NBER WORKING PAPER SERIES

MOORE'S LAW AND LEARNING-BY-DOING

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Working Paper 8762
http://www.nber.org/papers/w8762

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
February 2002

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JEL No. O3, N1

ABSTRACT

We model Moore's Law as efficiency of computer producers that rises as a by-product of their experience. We find that

- Because computer prices fall much faster than the prices of electricity-driven and diesel-driven capital ever did, growth in the coming decades should be very fast, and that
- The obsolescence of firms today occurs faster than before, partly because the physical capital they own becomes obsolete faster.

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Boyan Jovanovic and Peter L. Rousseau*

January 20, 2002

Abstract

We model Moore's Law as efficiency of computer producers that rises as a by-product of their experience. We find that

- Because computer prices fall much faster than the prices of electricity-driven and diesel-driven capital ever did, growth in the coming decades should be very fast, and that
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1 Introduction

In 1965, the co-founder of Intel, Gordon Moore, predicted that the number of transistors per integrated circuit would double every 18 months. This has come to be known as Moore's Law. The Pentium 4 processor arrived in 2000 with 42 million transistors. The 2001 arrival of the Itanium processor, with 320 million transistors, is ahead of Moore's schedule. Recently, even Moore has wondered if this kind of growth can continue. But Meindl, Chen, and Davis (2001) suggest that it can go on for at least another 20 years. By then, a chip will have more than a trillion transistors and the computing power of the human brain.

Moore's Law states, in other words, that the efficiency of computer producers grows very fast. We argue that the Law is an example of a rise in efficiency that always occurs among producers of any good as a by-product of their experience with making and selling it. Electricity and internal combustion, for example, are technologies for

*The University of Chicago and NYU, and Vanderbilt University. We thank the National Science Foundation for support, and Peter Thompson for comments. Chia-Ying Chang, Jong-Hun Kim and John T. Roland provided research assistance.

which similar laws have held over long periods, although the improvements were less dramatic.[1]

We adopt an Arrow (1962) type of formulation in which aggregate experience fully determines the growth of efficiency. Our results are:

1. The long-run growth rate and the approach to it depend on three parameters (Proposition 1): (*i*) The share in output of the capital to which the law applies, (*ii*) the elasticity of capital-producers' efficiency with respect to experience, and (*iii*) proportionally on the rate of labor growth,

2. The approach to the steady-state is slower than it would be in Solow (1956). The bigger the technology's learning potential, the longer the transition (Proposition 2),

3. Firms' market–to-book values reflect the age and type of capital that the firms own; they decline faster with age in high-tech epochs and high-tech sectors and,

4. After fitting the model to three technologies – Electricity, internal combustion, and information technology – it predicts that in the coming decades consumption will grow much faster than it did during the 20th century because the cost of computing falls much faster than the cost of machines did 70-100 years ago. We do not have a precise forecast, but the best fit of the model implies a long-run productivity growth of 7.6 percent per year.

Why focus on experience?—The engine of growth in our model is not investment, but experience. Now, we know that R&D raises firms' profits and efficiency and that schooling and on-the-job training raise workers' pay and productivity. Such investment raises output, but by just how much depends on the return to the investment. That rate of return depends, in turn, on just what kind of investment is made. And this is where experience comes in. It teaches us what kind of research will yield fruit, which subjects students should learn in school, and what kind of training workers should get on the job. Vernon (1966) argues that the American firm maintains its lead because it sells to the world's richest and most sophisticated customer, and so learns from him and adapts to his wants. This customer's wants dictate the kind of product that he will buy, and his skills dictate the technology that his employer must use. Dealing with him keeps the firm on its toes and ahead of the pack.

Sustained productivity growth is probably impossible if nothing is invested in education, training, or research, but the payoff to that investment will depend on

[1] Neither Thomas Edison nor Rudolf Diesel were as good as Moore at predicting the future development of the technologies that their ideas helped spawn. They were overly optimistic. For example, in 1912 Diesel predicted that diesel motors would soon use plant oils (Anso and Bugge, 2001) and in 1922, Thomas Edison predicted that "the motion picture is destined to revolutionise our educational system and ... in a few years it will supplant largely, if not entirely, the use of textbooks" (Oppenheimer, 1997).

what precise products and processes are targeted. Market experience provides firms with the signals they need in order to make the best choices. With a general-purpose technology (GPT), the big impact of experience lies probably in the development of the GPT's applications. For computers, the applications are software and the internet, for electricity they were household appliances and light industrial equipment, and for the internal combustion engine they were automobiles and trucks. These are the products that link the GPT to the ultimate wants of the consumer and the cost-saving needs of the manufacturer, and this is where experience really counts.

2 Three learning curves

The learning law.—If returns to scale are constant and if competition is atomistic, the average cost of producing a good equals its equilibrium price. Thus we can simply assume that price, p, is a function of the cumulative output of all producers combined, K:

$$p = \left(\frac{K}{B}\right)^{-\beta}, \tag{1}$$

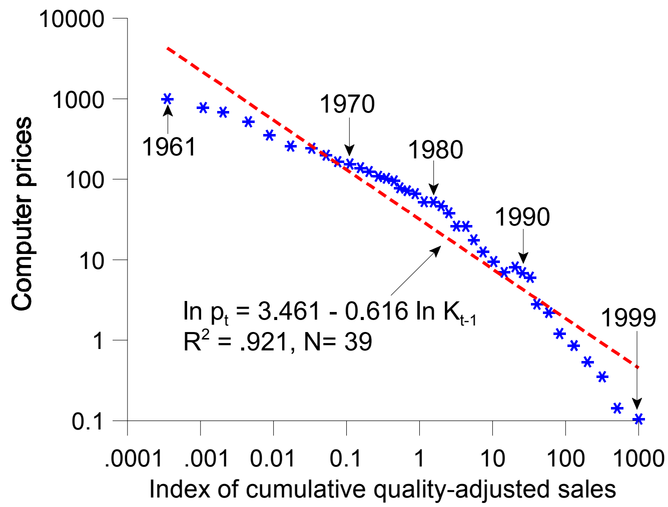
where B is a constant. The log-linear version of (1) is

$$\ln p_t = \beta_0 - \beta \ln K_{t-1},$$

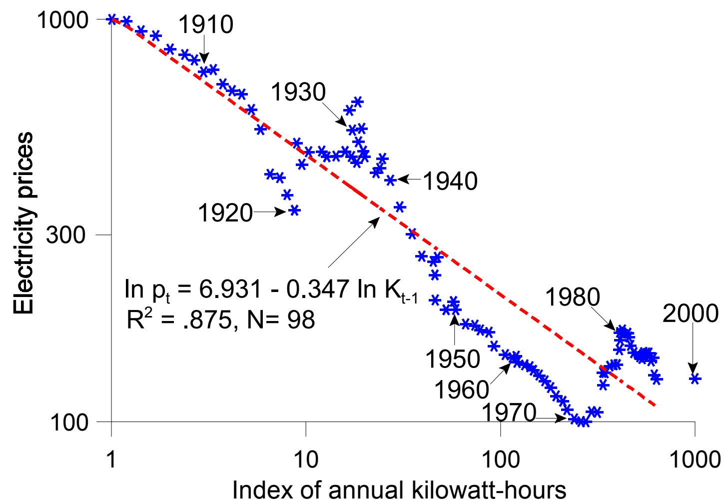
where $\beta_0 = -\beta \ln B$. We estimate this equation for three general-purpose technologies: Computers, electricity, and the internal combustion engine. Figure 1 presents pairwise combinations of $\ln p_t$ and $\ln K_{t-1}$ on an annual basis for each technology and plots a regression line through the points. The axes denote indices of the variables p and K but on a log scale.

Estimates of β.—Table I shows our estimates of β and the average growth rates of p and K, denoted by g_p, and g_K. The computer has by far the highest β, $|g_p|$, and g_K.[2] The process started slowly – the 1960's were the age of the mainframe and minicomputer, and in spite of a fast-growing K as indicated by the horizontal spacing between the points, the decline in p was relatively slow – and since then it has kept

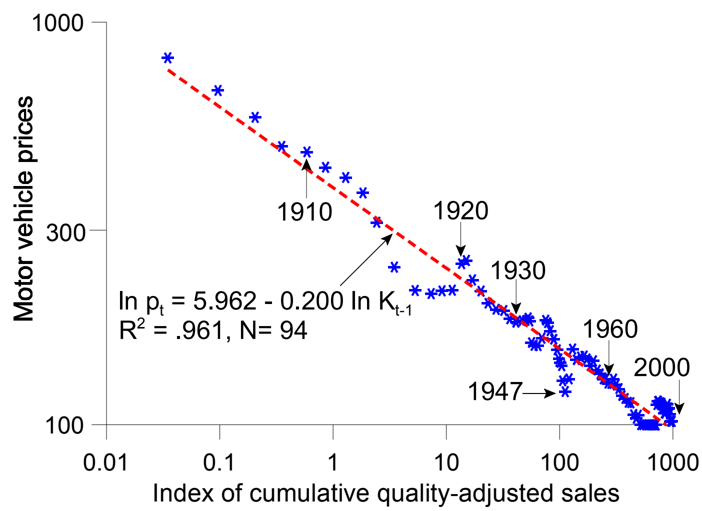
[2] To construct a quality-adjusted price index for computers, we join the "final" price index for computer systems from Gordon (1990, table 6.10, col. 5, p. 226) for 1960-78 with the pooled index developed for desktop and mobile personal computers by Berndt, Dulberger, and Rappaport (2000, table 2, col. 1, p. 22) for 1979-99. Since Gordon's index includes mainframe computers, minicomputers, and PCs while the Berndt et al. index includes only PCs, the two segments used to build our price measure are themselves not directly comparable, but a joining of them should still reflect quality-adjusted price trends in the computer industry reasonably well. We then obtain a quality-adjusted measure of computer production by deflating the nominal dollar value of final computer sales from the National Income and Product Accounts (Bureau of Economic Analysis, 2001, table 7.2, line 17) with our price index, cumulating the result over time, and setting the index to 1000 in the final year of the series (i.e., 1999). Finally, we divide our price index for computers by the implicit price deflator for GDP (Bureau of Economic Analysis, 2001, table 3) to build the normalized price index that appears on the vertical axis of Figure 1 and in the regressions used to estimate β, and set the index to 1000 in the first year of the series (i.e., 1960).



(a) computer systems



(b) electricity



(c) autos, trucks, and buses

Fig. 1. Prices and cumulative quantities of "New" Economy products.

TABLE I
Estimates of β

Technology	$\hat{\beta}$	g_p	g_K
Computer	0.62	-24.12	39.11
Electricity	0.35	-2.12	7.11
Automobile	0.20	-2.19	13.29

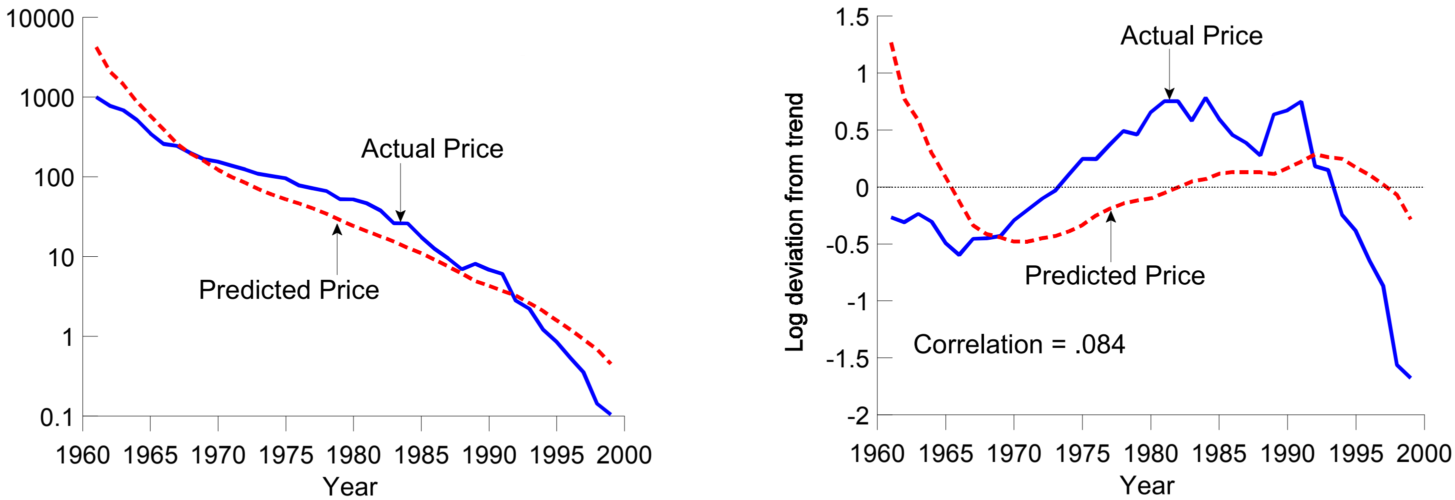
accelerating. The wider vertical spacing after 1990 suggests that the effects of learning by doing have now become even stronger. Our estimate of β exceeds Gordon's (2000), partly because his data do not cover the latest price declines, and partly because we use different sources.[3] Nevertheless, while rising at the very high rate of 24% per year, the quality of capital per dollar spent doubles only every 2.9 years. This is very fast, but not as fast as the 18 months that, according to Moore's Law, it takes the efficiency of computer chips to double. Evidently, other components of computers do not evolve quite as fast as computer chips.

Panels (b) and (c) of Figure 1 and the last two rows of Table I show that for electricity usage and automobile sales the relation between K and p is flatter than it has been for computers.[4] We choose annual electricity output rather than a cumulative measure because the accumulation of electrically-powered and long-lasting equipment is probably proportional not to cumulative but to *current* electricity usage. (Cumulative usage leads to similar estimates of β). For motor vehicles, we use

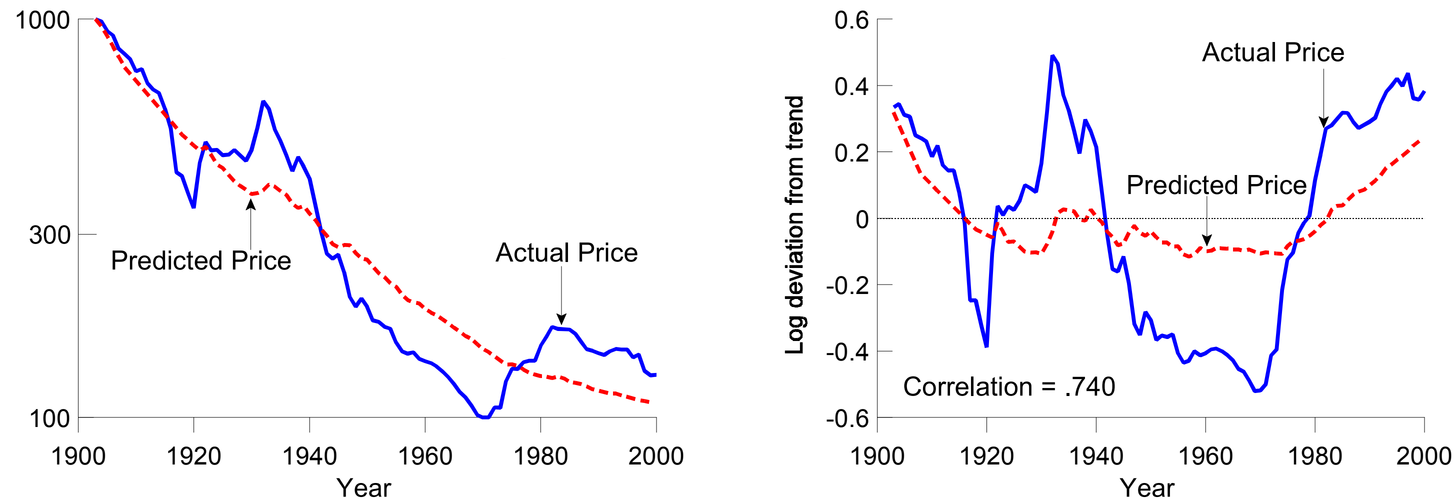
[3] We also estimate the learning parameter with a time trend in the specification. The trend term is negative and statistically significant for computers and positive and significant for electricity and automobiles. The β coefficient for computers falls to -0.87 and is no longer statistically significant, while the β's for electricity and autos become -0.745 and -0.230 respectively and remain significant. Since our learning model does not include a time trend in the pricing process, we use the β's from the trendless specification in our analysis.

[4] Electricity prices are averages of all electric energy services in cents per kilowatt hour from the *Historical Statistics of the United States* (U.S. Bureau of the Census, 1975, series S119, p. 827) for 1903, 1907, 1917, 1922, and 1926-70, and from the *Statistical Abstract of the United States* for 1971-89. We interpolate under a constant growth assumption between the missing years in the early part of the sample. For 1990-2000, prices are U.S. city averages (June figures) from the Bureau of Labor Statistics (*http:www.bls.gov*). We then divide the price index by the implicit price deflator for GDP, joining the series from Balke and Gordon (1986, table 1, pp. 781-782) for 1903-1929 with that of the Bureau of Economic Analysis for later years, and set it to 1000 in the first year of the series (i.e., 1903).

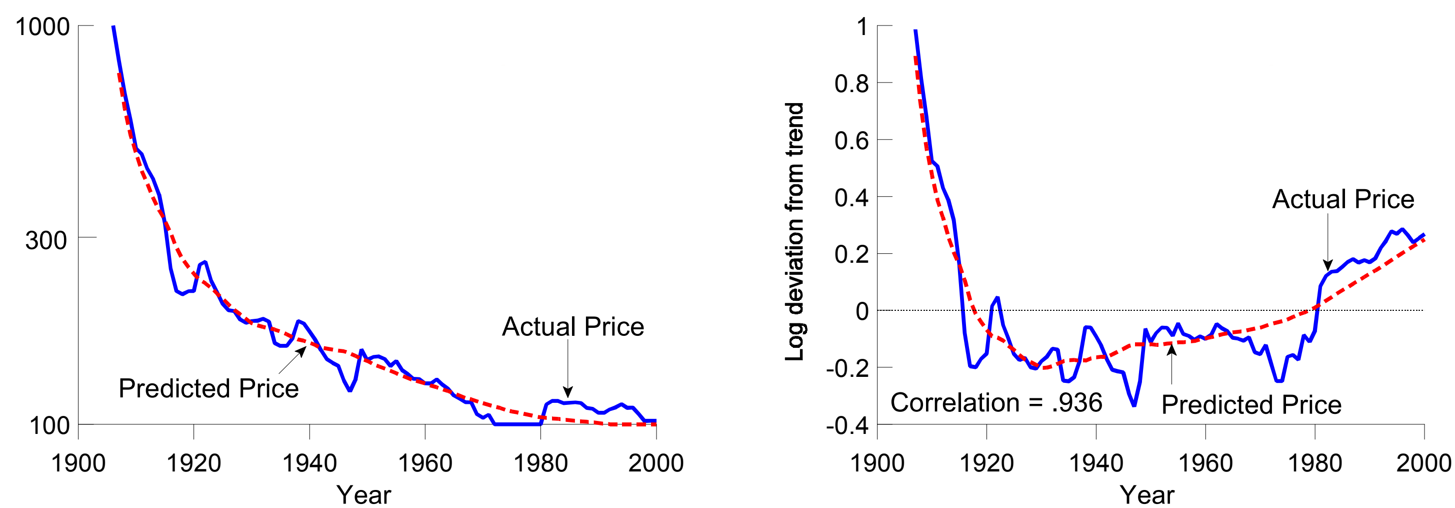
We construct the quantity measure as the total use of electric energy (kilowatt-hours) for 1902, 1907, 1912, 1917, and 1920-70 from *Historical Statistics* (series S120, p. 827), again interpolating between missing years assuming constant growth. For 1971-2000, we join the total electric energy consumed by the commercial, residential and industrial sectors (in BTU's) from the U.S. Federal Power Commission. We then set the index to 1000 in the final year of the series (i.e., 2000).



(a) computer systems



(b) electricity



(c) autos, trucks, and buses

Fig. 2. Actual and predicted prices of “New” Economy products.

the quality-adjusted value of cumulative sales.[5]

Is learning faster in booms?—The relation between K and p is negative, but does a rise in K cause p to fall as (1) would imply? Do investment booms lead to faster price declines? Apparently so. Let us take a look at low-frequency co-variation between K and p. In Figure 2, we use the three estimates of (1) reported in Figure 1 to compute a series of price predictions, $\hat{p} \equiv \hat{\beta}_0 - \hat{\beta} \ln K_t$, and plot them along with the data – not as a function of K (as we did in Figure 1) but as a function of t. In the left panels we plot the logs of $\hat{p}_t$ and p_t, and in the right panels we plot the deviations of their logs from linear time trends. The two series are in all three cases positively and significantly correlated. For example, both electricity and autos boomed in the late 1910's and 1920's, and their $\hat{p}_t$'s also decline sharply at these times. Then they both slumped during the Great Depression and showed very little price decline. Figure 2 also shows that the post-1990 acceleration in the price decline for computers is not due to a failure of (1) but, rather, mostly to a speed-up in the growth of K. For computers, however, price declines lead output growth.

Other evidence on the learning curve in (1).—Klenow (1998) notes that plant-level productivity-growth and labor input are positively correlated, which indirectly supports (1). Most micro evidence would reject the extreme form of (1) because a firm's own experience matters more to its efficiency than the experience of others. In quarterly data, for example, Irwin and Klenow (1994) find that semiconductor firms learn only about a third as much from the experience of others as they do from their own experience, and in monthly data on wartime shipbuilding, Thompson and Thornton (2001) find that the contribution of the experience of others is even smaller. The difference arises probably because the transfer of information from firm to firm is slow and incomplete. When information flows fully and instantly – as it did among subjects in some experiments run by Merlo and Schotter (2000) –

[5]Quality-adjusted (hedonic) prices for new motor vehicles for 1906-40 are from Raff and Trajtenberg (1997, table 5.4). We linearly interpolate between these estimates, which are available every two years, to construct an annual series. For 1947-83, we use hedonic prices from Gordon (1990, table 8.8, col. 6, p. 345) as joined by Raff and Trajtenberg to their series. We use fluctuations in the wholesale prices of motor vehicles and equipment from *Historical Statistics* (series E38, p. 199) to approximate the series between the endpoint of Raff and Trajtenberg (i.e., 1940) and the starting point of Gordon (i.e., 1947). For 1984-2000, we use producer prices of motor vehicles from the Bureau of Labor Statistics (*http://www.bls.gov*). This final segment is not adjusted for quality, yet quality improvements in the auto industry have been far less dramatic in recent years than in the earlier part of our sample. We join the various components to form an overall price index.

We build a quantity index using the value of factory sales of cars, trucks and buses for 1906-70 (*Historical Statistics*, series Q149 and Q151, p. 716), ratio-spliced to the industrial production index for automotive products (*Economic Report of the President, 2000*, table B-52) for 1970-2000. We then obtain a quality-adjusted measure of motor vehicle production by deflating with the price index described above, cumulating the result over time, and setting the index to 1000 in the final year of the series (i.e., 2000). We then divide our price index for motor vehicles by the GDP deflator and set the result to 1000 in the first year of the series (i.e., 1906) to obtain the normalized prices that appear on the vertical axis in Panel (c) of Figure 1.

watching someone else perform a task is as efficiency-enhancing as learning by doing. In reality, the distinction between own and outside experience probably fades only at low frequencies so that in annual data the distinction probably still matters. But the simplicity of (1) delivers the analytic results and is thus a good place to start.

3 Model

The model is a version of Arrow (1962) but with a production function for final goods the form of which is Cobb-Douglas and not Leontief.

Preferences.—Lifetime utility is

$$\int_0^\infty e^{-\rho t}\frac{c_t^{1-\sigma}}{1-\sigma}dt,$$

where c is per capita consumption, ρ is the discount factor and σ is the elasticity of substitution. From this we have the relation between $g_{c,t}$, the growth rate of per capita consumption at date t, and the rate of interest r_t:

$$g_{c,t} = \frac{r_t - \rho}{\sigma}. \tag{2}$$

Final good.—The constant-returns-to-scale production function for final goods is

$$Y = Nf(k),$$

where K is capital, N is labor in efficiency units, $k = K/N$, and $f(\cdot)$ is increasing and concave. Assume that N grows at the rate g_N.

Capital.—We set physical depreciation at zero. The resource constraint is

$$Nc + \frac{1}{q}\frac{dK}{dt} = Y, \tag{3}$$

where c is consumption per worker and q is the number of new computers per unit of output foregone. The number of new machines produced is $\frac{dK}{dt} = q(Y - Nc)$.

Learning by capital producers.—Since capital does not depreciate the current stock, K, is also the cumulative output of capital. We assume that the law in (1) holds. Competitive supply of capital then means that the price of K always equals the cost of production:

$$p = \frac{1}{q} = \left(\frac{K}{B}\right)^{-\beta}. \tag{4}$$

If $\beta = 0$, q is a constant and this is a one-sector Solow (1956) type model with no technological progress.

Investment.—A firm is too small to affect K and it perceives p_t as given. It will invest to the point where the cost of a machine equals the present value of its marginal products:

$$p_t = \int_t^{\infty} e^{-\int_t^s r_\tau d\tau} f'(k_s)\, ds, \tag{5}$$

and this implies that

$$\begin{aligned} \frac{dp}{dt} &= -f'(k_t) + r_t \int_t^{\infty} e^{-\int_t^s r_\tau d\tau} f'(k_s)\, ds \\ &= -f'(k_t) + r_t p_t. \end{aligned} \tag{6}$$

The implied rental price, $f'(k)$, equals the user cost of capital $rp - \frac{dp}{dt}$, so that the marginal product of a dollar of foregone consumption satisfies the equation

$$\frac{1}{p} f'(k) = r - g_p. \tag{7}$$

3.1 Long-run growth

Assume that

$$y = Ak^{\alpha}; \qquad \alpha + \beta < 1. \tag{8}$$

The model's long-run properties are as follows:

Proposition 1 *The long run growth-rates of c, p, k and K are*

$$g_c = \frac{\alpha\beta}{1-\alpha-\beta} g_N. \tag{9}$$

$$g_p = -\frac{\beta(1-\alpha)}{1-\alpha-\beta} g_N. \tag{10}$$

$$g_k = \frac{\beta}{1-\alpha-\beta} g_N. \tag{11}$$

and

$$g_K = g_k + g_N = \frac{1-\alpha}{1-\alpha-\beta} g_N. \tag{12}$$

Proof. With f as in (8), (6) reads

$$g_p = r - \frac{\alpha A k^{\alpha-1}}{p}. \tag{13}$$

Since $k = N^{-1}Bp^{-1/\beta}$, (13) reads

$$g_p = r - \alpha A \left(\frac{N}{B}\right)^{(1-\alpha)} p^{-1+(1-\alpha)/\beta}.$$

If r, g_N and g_k are constants, the second term on the right-hand side must also be constant, which means that

$$(1-\alpha)\,g_N + \left[\frac{(1-\alpha)}{\beta} - 1\right] g_p = 0.$$

This in turn implies (10). Since $g_k + g_N = -g_p/\beta$, we have (11), and since $g_y = \alpha g_k$, this implies that the per capita growth of output and consumption is (9). (12) follows at once. ∎

Properties.—Growth is proportional to the growth of labor, g_N, and increasing in α and β. It becomes infinite as $\alpha + \beta \to 1$. The parameters of the utility function affect only the level of output and the rate of interest.

3.2 The transition

We now solve for the evolution of K_t from some starting value K_0. We do it only for the special case of linear utility – i.e., $\sigma = 0$. This fixes the interest rate at $r = \rho$.

Free riding causes diffusion lags.—When $\sigma > 0$, we expect diffusion lags would arise because rapid accumulation of K would bid up r. But when $\sigma = 0$, r is constant at ρ, and any lags that may arise in the diffusion of K will occur for one reason alone: The desire to free ride by waiting for the price of K to decline further. This is clear from the user cost formula (7). A major difference between our model and Solow's, however, is that the explicit solution (15) is based on the assumption that $\sigma = 0$, and for this case convergence in Solow's model is instantaneous, or at least the Solow economy would invest its entire output until the steady state capital-labor ratio is reached. The same extreme outcome occurs here, but only when σ and β are both zero. This makes sense because when $\beta = 0$ our model collapses to Solow (1956).

The transition.—We shall solve for the time path of the variable

$$z \equiv \frac{K^{1-\alpha-\beta}}{N^{1-\alpha}}.$$

Let

$$a = (1-\alpha)\,g_N + (1-\alpha-\beta)\,\frac{\rho}{\beta}, \tag{14}$$

and $b = (1-\alpha-\beta)\,\frac{\alpha}{\beta} A B^{-\beta}$. Then

Proposition 2 *The solution for z_t is*

$$z_t = z_0 e^{-at} + \frac{b}{a}\left(1 - e^{-at}\right). \tag{15}$$

It starts at z_0, and converges to

$$\frac{b}{a} = \frac{(1-\alpha-\beta)\,\frac{\alpha}{\beta} A B^{-\beta}}{(1-\alpha)\,g_N + (1-\alpha-\beta)\,\frac{\rho}{\beta}}$$

at the exact rate a given in (14).

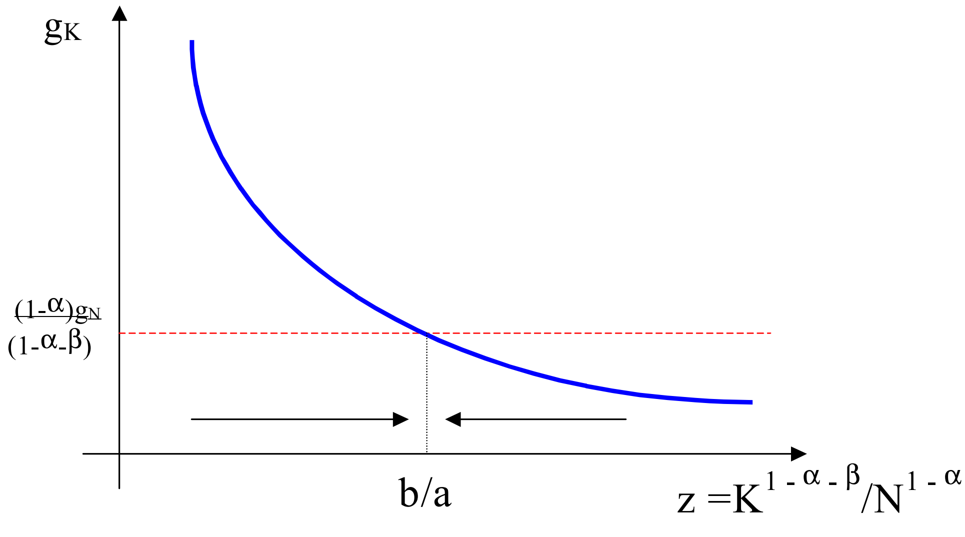


Figure 3: Growth of K as a function of z.

Proof. Since $\sigma = 0$, $r_t = \rho$ for all t. Using (13),

$$g_p = \rho - \alpha A \frac{k^{\alpha-1}}{p} = \rho - \alpha A \left(\frac{K}{B}\right)^{\beta} \left(\frac{K}{N}\right)^{\alpha-1}.$$

By (1), $g_p = -\beta g_K$, which allows us to eliminate g_p and get to

$$g_K = -\frac{\rho}{\beta} + \frac{\alpha}{\beta} A B^{-\beta} N^{1-\alpha} K^{-(1-\alpha-\beta)}. \tag{16}$$

From the definition of z, this equation reduces to

$$g_K = -\frac{\rho}{\beta} + \frac{\alpha}{\beta} A B^{-\beta} z^{-1}.$$

But, also from the definition of z,

$$\begin{aligned} g_z &= (1-\alpha-\beta)\, g_K - (1-\alpha)\, g_N \\ &= -a + \frac{b}{z}. \end{aligned} \tag{17}$$

Solving (17) leads to (15). ■

Having solved for z_t, we then can solve for K_t and all the other variables. Equation (17) allows us to also express how the growth of g_K converges to its steady state value as z reaches b/a. Figure 3 shows that relation.

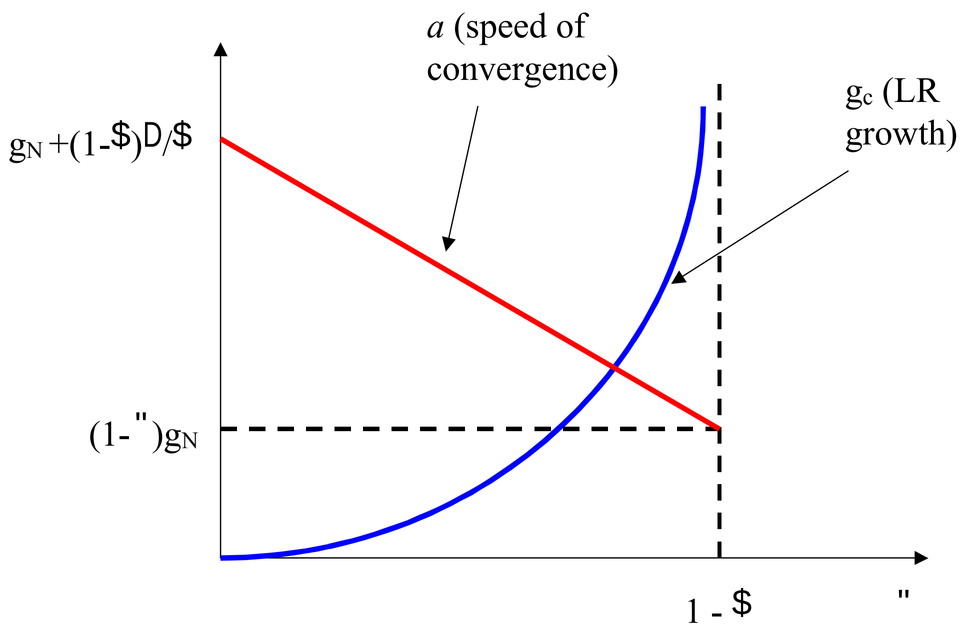


Figure 4: The effect of α on a and g_c.

The speed of convergence.—Eq. (14) shows that the speed with which z converges to its steady-state value is decreasing in α and β. A higher α means that the marginal product of capital diminishes more slowly. A higher β offsets the decline in the marginal product of capital by reducing the price of new capital. As $\beta \to 0$, $a \to \infty$ because the free-riding incentives disappear, and convergence is immediate.

The dual effect of α.—The Cobb-Douglas form of (8) implies that the share of new capital is constant. A higher α slows down the transition rate, a, but raises long-run consumption growth $g_c = \alpha\beta/(1-\alpha-\beta)$. Herein lies the tension we face in fitting the transition and in getting a realistic rate for long-run consumption growth. The tension is evident in Figure 4, which will be useful in explaining the results of the projections that we shall make. Note how sensitive long-run growth is to α as it approaches the value $1-\beta$ and as the rate of convergence approaches its lowest value of $(1-\beta)\, g_N$.

Incorporating a second capital.—Computers are not the only capital in the economy and, hence, some capital does not take part in the learning. The value of α is therefore smaller than capital's share in output. We now introduce a second capital, the price of which is fixed at unity. Only a few lines of algebra are needed. The resource constraint becomes $Y = Nc + (1/q)\, dK/dt + dX/dt$, and the intensive production function is

$$\tilde{f}(k,x) = A^* k^{\alpha^*} x^{\gamma}.$$

Assuming that x depreciates at the rate δ, its rental, $r+\delta$, would be equated to its marginal product, $\gamma A k^{\alpha^*} x^{\gamma-1}$, so that the optimal stock of x would be

$$x = \left(\frac{\gamma A k^{\alpha^*}}{r+\delta}\right)^{1/(1-\gamma)}.$$

Output per worker would then be

$$\begin{aligned} y &= \left[A^* \left(\frac{\gamma}{r+\delta}\right)\right]^{\gamma/(1-\gamma)} k^{\alpha^*/(1-\gamma)} \\ &= Ak^{\alpha}, \end{aligned}$$

where $A = \left[A^* \left(\frac{\gamma}{r+\delta}\right)\right]^{\gamma/(1-\gamma)}$, and where

$$\alpha = \frac{\alpha^*}{1-\gamma}. \tag{18}$$

The analysis goes through exactly as before, but with α given by (18).

4 Simulations

In this section we report the results of simulations that focus on the diffusion of information technology and on the diffusion of a composite technology that includes both electricity and internal combustion. We could find adequate data only for the United States and confine our parameter choices accordingly even though we think of the world economy as the right unit just as Kremer (1993) did in a similar context. In the solution for z_t in (15), the parameters α, β, and g_N are given to us from data other than k_t. Table 2 reports the values for these parameters that we will use in two sets of calibrated simulations, which we refer to as "baseline" and "adjusted".

TABLE II
Parameter Choices for Simulations

	Baseline			Adjusted		
Technology	$\hat{\alpha}$	$\hat{\beta}$	$\hat{g}_N$	$\hat{\alpha}$	$\hat{\beta}$	$\hat{g}_N$
Computers.	0.21	0.62	2.05	0.35	0.62	1.05
Electricity	0.27	0.35	2.27	0.44	0.42	1.27
Autos	0.04	0.20	2.26	0.08	0.28	1.26
Electricity+Autos	0.29	0.34	2.26	0.47	0.41	1.26

Baseline simulations.—For this set of simulations, we picked the parameters as follows:

1. For α, we use data on shares of the GPT-capital, α^*, and the remaining capital, γ, and apply (18). The share of computers in equipment investment over 1960-2000 is about 30 percent. But if we include software and other forms of IT-related investment, the share is now nearly 60 percent (Bureau of Economic Analysis, 2001, table 1). If capital's share in output, after allowing for structures, is about 30 percent, this implies an α^* of 0.18 for the share of computers in output and a γ of 0.12. Eq. (18) then gives an α of 0.21 for computers. Autos and electricity are concurrent and so we consider them both individually and together. For 1900-1940, Devine (1983, pp. 349, 351) reports that electric motors were the source of mechanical drive for about 87 percent of machinery by 1939, with internal combustion being the source of another 2 percent. Since the latter must have excluded cars and trucks, it is an underestimate, and we will assume a share of 10 percent. We choose shares from 1939 because they are the closest available observations to the mid-point of our sample. Assuming once again a 30 percent share of capital in output delivers an $\alpha^*$of 0.26 for electricity, 0.03 for autos, and 0.29 for the two combined. These imply γ values of 0.04, 0.27, and 0.01 respectively, from which we compute the estimates of α reported in the left panel of Table II.

2. For β we use the elasticities reported in Table I. When building the composite for electricity and motor vehicles, however, we weight the β's for the individual technologies by their share in the sum of the composite α^* (i.e., $\left(\frac{.26}{.29} \times .35\right) + \left(\frac{.03}{.29} \times .20\right) = 0.34$).[6]

3. For g_N we use the U.S. population growth plus one percent per year as an adjustment for the growth of labor quality – this adjustment is based on Denison (1962, Table 32, p. 266), who reports a contribution of 0.67 percent of education to the growth in national income over the 1920-57 period.[7] We round this number upward to 1 percent to account for changes in the quality of education.

Adjusted simulations.—For this set of simulations, we treat labor quality differently, and adjust β upwards. The details are as follows:

[6] We also weight the price and quantity indices for electricity and motor vehicles in this way when constructing the composites used in our simulations.

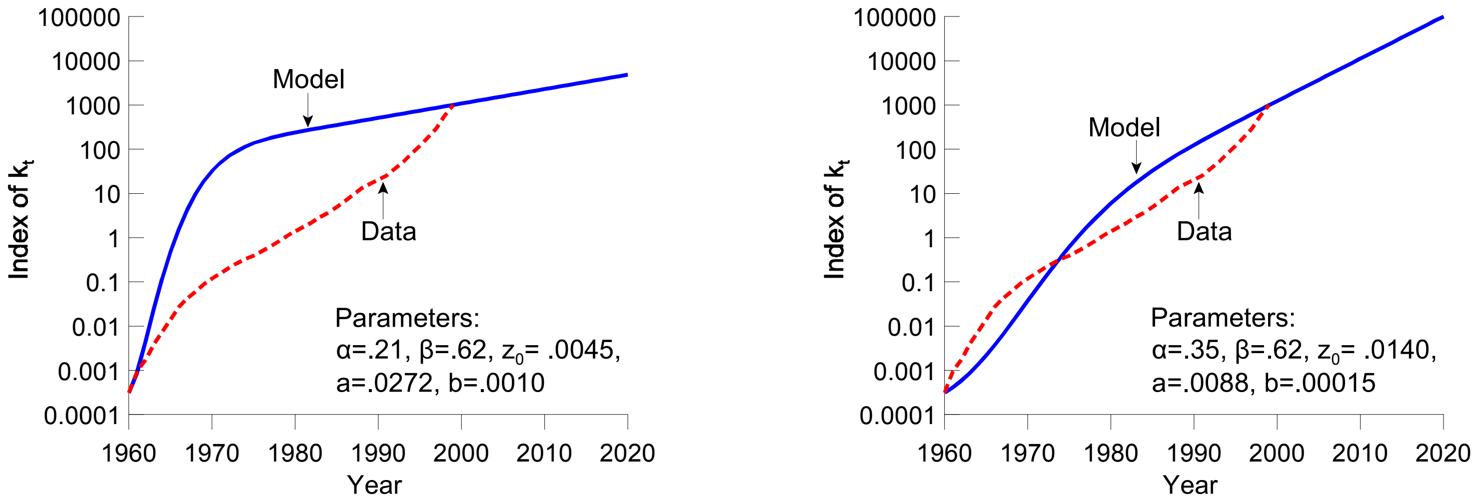
[7] We obtain population data from Bureau of the Census, "Historical National Population Estimates" (Census Bureau web page), which includes July 1 estimates of the resident population for 1900-99. Members of the Armed Forces overseas are included in the totals for 1940-79 only. Data for real personal consumption expenditures are from the *Survey of Current Business* (August 2000, table 2A) for 1929-2000, and from Balke and Gordon (1986, pp. 787-8) for 1900-28.

1. Instead of adjusting g_N for quality, we raise capital's share. In the context of Solow's model, to get realistic convergence speeds, Barro and Sala-i-Martin (1992, p. 227) use a "broad" capital share of 0.8. In that case $\alpha = \alpha^* / (1 - \gamma)$ is higher because γ includes human capital. Given the size of our β estimate for computers, however, using a capital share of 0.8 would violate the constraint that $\alpha + \beta < 1$. We therefore will use a more modest value for the "broad" capital share of $\alpha^* + \gamma = 0.67$ in the adjusted simulations.

2. Measurement error in K would cause our procedure to underestimate the absolute value of β. Also, the price-index for computers may inadequately recognize quality – the computer performs a lot of functions and it is unlikely that we could measure them all. The auto price series is quality-adjusted for the 1906-40 period and the 1947-83 periods, but the limited number of product characteristics that Raff and Trajtenberg (1997) could reliably use in constructing these hedonic prices, when coupled with rapid changes in the quality of the characteristics themselves, suggests that, per quality unit, auto prices fell faster than our Figure 1 reports. This means that the true beta for autos is larger than the one that we estimate, at least before the Second World War. To correct for measurement error and the possibility of inadequate adjustment for quality changes, we increase the β for motor vehicles by 40 percent. Finally, our use of electricity production as a stand-in means that we probably do not measure electricity-capital well. This is because one kilowatt produces more utils now than it did earlier in our sample period due to substantial improvements in the quality of equipment. We correct for this by raising the β for electricity capital by 20 percent.

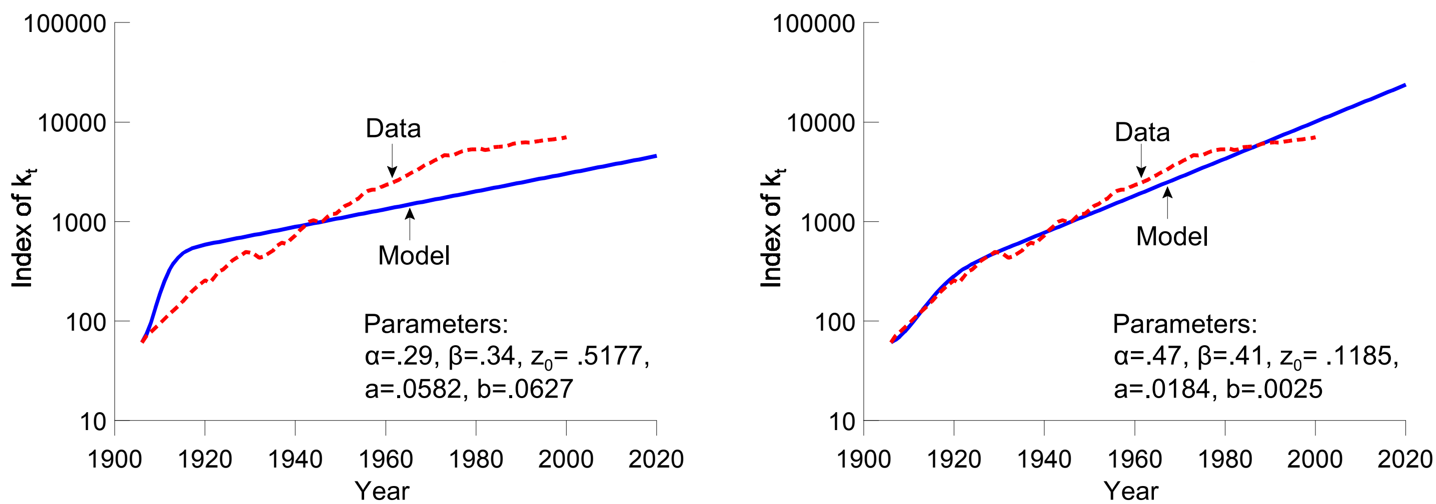
3. For g_N we use the U.S. population growth and do not adjust for quality, since it is now included in the broader capital share.

Figure 5 presents the transitional dynamics for computers, and Figure 6 shows them for the electricity-auto composite. With α and β pinned down by the data, we are left with two free parameters: z_0 and A/B^β (or, simply, b). To facilitate comparisons across the technologies, we choose values for these two parameters so that the predicted time-path of k_t passes through the first and fortieth year of the empirical time-path of k_t. Panel (a) in each figure uses the baseline values of α and β from the left panel of Table II, and reports the values of a, b, and z_0 implied by our fitting of the time paths. Panel (b) in each figure shows that a dramatic shift in the time path of k_t is possible when we simultaneously raise α, β, and the share of capital in output as indicated for the "adjusted" model. These adjustments generate diffusions with an S-shape. In other words, the transition path for z must always be concave, as (15) makes clear, but because k is a transform of z that essentially takes z to a power greater than unity, k can acquire a convex portion early on when β is large enough. Our "adjusted" parameter settings, when substituted into (9), imply



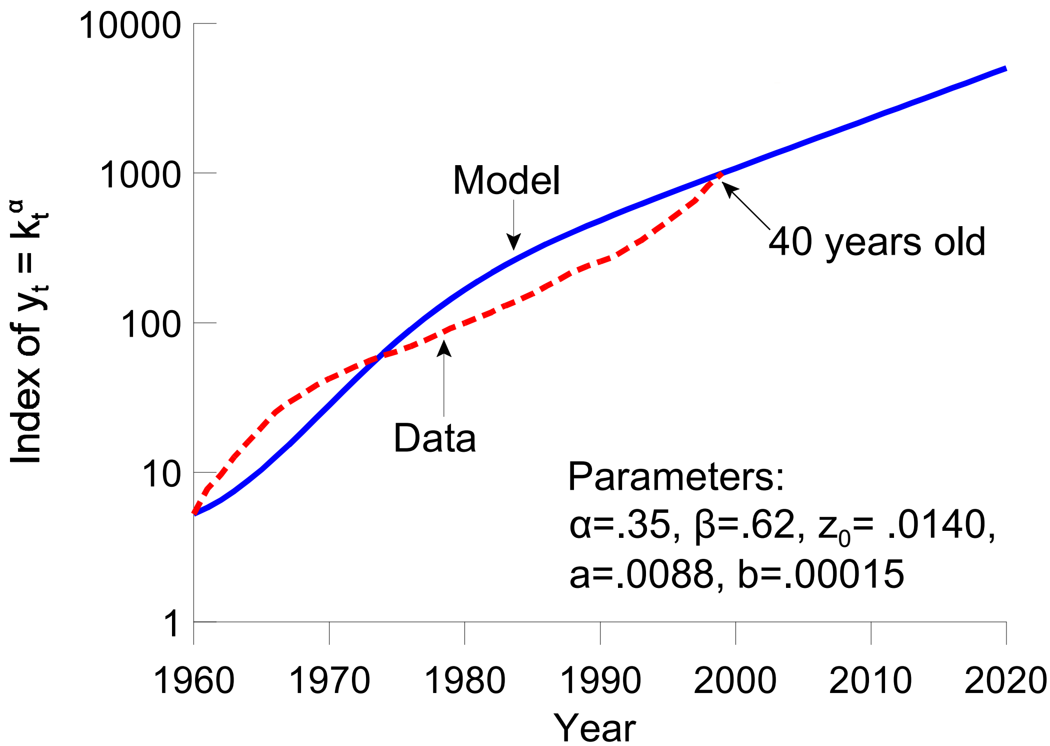
(a) baseline model (b) adjusted model

Fig 5. Computer systems: Actual and predicted diffusions.

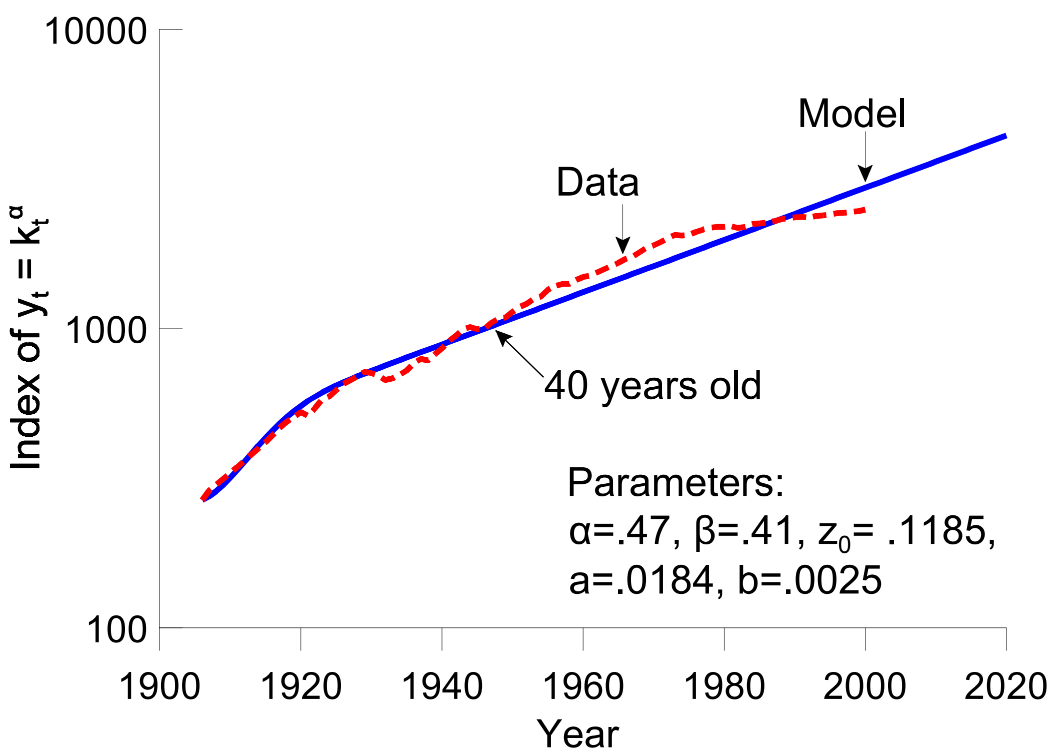


(a) baseline model (b) adjusted model

Fig. 6. Electricity and motor vehicles: Actual and predicted diffusions.



(a) Computer systems



(b) Electricity and motor vehicles

Fig. 7. Productivity growth: Actual and predicted.

a steady-state growth rate for consumption of 7.6 percent per year, and thus an optimistic outlook for consumption in the 21st century.

Fitting the model to productivity growth after 1960 and after 1900.—Figure 7 compares productivity growth for the two sets of technologies. We have forty years or so of coverage for the computer and about a hundred years for electricity and internal combustion. All three technologies were around for decades before they appear on our diagrams, but one can argue that when they come into our view, they are at a similar stage of development. In any event, this is what we shall assume, and therefore we can extrapolate the future of the computer from the experience of the other two technologies. The figure shows that the model overpredicts the productivity growth of the economy between 1975 and the end of the sample. This is the well known productivity slowdown paradox, and our model does nothing to resolve it. The model also overpredicts productivity between 1910 and 1924. Then, in both cases, there is a period of underprediction, followed in the end by a period of overprediction. We summarize all of this in Table III.

TABLE III
Implications of Model Extrapolations

	Electricity and Autos	Computers
underpredict	1903–1908 (5 years)	1960–1973 (13 years)
overpredict	1909–1940 (31 years)	1974–1999 (25 years)
underpredict	1941–1993 (52 years)	2000– ?

5 The firm's age and its market-to-book value

When there are no costs to adjusting capital, the value of capital inside a competitive firm must equal the value of capital outside of it. Our model predicts that a fall in the price of capital should manifest in the market values of those firms that use that type of capital – the GPT-using firms. To support this claim, we shall now establish the following facts: The faster is the decline in the price of new capital, the faster will the value of capital inside the firm decline, especially in the sectors that use the capital in question.

Market-to-Book ratios for firms.—As capital does not depreciate, the book value of a unit of capital purchased at date τ is always p_τ. At date $t > \tau$, the market-to-book ratio for that unit of capital is just

$$\frac{p_t}{p_\tau} = e^{g_p(t-\tau)}. \tag{19}$$

A firm owns capital of various ages. Let K_s be the amount of vintage-s capital that the firm owns, and let τ be the date that the firm started up. At date $t > \tau$, the market-to-book ratio for that firm is just

$$\frac{M}{B} = \frac{p_s \sum_{\tau=t}^{s} K_\tau}{\sum_{\tau=t}^{s} p_\tau K_\tau} = \frac{1}{\sum_{\tau=t}^{s} e^{-g_p(\tau-t)} \kappa_\tau}, \tag{20}$$

where $\kappa_\tau = K_\tau / \sum_{\tau=t}^{s} K_\tau$ is the fraction of the firm's capital that is of vintage τ. We shall ignore Jensen's inequality in (20) and use the approximation

$$\sum_{\tau=t}^{s} e^{-g_p(\tau-t)} \kappa_\tau \approx e^{-g_p T^K} = e^{\frac{\beta(1-\alpha)}{1-\alpha-\beta} g_N T^K},$$

where we used (10), and where

$$T^K = \text{The average age of the firm's capital stock.}$$

Substituting this approximation into (20) we have the baseline specification

$$\log\left(\frac{M}{B}\right)_j = -\frac{\beta(1-\alpha)}{1-\alpha-\beta} g_N T_j^K, \tag{21}$$

where "j" is a firm index. The equation (21) would arise in a steady state in which, for some reason, the age of capital differed over firms.

Market-to-book ratios vs. the age of the firm's capital.—We estimate (21). To compute a firm's $\hat{T}^K$, we take the opening book value of a firm's property, plant, and equipment (item 182) for the year that it enters Compustat and apportion it equally to each pre-Compustat year, using the year of incorporation as the start-up date and assuming a depreciation rate of 8.5 percent. Direct purchases of property, plant and equipment (item 128) and capital obtained through acquisitions of other firms (item 129) are available for later years. Using these annual investment figures, the depreciation rate, and the year of incorporation, we then compute the average age of the capital stock using the shares of each firm's 1998 capital attributable to past years as weights. Data on investment are available only for recent decades and so the 1998 cross-section is the only one that we analyze.[8] The results are in Table IV.

[8] We assume that a firm invests a constant amount I in each year from incorporation until appearance in the Compustat files. With this investment strategy, the average age of capital for a firm that appears on Compustat s years after incorporation is

$$age_{k,s} = \sum_{j=0}^{s-1} \left\{ \frac{(1-\delta)^j}{\sum_{j=0}^{s-1} (1-\delta)^j} \times j \right\},$$

where δ is the depreciation rate. Investments in later years are direct purchases of property, plant, and equipment (item 128). This item includes new and used equipment, but we treat them all as

TABLE IV
Regressions of Log Market-to-Book Ratios on the Age of Firm Capital, T^K, in 1998

	constant	T^K	R^2 (obs.)
IT firms	1.692	-0.082	.099
	(15.8)	(-4.17)	(155)
All firms	1.054	-0.035	.034
	(34.4)	(-8.74)	(2191)
All firms (with	1.337	-0.022	.161
sector effects)	(36.6)	(-5.32)	(2191)

Note: T-statistics appear in parentheses beneath the coefficient estimates.

In Table IV the coefficients on T^K are all negative and significant at the 5 percent level. The steeper slope for the IT firms continues to suggest a much higher rate of depreciation of firm-values for the IT firms than for firms in general. The coefficient-estimate of T^K is comparable to estimates that use plant-level data*:* Sakellaris and Wilson (2001) estimate that the quality of equipment in plants declines at 8-17 percent for each year of age, and Bahk and Gort (1993) estimate it at 13 percent. Others estimate much lower numbers. Our estimates are between 2.2 and 8.2 percent.

Market-to-book ratios vs. the age of the firm.—We have good measures of the age of the firm:

$$T_j^F = \text{ age of firm } j,$$

defined as the number of years since firm j incorporated or, alternatively, since it listed on a stock exchange.[9] Table V reports the regressions of M/B on T^F. It

new. The average age of the capital stock T years after appearance on Compustat is

$$age_{k,T} = \sum_{j=0}^{T} \left\{ \frac{(1-\delta)^j X_{T-j}}{K_0(1-\delta)^T + \sum_{j=0}^{T}(1-\delta)^j X_{T-j}} \times (T-j) \right\} + K_0(1-\delta)^T age_{k,s},$$

where K_0 is the capital stock at the time of Compustat listing, and X_i is direct investment in subsequent years. We also have the value of capital obtained through acquisition of other firms (item 129) and include it in updating the size of the total depreciated capital stock in each year. We assume, however, that this acquired capital enters at the average age of the firm's capital in the year of acquisition and then depreciates at the same rate as the rest.

The approximation ignores inflation. Correcting for inflation is not possible for the pre-listing period since the opening capital stock is a book value. Given that the vast majority of the firms in our 1998 sample entered Compustat after 1980, the lack of inflation adjustment for the subsequent annual invesment figures should have minimal effects. Overall, however, our computation will tend to understate the "true" age of a firm's capital.

[9]Listing years for 1925-98 are those in which firms enter the CRSP database. The CRSP files include all NYSE-listed firms from 1925, with AMEX firms added in 1962 and Nasdaq firms added in 1972. For 1885-1924, listing years are those in which prices first appear in the NYSE listings of *The Annalist, Bradstreet's*, *The Commercial and Financial Chronicle*, or *The New York Times.* We

TABLE V
Regressions of Log Market-to-Book Ratios on Firm Age (T^F)

	By incorporation date			By date of exchange listing		
	constant	T^F	R^2 (obs.)	constant	T^F	R^2 (obs.)
1998 Cross-section						
IT firms	1.561	-.0085	.035	1.384	-.0132	.018
	(20.3)	(-3.34)	(216)	(30.5)	(-3.47)	(637)
All firms	0.856	-.0007	.001	0.832	-.0017	.001
	(46.9)	(-2.00)	(3004)	(72.3)	(-3.27)	(6730)
All firms (with	1.137	-.0002	.175	1.077	-.0000	.136
sector effects)	(125.8)	(-0.64)	(3004)	(9.77)	(-0.04)	(6730)
1920 Cross-section						
Electricity-	-.0462	-.0039	.011	.0099	-.0106	.038
intensive firms	(-0.81)	(-0.40)	(36)	(0.09)	(-1.32)	(38)
Transportation	-.0285	-.0043	.011	.1405	-.0275	.115
firms	(-0.18)	(-0.65)	(18)	(0.87)	(-1.90)	(19)
Electricity excl.	-.0034	-.0060	.023	-.0855	-.0033	.006
transportation	(-0.02)	(-0.82)	(17)	(-0.65)	(-0.38)	(18)
All firms	-.3553	.0039	.018	-.2845	-.0024	.001
	(-6.59)	(2.85)	(239)	(-4.76)	(-0.53)	(233)
All firms (with	.0055	.0063	.151	.0186	0.029	.206
sector effects)	(1.07)	(3.64)	(239)	(2.24)	(0.69)	(233)

Note: T-statistics appear in parentheses beneath the coefficient estimates.

groups firms into GPTs and others. The upper panel of the table considers the 1998 cross section in which we take the IT firms to be GPT. The sample includes those firms in the Compustat database that were active in 1998, for which market and book values are available, and for which we could determine the year of exchange listing or incorporation.[10] We identify IT firms by their Standard Industry Classification (SIC) codes.[11] For "all firms," we estimate specifications of (10) with and without dummy variables for SIC two-digit sectors.

Using either measure of T^F, the coefficients on T^F are negative and significant at the 5 percent level for the IT firms in 1998. If we consider the mean age in the IT

obtain years of incorporation from *Moody's Industrial Manual* (1920, 1928, 1955, 1980), Standard and Poor's *Stock Market Encyclopedia* (1981, 1988, 2000), and various editions of Standard and Poor's *Stock Reports*. See Jovanovic and Rousseau (2001) for a detailed description of these data and sources.

[10]To compute market values, we take the value of common equity at current share prices, and add in the book value of preferred stock and short- and long-term debt. Book values are computed similarly, but use the book value of common shares rather than the market value. We omitted firms with negative values for net common equity from the plot since they imply negative market to book ratios.

[11]We identify "IT" firms as those with SIC codes for office equipment and computers (3570-79), and programming and data processing (7370-79).

sample of 13.7 years since incorporation, the coefficient on age (-.0085) in the upper left panel of Table V implies that an IT firm that is one year younger would have a market-to-book ratio that is 0.9 percent higher. The second line in Table V presents results for all firms in our sample, and the third line augments the specification with sectoral fixed effects. In both cases, the coefficients on T^F are much smaller in absolute value. For example, evaluated at the sample mean age of 20 years since incorporation, the coefficients in the regression without sectoral fixed effects relate one less year of life with a market-to-book ratio that is larger by less than 0.1 percent. The results with sectoral effects indicate an even smaller effect of age on market-to-book ratios. Note, too, that the inflation of the '70s and '80s eroded the book values of the older firms and acted to inflate their M/B ratios relative to those of the younger firms. This would bias the results *against* our hypothesis that the coefficient of T^F is higher today than it used to be.

The lower panel of Table V presents estimates of (21) for a sample of NYSE-listed firms in 1920. We compute market-to-book ratios using prices and the number of outstanding shares from our backward extension of the CRSP database, and using balance sheet items from the 1921 Moody's investor manuals.[12] We group the sample into firms that are "electricity-intensive," producers of transportation equipment, and all firms. The electricity-intensive firms are those identified by David (1991, Table 5, p. 329) as having more than 80 percent of their horsepower driven by electricity in 1919. These include tobacco products (SIC 2100), electrical machinery (SIC 3600), fabricated metals (SIC 3400), printing and publishing (SIC 2700), and transportation equipment (SIC 3700). Since transportation equipment firms, including those manufacturing autos, trucks, buses, motorcycles and railroad equipment, are a subset of the electricity-intensive group, we also examine the electricity firms with the transportation firms excluded.

The regression coefficients are negative for both measures of age for the electricity and transportation firms, though most of them are not statistically significant at the 5 percent level. The slopes are more steeply negative for the transport firms than for the electricity-intensive as well, suggesting that the internal combustion technology was evolving to render its immediate predecessors obsolete even more rapidly than in the case of electricity. This finding is consistent with the strikingly rapid declines in price and increases in quantities that characterize the auto industry in the 1910's

[12] To be precise, we draw balance sheet data from *Moody's Industrial Manual, Moody's Public Utilities Manual,* and *Moody's Transportation Manual.* Since balance sheet items are not as uniformly defined across firms in these early Moody's manuals as they are in today's Compustat, we must compute the market-to-book ratio for 1920 firms a bit differently. In this case, the numerator of the ratio is the book value of common equity (including surplus and retained earnings) less the book value of common shares, to which we add in the market value of common shares and the book value of long-term debt. The denominator is the sum of the book values of common equity and long-term debt. The difference between the measures for 1920 and 1998, then, is the inclusion of short-term debt in both numerator and denominator of the ratio in 1998. The omission of short-term debt in 1920 imparts an upward bias to the market-book ratios computed in that year.

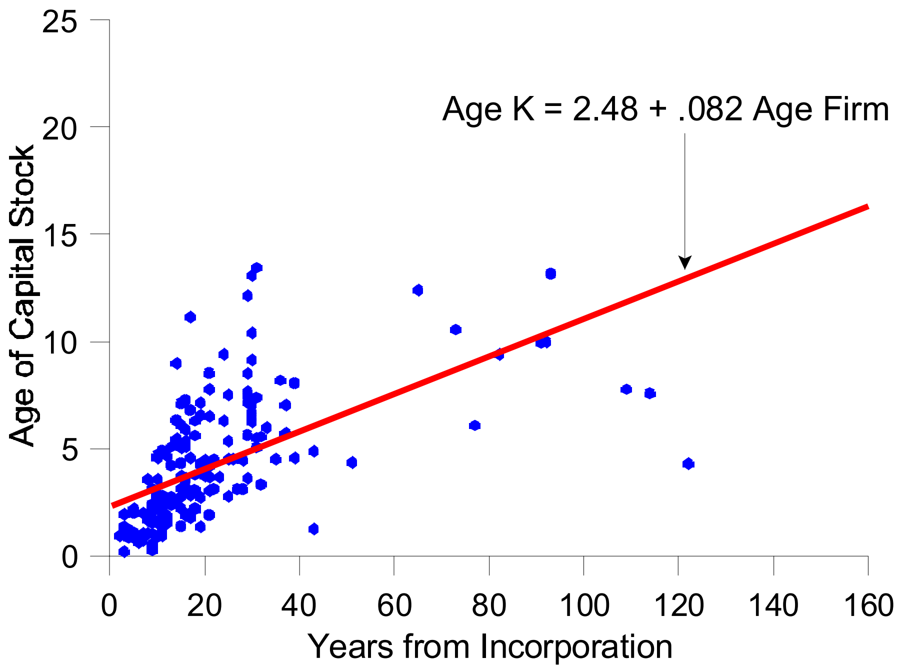


Figure 8: Capital age vs. firm age for IT firms in 1998

(see Figure 1). Interestingly, when we expand the sample to include all firms in 1920, we find positive coefficients on T^F in three of the four specifications, and a very small negative coefficient in the exception case.

Why do old firms have lower M/B values?—How much of the loss in market-to-book value is from the aging of the firm's capital stock? Is aging capital the only reason why older firms have lower M/B values? Table VI reports the regressions of

TABLE VI
Regressions of T^K on T^F in 1998

	constant	age (T^F)	R^2 (obs.)
IT firms	2.484	0.084	.333
	(9.23)	(9.16)	(155)
All firms	3.378	0.068	.389
	(38.8)	(38.1)	(2191)

Note: T-statistics appear in parentheses beneath the coefficient estimates.

T^K on T^F. They show that T^F raises T^K by 0.085 in the IT sector and only by 0.068 in other sectors. Figures 8 and 9 are scatterplots of these relations.

If the negative coefficient of T^F were entirely due to the aging of physical capital,

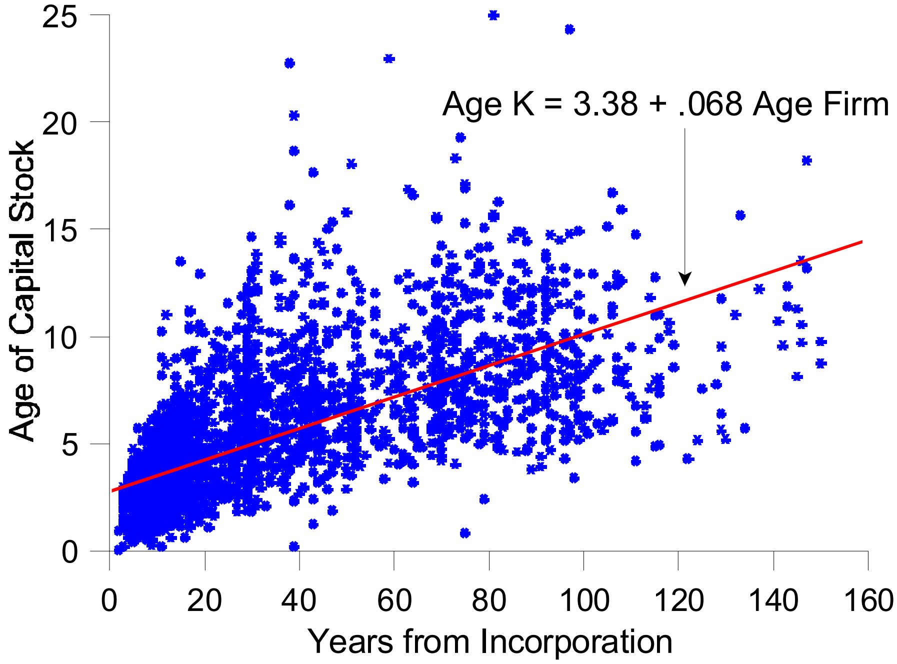


Figure 9: Capital age vs. firm age for all firms in 1998

the following equality would hold:

$$\frac{d}{dT^F}\log\left(\frac{M}{B}\right)=[\frac{d}{dT^K}\log\left(\frac{M}{B}\right)]\frac{dT^K}{dT^F}. \tag{22}$$

The coefficients of T^F in the top panel of Table V and the coefficients of T^K in Table IV can then be used with the estimate of dT^K/dT^F from Table VI to compute both sides of (22). The comparison is feasible only for 1998. The results are in Table VII.

TABLE VII
Estimates of (22) in 1998

	Actual decline −[LHS of (22)]	Explained via T^K −[RHS of (22)]	Unexplained decline [LHS−RHS]
IT firms	0.0132	$0.082(.084) = 0.0069$	0.0063
All firms	0.0017	$0.035(.068) = 0.0024$	-0.0007

Table VII shows that the obsolescence of physical capital plays a more important role in the obsolescence of IT firms than it does in the obsolescence of non-IT firms. On the other hand, other, unexplained factors are also more important for IT firms, whereas all of the obsolescence of the non-IT firms seems to be explained by the obsolescence of their capital stocks.

The effect of underreported book values.—For tax reasons, firms tend to depreciate their capital faster than it wears out physically. Thus the book value of capital understates the historical cost of the *surviving* capital, and this bias is strongest for old capital. If p_K were constant, this bias would lead to the finding that older firms have higher M/B ratios than young firms, and that older capital fetches a higher market value per unit of book. This all means that our estimates of the effects of T^K and T^F on M/B are both biased towards zero. In spite of that, our estimates show them both to be significantly negative.

6 Relation to other growth models

Several growth models are related to ours.

Arrow (1962):—Learning by Arrow's capital-goods producers is the same as in our model, i.e., (1). But he assumes that in the final-goods sector there are fixed proportions between capital and labor, and this complicates the analysis so that he can calculate only the steady state growth path. Our limiting growth rate is proportional to the rate of labor growth, as in Arrow (1962) and also in Jones (1995) where the scale effect works not through the accumulation of experience but through research. Another interpretation of (1) is implicit in Aghion and Howitt (1998) who explain how, by raising income, a larger capital stock raises the demand for new research and thus raises the efficiency of future capital. One can view (1) as a summary of such a process.

Frankel (1960) *and Romer* (1986):—In these models aggregate capital affects the production of final goods directly. The effect appears similar to ours if we write

$$y = qf(k), \quad \text{where, again,} \quad \frac{1}{q} = \left(\frac{K}{B}\right)^{-\beta}.$$

The price of capital is unity. The investment condition is

$$\left(\frac{K}{B}\right)^{\beta} f'(k) = r. \tag{23}$$

The incentives to invest in the Frankel-Romer model, as summarized by (23), are therefore quite different from the incentives in our model. When our marginal condition (7) is combined with (4), it reads

$$\left(\frac{K}{B}\right)^{\beta} f'(k) = r - g_p. \tag{24}$$

Since $g_p < 0$, our firms will invest less, and our transition will be slower than in the Frankel-Romer model, in which the final goods producer benefits from spillovers on all the units of his capital, k, regardless of when they are installed. Our model, on the other hand, is a vintage-capital model in which the owner of a machine does not benefit from future technological improvements, and that is why $-g_p$ deters investment.

Barro and Sala-i-Martin (1995).—The rate in (14) is exact, but that comes at the expense of assuming $\sigma = 0$. Barro and Sala-i-Martin (1995, ch. 2) work with a positive σ, and so their results are not a special case of ours, but their rates are only approximations around the steady state. When $\sigma = 0$, their result is the same as ours when $\beta = 0$. In this case convergence is instantaneous.

7 Conclusion

We modelled Moore's law as arising from learning by doing in the sector that makes computers. We assumed that the law would continue to operate for ever, and derived long-run implications and worked out the transitional dynamics. We found that combining this model with Arrow-style learning can slow down the speed of convergence, perhaps even to realistic levels. We also found that incumbent firms are losing ground faster today than they did eighty years ago, and we argued that this is so largely because old firms use older capital.

Nothing like Moore's Law has ever operated for as sustained a period of time and for as large an investment item. Never before, in other words, have capital goods declined in price as fast as they are doing at present. If population or the quality of labor continue to grow at historical levels, in the coming decades consumption growth will probably rise well above its twentieth-century average.

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