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ESTIMATING THE EFFECTS OF R&D ON BELL SYSTEM PRODUCTIVITY: A MODEL OF EMBODIED TECHNICAL CHANGE

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ABSTRACT

This paper develops an econometric model of the effects of R&D effort on the magnitude and characteristics of technical change in the Bell system. We estimate simultaneously a vintage capital production function, embodying several distinct types of capital, and various factor demand functions for the Bell system during the post-war period. Each vintage of capital is assumed to differ in productivity according to a parametric function of R&D effort embodied in that vintage of capital. Allowance is also made for augmenting technical change in the non-capital inputs. The model is estimated on a new, extensive data set which contains detailed information on the vintage structure of investment in different types of capital in the Bell system.

Most previous papers in the field have assumed that technical change is disembodied. However, we find that a model assuming capital-embodied technical change fits the data much better than one making the traditional assumption that technical change is disembodied. We use the parameter estimates to calculate the ex post rate of return earned on R&D expenditures at Bell Laboratories and the improvements in the productivity of specific capital inputs which are due to those R&D expenditures. The results suggest not only that the return to R&D expenditures has been very high, but also that it has been growing over time. In addition, the rate of increase in the productivity of capital inputs has risen over time. The model fails to produce a plausible estimate for the degree of returns to scale, but the results on the return to R&D effort are reasonably insensitive to what we assume about the degree of economies of scale.

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This paper develops an econometric model of the effects of R&D effort on the magnitude and the characteristics of technical change in the Bell System. To do this, we estimate simultaneously a vintage capital production function and various factor demand functions for the Bell System during the post-war period. Each vintage of capital is assumed to differ in productivity -- the degree to which later vintages are more productive than earlier vintages is measured by a parametric function of R&D effort embodied in one vintage and not the other.

We therefore assume in our analysis that technical improvements are embodied in new capital equipment. Since almost all previous studies have assumed, by contrast, that technical change is entirely disembodied, we also estimate for comparison a model with disembodied technical change. The model with embodied technical change proves to be much more successful in fitting the data.

We use the parameter estimates to calculate, under various assumptions, the *ex post* rate of return earned on R&D expenditures at Bell Laboratories and the improvements in the productivity of specific capital inputs which are due to those R&D expenditures. The results suggest not only that the return to R&D expenditures has been very high, but also that it has been growing over time. In addition, we find that the increase in the productivity of capital inputs has itself risen over time. In this sense, there is no evidence of a productivity slowdown in the Bell System.[1]

The key advantage that we had over past studies of technical change is that we had access to a data set that was far more extensive and detailed than those used in previous studies. Having available such a rich data set allowed us to avoid many of the approximations which plague other studies in the field.

The first section of this paper develops in stages the specification of the model to be estimated. Our specification differs in many ways from those used in previous studies, and the motivation for each change is discussed in turn. The second section of the paper presents and interprets the coefficient estimates derived when the model is estimated using annual post-war data for the Bell System. The paper ends with a summary of our principal conclusions.

1. For evidence of a productivity slowdown in other industries, see Baily [1982] or Kendrick [1979].

I. Specification of the Model

Technical change results in increased output relative to the amount of inputs needed to produce the output, and perhaps different and more attractive forms of output. In the telecommunications industry during our sample period, however, the form of output, principally transmitted telephone calls, changed little. As a result, our study, along with past studies of the industry, focuses on cost-reducing forms of technical change.

A. Measures of Productivity Growth

In measuring the degree of cost reduction in producing a given type of output the basic problem is to control for changing quantities of inputs when examining the degree to which output changes over time. A common procedure for doing this is to compare at each date t a measure of real output with a measure of the real cost of the inputs, capital and labor, used in production.[2] In particular, if in year t output, measured by real revenues,[3] is Q_t, the quantity of labor input is L_t, hired at wage w_t, the real capital stock is K_t, generating annual costs of r_t per unit real capital, and if real quantities are measured in dollars of year s, then the proposed procedure involves comparing Q_t, the measure of real output, with $w_sL_t + r_sK_t$, the real cost of inputs. Productivity change is then measured by changes in the ratio $Q_t/(w_sL_t + r_sK_t)$. Kendrick [1973], Kendrick and Grossman [1980], among other, have calculated such figures for many industries over an extended period of time. The *Bell System Productivity Study 1947-1979*, hereafter denoted by *BSPS*, reports equivalent figures, calculated with great care, for the Bell System.

2. To simplify the discussion, we assume there are only these two inputs, though in actual calculations, many other inputs may appear.

3. Quality improvements in the form of output, to the degree to which they do occur, would not normally be captured in real revenues. Due to regulation, most of the gain would be passed on to the customers, leaving real revenues unaffected. Even if prices of existing services were allowed to increase somewhat in response to quality improvements, this increase would not show up in the measure of real revenues, as the procedure for correcting nominal revenues for price changes due to inflation would also eliminate the effect of price changes due to quality improvements. Quality improvements through the provision of new services may affect real revenues, however.

B. More General Specifications of the Production Function

This measure of productivity change implicitly models the production function in year t by

$$Q_t = (w_s L_t + r_s K_t) g(N_t), \tag{1}$$

where N_t represents the state of technical know-how in year t, and $g(N_t)$ indicates the value in production of knowledge N_t. Here, w_s and r_s now play the role of technological parameters as well as market prices. Cost minimization in year s implies that the technological parameter for factor i must equal the real cost of hiring factor i.

Viewed as a description of the production function, however, this specification is very unattractive. It assumes that capital and labor are perfect substitutes in production, and that there are constant returns to scale, given N_t. The general class of production functions, of which equation (1) is a special case, is $Q_t = f(L_t, K_t, N_t)$. To the degree that $f(\ )$ displays economies of scale at a given N_t, equation (1) overestimates the contribution of R&D to increasing productivity since productivity improvements arising solely from expansion in the size of the company are inappropriately attributed to increasing technological know-how. In contrast, use of equation (1) underestimates the contribution of research in any year after year s (and overestimates it in earlier years) to the extent that $f(\ )$ is a concave function of capital and labor, as normally assumed. To see this, note that in period s, cost minimization implies that $(w_s L_s + r_s K_s)$ is minimized given Q_s. However, in any other year, $(w_s L_t + r_s K_t)$ is *not* minimized, given Q_t; instead, $(w_t L_t + r_t K_t)$ is minimized. After year s as a result, measured inputs, $(w_s L_t + r_s K_t)$, increase relative to output to the extent that input prices change, a change that the *BSPS* procedure would attribute to technical deterioration.

Several parametric specifications of the function $f(\ )$ have been estimated in the economics literature, both with firm and industry data, to identify the role of R&D in the production process. For example, Griliches [1980] and Mansfield [1980] assume that the production function is Cobb-Douglas. Nadiri and Schankerman [1981], and Schankerman and Nadiri [1985] have estimated more general specifications of $f(\ )$ using Bell System data.[4]

The objective of this paper is not to test a yet more general functional form for $f(\ )$. We assume that $f(\ )$ is CES in the non R&D inputs, so that, given N_t, $f(L_t,K_t) = (\alpha_1 L_t^\gamma + \alpha_2 K_t^\gamma)^{\delta/\gamma}$. This functional form is a more restrictive specification than that used in some previous studies of the Bell System, though more general than a Cobb-Douglas specification.

C. Embodied vs. Disembodied Technical Change

Our focus is instead on how R&D enters the production function. One characteristic of all the specifications discussed above is that technical change is assumed to be disembodied.[5] These past studies assume that R&D effort, perhaps after a lag, results in improved productivity equally for all inputs--capital vs. labor, different types of capital, and new vs. old capital. The time needed to translate R&D into productivity gains is assumed to be fixed, and so is independent of the rate at which new investment occurs.

We feel that each of these implicit assumptions is a poor description of how technological change occurs, at least in the Bell System. Until the recent emphasis on software development, almost all technical change in the Bell System involved improved designs for capital items serving a particular function in production. Technical change could occur only to the degree that capital using the new technology was purchased and put into place. Older technological vintages of capital remaining in place would not normally change in productivity as a result of new technological vintages being used elsewhere in the network. Under this description, if each capital item is a perfect substitute after adjusting for quality, then the capital stock at date t, measured in efficiency units and denoted by K_t^e, can be represented by

$$K_t^e = \sum_v K_{vt}\, g(N_v), \tag{2}$$

where K_{vt} is the amount of capital of technological vintage v in place in year t, and

4. In particular, Nadiri and Schankerman [1981] estimate a translog long run cost function. A Cobb-Douglas production function is a special case of this specification. Schankerman and Nadiri [1985] study a short run cost function in which capital and R&D are quasi-fixed inputs.

5. Writing the production function as $f(L_t,K_t,T_t)$, where T_t represents the state of knowledge in year t, disembodied technical change implies that R&D (or other factors) leads to changes in T_t without the requirement of intervening investment in the new technology.

N_ν is the accumulated state of knowledge as of the date when vintage ν was designed.

This representation of the capital stock probably captures well the shift in transmission technology from copper wire to microwave and satellite and now to fiber optics. It probably captures less well the shift from analogue to digital transmission, where investment in a device which translates a voice signal between analogue and digital representation improves dramatically the productivity of existing copper wire. While not modeling well all technological change, we feel that this approach provides a much better characterization than those used in previous studies.

While previous studies have been forced to assume that capital can be represented by a single number, it is clearly the case that each capital item is not a perfect substitute, and in addition that rates of technical change differ dramatically between types of capital, e.g. transmission equipment vs. switching vs. station equipment (primarily telephones). For example, while 35% of the capital stock of the Bell System is station equipment, only 12% of the R&D effort historically has focused on its design. Having much more detailed data than were available to past researchers, we decomposed the capital stock into four types: transmission capital, switching capital, station equipment, and everything else. For the first three types of capital, capital of type i was measured in efficiency units, denoted by K^{ϵ}_{it}, where

$$K^{\epsilon}_{it} = \sum_{\nu} K_{\nu it}\, g_i(N_{\nu i}), \tag{2a}$$

Here $K_{\nu it}$ is the amount of capital of type i of vintage ν in place in year t, while $N_{\nu i}$ represents the accumulated R&D effort focused on capital of type i up through the date of vintage ν. No embodied technical change was allowed for in the last type of capital, a category including mainly land and buildings.

Output was then assumed to be a CES function of the three types of capital measured in efficiency units, other capital, labor, and a sixth residual input which includes materials plus real expenditures on services and rents. In particular, the production function was specified as

$$Q_t = \left(\sum_{i=1}^{3} (\alpha_i\, K^{\epsilon}_{it})^{\gamma} + (\alpha_4\, K_{4t})^{\gamma} + (\alpha_5\, M_t)^{\gamma} + (\alpha_6\, L_t)^{\gamma}\right)^{\delta/\gamma} \tag{3}$$

where M_t denotes materials.

For simplicity, we defined vintage v to equal that capital put into place in year v. Implicitly, all capital of a given type put into place in a given year is assumed to be equally productive. Using information about the basic technological design, as well as the date of investment, when defining vintage proved to require more data than were available.

This specification assumes embodied factor-augmenting technical change, though at different rates for each form of capital. However, R&D might also affect production in a variety of other ways. For example, at various times research has focused on labor saving techniques, e.g. research on direct dialing. Such research should change the shape of the production function $f(K,L)$, and not merely involve an augmentation of the effective capital stock. There would be many ways to parameterize such changes over time in the shape of the production function. We chose a very simple one. In particular, we allowed the weights α_i, $i = 4,5,6$ to change exponentially over the course of the sample period, so that, for example, α_i was replaced by $\alpha_i\, e^{\phi_i t}$. We did not attempt to explain what research or what capital investment might have caused any estimated changes in the shape of the production function. The data were inadequate to allow us to differentiate among many competing explanations.

For purposes of comparison with previous studies, we also estimate below a specification assuming solely disembodied technical change. In this specification, we assume that R&D increases the productivity of existing capital to the same degree that it increases the productivity of new investment.

D. Capacity Utilization of Capital

Capital stock figures, as maintained internally by the Bell System, are based on gross investment and retirement of capital figures for each type of capital at each date. They do not take into account how much of the capital is actually in use in the network at any date. Due to economies of scale in installation, often much more capacity is added at any date than is needed at that time. Also, since the desired configuration of the network changes in unexpected ways over time, (because of changing technology and population movement), spare capacity is intentionally kept available to handle these unexpected events.

In describing the production technology, however, it would be desirable to have a measure of the capital in use at each date, and not the capital available for use. Fortunately, the Bell System has kept some measures for recent years of the percent of available capital that is being used in the network. However, these data do not cover our entire sample period, and do not have the detail, either by type of capital or by vintage of capital, that would be desirable. In using these data, we were therefore forced to make several simplifying assumptions. In particular, we assumed 1) that prior to our earliest available capacity utilization data, the capacity utilization was equal to its first observed value, and 2) the capacity utilization was the same for all vintages of capital covered by each available data series. We therefore multiplied our measures of the effective capital stocks of transmission and switching equipment by a utilization factor $U_{it}, i=1,2$. For purposes of comparison, we also estimated the model omitting this correction.

E. Measurement of Output and Inputs

Following the BSPS and Nadiri and Schankerman [1981], we measure the output and inputs of Long Lines (LL) plus the twenty-two Bell operating companies (BOC's). As a result, we make no attempt to measure technical change in production at Western Electric or at Bell Laboratories. Since process innovation in manufacturing at Western Electric is a major focus of R&D effort in the company, this is an important omission, but an unavoidable one.

Inevitably, there were conceptual difficulties in measuring each of the needed data series. In this section, we describe how each data series was constructed, and what some of the implications are of the specific measures chosen.

To begin with, we measure output by real revenues, as did BSPS and Nadiri and Schankerman [1981]. By doing so, we measure what was actually produced rather than what the system was capable of producing. Fortunately, there is very little variation in measured real revenues over the business cycle. Another problem with revenues is that the relative prices charged for different forms of output do not correspond to their relative costs. As a result, when output composition changes, the implied change in revenues does not correspond to the implied change in costs.[6] Unfortunately, we could not find any better measure of output which was available for the entire sample period.

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6. What biases this creates in our study are unclear. The relative increase in long distance calls over time probably was given too much weight, as long distance rates are normally viewed to be high relative to costs. This should lead measured output to grow too quickly. However, new households are charged a relatively low price for a connection to the network, so that the increase in new households with the baby boom would be given too little weight, thereby underestimating the growth in output.

Labor input was measured by a weighted sum of man-hours for each of 22 categories of workers, where their relative wage rates in 1967 were used as weights. This measure ought to correct for the effects of a changing composition of the labor force, but may not adequately correct for changing quality of workers within any given category.

As in Nadiri and Schankerman [1981], we measure the quantity of materials, rents, and services, by real expenditures on these activities. In converting nominal expenditures to real expenditures, we used the producer price index for materials and components in manufacturing, taken from the *Economic Report of the President*.

In order to measure the effective capital stock, data are needed for each value of K_{vit}. Such a decomposition of the capital stock at each date by type of capital and date of investment is rarely available. For the Bell System, it was available in just this form for 1959, 1966, 1972, and yearly since 1977. In other years, gross investment and gross retirements as well as total capital by type of capital were available, but not broken down by calendar vintage.

In order to fill in the data set for missing years, we estimated a survival probability curve for each of five types of capital (switching, transmission, buildings, telephones, and other) using the available data. The parametric specification chosen for the survival probability curve was

$$P(t) = s^t h^{(c^t - 1)} \tag{4}$$

where $P(t)$ is the fraction surviving to age t, and s, h, and c are the parameters to be estimated. This functional form, taken from the demography literature, provides a very flexible approximation to actual survival curves. The estimated survival curves were then used to forecast how much capital from each calendar vintage would still be in use in each year, given the initial investment in that vintage. For further details on our procedure, see the appendix.

This procedure provides us with a measure of the historic cost of the capital of each age still in use at a given date. We calculated their real cost using a set of very detailed price indices for Western Electric products.[7]

7. Most capital acquired by Long Lines and the operating companies during this period was purchased from Western Electric. To the degree that capital was acquired from outside vendors, our procedure may improperly attribute any quality change in this capital relative to its price to R&D done in the Bell System. Fortunately, relatively little was purchased from

Real capital purchases in any year in principle equal dollar payments for each type of capital, divided by the price index for that type of capital, summed over types of capital. As a result, real capital purchases of existing products change over time in principle solely due to changes in the number of items purchased of each product, and not due to changes in the *price of each* product (resulting for example from cost reductions in manufacturing).[8]

New and improved products lower the effective cost of capital inputs purchased by the BOC's and LL, but only to the degree that the initial price set for that new product is such as to make it a better "buy" than previous products. If the initial price is set so high as to offset the benefits of the technical change, then the BOC's and LL gain nothing *at that date* from the availability of the new product. While the price of the new product may drop later, perhaps dramatically, however, we have just argued that a price drop for an existing product will not lower the measure of real capital inputs. Therefore, new and improved products will result in observed productivity gains only to the degree that the *initial* price for the new product makes it a better "buy" at that date.[9]

Given how we measure capital inputs, we should therefore observe technological change only when a new product is introduced and when the initial price for that new product is favorable. Fortunately, any nonnegligible change in the design of a Western Electric product results in a new product classification. In addition, Western Electric prices, due to regulation, are set primarily to reflect manufacturing costs, and not what the market will bear. Therefore, the value of technological improvements embodied in new products is mostly passed on to the BOC's and LL, and so should show up as increased productivity. Our procedure should therefore capture most all the technological gains from new product designs, though none of the gains through cost reductions in manufacturing existing products.

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outside vendors.

8. Use of a few price indices for many heterogeneous products, rather than separate price indices for each product, makes these assertions only approximately true.

9. In practice, the commodity bundle used in calculating each price index for Western Electric products is not revised annually, but only when the sales pattern of the products appearing in the bundle has changed significantly. The "initial" price for a new product therefore represents the price prevailing at the first data the commodity bundle is revised following the introduction of the new product, which may be several years later.

Manufacturing costs do include amortized R&D expenses paid for by Western Electric, however. Since R&D costs are passed through to the BOC's and LL, productivity change will be observed in our data only to the degree that new capital increases the value of output by more than the cost of the associated R&D.[10] [11]

F. Specification of the State of Knowledge

In the above discussion, we denoted the quality of a given vintage of capital by $g_i(N_{vi})$, where N_{vi} represented the state of knowledge embodied in vintage v of capital of type i. How best to characterize this state of knowledge at any date is not clear, however. Existing output measures from R&D, such as number of patents or number of published papers, are likely to be quite unreliable indicators. The degree to which management encourages patenting or publishing varies over time and across activities. Also, patents or papers can differ dramatically in commercial value, making a simple sum unreliable.

We therefore chose to measure the state of knowledge by how much was spent trying to produce the knowledge, rather than by some measure of how much was actually learned. In particular, we gathered data on real R&D expenditures at each date t which focused on the design of capital of each type i,[12] denoting this value by R_{it}. We then assumed that the productivity of a unit of capital of type i and vintage v can be represented by

10. Not all R&D effort at Bell Laboratories is paid for by Western Electric. Historically, about 40% of nonmilitary R&D, primarily basic research and research on "common technologies," was paid for through the license contract, a direct payment from the BOC's and LL to Bell Laboratories. Only the benefits, and not the costs, of this fraction of the R&D effort affect the price of capital equipment sold by Western Electric.

11. R&D expenses paid for by Western Electric are commonly amortized over about five years, rather than over the life of the new product. Therefore, the initial price of a new product includes a disproportionate share of the R&D costs. Measured productivity gains resulting from a new product are biased downwards as a result. Measures of productivity change, as argued above, depend on the initial price of a new product, and the five year amortization procedure leads to an unduly high initial price.

12. We included all R&D expenditures at Bell Labs, but omitted R&D expenditures at Western Electric, since R&D there focuses solely on process innovation. In converting nominal into real R&D expenditures, we used the GNP price deflater. The breakdown of R&D expenditures between categories was not available prior to 1937. We therefore assumed that the percentage breakdown observed in 1937 applied as well to all earlier years.

$$g_i(N_{ti}) = (1 + \theta_i \sum_{j=3}^{\infty} R^{\beta}_{i,t-j})^{a} \tag{5}$$

where the θ_i,β, and a, are parameters to be estimated. Here, we assume a three year lag between research and embodiment of the results in the manufactured product. [13]

We chose such a complicated specification for two reasons. First, unless we allowed for diminishing returns to R&D effort in each year (i.e. $\beta < 1$), the optimal level of R&D effort implied by our estimates would fluctuate wildly and in some circumstances would not even be finite. Second, we wanted to allow for secular diminishing returns to R&D effort ($a < 1$), to test whether technological change has been getting more difficult over time. Several commonly used specifications of R&D effort, e.g. $exp(\theta_i \sum_{j=3}^{\infty} R_{it-j})$ are special cases of this specification.[14]

G. Implications of Cost-Minimizing Behavior

So far, our specification is nonstochastic. Many sources of stochastic variation are possible, including for example random success in R&D, measurement error, and specification error. We assumed that the primary source of stochastic variation in equation (4) is simply measurement error in Q_t. Several reasons for expecting measurement error in Q_t to be important were described in the previous section. In particular, we multiplied the right hand side of equation (4) by an extra term e^{ε_t}.

Altogether, there are sixteen parameters in this specification, including the parameters implicit in the $g_i(.)$ functions, too large a number to be estimated reliably given only thirty-five annual observations. However, how much of each factor input was chosen by the firm at each date, given input prices, provides more information about the form of the production function. Each factor demand equations ought to depend on the same underlying parameters, so aid in estimating these parameters.

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13. A three year lag fit marginally better than other lags we tried, and seems reasonable from anecdotes concerning embodiment.

14. As a grows without bound, holding constant $\theta_i a$, the specification converges to an exponential form with parameter $\bar{\theta}_i = \theta_i a$

In particular, we assumed that the company chooses factor inputs ex ante (before observing ϵ_t) so as to minimize costs subject to the regulatory constraint that capacity must be sufficient to successfully satisfy realized demand without undue delays, for example, in completing a call or in getting a new line installed.[15] If the level of capacity needed at date t to obtain this quality of service, given the distribution of possible demands, is Q_t^*, then the firm is assumed to choose input quantities so as to satisfy

$$\min_{F_{it}} \left[\sum_{i=1}^{6} p_{it} F_{it} - \lambda_t [Q^c(F_{1t}, F_{2t}, F_{3t}, F_{4t}, F_{5t}, F_{6t}) - Q_t^*] \right]. \tag{6}$$

Here, F_{it}, $i = 1, 6$, represents the six factor inputs, p_{it} represents the implicit real cost of hiring a unit of factor i in year t, while $Q^c(\cdot)$ represents capacity output, given inputs, which we assume equals the nonstochastic component of the production function in equation (3).[16] With respect to capital inputs, marginal decisions are assumed to involve solely the latest vintage of each type--earlier vintages of capital, net of depreciation, are taken as given.

The first-order conditions characterizing relative factor demands can be expressed as follows:

$$log \left[\frac{\sum_{v=1}^{t} K_{vit} U_{it} g_i(N_{iv})}{L_t} \right] = \frac{1}{\gamma - 1} \; log \left[\frac{\alpha_6 p_{it}}{\alpha_i p_{6t} U_{it} g_i(N_{iv})} \right], \tag{7a}$$

for each of the first three types of capital, and

$$log \left[\frac{X_{it}}{L_t} \right] = \frac{1}{\gamma - 1} \; log \left[\frac{\alpha_6 \; p_{it}}{\alpha_5 \; p_{6t}} \right] \tag{7b}$$

15. Averch-Johnson [1962] argued to the contrary that a regulated firm will not use a cost-minimizing technology. However, Bawa-Sibley [1980] showed that if regulators set the price rather than the rate of return, then a regulated firm would choose a cost-minimizing technology.

16. More generally, $Q^c(\cdot)$ is assumed to be proportional to the expression appearing in equation (3), since any proportionality factor can be eliminated through a suitable redefinition of λ_t and Q_t^*.

for $i=4,5$ where $X_{4t}=K_{4t}$ and $X_{5t}=M_t$. To complete the specification of these equations, we need data on each of the factor prices. The materials price, p_{5t}, was set equal to the real price of materials in manufacturing in each year, while the labor price, p_{6t}, was set equal to the real wage in each year.

In constructing a measure for the cost of each of the four types of capital, we used a modified version of the cost of capital developed by Hall-Jorgenson [1967]. In particular, we set p_{it} equal to:

$$p_{it} = [(r_t + d_i + b_{it})(1 - u_t z_{it} - k_{it})/(1 - u_t) + x_t]P^k_{it} \tag{8}$$

where P^k_{it} equals the asset price for capital of type i in each year; u_t equals the statutory corporate tax rate in each year; r_t equals the real discount rate used by shareholders, arbitrarily set to a constant value of 0.04;[17] the parameters k_{it}, z_{it}, and x_t, equal the investment tax credit rate, the present value of depreciation deductions, and the indirect rate of tax on capital, respectively, each measured using the figures employed by Nadiri and Schankerman [1981]; and d_i equals the depreciation rate for each type of capital, measured using an exponential approximation to the retirement schedule that we estimated for each type of capital using company data.

The one new element in equation (8) is b_{it}, the obsolescence rate for each type of capital. While prior research on investment uniformly ignored obsolescence when measuring the cost of capital, we could not since obsolescence was the focus of our study. In constructing a measure of the rate of obsolescence, we assumed that the firm anticipates obsolescence to occur at a rate constant over time and equal to the rate of improvement in technology that year.[18] This rate of improvement in technology equals the percent change in $g_i(N_{it})$ that year, which, given our specification of technological change, equals approximately

17. Measuring how shareholder discount rates vary over time would be difficult and problematic.

18. The marginal product of the new vintage of capital rises by the rate of improvement that year. If the price of the new capital does not reflect this productivity improvement, then the value of capital of the previous vintage must decline by that percentage, which represents the rate of obsolescence. This argument would not be correct if the price of new capital rose to reflect the productivity improvement, but as we argued earlier, Western Electric prices generally do not reflect productivity improvements in new product design.

$$a\,\theta_i\,\frac{R_{it-3}^{\beta}}{(1+\theta_i\sum_j R_{it-j}^{\beta})}$$

This expression was substituted for b_{it} and estimated simultaneously with the rest of the model.

The factor demand equations, as written, are nonstochastic. We assumed that the actual relative factor demands are stochastic, given observed prices, and in particular added a residual to the right-hand side of each of the relative factor demand equations. Specifically, new investment in the latest vintage of each type of capital, and demand for materials, were viewed to be endogenous. One justification for this approach is that our information about input costs captures only some components of these costs, whereas actual demand depends also on many unobserved factors such as risk, time variation in interest rates, deviations from myopic expectations, etc. Obviously, other stories for why the data do not satisfy the specified factor demand equations exactly could be told.

In total, therefore, there are six random variables in the model: ϵ_t and the five factor demand residuals. We allowed in the estimation for an arbitrary pattern of covariances among these residuals. We also explored for the presence of first-order autocorrelation in each residual.

We did not attempt to include first-order conditions for optimal R&D expenditures. Since our ultimate aim is to test whether R&D earns an adequate return in each area of research, it would be inappropriate to constrain our coefficients to guarantee this result. However, we do attempt to calculate in each case the economic return from spending an extra dollar on R&D implied by our estimates.

II. Estimation Results

We first attempted to estimate equations (3) and (7a-b) by maximum likelihood techniques, assuming that the six residuals were jointly normally distributed, had an arbitrary variance-covariance matrix, and had first-order autocorrelation. (To limit the number of parameters, we assumed that each of the factor demand residuals had the same degree of autocorrelation.) In doing so, we immediately faced three separate problems. First, the estimate of the elasticity of substitution in the production function moved as close to zero as numerical stability would allow without converging. This result does not seem grossly inconsistent with what we were told about the technology of the company. While, for example, operators can substitute for switching capital, and more sophisticated switching capital can make more efficient use of the transmission network, and so substitute for transmission capital, such possibilities for substitution among factors are normally very limited. Yet fewer alternative technologies are close to being economically attractive.

When the elasticity of substitution is zero, the production function simplifies to a Leontief specification, where

$$Q_t = \min(\{\alpha_i F_{it}\}, i = 1,6) .$$

We attempted to estimate this Leontief specification directly, but found doing so very difficult since the first derivatives of the implied likelihood function are discontinuous in the parameters. The best strategy we could find for estimating the model was to return to the CES specification, but constrain the elasticity of substitution to a very low value (we chose the value 0.1), though not so low as to cause numerical instability, then estimate the other parameters. At this low an elasticity of substitution, the CES function provides a reasonably close approximation to the Leontief specification, but one whose likelihood function possesses continuous first derivatives.

The second problem we encountered was that the parameters in the specification of the R&D technology failed to converge. In particular, the parameter a keep growing without bound, while the θ_i's kept shrinking in an offsetting fashion towards zero. But as a increases, the specification of the technology converges towards

$$exp\,(a\theta_i \sum_{j=3}^{\infty} R^{\beta}_{i,t-j}) \tag{9}$$

We therefore adopted the limiting exponential specification

$$exp\,(\theta_i \sum_{j=3}^{\infty} R^{\beta}_{i,t-j}) \tag{9a}$$

where, with a slight abuse of notation, we have replaced the term $a\theta_i$ in (9) with θ_i in (9a). Under the exponential specification, a given level of expenditures will produce the same percent improvement in the productivity of new capital in each year of our sample. The data, therefore, suggest that technological change is no more difficult now than it was at the beginning of our sample -- we find no evidence of a technological slowdown.

In order to get parameters to converge, we therefore adopted equation (9a) as our specification of embodied technological change and reestimated the model. The third problem we encountered is that we were unable to obtain a plausible estimate of returns to scale. In particular, without constraint, the data suggested sharply *declining* returns to scale and correspondingly large rates of technical change. We have been unable to discern why this should be so. But this result is so implausible that we have estimated our model at a variety of fixed returns to scale, i.e., $\delta=.8$, 1.0, and 1.25. Below, we examine the results for constant returns to scale rather exhaustively, but report some estimates for the other cases as well.

A. Analysis of Results for the Basic Model

The coefficient estimates and log-likelihood function value (LLF) that result when $\delta = 1.0$ are listed in the first column of Table 1; ρ_1 and ρ_2 are the autocorrelation coefficients for the production and input equations, respectively. Asymptotic standard errors are computed using the procedure derived in White [1982]. The estimated values of all the coefficients are very plausible, and all but the three θ_i are very tightly estimated. The reason for these large standard errors is that the data are not rich enough to allow us to differentiate clearly the values of the θ_i relative to the value of β. When we constrain the value of β to its estimated value and reestimate, the reported standard errors for the θ_i drop to less than one-tenth their previous size.

The three θ_i coefficients are not directly comparable to the other R&D coefficients. The values of ϕ_i for other capital, labor, and materials, measure the fraction by which the productivity of that factor improves each year. For example, the estimates suggest that labor has been increasing in productivity by 5.3% per year. New investment in one of the first three factors increases in productivity each year by approximately $\theta_i R_{t-3}^{\beta}$, a fraction which grows throughout the sample period since R&D expenditures grow throughout the period. These coefficients imply that at the beginning of our sample period, productivity of new investment in these factors was growing at between one and two percent per year, while at the end of our sample period, productivity was growing between 4.6% and 6.2% per year.

These estimates imply that during most of the sample period technical change has been increasing the productivity of labor relative to that of other factors. Given a Leontief production function, this implies that the forecasted demand for labor drops during the sample period relative to that for other factors as a result of technical change -- technical change does appear to have been labor saving in

Table 1

Parameter Estimates for Models with Embodied Technical Change

PARAMETER	$\delta=1$	$\delta=.8$	$\delta=1.25$
α_{COE}	1.053 (0.97)	2.386 (.401)	.564 (.018)
α_{TR}	.428 (.052)	.897 (.153)	.252 (.015)
α_{SE}	1.040 (.101)	2.309 (.322)	.571 (.027)
α_{OTH}	.708 (.074)	1.209 (.165)	.496 (.055)
α_{MAT}	4.612 (.548)	8.026 (1.192)	3.445 (.447)
α_{L}	.222 (.021)	.392 (.043)	.164 (.019)
θ_{COE}	.980 e-03 (.986 e-03)	6.270 e-03 (3.922 e-03)	.113 e-04 (.074 e-04)
θ_{TR}	1.598 e-03 (1.532 e-03)	8.598 e-03 (5.074 e-03)	.294 e-04 (1.92 e-04)
θ_{SE}	2.384 e-03 (1.743 e-03)	10.527 e-03 (4.605 e-03)	.728 e-04 (.397 e-04)
ϕ_{OTH}	.0241 (.0023)	.0428 (.0030)	.0106 (.0024)

PARAMETER	$\delta=1$	$\delta=.8$	$\delta=1.25$
ϕ_{MAT}	.0118 (.0024)	.0303 (.0030)	-.0032 (.0027)
ϕ_L	.0526 (.0021)	.0707 (.0022)	.0380 (.0026)
β	.669 (.202)	.400 (.125)	1.390 (.121)
ρ_1	.666 (.080)	.682 (.088)	.713 (.056)
ρ_2	.829 (.046)	.850 (.039)	.825 (.055)
LLF	-1043.92	-1028.82	-1061.80

form.

Various procedures can be used to estimate what the marginal rate of return was to extra R&D expenditures, based on our coefficient estimates. To begin with, let us ignore any role of R&D in the productivity changes in labor, materials, and other capital, and measure just the value of the increase in productivity of new investment in the first three forms of capital. If an extra dollar is spent on R&D in year t, focusing on the technology of capital of type i, then the productivity of new investment in this type of capital increases by approximately $\theta_i \beta R_{it}^{\beta-1}$ percent starting in three years. If new capital is a% more productive, then a% less need be invested, at a saving of a% of the expenditures on this new capital. These savings continue indefinitely, making the calculation of the total savings very difficult. However, if R&D expenditures were simultaneously reduced in year $t+1$ by the "right" amount, then the productivity of new investment in years starting in $t+4$ would be left unaffected. Simple algebra shows that the right amount is $(R_{it}/R_{it+1})^{1-\beta}$. With this pair of changes in R&D, new investment improves in productivity by the above a% only in year $t+3$. The cost of this savings is the dollar extra spent on R&D in year t, less the present value of the amount less spent on R&D in year $t+1$. If the real rate of interest is r, then the ratio of savings relative to cost for extra expenditures on R&D, (i.e., the benefit/cost ratio for the marginal R&D expenditure), can be expressed as:

$$\frac{(\theta_i \beta K_{t+3,i,t+3})}{[(1+r)^3 R_{it}^{1-\beta} - (1+r)^2 R_{it+1}^{1-\beta}]} \tag{10}$$

where $K_{t+3,i,t+3}$ is the amount of vintage $t+3$ type i capital surviving at $t+3$, i.e. the new investment made at $t+3$. If this ratio is above one, then the expenditure is clearly worthwhile.

If we assume that the firm carries out R&D until the benefits of the last dollar spent equal the cost evaluated at some value for r, we can equate (10) to unity and solve for r to obtain the internal rate of return to R&D expenditures. In Table 2, we report the results of this exercise averaged over three sample periods for R&D expenditures on each of the three types of telephone-specific capital. The fourth row reports the average of the weighted mean of the capital-specific returns, with the weights being the proportion of total R&D expenditures specific to each capital type.

Examining Table 2, we find that rates of return to R&D have been increasing over time, and that the rank order of rates of return is station equipment,

Table 2

Real Rates of Return to R&D

Assuming Embodied Technical Change and

Constant Returns to Scale (Percent)

	1947-56	1957-66	1967-78
Central Office Equipment	3.63	4.98	8.34
Transmission	15.6	20.4	22.8
Station Equipment	29.7	38.0	43.4
Average	11.5	15.4	18.1

transmission, and central office equipment. We also find there that the weighted average (real) rate of return to R&D is well above the rate generally prevailing in the economy. For example, the risk-free real rate is at best 4%; while the average return to corporate capital has been estimated by Feldstein and Summers [1977] to be about 10.5%-12%. In comparison, the weighted average rate of return to R&D is estimated to be 18%. Since R&D is arguably riskier than most capital investment activities, 18% may well be appropriate after adjusting for risk.[19]

The figures in Table 2, however, ignore the productivity gain in labor, materials, and other capital. Presumably these gains were also the result of the same R&D effort, though we have not attempted to parameterize this relationship. To indicate the importance of including the effect of these productivity gains in the last three factors in any measure of the return to R&D effort we present in Table 3 average annual increases in productivity for each of the six inputs, as well as the proportion of total costs accounted for by each. For each of the last three inputs--other capital, materials, and labor--a constant percentage annual increase in productivity is directly estimated by the model (i.e. ϕ_j). For the telephone-specific capital inputs, productivity is given by the function $g_i(N_{it})$ defined in (9a), which is dependent on the history of R&D expenditures. However, for purposes of comparison, we can convert figures of the latter type to (average) percentage annual increases in input productivity. (To do this, suppose z_0 is the productivity of new capital at time t_0, and z_t the productivity at t; then the value we seek is ϕ satisfying $z_t = z_0 e^{\phi(t-t_0)}$).

Examining Table 3, we see that there has been a distinct acceleration of technical progress in the telephone-specific capital inputs, but that technical progress in labor has been equally large.[20] Since labor is an important input (accounting for 30.5% of costs), our figures in Table 2 substantially underestimate the return earned on R&D effort. We have no direct evidence on how to attribute this other prodctivity gain to each of the three categories of R&D effort.

19. This finding is quite consistent with the estimated rate of return to R&D in Schankerman and Nadiri [1985]. Using a model of disembodied technical change and a somewhat different concept of the rate of return, they estimate the average return to R&D over the period 1947-1976 at about 10%-15%.

20. Recall from Section 1 that the rates of productivity increase reported in Table 3 for the first three categories of capital represent the rate of obsolescence induced by technical change. These rates of technological obsolescence compare with the physical depreciation rates of 6.9%, 5.8%, and 12.5%, for the three types of capital, respectively.

Table 3

Annual Rates of Productivity Increase,

by Input (Cost Shares in Parentheses)

	1947-1981	1971-1981
Central Office equipment	2.49 (.114)	4.07 (.110)
Transmission equipment	3.76 (.227)	5.58 (.244)
Station equipment	2.26 (.143)	3.67 (.141)
Other capital	2.41 (.070)	2.41 (.072)
Materials	1.18 (.115)	1.18 (.127)
Labor	5.26 (.332)	5.26 (.305)

However, casual evidence suggests that labor savings may have been due primarily to R&D in switching technologies,[21] so that the relative rates of return to the different categories of R&D may have been more equal that the figures in Table 2 suggest.

A rough idea of the size of this effect can be derived as follows. Using the second column of Table 3, one can calculate an overall annual productivity increase of about 4.25% (the summation of the products of the cost shares and productivity increases). Of this, about 1.6% is due to increases in labor productivity, and about .45% due to embodied productivity gains in central office equipment. If we arbitrarily assume, for example, that half of the 1.6% gain in labor productivity is in fact due to improvements in central office equipment, and the other half is due to labor quality improvements relative to wage rates, then the estimated benefits of central office equipment research would about triple. Thus, an important source of the returns to R&D in central office equipment research is likely to take the form of labor-saving rather than capacity-improving technical change. Making this assumption and recalculating Table 2, we find that the rate of return to central office equipment R&D becomes, by decade, 10.5, 14.0, and 21.4 percent (as opposed to 3.63, 4.98, and 8.34 percent), respectively. Similarly, the average returns to R&D become 14.6, 19.5, and 24.5 percent (compared to 11.5, 15.4, and 18.1 percent), respectively. Thus, if improvements in central office equipment are largely responsible for the labor savings the Bell System experienced, rates of return to central office equipment R&D are comparable to those for transmission R&D.

Finally, it should be recognized that even these estimates of the return to R&D are likely to be underestimates, to the degree that Western Electric funded R&D expenditures at Bell Labs. To the degree that Western recovered its expenditures through increased prices for its equipment (as discussed in section 1), our figures measure surplus return over costs on R&D, rather than total return. Since about 60% of Bell Labs' research was funded by Western, our rates of return should be increased by about half.[22]

21. For example, direct dialing led to a reduction in operators, and stored program controlled electronic switching led to a reduction in maintenance labor.

22. As argued in footnote 11, even these figures will be a slight underestimate, since Western Electric amortizes R&D very quickly.

B. Results for Alternative Models

In addition to the above specification, we also estimated several variations on it. For example, if we assume that all capital is utilized, ignoring our data to the contrary, then the coefficient estimates hardly change at all, though the value of the likelihood function is slightly worse. (The value of the log likelihood function falls by 4.1) We also tested the sensitivity of our results to changing the assumed degree of economies to scale. In the second and third columns of Table 1, we report summary results when we set the economies to scale parameter to either 0.8 or 1.25. As reported earlier, the value of the likelihood function is larger the lower the degree of economies to scale. Not only is the value of the likelihood function smaller, however, when we assume economies to scale, but also the value of β is no longer plausible -- whenever β is above one, it is preferable to concentrate R&D effort in one year rather than doing it steadily over time. Taken together, this provides weak evidence against important economies to scale in the Bell System. However, the calculated benefit-cost ratios and rates of return for marginal R&D expenditures do not change markedly as the assumed economies to scale varies. In Table 4 we report average rates of return for 1967-1978 for the three models reported in Table 1. There we find that estimated returns to R&D *increase* as the assumed returns to scale increase. This is due to the higher estimates of β corresponding to higher values of δ. For the more plausible estimates of β coresponding to δ's of .8 and 1.0, the estimated rates of return are quite similar. Thus, even if we remain uncertain about the degree of economies to scale, we can be reasonably confident about the general magnitude of the return to R&D effort.

In the final specification that we report, we assume that technical change is entirely disembodied. In particular, we assume that R&D effort on capital of type i in year t increases the productivity of all capital of type i in place in year $t+3$, and not just the productivity of new investment. Summary results are reported in Table 5. The value of the likelihood function is substantially worse here than previously. Otherwise, the results continue to look very plausible.

The procedure for calculating the benefit-cost ratio for R&D expenditures with this specification is slightly different than before. As before, if a dollar more is spent on R&D of type i in year t, and $(R_{it}/R_{it+1})^{1-\beta}$ dollars less is spent in year $t+1$, then productivity changes only in year $t+3$. Now, however, the entire capital stock of type i increases in productivity. The resulting measure of benefits relative to costs would be

Table 4

Real Rates of Return to R&D 1967-1978

Assuming Embodied Technical Change Under

Alternative Assumptions on δ

	$\delta=.8$	$\delta=1.0$	$\delta=1.25$
Central Office Equipment	6.7	8.3	12.1
Transmission	18.1	22.8	36.2
Station Equipment	39.2	43.4	50.4
Average	15.0	18.1	25.6

Table 5

Parameter Estimates for Model with

Disembodied Technical Change and

Constant Returns to Scale

PARAMETER	VALUE	STANDARD ERROR
θ_{COE}	2.078 e-04	1.753 e-04
θ_{TR}	3.333 e-04	2.654 e-04
θ_{SE}	7.906 e-04	4.861 e-04
ϕ_{OTH}	.0222	.0018
ϕ_{MAT}	.0126	.0019
ϕ_{L}	.0542	.0020
β	.887	.157
ρ_1	.589	.064
ρ_2	.797	.060

LLF = -1066.31

$$\frac{\theta_i \beta (\sum_{v} K_{vit+3})}{[(1+r)^3 R_{it}^{1-\beta} - (1+r)^2 R_{it+1}^{1-\beta}]} \tag{11}$$

The internal rates of return implied by setting this ratio to unity are reported in Table 6 for the same time periods as previously. While the figures for the first two decades are smaller than the equivalent figures in Table 2, those for the remaining years are larger; taken together, Table 6 implies a greater acceleration in technical progress than does Table 2. This greater acceleration arises primarily from the higher estimate for β in the disembodied model. With a higher β, the marginal value of extra R&D does not drop as quickly when the R&D budget is larger.

The higher estimates of the recent rate of return to R&D with the model of disembodied technical change do not necessarily imply more rapid rates of annual productivity gain, however. With disembodied technical change, the benefits from improved productivity are immediately realized on the entire capital stock (rather than on new capital only) so the present value of the benefits can be larger even if the overall productivty gain each year is not. For example, the estimates from Table 5 imply an annual productivity gain for transmission capital during the period 1971-1981 of 4.62%, which is less than the 5.58% annual gain reported previously in Table 3. In spite of this the estimated return to R&D implied by the disembodied model is higher (37.4% vs. 22.8%).

The evidence of this paper suggests that the embodied model of technical change is more consistent with the data than the disembodied model is, as *a priori* considerations would suggest. However, for the Bell System, the estimated return to R&D is high under either specification.

III. Conclusion

This paper developed an econometric model of the effects of R&D effort on the magnitude and the characteristics of technical change in the Bell System. Our principal conclusions from our empirical results were:

1. The return to R&D effort has been very high and increasing over time.

2. The data support our presumption that technical change has been capital-embodied rather than disembodied.

3. However, technical change is not solely capital-augmenting. There are important improvements in labor productivity during the sample period.

Table 6

Real Rates of Return to R&D

Assuming Disembodied Technical Change and

Constant Returns to Scale (Percent)

	1947-56	1957-66	1967-78
Central Office Equipment	2.50	4.28	11.9
Transmission	7.23	13.77	37.4
Station Equipment	12.9	23.0	50.6
Average	5.62	10.5	26.2

4. The results provide limited evidence against important returns to scale in the Bell System.

5. The estimated elasticity of substitution in our CES production function is close to zero, suggesting that a Leontief production function may be a good approximation.

These results differ in a number of ways from those found in earlier studies. While the finding of a Leontief or nearly Leontief technology is perhaps not surprising, it is inconsistent with most studies of the industry, including Nadiri and Schankerman [1981], Schankerman and Nadiri [1985], and Evans and Heckman [1981]. Those models, however, did not disaggregate capital, and so are somewhat less realistic than ours in this regard. However, we have assumed the more restrictive CES functional form. A critical factor in estimating the elasticity of substitution is good quality data on factor prices--random errors in the measurembnt of factor prices should lead to a downward bias in estimates of the elasticity. For the most part our data on factor prices were very similar to those used in previous studies. However, unlike previous studies we allow for the various effects of technical change on relative *hedonic* factor prices, that is, factor prices adjusted for changes in the productivity of each input. Another problem with our results is that our model failed to produce a plausible estimate for the degree of economies of scale. However, our results on the return to R&D effort are reasonably insensitive to what we assume about the degree of economies to scale.

Even with these shortcomings, however, we believe that the models presented here are substantial improvements over the conventional methodology for measuring the impact of R&D on technical progress. Our principal advantage over previous studies was access to a much richer data base, including data on the vintage decomposiiton of the capital stock. Our results support a presumption that technical change is embodied in new capital, and suggests that any estimates of the rate of return to R&D or of how it has changed over time are likely to be very sensitive to the way in which the process of technical change is modeled.

REFERENCES

Averch, H. and L.L. Johnson. "Behavior of the Firm under Regulatory Constraint." *American Economic Review* 52 (Dec., 1962), 1052-1069.

Baily, Martin N. "The Productivity Growth Slowdown by Industry." *Brookings Papers on Economic Activity* (1982:2), 423-455.

Bawa, Vijay S. and David S. Sibley. "Dynamic Behavior of a Firm Subject to Stochastic Regulatory Review." *International Economic Review* 21 (Oct., 1980), 627-642.

Evans, D. S. and J. J. Heckman. "Multiproduct Cost Function Estimates and Natural Monopoly Tests for the Bell System." in D. S. Evans, ed. *Breaking Up Bell: Essays on Industrial Organization and Regulation*. New York: North-Holland, 1983.

Feldstein, M. S. and L. H. Summers. "Is the Rate of Profit Falling?" *Brookings Papers on Economic Activity* (1977:1), 211-228.

Griliches, Zvi. "Returns to Research and Development Expenditures in the Private Sector." In Kendrick, J.W. and B. W. Vaccara, eds. *New Developments in Productivity Measurement and Analysis*. Chicago: University of Chicago Press, 1980.

Griliches Zvi and Jacques Mairesse. "Productivity and R&D at the Firm Level." N.B.E.R. Working Paper #826, 1981.

Hall, Robert E. and Dale W. Jorgenson. "Tax Policy and Investment Behavior." *American Economic Review* 57 (June, 1967), 391-414.

Kendrick, John. *Postwar Productivity Trends in the United States 1948-1969*. New York, 1973.

__________. "Productivity Trends and the Recent Slowdown." In William Fellner, ed. *Contemporary Economic Problems*. Washington, 17-69

Kendrick, John W. and Elliot S. Grossman. *Productivity in the United States:*

Trends and Cycles. Baltimore: John Hopkins University Press, 1980.

Mansfield, Edwin. "Basic Research and Productivity Increase in Manufacturing." *American Economic Review* 70 (Dec., 1980), 863-873.

Nadiri, M.I., and M.A. Schankerman. "The Structure of Production, Technological Change, and the Rate of Growth of Total Factor Productivity in the U.S. Bell System," in T. Cowing and R. Stevenson, eds. *Productivity Measurement in Regulated Industries*. New York: Academic Press, 1981.

Schankerman, Mark and M.I. Nadiri. "A Test of Static Equilibrium Models and Rates of Return to Quasi-Fixed Factors, with an Application to the Bell System," unpublished paper, New York University (1985).

White, Halbert. "Maximum Likelihood Estimation of Misspecified Models," *Econometrica*, 50 (1982), 1-26.

Appendix

Construction of Capital Stock Data

In the estimation, data were needed for each value of K_{vit}. Such a decomposition of the capital stock at each date by type of capital and data of investment is rarely available. For the Bell System, it was available in just this form for 1959, 1966, 1972 and since 1977. In other years, gross investment and gross retirements as well as total capital, by type of capital, were available, but not broken down by calendar vintage.

In order to fill in the data set for missing years, we estimated a survival probability curve for each of five types of capital (switching, transmission, buildings, telephones, and other) using the available data. The parametric specification chosen for the survival probability curve was

$$P(t) = s^t h^{(c^t - 1)}, \tag{A.1}$$

where $P(t)$ is the fraction surviving to age t, and s, h, and c are the parameters to be estimated. This functional form, taken from demography literature, provides a very flexible approximation to actual survival curves. The three parameters were chosen so as to minimize the sum of squared deviations of observed percents surviving from forecasted percents surviving for investment occurring after 1927, as observed in any of the nine surveys of the decomposition of the capital stock, separately for each of the five types of capital. Note that we implicitly assume that rates of retirement of older technologies are exogenous, rather than depending on the relative cost advantage of later technologies. This assumption greatly simplifies the analysis.

The estimated survival curves were then used to construct an age breakdown of the capital stock at each date for each of the five types of capital. All designs of a given type of capital were assigned the same survival curve. The basic approach was to use the survival curve to forecast how much capital from each calendar vintage would still be in use in each year, given the initial investment in that vintage.

In constructing values for the missing observations of K_{vat}, however, several problems had to be faced. First, we had no data on the amount of new investment in each type of capital prior to 1928, though did observe the total capital stock of each type in 1928. Rather than attempting to decompose this initial capital stock into various calendar vintages by some procedure, we simply assumed that the entire initial capital stock had been purchased in one particular year prior to 1928. The particular year selected varied by type of capital, and was chosen so as to minimize the average error in our forecast for the aggregate capital stock of a given type during the period 1928-1937.

Another problem faced in constructing the K_{vit} was that the aggregate capital stock of a given type observed in the data each year invariably differed from our forecast for this aggregate capital stock (the sum of our forecasts for the surviving capital from each calendar vintage). Also the actual and the forecasted figures for the surviving capital stock from each vintage differed slightly, in the years in which actual figures were available. While all these differences were small, particularly in recent years, we chose to modify our forecasts slightly so as to match exactly both the observed surviving vintage capital stocks, where they existed, and the observed aggregate capital stocks of each type in each year.

Our first step was to reconcile the actual figures on surviving capital 1959 with the forecasted figures, $p_a(59-t)\cdot K_{tit}$, where K_{tit} is the initial investment in type i in year t. In doing so, we assigned each vintage of capital of each type a virtual age A_{it} in 1959, differing from its calendar age, chosen so that at this virtual age, actual and forecasted figures for surviving capital in 1959 match exactly. For each year y between t and 1959, the forecasts for surviving capital were then modified to $p_i(A_{it}(Y-t)/(1959-t))\cdot K_{tit}$.

In order to reconcile our forecasts of the aggregate capital stocks of each type in each year with the actual observations, we proceeded as follows. Note first that totals match in 1959, since all figures are observed. In 1958, however, actual and forecasted aggregate figures differed slightly. To reconcile the two, we modified the extent of aging between 1958 and 1959 from exactly one year for all vintages, until the actual and forecasted figures matched exactly. In particular, the vintage capital stocks in 1958 were set equal to $p_i(A_{it}(59-t-\lambda_{i58})/(59-t))\cdot K_{tit,}$ where the γ_{i58} were chosen so that the actual and the forecasted aggregate figures matched. For 1957, the procedure was the same, now treating 1958 as if it were actual data, so that vintage capital stocks in 1957 equaled $p_i([A_{it}(59-t\gamma_{i58})/(59-t-\gamma_{i57})/(58-t)][(58-t-\gamma_{i57})/(58-t)])\cdot K_{tit}$. This procedure for constructing the K_{vtit} was carried back until 1947, the beginning of our estimation sample.[23]

In interpolating between surveys of the vintage composition of the capital stock since 1959, we used a much simpler procedure, since inconsistencies between actual and forecasted figures were very small for the recent data. In particular, we extrapolated forward from the last available observation on the vintage capital stocks, for example setting the vintage capital stocks in 1969 equal to $K_{66it}P(1969-t)/P(1966-t)$.

23. If at any time, the constructed age for a unit of capital was negative, it was assumed to have an age of zero.