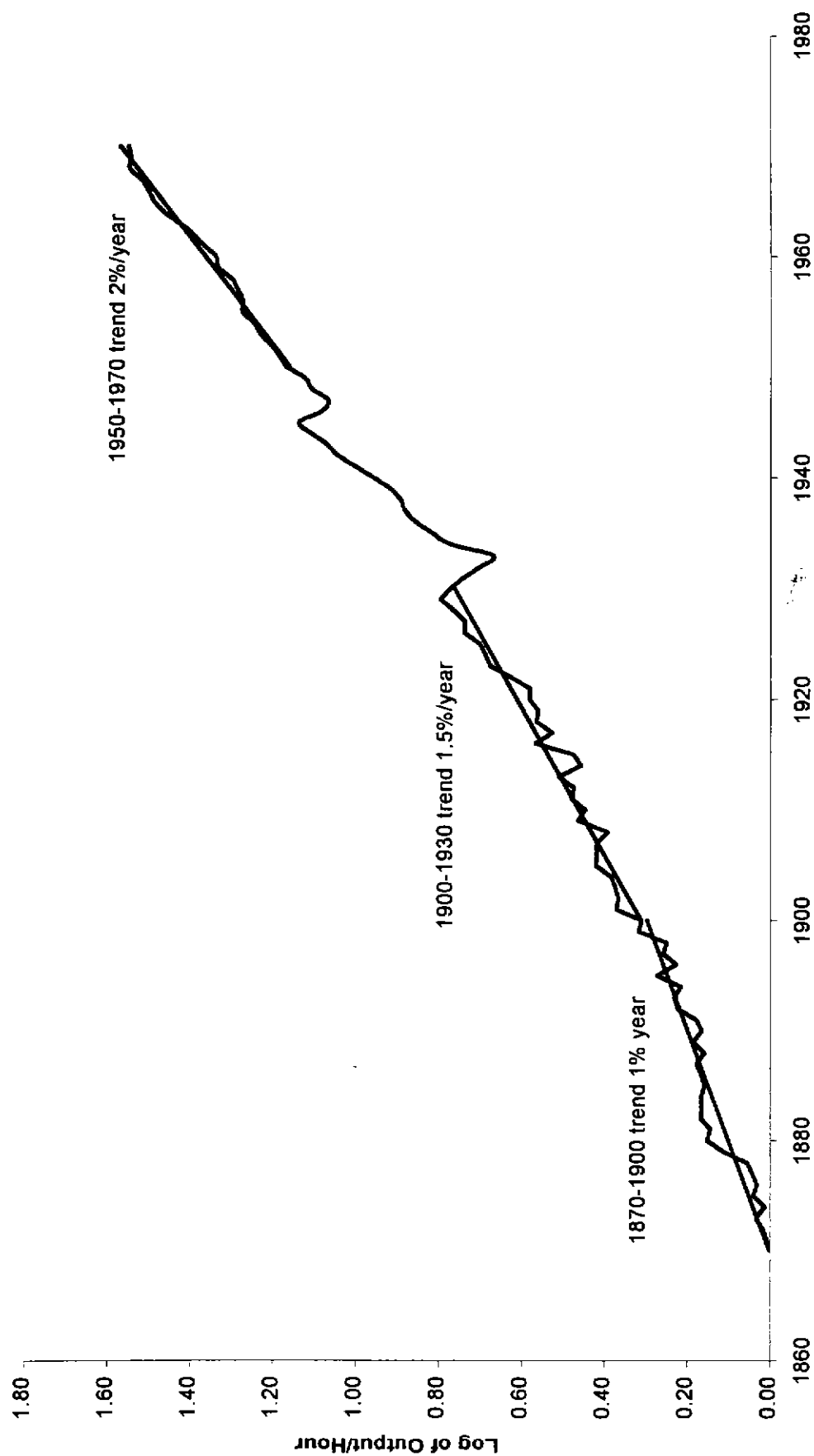


Figure 3:
Solow Residual 1870-1970
Source: Gordon (2000b) (Figure 3)

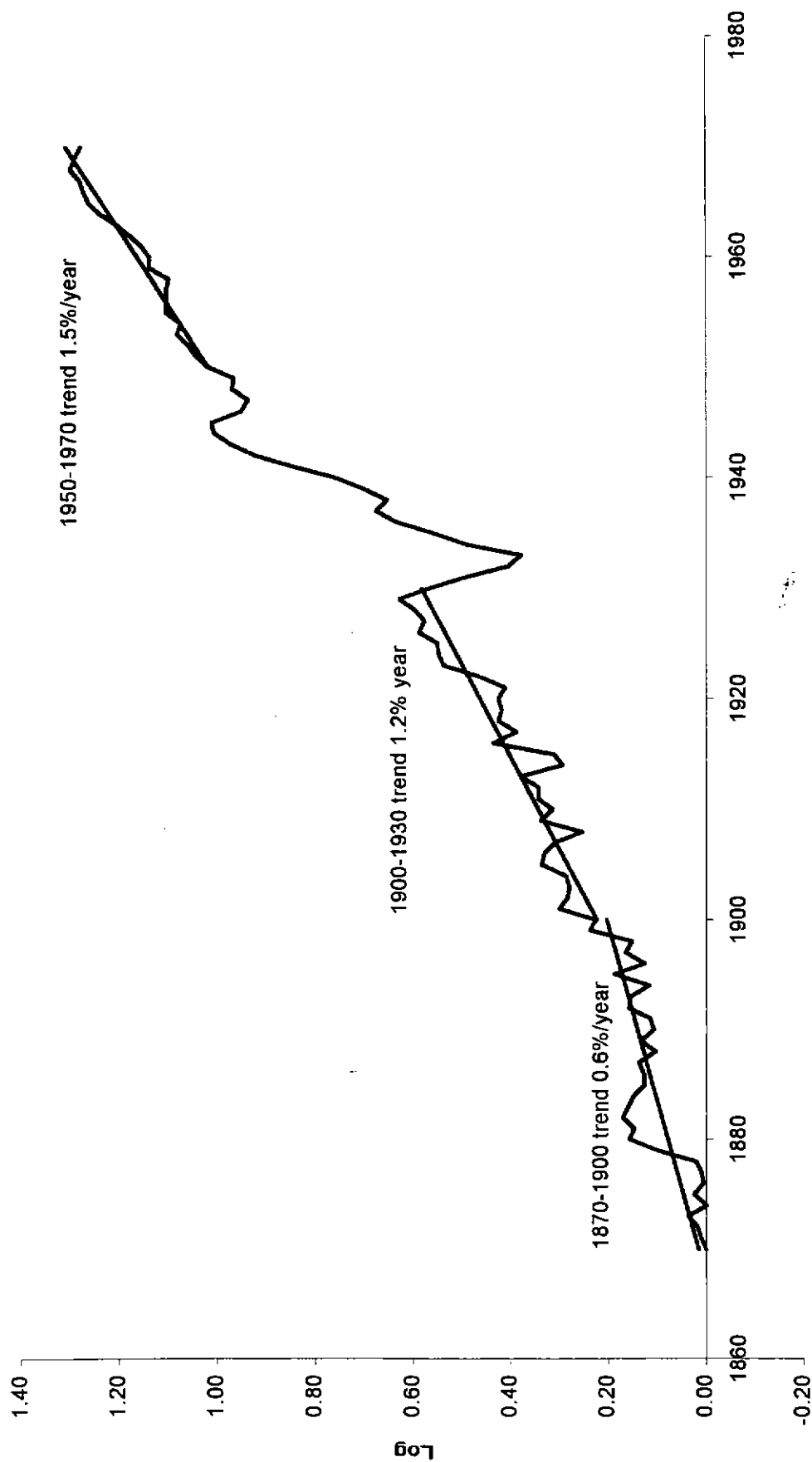
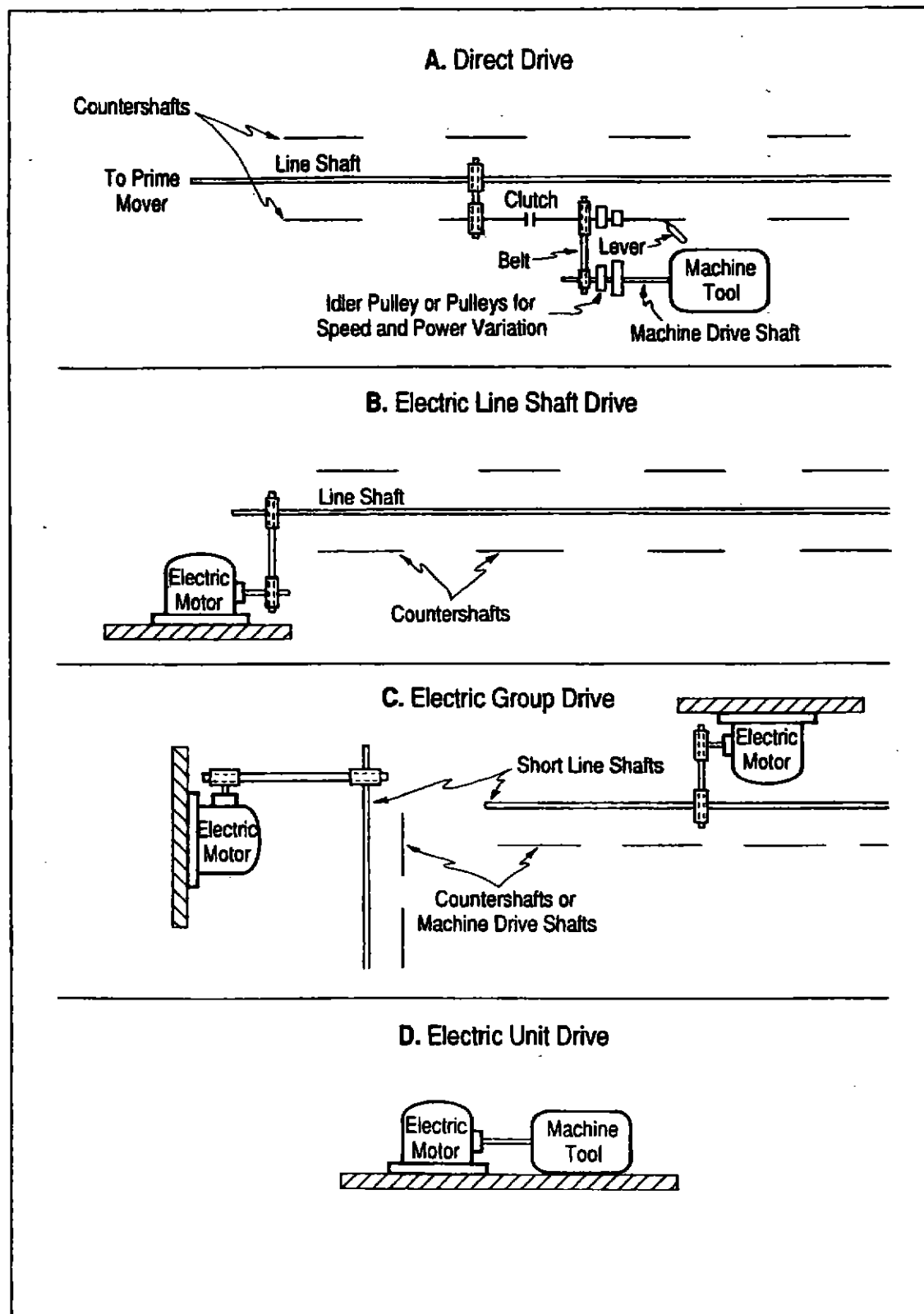


Figure 4 Evolution of Power Distribution in Manufacturing



(B) Rise of Alternating Current; (C) Share of Power for Mechanical Drive Provided by Steam, Water, Electricity; (D) Key Technical and Entrepreneurial Developments. (The percentages shown in "C" do not necessarily add up to 100 because sources of mechanical power other than steam, water, and electricity are not shown.)

A. Direct drive

Group drive

Unit drive



Dc motors in manufacturing

"Battle of the currents"

Ac transmission

Ac motors in manufacturing

C.	Steam 52%
	Water 48%

Steam	64%
Water	36%

Sleam	78%
Water	21%
Elec.	< 1%

Steam	81%
Water	13%
Elec.	5%

Steam	65%
Elec.	25%
Water	7%

Elec.	53%
Steam	39%
Water	3%

Elec.	78%
Steam	16%
Water	1%

④

1870 Dc electric generator (hand-driven)
1873 Motor driven by a generator

1070 Electricity generated using steam engine

1879 Practical incandescent light

1882 Electrically marketed as a commodity

1003 Mills used in manufacturing
1894 Steam turbine developed

1884 Chamberlain described

1888 Tesla develops ac motor

1891 Ac power transmission for industrial use

1892 Westinghouse markets ac polyphase induction motor, General Electric Company formed by merger

1893 Samuel Insull becomes president of Chicago Edison Company

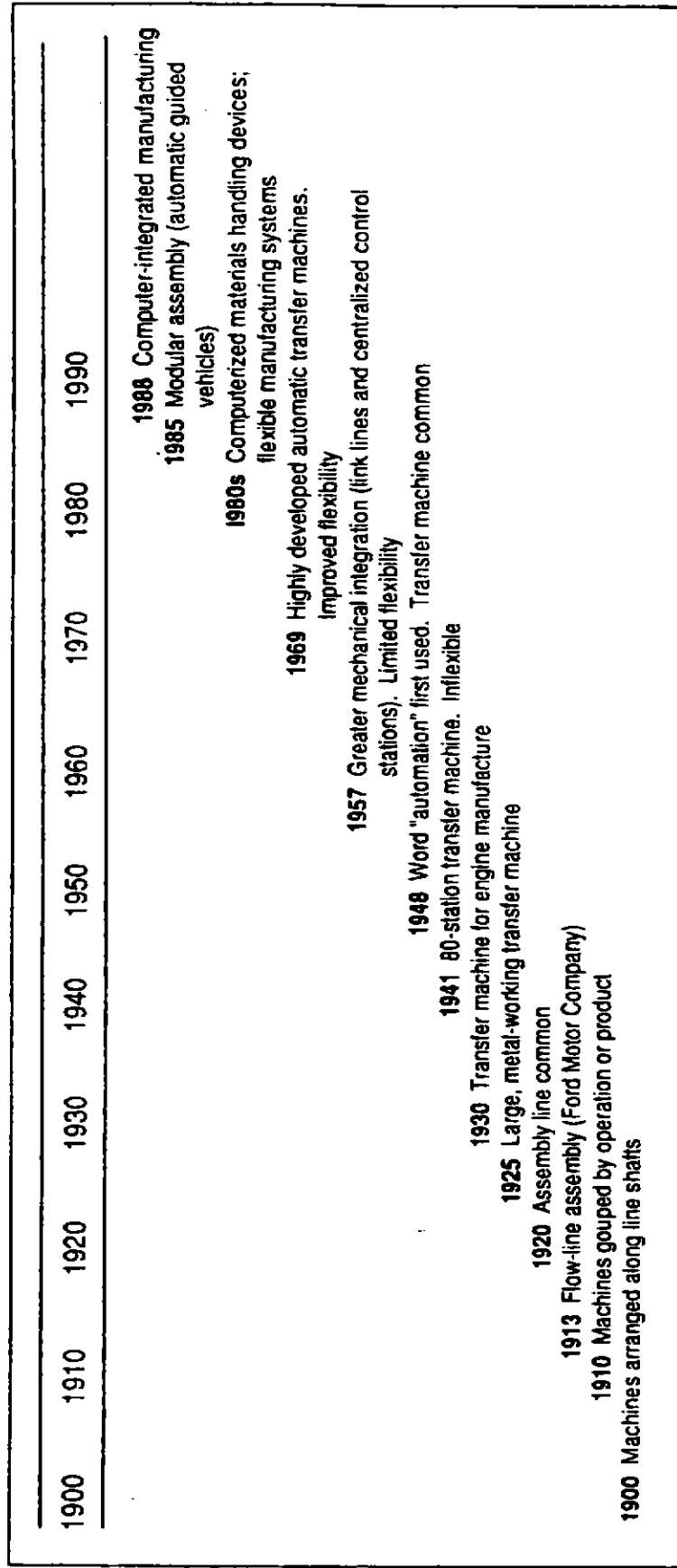
1893 AC generation at Niagara Falls

1907 State-regulated territorial

1917 Primary m

1917 Primary motors predominate; capacity and generation of utilities exceeds that of industrial estab.

Figure 6 Milestones in the Evolution of Production Organization



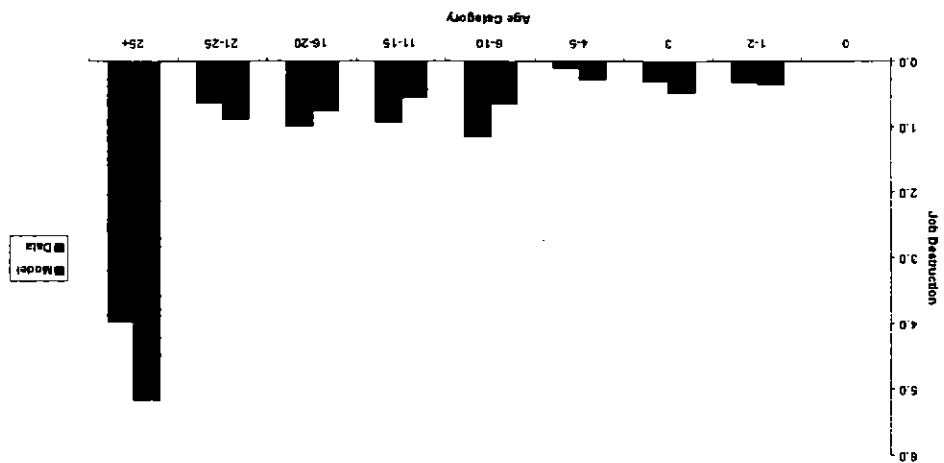


Figure 7A. Employment Shares by Age Category

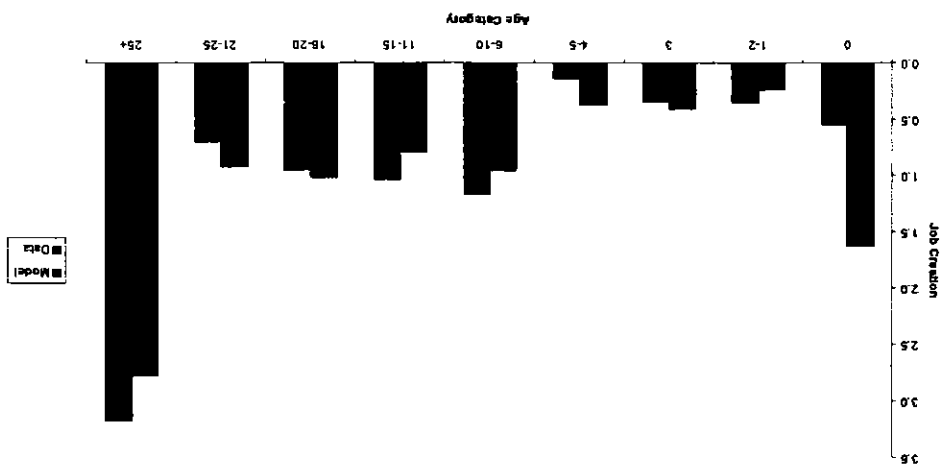


Figure 7B. Job Creation by Age Category

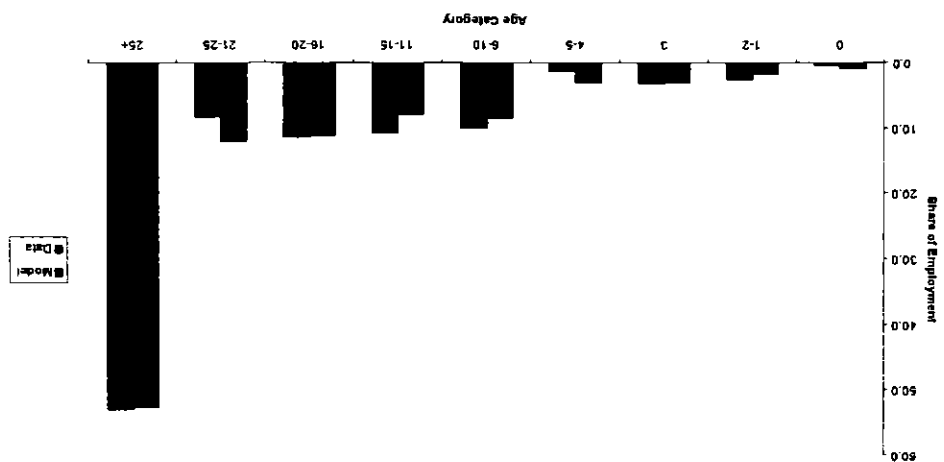


Figure 7C. Job Destruction by Age Category

Figure 8:
Diffusion of Electric Power 1870-1940
Model and Data

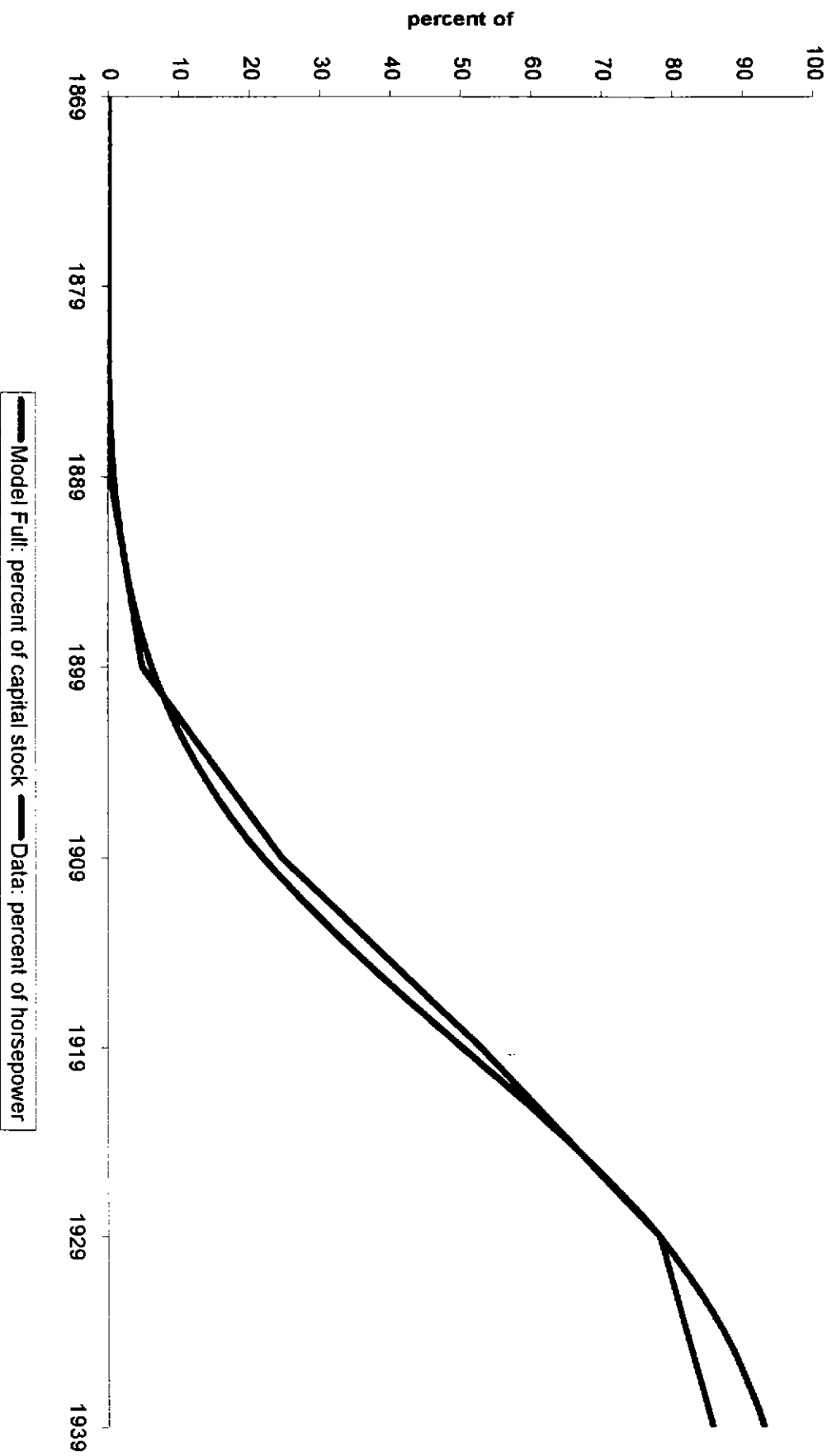


Figure 9:
Log of Output/Hour in the Model 1870-1970

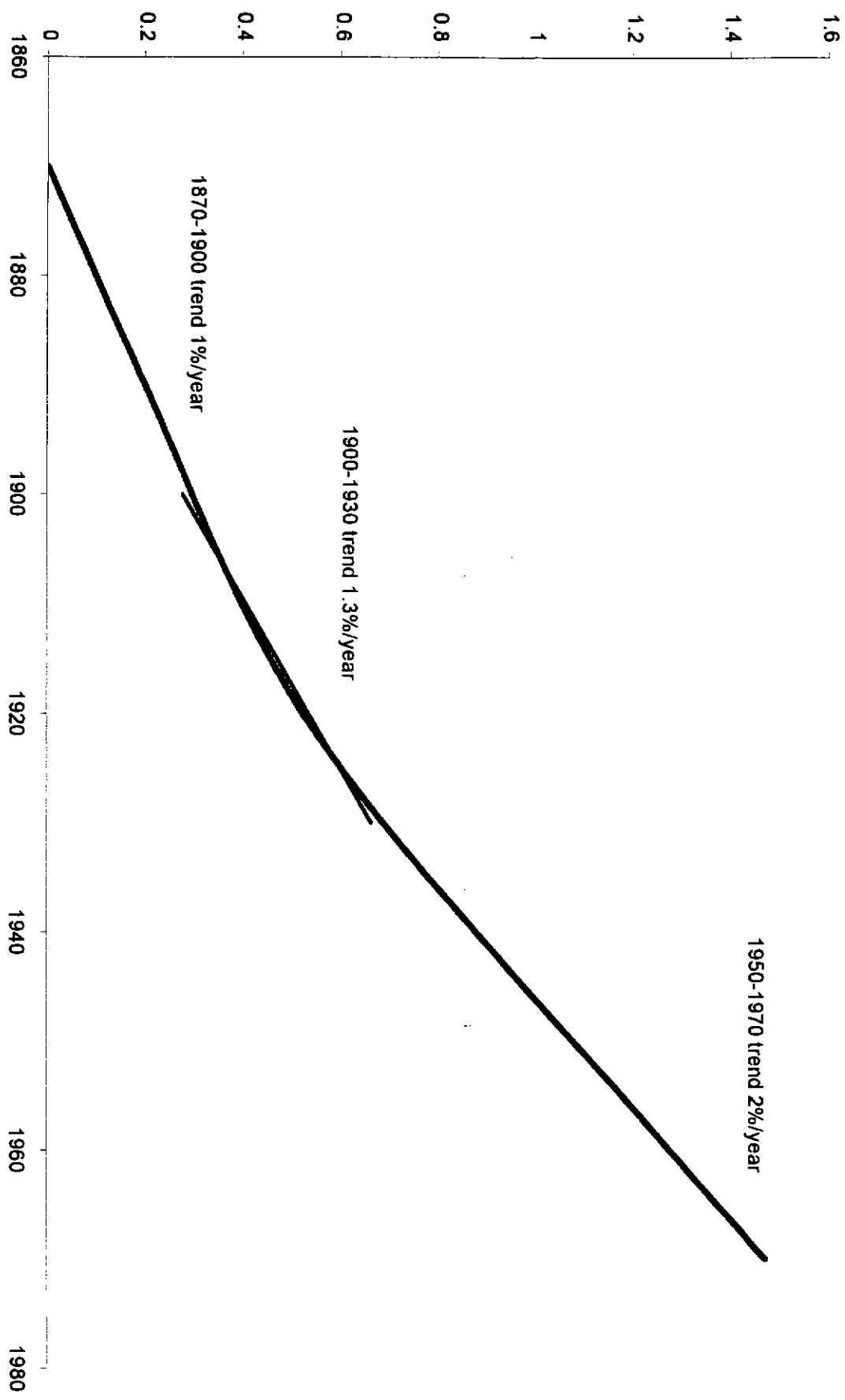


Figure 10:
Log of the Solow Residual in the model
1870-1970

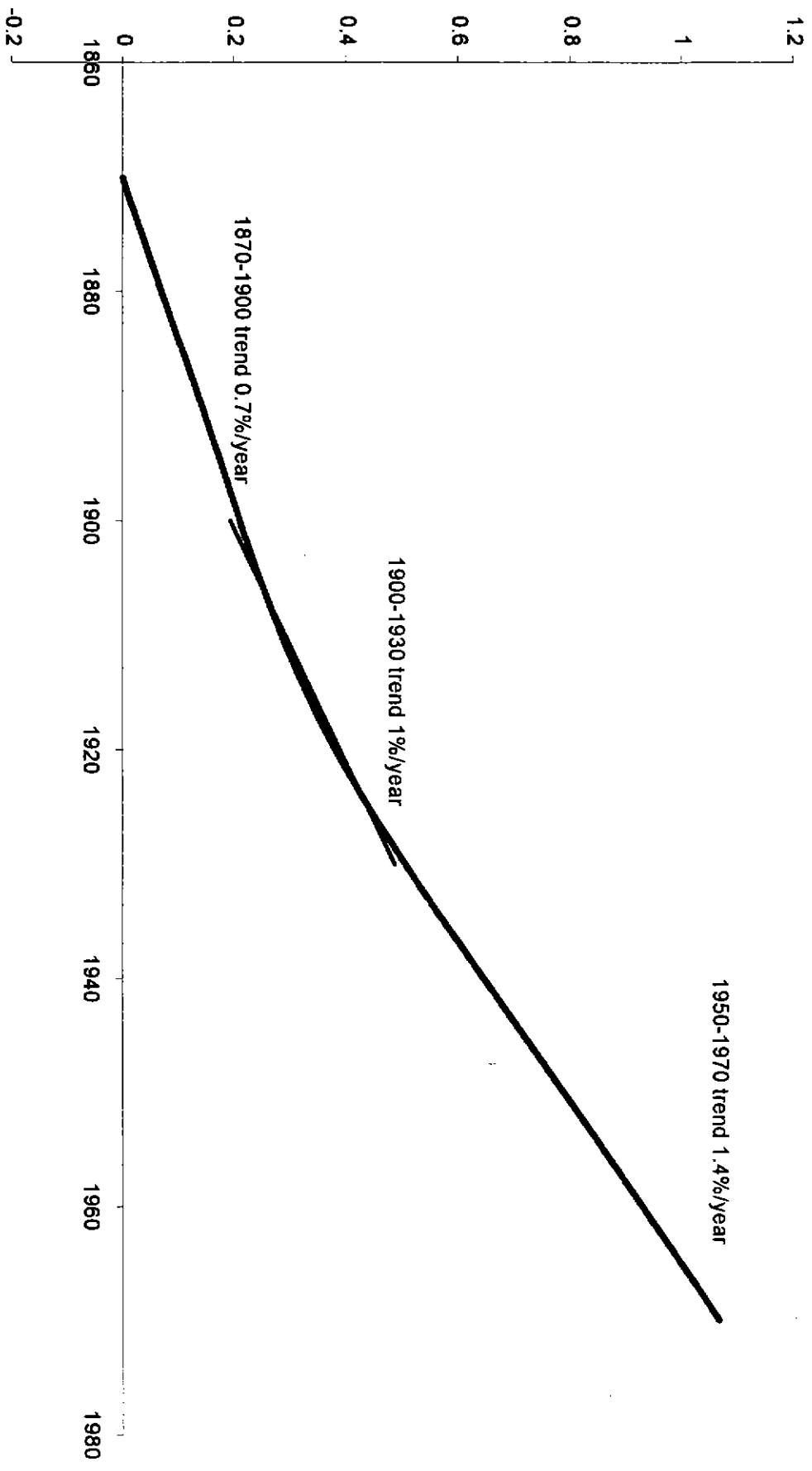


TABLE 1

Share of Manufacturing Employment in Plants by Age Group
Stated as the share per one-year cohort in age group

Age Group	Employment Share	Share per one-year cohort
Births	0.3	0.3
1-5	6.7	1.3
6-10	10.0	2.0
11-15	10.7	2.1
16-20	11.3	2.3
21-25	8.2	1.6

Source Data

1988 Panel of the LRD as reported on John Haltiwanger's Website
<http://www.bsos.umd.edu/econ/haltiwanger/>

Table 2

Macro Parameters	
Original steady-state growth rate g	1.0
New steady-state growth rate g	2.0
Discount factor β	.96
Depreciation rate δ	.08
New steady-state physical capital/output ratio k/y	2.0
Implied physical capital share $v\theta$	.29
Span of control parameter v	.85
Parameters of Shocks to Size	
maximum age for which shocks change with age S	100
γ_1	-.1194
γ_2	.1925
implied mean shock to log of employment for new plants	.0731
implied mean shock to log of employment for plants of age S and above	-0.1194
γ_3	.1409
γ_4	.0599
implied standard deviation of shocks to log of employment for new plants	.2008
implied standard deviation of shocks to log of employment for plants of age S and above	.1409

Table 3
Source Bartlesman and Dhrymes 1998

Panel A
Average Productivity of Plants by Age Category

Age Categories	Average Productivity
1-2	5.65
3-4	5.79
5-6	5.77
7-10	5.6
11-14	5.53
15-20	5.51
21-26	5.61
over 26	5.36

Panel B
Average Productivity of Plants by Size Decile

Size Decile	Average Productivity
1	5.62
2	5.64
3	5.62
4	5.55
5	5.48
6	5.4
7	5.37
8	5.55
9	5.45
10	5.4

