Moore's Law and Learning-By-Doing

Boyan Jovanovic and Peter L. Rousseau*

October 21, 2001

Abstract

We model Moore's law as the outcome of learning by doing in the sector that makes computers. That is, the more computers we make, the better and cheaper they get.

We fit the model to data on three technologies: Electricity, internal combustion, and computers. We project the future of the computer based on how the other two technologies developed as they got older than the computer is today. Because computers are enjoying much faster technological progress than the other two technologies did, this exercise yields a rosy forecast for future productivity growth, perhaps double that of the twentieth century.

What else is new in the new economy? It seems that organization capital is becoming obsolete much faster today than it did eighty years ago, perhaps because current pace of change imposes a higher tax on management and team-specific skills.

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 was introduced in 2000 with 42 million transistors. The 2001 introduction of the Itanium processor, with 320 million transistors, is ahead of Moore's schedule. Recently, even Moore has wondered how much longer 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.

The model we construct and calibrate predicts that in the long run the computer and all that goes with it will raise consumption growth by more than two earlier great technologies did – electricity and the internal combustion engine. We then check the

*The University of Chicago and NYU, and Vanderbilt University. We thank the National Science Foundation for support, and Peter Thompson for comments.

reliability of the model by fitting it to the U.S. experience for all three technologies. To do this, we first assume that productivity is related to cumulative output and estimate the learning speed for each technology. Together with the observed income-shares of these technologies, the learning speeds then tell us how the capital-labor ratio should evolve. The transition to the steady-state capital-labor ratio turns out to be slower than it would be in Solow (1956), but still not quite slow enough. The greater are the learning prospects that a technology offers, the longer the economy takes to respond fully to the arrival of the technology. Our long run forecasts for consumption growth are not too accurate, but the version of the model that fits the aggregate data best – though somewhat loosely pinned down on the micro side – forecasts growth of 7.6 percent per year.

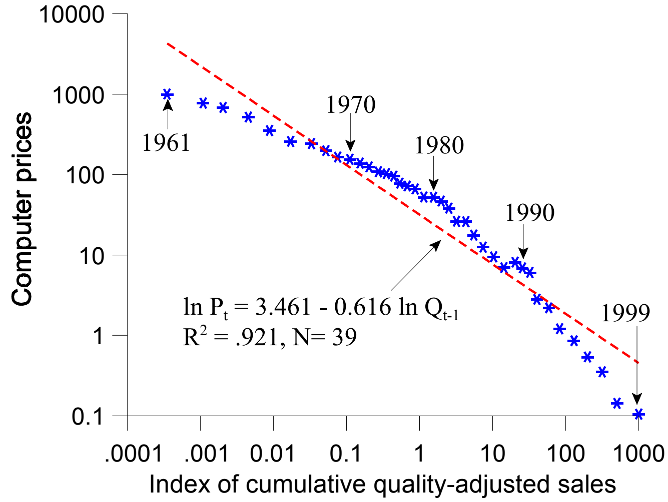
2 Cumulative output and prices for three technologies

Why is the United States the world's technological leader? Is it because American firms do a lot of R&D? Vernon (1966) argues that the United States leads the world because its firms sell to – and learn from and adapt to the wants of – the world's richest and most sophisticated customer. This customer's wants and the high cost of his labor dictate the kind of product that he will buy and the technology that his employer will use. Research done by firms elsewhere produces few inventions that the consumer wants, and so American firms remain at the top. Before computers, the United States had also led the way with the development of electricity-related capital and, after a certain point, the internal combustion engine. We shall follow Arrow (1962) and Frankel (1962), and emphasize the role of experience in growth.

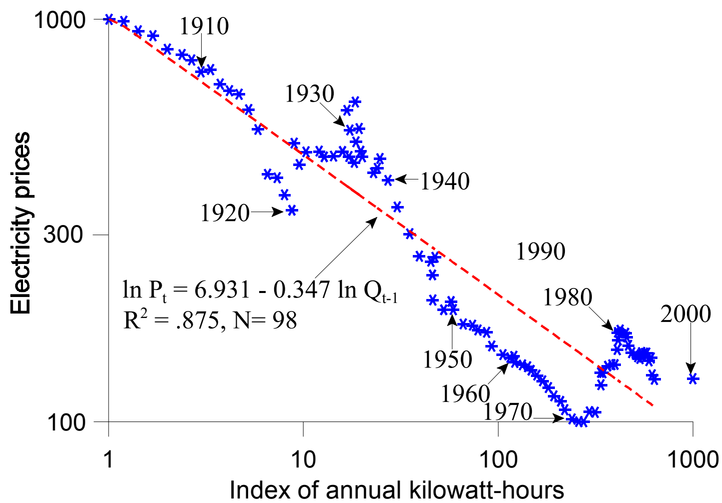
We still are not quite sure how much computers raise productivity, but we have never before seen a productive input that has declined so much in price over such a short time. The same thing happened 70-100 years ago, but not as dramatically, to producer durables based upon the internal combustion engine and to electricity-related capital.

Research and engineering led to major breakthroughs in all three technologies, but the direction of the research effort may have been dictated by the market, and we will see some feedback from market output to lower prices. Of the three technologies, computers have enjoyed by far the largest price decline, and also by far the largest growth in output. Moreover, booms in output growth seem to have brought on declines in the prices of electricity and automobiles, while with computers the relationship is more simultaneous. The relation between the price of a good, p, and the cumulative output of that good, Q, is usually taken to be

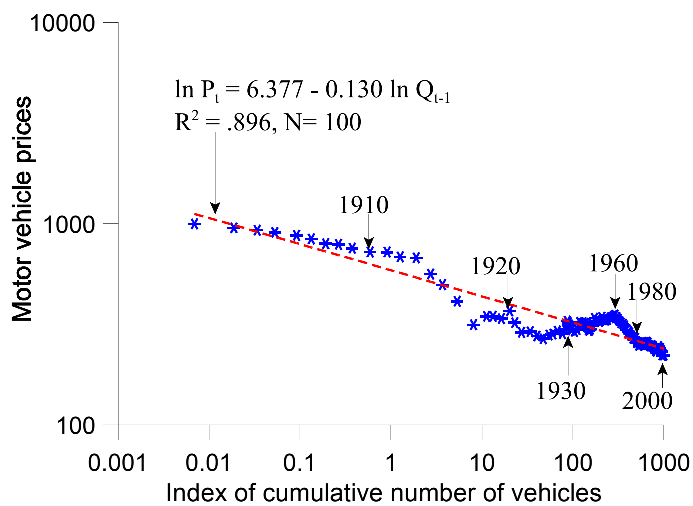
$$p = p_0 Q^{-\beta}. \tag{1}$$



(a) computer systems



(b) electricity



(c) autos, trucks, and buses

Fig. 1. Prices and Cumulative Quantities of "New" Economy Products

or in growth-rates, $g_p = -\beta g_Q$. In this specification, only aggregate cumulative output matters to every seller's productivity and, hence, to price. In fact, a firm's own contribution to Q seems to matter more than that of other firms, especially at high frequencies. Using quarterly data, 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 using monthly data on wartime shipbuilding, Thompson and Thornton (2001) find that the contribution of the experience of others is even smaller. At lower frequencies, however, the distinction between own and outside experience should fade. We adopt (1) to keep things simple.

Since cumulative output Q refers to collective experience and not experience per producer, the learning mechanism in (1) has a scale effect. The efficiency of the capital sector and the productivity of the sectors that it supplies are increasing in the size of the "economy," i.e., the market within which the learning effect is confined. Kremer (1993) argues persuasively that we should think of learning as proceeding at the world level but we do not have the world data to which we our model applies and, out of necessity, use only U.S. data.

For the three "general purpose technologies" (GPTs), the computer, electricity, and the internal combustion engine, we shall estimate the parameters p_0 and β from the equation

$$\ln p_t = a - \beta \ln Q_{t-1}.$$

Given the social role that experience probably plays in enhancing the quality of peripherals, we expect a departure from this law in the beginning. This is because when there are no peripherals, the basic technology is developed more through research and engineering. But after a while the peripherals start to arrive, and the more experience we have, the better the peripherals get. Therefore we should perhaps see faster productivity growth once things are "in full swing."

Figure 1 presents pairwise combinations of $\log(p)$ and $\log(Q)$ on an annual basis for each technology and plots a regression line through the points. Table 1 shows our estimates of the learning parameter β and the average growth rates of price and cumulative quantities. The computer, displayed in panel (a), shows by far the most

Table 1: Estimates of β

Technology	$\hat{\beta}$	g_p	g_Q
Computer	0.62	-24.12	39.11
Electricity	0.35	-2.12	7.11
Automobile	0.13	-1.52	12.00

dramatic technological change as measured by the fall in p.[1] The 1960's were the age of the mainframe and minicomputer, and in spite of a fast-growing Q as indicated by the horizontal spacing between the points, the decline in p was relatively slow. The wider vertical spacing after 1990 suggests that the effects of learning by doing have now become even stronger. Our estimate of β exceeds that which Gordon reports partly because his data miss some of the late acceleration in price declines, and partly because we use slightly different sources.[2]

The downside of (1) is that if the law applies to a narrowly defined product like the automobile or the computer, once the market is saturated with the good, its productivity growth stops. More generally, (1) says that p should decline faster in booms when Q grows faster. Panels (b) and (c) of Figure 1 show this to be the case for electricity usage and automobile sales, as both boomed in the late 1910's and 1920's, slumped in the Great Depression, and showed very little subsequent price decline in the early 1930's.[3] Both technologies also saw sharp price declines during the vigorous output expansions of the 1910's and 1920's. We choose annual electricity output rather than a cumulative measure here because the accumulation of electrically-

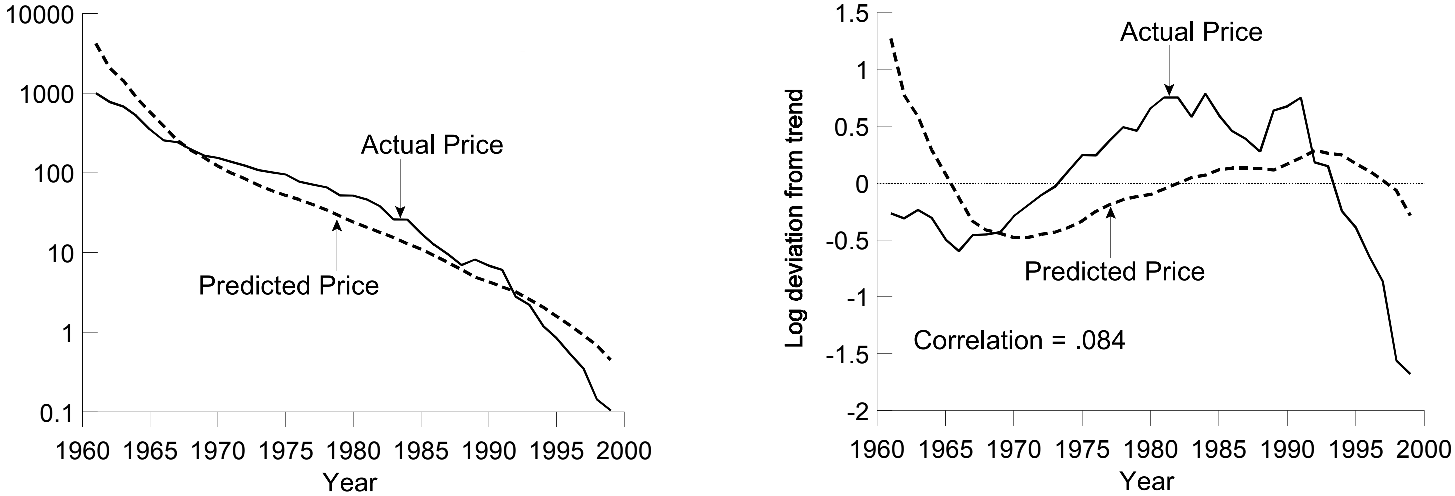
[1] To construct a quality-adjusted price index, we join the "final" price index for computer systems from Gordon (1990, table 6.10, col. 5, p. 226) for 1960-78 with the pooled index developed for desktop and mobile personal computers by Berndt, Dulberger, and Rappaport (2000, table 2, col. 1, p. 22) 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 prices trends in the computer industry reasonably well. We set the index to 1000 in the first year of the sample (i.e., 1960).

We 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, table 7.2, line 17) with our price measure, and then cumulating the result over time. We then set the index to 1000 in the final year of the sample (i.e., 1999).

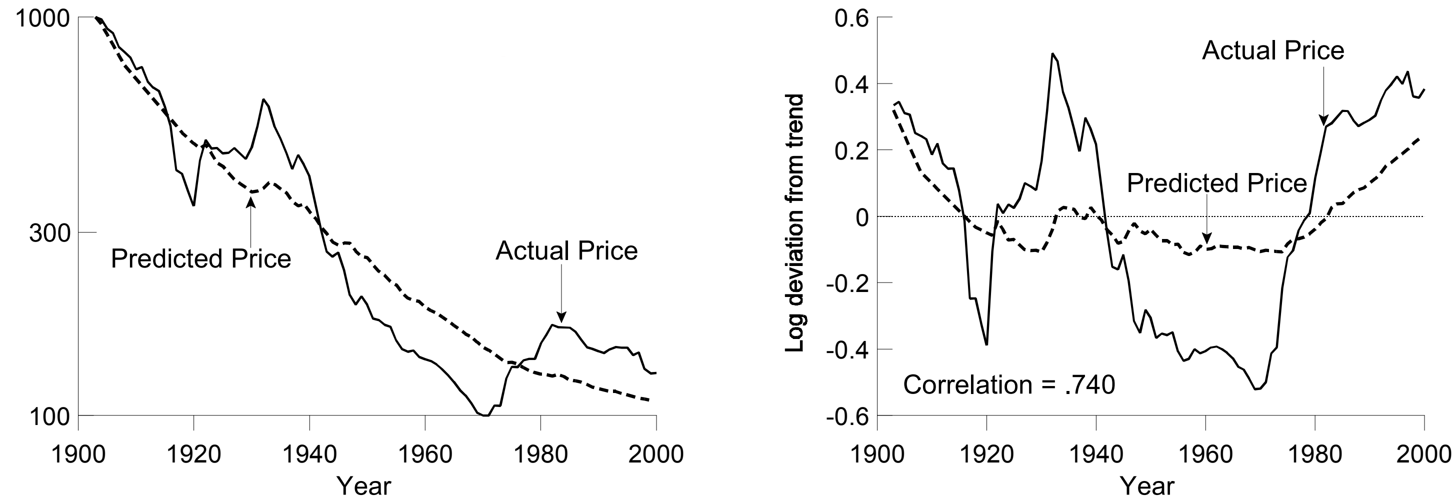
[2] We also estimate the learning parameter with a time trend in the specification. The trend term is negative and statistically significant for computers and positive and significant for electricity and automobiles. The β coefficient for computers falls to -0.87 and is no longer statistically significant, while the β's for electricity and autos become -0.745 and -0.147 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.

[3] 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 set the index to equal 1000 in the first year of the sample (i.e., 1903).

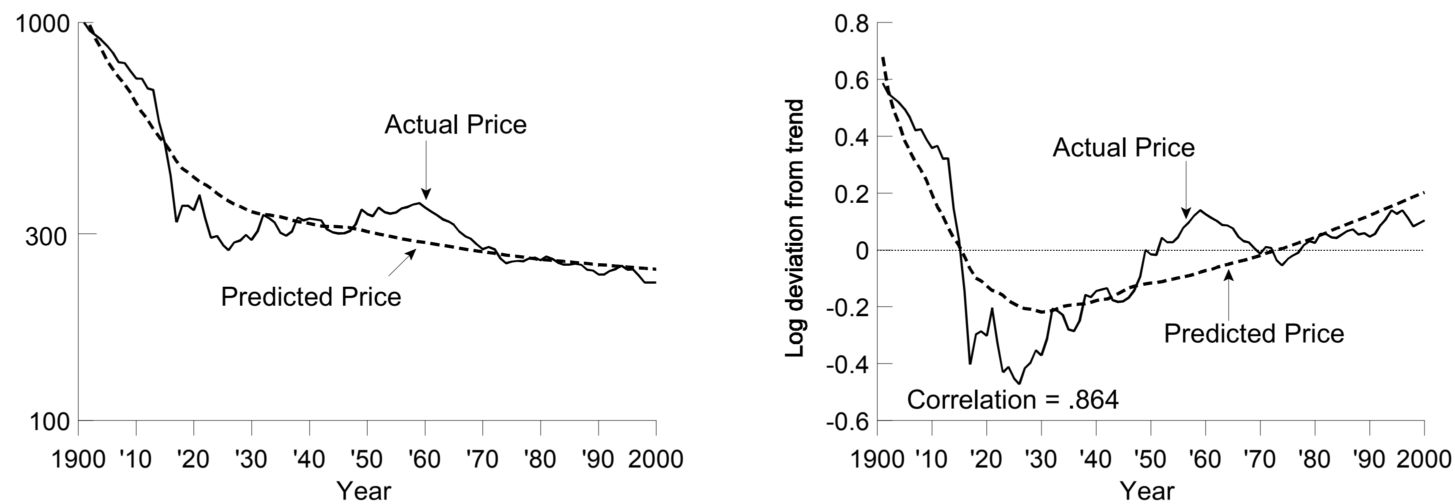
We construct the quantity measure as the total use of electric energy (kilowatt-hours) for 1902, 1907, 1912, 1917, and 1920-70 from *Historical Statistics* (series S120, p. 827), again interpolating between missing years assuming constant growth. For 1971-2000, we join the total electric energy consumed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



(a) computer systems



(b) electricity usage



(c) car, truck, and bus sales

Fig. 2. Actual and Predicted Prices of "New" Economy Products

powered equipment is probably not proportional to cumulative electricity use. Rather, current usage, assuming zero depreciation as our model will, reflects the power required to operate the stock of electrically-powered equipment. As such, it should reflect the cumulative stock of this equipment more closely than cumulative kilowatt hours. For motor vehicles, of course, we continue to use cumulative unit sales.[4]

In Figure 2, we use the three estimates of (1) reported in Figure 1 (i.e., $\ln \hat{p}_0 - \hat{\beta} \ln Q_t$) to generate a series of price predictions. In the left panels, we plot the predictions against the actual prices, and in the right panels we plot these series as deviations from their time trends. The actual prices are always positively and significantly correlated with the predictions, which is consistent with the view that learning by doing, as measured by cumulative production, is the driving force behind price reductions in the goods that embody the three GPTs.

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 Q. If learning by doing does raise the efficiency of a GPT, its biggest impact is 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 the capital goods used in production. Many of these applications connect the technology to the ultimate wants of the consumer, and this is where experience really matters. Since many applications become apparent only after the GPT has been around for a while, we may therefore expect that the benefits of experience really kick in once the GPT begins to see widespread adoption.

If a constant fraction of K is not measured, $\hat{\beta}$ should be unaffected. On the other hand, if our data on K include things that do not belong in K, then a standard errors-in-variables argument would cause our $\hat{\beta}$'s to understate the true β's in absolute value. The initial flatness in the top and bottom panels of Figure 1 may partly be caused by poor measurement initially rather than a failure of the law in (1).

[4] Motor vehicle prices for 1913-40 are annual averages of monthly wholesale prices of passenger vehicles from the National Bureau of Economic Research (Macrohistory Database, series m04180a for 1913-27, series m04180b for 1928-40, *http://www.nber.org*). From 1941-47, they are wholesale prices of motor vehicles and equipment from *Historical Statistics* (series E38, p. 199), and from 1948-2000 they are producer prices of motor vehicles from the Bureau of Labor Statistics (*http://www.bls.gov*). To approximate prices from 1901-1913, we extrapolate assuming constant growth and the average annual growth rate observed from 1913-24. We then join the various components to form an overall price index, and set it to equal 1000 in the first year of the sample (i.e., 1901).

Quantities are the numbers of cars, trucks and buses sold for 1900-65 from *Historical Statistics* (series Q148 and Q150, p. 716), ratio-spliced to the series assembled for 1966-2000 by the Board of Governor's of the Federal Reserve System (Historical Statistical Release G-17, table 3), and cumulated over the sample period. We then set the index to equal 1000 in the final year of the sample (i.e., 2000).

3 Model

Our model is much like that of Frankel (1962) and Romer (1986), but with elements of Arrow (1962) thrown in that make a big difference in the patern of accumulation, as we shall point out in note 6. To these models we have added the transitional dynamics. A related partial equilibrium analysis is in Jovanovic and Lach (1989).

Preferences: The lifetime utility function 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 rate of growth 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

$$Y = F(K, N) = N f(k)$$

where K is capital, N is labor, $k = k/N$, and $f(k) = F(k, 1)$. Assume that N grows at the rate g_N. Later, we shall add a second type of capital in which there is no learning. This will be straightforward.

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 forgone.[5]

If we were to set $q = 1$, we would have a one-sector Solow (1956) type of model in which there is, perhaps, growth in the labor force, but no technological progress and hence a steady state level of capital per worker and income per head. We set $\delta = 0$ because it implies that the current stock of capital is the same as the cumulative output of that capital, and this simplifies matters a lot, especially the analysis of the transition to the steady state.

[5] That is, the number of new machines is

$$\frac{dK}{dt} = q(Y - Nc).$$

Learning by capital producers Assume that each producer learns as much from the experience of other producers as he does from his own experience. That is, the technology for making K improves as a function of aggregate investment in K. Each new machine is a little better than its predecessor. We also assume that q is an increasing function of K. Competitive supply of capital means that the price of K always equals the cost of production: So, the cumulative output of machines, that is, the machine's serial number K, is a decreasing function of its price

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

where B is a constant.

Investment in machines and in computers Firms own their capital. The cost of buying a machine equals the discounted sum 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[6]

$$\frac{1}{p} f'(k) = r - g_p. \tag{9}$$

[6] Investment differs from that in the following version of Frankel-Romer (FR) model where the external effect appears directly in production so that

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

We do not scale the external effect q by labor as FR do, in order to maximize the superficial simnilarity between our setup and theirs. The FR price of capital is a constant and equals unity. FR's investment condition is not (9) but

$$\left(\frac{K}{B}\right)^{\beta} f'(k) = r. \tag{7}$$

Contrast Eq. (7) to (9) which, when combined with (4), reads

$$\left(\frac{K}{B}\right)^{\beta} f'(k) = r - g_p. \tag{8}$$

Thus the FR firms will invest more, and the transitional dynamics in the FR model will be faster.

3.1 Long-run growth

First we solve for the long run growth and then we do the transitional dynamics. Assume that production is Cobb-Douglas:

$$y = Ak^{\alpha}. \tag{10}$$

We maintain (4) and assume that $\alpha + \beta < 1$.[7] Now (6) reads

$$g_p = r - \frac{\alpha A k^{\alpha-1}}{p}. \tag{11}$$

Since $k = N^{-1} B p^{-1/\beta}$, (11) 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 RHS of the above equation 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 that

$$g_p = -\frac{\beta\,(1-\alpha)}{1-\alpha-\beta} g_N, \tag{12}$$

which, in absolute value, is increasing in α and β, and goes to infinity as $\alpha + \beta \to 1$.

Since $g_k + g_N = -g_p/\beta$, we have

$$g_k = \frac{\beta}{1-\alpha-\beta} g_N. \tag{13}$$

Since $g_y = \alpha g_k$, this implies that the growth of output and consumption per head is

$$g_c = \frac{\alpha\beta}{1-\alpha-\beta} g_N. \tag{14}$$

Finally,

$$g_K = g_k + g_N = \frac{1-\alpha}{1-\alpha-\beta} g_N. \tag{15}$$

Growth is proportional to the rate of population growth, g_N, as in Arrow (1962) and Jones (1995). The parameters of the utility function affect only the level of output and the rate of interest.

When $\beta = 0$, per capita income is constant in the long run; $g_p = g_k = g_c = 0$, and $g_K = g_N$.

[7] If $\alpha + \beta$ were to exceed unity, the economy could attain infinite output in finite time and, as Frankel (1962, p. 999) observed, if $\alpha + \beta = 1$ and labor is fixed, we get an "Ak" model and do not need population growth to have endogenous growth.

3.2 The growth of K in the transition phase

How does K behave when the technology is new? We can expect to see some discrepancy between fact and our theory simply because the Cobb-Douglas production function implies that the share of each type of capital is constant whereas, in fact, the share grows as the technology matures. Therefore, if we assume that all the investment in K is measured in our data, we can expect to overpredict this accumulation in the early years of a technology when its share in output is small. To make sense of the early years in a technology's life, our model forces us to assume that a part of the accumulation of K is not measured. As we noted in section 2, if what we measure does not exactly correspond to what enters (1) or, rather, (4), the true β's are larger than what we estimate them to be.

We now solve for K, the cumulative output of computers, from any initial conditions. We suppose that initially $K = K_0$ and that $N_t = N_0 e^{g_N t}$. Thereafter, we have the production function for K implied by (3) and (10)

$$\frac{dK}{dt} = q\,(Y - Nc) \qquad \text{and} \qquad q = \left(\frac{K}{B}\right)^{\beta},$$

where $Y = AK^{\alpha}N^{1-\alpha}$. Competition in the supply of K implies that

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

and, as before

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

Assume that $\sigma = 0$, as Arrow did, or else assume that the economy is small and open to capital inflows but closed to the inflow of technological information. Then $r = \rho$ for all t – a reasonable condition since real rates haven't changed much over the century. Then, since $g_p = -\beta g_K$, (6) implies the differential equation for K :

$$g_K = -\frac{\rho}{\beta} + \frac{\alpha}{\beta} AB^{-\beta} N^{1-\alpha} K^{-(1-\alpha-\beta)} \to \frac{1-\alpha}{1-\alpha-\beta} g_N, \tag{16}$$

using (15).

Now, (16) can be made simpler by a change of variables. Let

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

Then $g_K = -\frac{\rho}{\beta} + \frac{\alpha}{\beta} AB^{-\beta} z^{-1}$, and

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

where

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

Multiplying both sides of (17) by z, we find that (16) is equivalent to $\frac{dz}{dt} = b - az$ and has the solution

$$z_t = z_0 e^{-at} + \frac{b}{a}\left(1 - e^{-at}\right). \tag{18}$$

The steady state value of z is b/a, or

$$z^* = \frac{(1-\alpha-\beta)\, \frac{\alpha}{\beta} A B^{-\beta}}{(1-\alpha)\, g_N + (1-\alpha-\beta)\, \frac{\rho}{\beta}} = \frac{\alpha A}{B^{\beta}} \left(\rho + \frac{\beta\,(1-\alpha)}{1-\alpha-\beta} g_N\right)^{-1}.$$

As $\beta \to 0$, $z^* \to \alpha A/\rho$, and, in this case, since the rate of obsolescence of capital is zero, the marginal product of capital, $\alpha A\,(K/N)^{-(1-\alpha)}$, equals the interest rate, ρ.

The rate at which z_t converges from the initial condition z_0 to the steady state is

$$(1-\alpha)\, g_N + (1-\alpha-\beta)\, \frac{\rho}{\beta}, \tag{19}$$

which is increasing in α, β, ρ and g_N. It is similar to the approximations that Barro and Sala-i-Martin (1995, ch. 2) derive for Solow's model. In particular, it is decreasing in α and in ρ. On the other hand, it is increasing in g_N which is opposite to the Solow model convergence. Finally, the parameter β, absent from the Solow model, acts to slow down convergence because it mitigates the decline in the marginal product of capital as k rises.

A major difference, however, is that we have assumed that $\sigma = 0$, and for this case convergence in Solow's model is instantaneous, or at least the Solow economy invests its entire output for as long as its capital-labor ratio is below its steady-state value. The same extreme outcome occurs here, but only when σ and β are both zero. This is as it should be, because the Solow model is a special case of ours. When $\beta > 0$, the external effect – operating through a higher user cost of capital – causes investors to delay and free ride on the spending of others. Therefore, for any positive β, diffusion is slower than in Solow's model. Since $K = \left(zN^{1-\alpha}\right)^{1/(1-\alpha-\beta)}$,

$$k_t = z^{1/(1-\alpha-\beta)} N_t^{\beta/(1-\alpha-\beta)}.$$

3.3 Plotting the transitions

We now turn to plotting the path of k_t. In the solution for z_t in (18), the parameters α, β, and g_N are given to us from data other than k_t. But α needs special treatment because the value that is appropriate depends on the possible presence of other capital that does not participate in the learning mechanism (1).

The effect of a second capital, X 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

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

and output per worker would be

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

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

$$\alpha = \frac{\alpha^*}{1-\gamma} \tag{20}$$

and the analysis goes through as before.

3.3.1 The transitions

To pin down the parameter α, we use data on shares of the GPT-capital, α^*, and the remaining capital, γ, and apply (20). For computers, we use information on the share of IT in equipment investment over 1960-1999, which is about 30 percent. But if we count software, that number is now more than fifty percent. We therefore choose an α^* of 0.18 for the share of computers in output – we mean to include here all the information-technology related investments. If capital's share in output, after allowing for structures, is about 30 percent, this implies a γ of 0.12 and an α of about 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 gives us 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 Panel A of Table 2. The parameter β is pinned down from the elasticities reported in Table 1, and g_N is the U.S. population growth rate per year. Using U.S. population growth assumes that the U.S. economy is the entire world, even though our measures include U.S. exports of computers and motor vehicles.[8]

Panel A of Table 2 reports the steady state growth rates of prices, cumulative output, and consumption implied by the model and the data for the three technologies.[9] In all cases, the growth rates predicted by the model are much smaller than those observed in the data. It is likely, however, that the values of α and β are both actually higher than those used in this first set of computations.

Table 2. Steady State Growth Rates Implied by the Model and the Data

Technology	$\hat{\alpha}$	$\hat{\beta}$	$\hat{g}_N$	$g_p = -\frac{\beta(1-\alpha)}{1-\alpha-\beta} g_N$		$g_K = \frac{1-\alpha}{1-\alpha-\beta} g_N$		$g_c = \frac{\alpha\beta}{1-\alpha-\beta} g_N$	
				pred	fact	pred.	fact	pred.	fact
Panel A: Data-based parameter values									
Computers.	0.21	0.62	1.05	-3.0	-24.1	4.9	39.1	0.80	2.0
Electricity	0.27	0.35	1.27	-0.9	-2.1	2.4	10.1	0.32	1.4
Autos	0.04	0.13	1.28	-0.2	-1.5	1.5	12.0	0.01	1.4
Electricity+Autos	0.29	0.33	1.28	-0.8	-2.0	2.4	10.4	0.32	1.4
Panel B: β adjusted for probable measurement error and γ=0.67									
Computers	0.35	0.62	1.05	-15.2	-24.1	22.8	39.1	7.60	2.0
Electricity	0.44	0.42	1.27	-2.1	-2.1	5.1	10.1	1.67	1.4
Autos	0.08	0.18	1.28	-0.3	-1.5	1.6	12.0	0.03	1.4
Electricity+Autos	0.47	0.40	1.28	-2.1	-2.0	5.2	10.4	1.85	1.4

First, $\alpha = \alpha^*/ (1-\gamma)$ should probably be higher because γ should, perhaps, also include human capital. Indeed, to get convergence speeds that are realistic, Barro and Sala-i-Martin (1992, p. 227) use a "broad" capital share of 0.8. Moreover, most production processes rely more and more on brain and less and less on brawn, so that the share of human capital has probably been rising. Second, measurement error in K would cause our procedure to underestimate the absolute value of β. So does inadequate control for quality. The computer performs a lot of functions and it is unlikely that we could measure them all. Nevertheless, we do attempt to adjust our

[8] 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.

[9] When combining electricity capital and autos, we build a composite series for cumulative output by weighting each component by its α^*.

computer series for quality. On the other hand, our auto price series is not quality adjusted at all. Per quality unit, prices of cars fell faster than our Figure 1 reports, and therefore the true beta should be much larger, at least before the Second World War. Finally, as discussed in section 2, our use of electricity production as a stand-in means that we probably do not measure electricity-capital well.

Panel B of Table 2 presents the steady state growth rates that we obtain after setting $\alpha^* + \gamma$ to 0.67. This represents a more conservative estimate of the share of "broad" capital in output than Barro and Sala-i-Martin used. We also raise β by 20 percent for electricity-capital to account for measurement error, and by 40 percent for autos to account for both measurement error and the lack of quality adjustment in the data. The results are much better for our model after performing these adjustments, though we overpredict consumption growth by a factor of nearly 4 in the case of computers. Also, computers show an acceleration in g_K that the model does not predict. Since

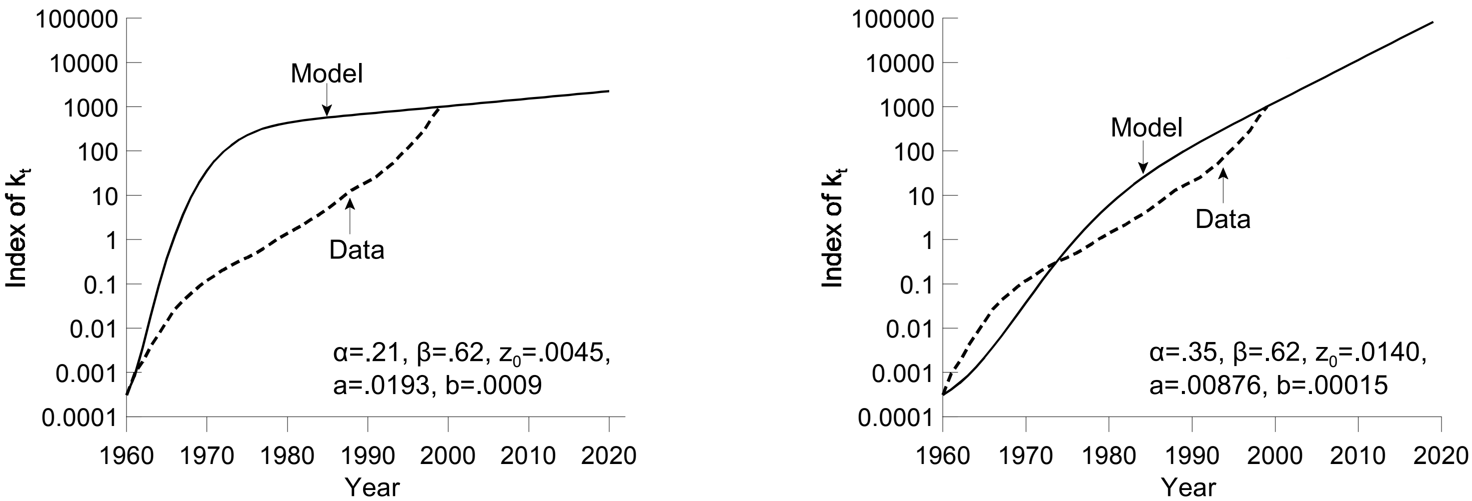
$$g_p = -\beta g_K,$$

as g_k falls, so should $|g_p|$. Therefore the recent acceleration in $|g_p|$ that Figures 1 and 2 showed also contradicts the model. It seems that in 1990 or so, computing got a second wind.

Figure 3 presents the transitional dynamics for computers, and Figure 4 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 upper panel of Table 2, 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 to the values reported in the lower panel of Table 2. These adjustments generate diffusions with an S-shape. In other words, the transition path for z must always be concave, as (18) 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.

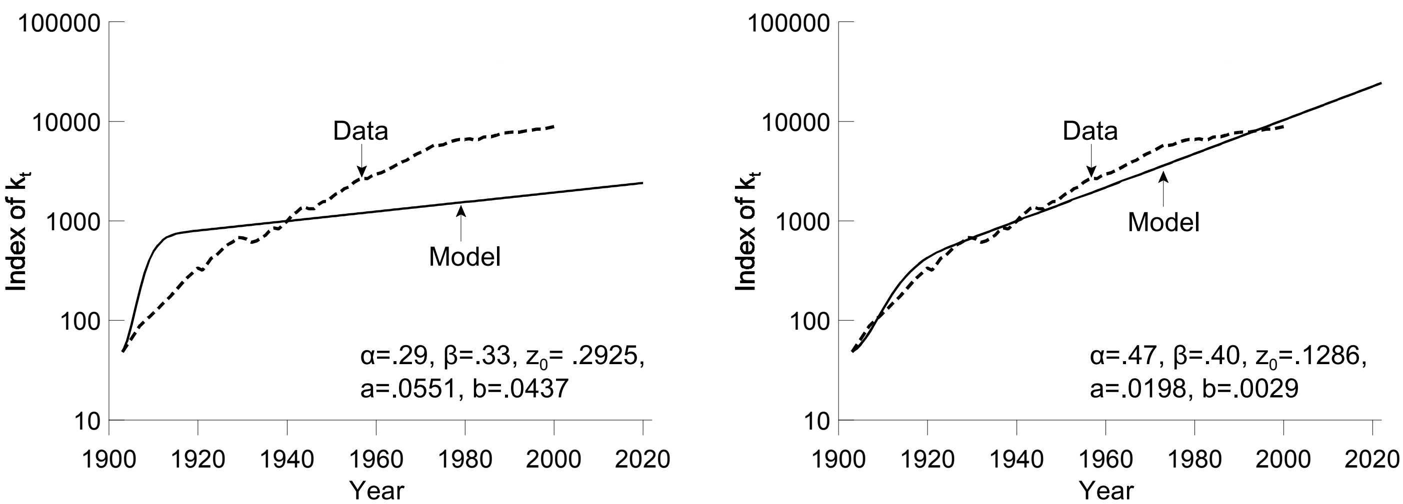
4 Productivity growth in the two diffusion episodes

Figure 5 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 make the case that at the point when they come into our view, they were at roughly the same level of development. In any event, this



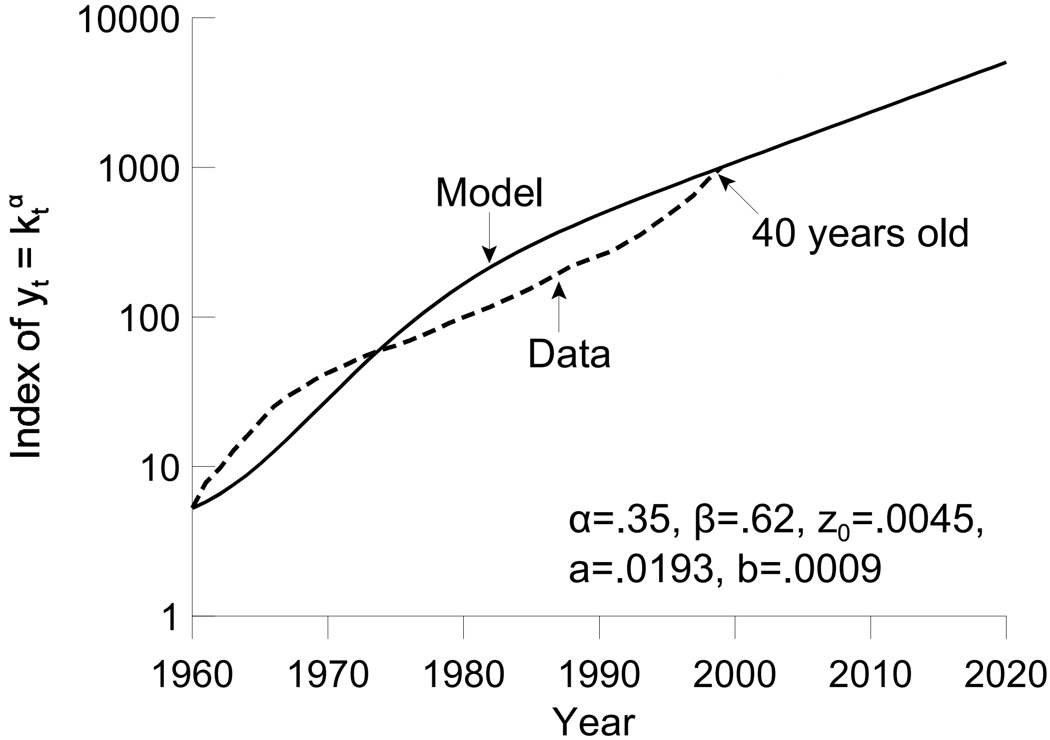
(a) baseline model (b) parameter-adjusted model

Fig. 3. Computer Systems: Actual and Predicted Diffusions

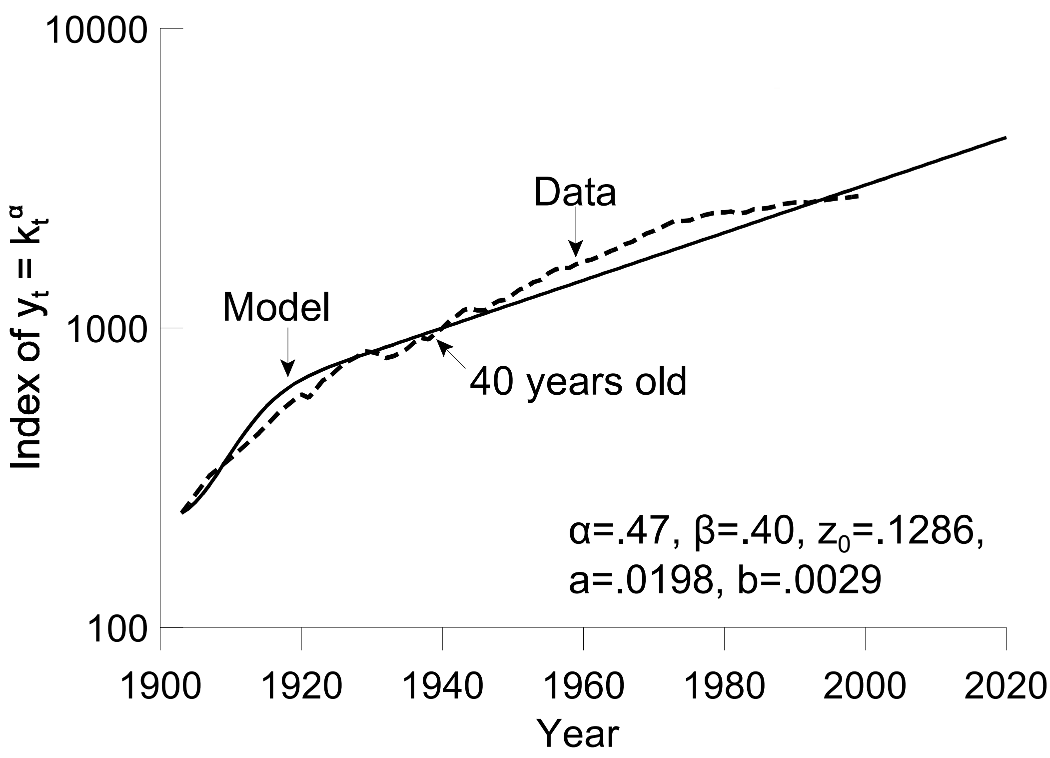


(c) baseline model (d) parameter-adjusted model

Fig. 4. Electricity and Motor Vehicles: Actual and Predicted Diffusions



(a) Computer Systems



(b) Electricity and Motor Vehicles

Fig. 5. Productivity Growth: Actual and Predicted

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 3.

Table 3. 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 Obsolescence of firms and their capital

Suppose final goods firms buy the capital that they use and hire labor on a spot market. Date-t investment is

$$p_t \frac{dk_t}{dt} \equiv B_t.$$

If all the capital were recognized as such, B_t would then be the "book value" of generation t investment.

The market value of date-t capital at some later date $s > t$, would be

$$M_s = p_s \frac{dk_t}{dt} = \left(\frac{p_s}{p_t}\right) B_t.$$

Using (12) the *market-to-book* value of the capital would then be

$$\frac{M_s}{B_t} = \frac{p_s}{p_t} = \exp\left\{-\frac{\beta\,(1-\alpha)}{1-\alpha-\beta} g_N\,(s-t)\right\}.$$

This is decreasing in $s - t$, which is the age of the capital, and is another way that we see new capital making old capital obsolete.

Age of capital vs. age of firm: If new firms enter with new capital, then entry of firms makes old *firms* obsolete, as in Jovanovic and Lach (1989) where the age of a firm was the same as the age of its capital. In fact, the correlation will be far from perfect, but if it is positive, market-to-book value should depend negatively on the age of the firm. The coefficient of age should, however, be stronger for firms that buy a lot of computers, or more generally for firms that invest in new GPTs.

To test this implication, we use a set of regression models with the baseline specification

$$\frac{M}{B} = a_0 + a_1 \log(1 + age), \tag{21}$$

where we measure age as the number of years since incorporation or listing on a stock exchange.[10] We add one to the firm's age to enable the log transformation. Our strategy is to compare, at a given point in time, the coefficient on age (a_1) for firms that were active "GPT-users" with that obtained for all firms in our sample. We display the results in Table 4 and in Figures 6 and 7.

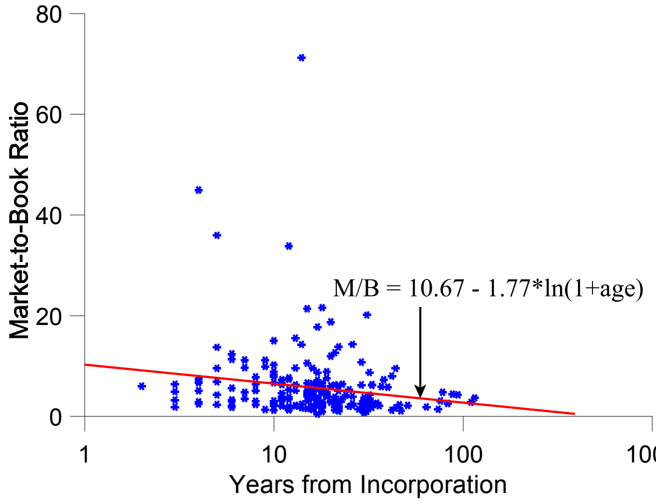
Table 4-Regressions of Market-to-Book Ratios on Age

	By incorporation date			By date of exchange listing		
	constant	log(1+age)	r^2 (obs.)	constant	log(1+age)	r^2 (obs.)
1998 Cross-section						
IT firms	10.67	-1.77	.032	7.94	-0.84	.001
	(5.07)	(-2.72)	(216)	(6.28)	(-1.86)	(637)
All firms	4.42	-0.42	.003	4.12	-0.35	.001
	(7.23)	(-2.68)	(3004)	(15.8)	(-3.88)	(6730)
All firms (with	4.44	-0.39	.036	3.46	-0.21	.021
sector effects)	(7.30)	(-2.14)	(3004)	(9.35)	(-2.34)	(6730)
1920 Cross-section						
Electricity-	1.307	-0.129	.052	1.271	-0.133	.057
intensive firms	(5.28)	(-1.57)	(36)	(7.23)	(-1.94)	(38)
Transportation	1.457	-0.188	.063	1.512	-0.245	.096
firms	(3.80)	(-1.32)	(18)	(5.81)	(-2.14)	(19)
Electricity excl.	1.408	-0.163	.108	1.089	-0.065	.027
transportation	(5.49)	(-2.06)	(17)	(4.98)	(-0.80)	(18)
All firms	0.801	0.020	.002	0.900	-0.028	.003
	(10.03)	(0.81)	(239)	(13.41)	(-1.05)	(233)
All firms (with	0.960	0.047	.151	1.010	0.013	.167
sector effects)	(24.98)	(1.69)	(239)	(33.97)	(0.48)	(233)

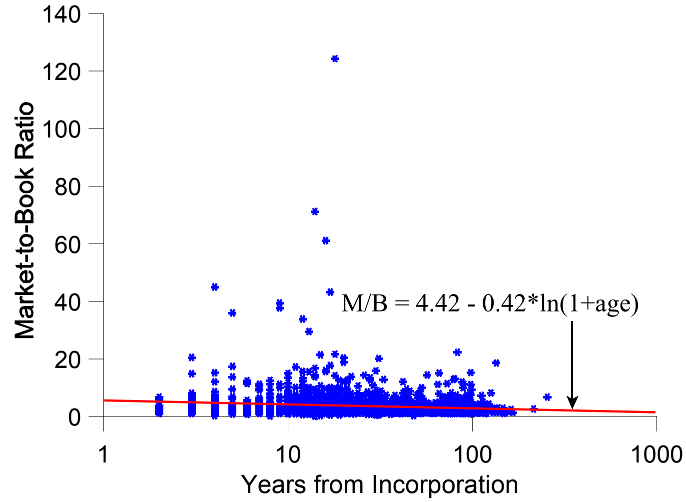
Note: T-statistics appear in parentheses beneath the coefficient estimates.

The upper panel of Table 4 considers the computer as GPT. The sample includes those firms in the 1998 Compustat database for which market and book values are

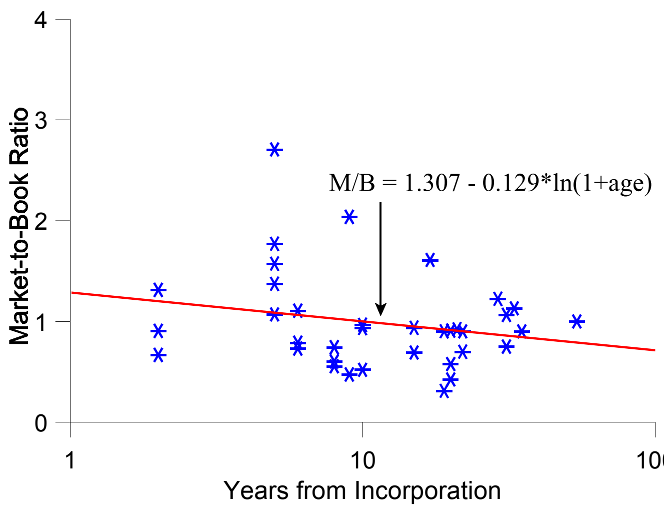
[10] Listing years for 1925-98 are those in which firms enter the CRSP database. The CRSP files include all NYSE-listed firms from 1925, with AMEX firms added in 1962 and Nasdaq firms added in 1972. For 1885-1924, listing years are those in which prices first appear in the NYSE listings of *The Annalist,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



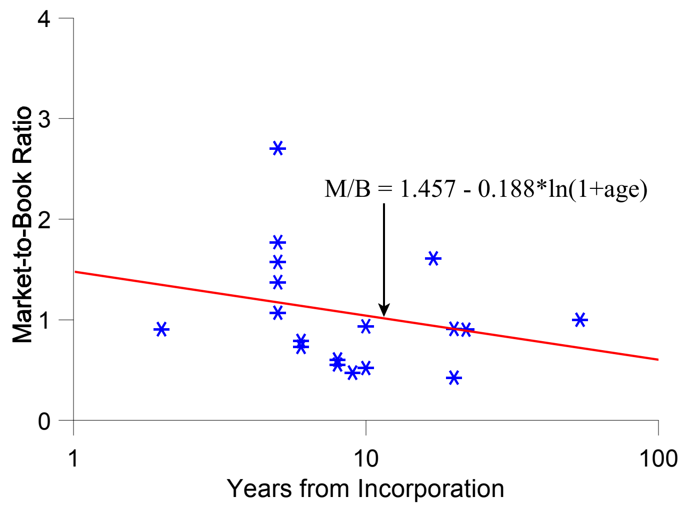
(a) IT firms in 1998



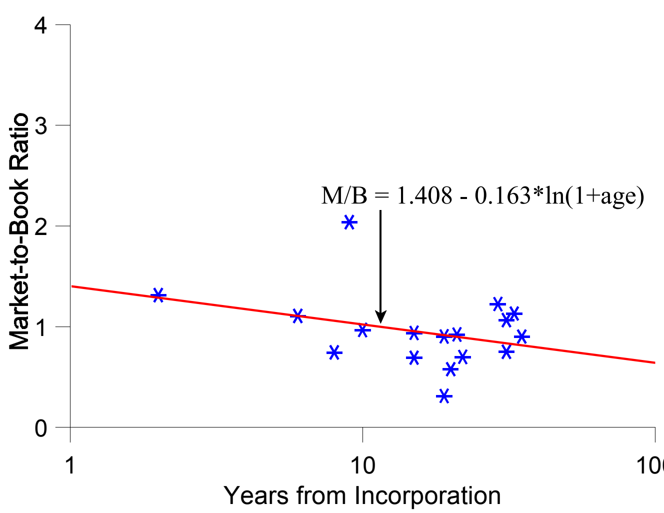
(b) All Compustat firms in 1998



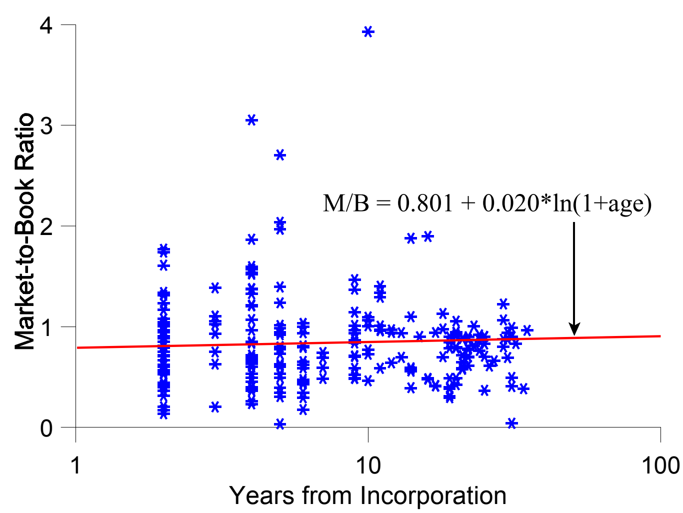
(c) "electricity-intensive" sectors in 1920



(d) transportation sector in 1920

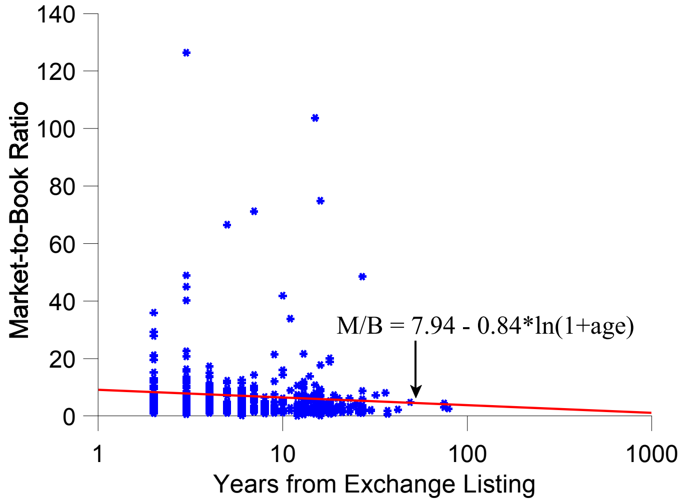


(e) electricity excluding transport in 1920

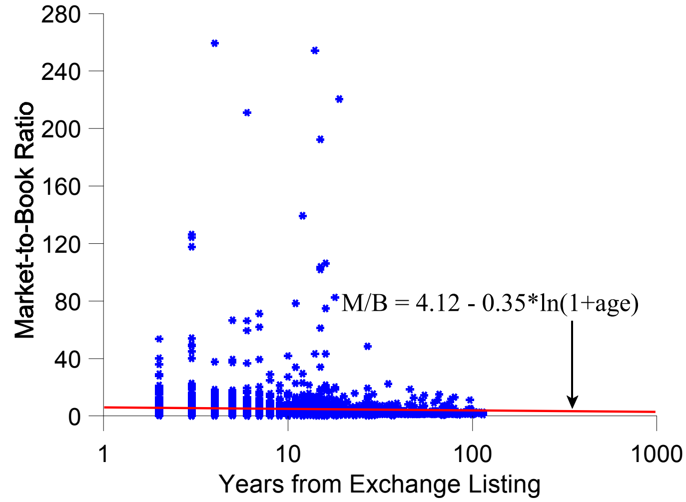


(f) all exchange-listed firms in Moody's in 1920

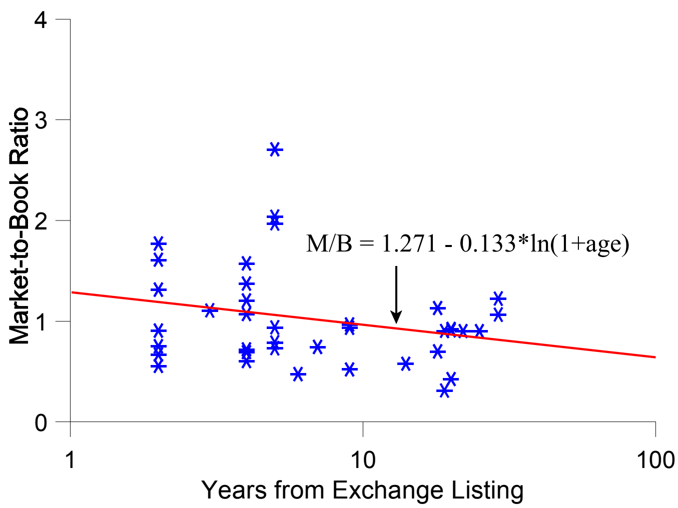
Fig. 6. Regressions of Market-Book Ratios on Years from Incorporation



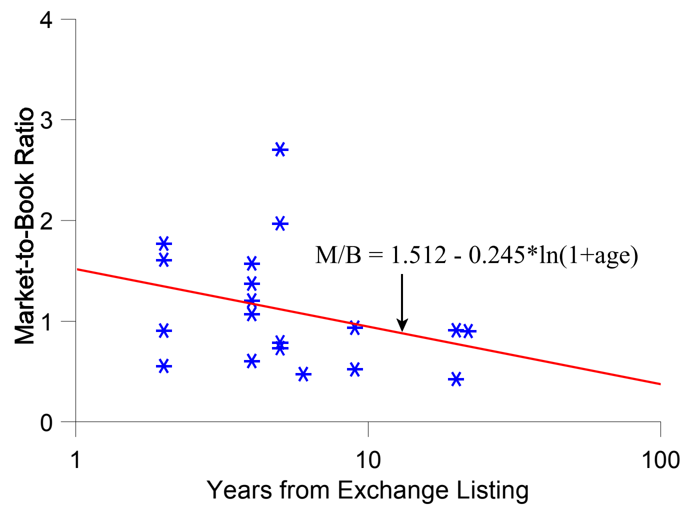
(a) IT firms in 1998



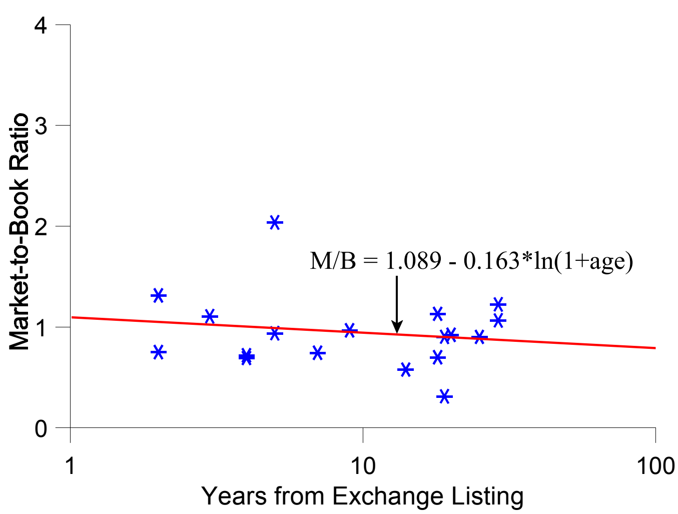
(b) All Compustat firms in 1998



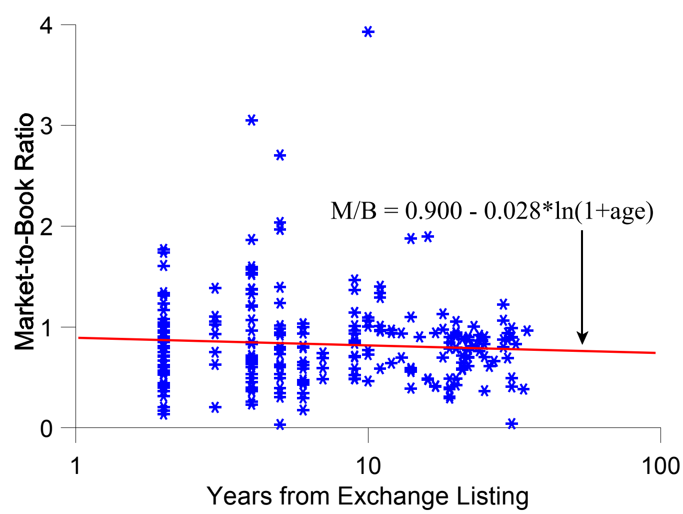
(c) “electricity-intensive” sectors in 1920



(d) transportation sector in 1920



(e) electricity excluding transport in 1920



(f) all exchange-listed firms in Moody’s in 1920

Fig. 7. Regressions of Market-Book Ratios on Years from Exchange Listing

available and for which we could determine the year of exchange listing from the CRSP database or the year of incorporation from our other sources.[11] The regressions focus on two groups of firms: those that we call "information technology firms" and "all firms," where we identify IT firms by their Standard Industry Classification (SIC) codes.[12] For "all firms," we estimate specifications of (12) with and without dummy variables for SIC two-digit sectors.

With age defined as years since incorporation (left side of upper panel), the slope coefficients on log(1+age) are always negative and statistically significant at the 5 percent level for the 1998 Compustat sample. The size of the coefficients also imply relationships that are economically meaningful. For example, if we consider the mean age in the IT sample of 13.7 years, the coefficient on age (-1.77) implies that an IT firm that is one year younger would have a market-to-book ratio that is 2 percent higher. And though the R^2 from the regression indicates that much of the variance in market-to-book ratios remains unexplained, the scatterplot from the regression, displayed in Figure 6, shows a clear downward slope. The second line in Table 4 presents results obtained for all firms in the sample, and the third line augments the specification with sectoral fixed effects. In both cases, the coefficients on age are smaller than those observed for IT firms, though in the larger sample they are estimated more precisely. For example, evaluated at the sample mean age of 20 years, the coefficients in the regression without sectoral fixed effects relate one less year of life, as measured by years since incorporation, with a market-to-book ratio that is larger by only 0.9 percent. The results with sectoral effects indicate an even smaller effect of log age on market-to-book ratios.

The right side of Table 4 uses the number of years since stock exchange listing as the measure of age. This measure is less desirable than years from incorporation on conceptual grounds since firms often live for many years prior to formal exchange listing and financial market innovations over the past three decades have probably accelerated the pre-listing phase for reasons that are less applicable to the length of the pre-incorporation phase (see Jovanovic and Rousseau, 2001). Using years from exchange listing, however, does allow us to work with about three times as many observations for IT firms as are available using years from incorporation, and about twice as many observations for the sample as a whole. The slope coefficient on age for the IT firms is not as steep using this definition (compare Figures 6 and 7), but the coefficient for the IT-based sample still exceeds those for the full sample with and without sectoral fixed effects. Note, too, that the inflation of the '70s and '80s eroded

[11] To compute market values, which comprise the numerator of our market-to-book ratios, 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.

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

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 a_1 is higher today than it used to be.

The lower panel of Table 4 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 extended CRSP database, and using balance sheet items from the 1921 Moody's investor manuals.[13] 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.

In the lower panel, we report negative coefficients on both measures of age for the electricity and transport firms. And though not all slope coefficients for these subsets are statistically significant, at least one of the age measures comes in significantly at the 5 percent level for every subset. The slope coefficients for the transportation firms are more steeply negative than for the electricity-intensive firms in all cases, 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 (see Figure 1). Interestingly, it is only in the technology-based sectors that a significant negative relationship is observed between market-book ratios and age in 1920. This is evidenced by the insignificant coefficients on age for the regressions that include all firms. Further, the inclusion of two-digit sectoral dummy variables even produces a positive coefficient on age!

The main point is that $\hat{a}_1$ is a lot higher in the currently high-tech sector compared to everything else and compared, in particular, to the high-tech sector 80 years ago, and this in spite of the inflation bias that we just mentioned. We interpret all of this as support for our model of the GPT-using sectors.

[13] 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.

6 Conclusion

We modelled Moore's law as arising from learning by doing in the sector that makes computers. The assumed learning process took the form of a relation between cumulative output and productivity that is common in fact. We compared the model to the data on the diffusion of each technology in its infancy, and then made some long-run projections.

Our model adds Arrow-style learning to the Solow (1956) model. We found that the effect on the speed of convergence of the potential to learn, β, is much the same as the effect of capital's share. The Solow (1956) model is used less now partly because of the rapid convergence that it implies when realistic capital shares are used. But we have found that combining this model with Arrow-style learning can slow down the speed of convergence, perhaps even to realistic levels.

What is new in the new economy? Computers have a higher β than the earlier technologies, and this means that IT will add more consumption-growth than the other two technologies did. Mildly supportive is the evidence that organization capital gets obsolete faster today than it did eighty years ago.

References

[1] *The Annalist.* New York: The New York Times Co., 1912-1928, various issues.

[2] Arrow, Kenneth. (1962). "The Economic Implications of Learning by Doing," *Review of Economic Studies* **29**(3), 155-173.

[3] Balke, Nathan, and Gordon, Robert J. (1986). "Appendix B: Historical Data." In R. J. Gordon (ed.), *The American Business Cycle: Continuity and Change.* Chicago: University of Chicago Press.

[4] Barro, Robert, and Xavier Sala-i-Martin. (1995). *Economic Growth.* New York: McGraw-Hill.

[5] Barro, Robert, and Xavier Sala-i-Martin. (1992). "Convergence." *Journal of Political Economy* **100**(2), 223-251.

[6] Berndt, Ernst R., Dulberger, Ellen R., and Rappaport, Neal J. (2000). "Price and Quality of Desktop and Mobile Personal Computers: A Quarter Century of History," working paper.

[7] Board of Governors of the Federal Reserve System. (2001). *Historical Statistical Release G-17.* Washington, DC.

[8] *Bradstreet's.* New York: Bradstreet Co., 1885-1928, various issues.

[9] *The Commercial and Financial Chronicle.* 1885-1928, various issues.

[10] *Compustat database*. (2001). New York: Standard and Poor's Corporation.

[11] *CRSP database*. (2000). Chicago: University of Chicago Center for Research on Securities Prices.

[12] Brynjolfsson, Erik, and Shinkyu Yang. (1997). "The Intangible Benefits and Costs of Computer Investments: Evidence from the Financial Markets." *Proceedings of the International Conference on Information Systems*.

[13] David, Paul. (1991). "Computer and dynamo: The modern productivity paradox in a not-too-distant mirror." In *Technology and Productivity: The Challenge for Economic Policy.* Paris: OECD.

[14] Devine, Warren D. Jr. (1983). "From Shafts to Wires: Historical Perspective on Electrification." *Journal of Economic History* **43**(2), 347-372.

[15] Frankel, Marvin. (1962). "The Production Function in Allocation and Growth: A Synthesis." *American Economic Review* **52**(5), 995-1022.

[16] Gordon, Robert J. (1990). *The Measurement of Durable Goods Prices.* Chicago: University of Chicago Press.

[17] Gordon, Robert J. (2000). "Does the New Economy Measure Up to the Great Inventions of the Past?" *Journal of Economic Perspectives* **14**(4), 49-74.

[18] Greenwood, Jeremy, and Yorukoglu, Mehmet. (1997). "1974." *Carnegie-Rochester Series on Public Policy.*

[19] Irwin, Douglas A. and Klenow, Peter J. (1994). "Learning-by-Doing Spillovers in the Semiconductor Industry," *Journal of Political Economy* **102**(6), 1200-1227.

[20] Jovanovic, Boyan and Lach, Saul. (1989). "Entry, Exit and Diffusion with Learning by Doing." *American Economic Review* **79**(4), 690-699.

[21] Jovanovic, Boyan and Rousseau, Peter L. (2001). "Why Wait? A Century of Life Before IPO," *American Economic Review **91***(2), Papers and Proceedings, 336-341.

[22] Jones, Charles I. (1995). "R & D-Based Models of Economic Growth." *Journal of Political Economy* **103**(4), 759-784.

[23] Kremer, Michael. (1993). "Population Growth and Technical Change, One Million BC to 1990," *Quarterly Journal of Economics* **108**(3), 681-716.

[24] *Macrohistory Database. (2000).* Cambridge, MA: National Bureau of Economic Research.

[25] Meindl, James D, Chen, Qiang, and Davis, Jeffrey A. (2001) "Limits on Silicon Nanoelectronics for Terascale Integration." *Science* ***293***, 2044-2049.

[26] *Moody's Industrial Manual.* (1921). New York, NY: Moody's Investors Service.

[27] *Moody's Manual of Public Utilities.* (1921). New York, NY: Moody's Investors Service.

[28] *Moody's Transportation Manual.* (1921). New York, NY: Moody's Investors Service.

[29] Moore, Gordon E. (1965). "Cramming More Components onto Integrated Circuits", *Electronics* **39**(8), 1-4.

[30] *The New York Times.* 1897-1928, various issues.

[31] Romer, Paul M. (1986). "Increasing Returns and Long-Run Growth." *Journal of Political Economy* **94**(5), 1002-1037.

[32] Solow, Robert. (1956). "A Contribution to the Theory of Economic Growth." *Quarterly Journal of Economics* **70**(1), 65-94.

[33] *Stock market encyclopedia.* New York, NY: Standard and Poor's Corporation, 1981, 1988, 2000.

[34] *Stock reports.* New York, NY: Standard and Poor's Corporation, various issues.

[35] United States, Bureau of the Census, Department of Commerce. (1975). *Historical Statistics of the United States, Colonial Times to 1970.* Washington, DC: Government Printing Office.

[36] Thompson, Peter.and Rebecca A. Thornton. "Learning from Experience and Learning From Others. An exploration of learning and spillovers in wartime shipbuilding." *American Economic Review*, December 2001.

[37] United States, Bureau of the Census. *Statistical Abstract of the United States.* Washington, DC: Government Printing Office, various issues.

[38] Vernon, Raymond. (1966). "International Investment and International Trade in the Product Cycle." *Quarterly Journal of Economics* **80**(2), 190-207.