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THE DYNAMICS OF PRODUCTIVITY IN THE TELECOMMUNICATIONS EQUIPMENT INDUSTRY

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Technological change and deregulation have caused a major restructuring of the telecommunications equipment industry over the last two decades. Our empirical focus is on estimating the parameters of a production function for the equipment industry, and then using those estimates to analyze the evolution of plant-level productivity. The restructuring involved significant entry and exit and large changes in the sizes of incumbents. Firms' choices on whether to liquidate, and on input quantities should they continue, depended on their productivity. This generates a selection and a simultaneity problem when estimating production functions. Our theoretical focus is on providing an estimation algorithm which takes explicit account of these issues. We find that our algorithm produces markedly different and more plausible estimates of production function coefficients than do traditional estimation procedures. Using our estimates we find increases in the rate of aggregate productivity growth after deregulation. Since we have plant-level data we can introduce indices which delve deeper into how this productivity growth occurred. These indices indicate that productivity increases were primarily a result of a reallocation of capital towards more productive establishments.

KEYWORDS: Selection, simultaneity and production functions, productivity, telecommunications equipment and deregulation.

1. INTRODUCTION

THERE HAS BEEN A MAJOR RESTRUCTURING of the U.S. telecommunications equipment industry over the last two decades, and it can be explained, in large part, by a combination of two related factors. One was technological change which led to the development of many new products (e.g., digital switching equipment and fiber optics). The other factor was a gradual liberalization of the regulatory environment (in both the provision of telecommunication services and in the use of telecommunications equipment) which culminated in the divestiture of AT&T in January of 1984. Together these changes provided many new firms, both foreign and domestic, an opportunity to enter the industry, and caused dramatic changes in the sizes of incumbents. The empirical focus of this paper is on estimating the parameters of a production function for the equip-

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ment industry, and then using those estimates to analyze changes that occurred in the distribution of plant-level performance between 1974 and 1987, paying particular attention to the impact of the regulatory and technological changes on aggregate productivity.

The data at our disposal are a rich plant-level panel constructed from the files of the U.S. Bureau of the Census. It is clear from the data that during the period under investigation the restructuring of the industry involved significant entry and exit, and large changes in the size of continuing establishments.[2] As we show below, firms' choices of whether to liquidate, and of input quantities should they continue, depend on output (or deflated sales) per unit of inputs consumed, or their "productivity," a variable with substantial interplant variance and correlation over time.

As a result, to obtain consistent estimates of production function parameters we have to address two interrelated estimation problems: a selection problem generated by the relationship between the unobserved productivity variable and the shutdown decision, and a simultaneity problem generated by the relationship between productivity and input demands. Though this selection problem has been discussed in the empirical literature at least since the work of Wedervang (1965), we do not know of a previous estimation algorithm that takes explicit account of it. Formal analysis of the simultaneity problem dates back at least to the classic work of Marschak and Andrews (1944).[3]

The theoretical focus of this paper is on providing an algorithm for estimating production function parameters which takes explicit account of the self-selection induced by liquidation and the simultaneity induced by the endogeneity of input demands; an algorithm which we hope will be of more general use. To this end, we need a model which determines both exit times and input decisions. We introduce a dynamic model of firm behavior which allows for firm-specific, or idiosyncratic, sources of change, and for the equilibrating forces of entry and exit.

The model provides a framework for analyzing the biases in traditional estimators that result from selection and simultaneity, and for building alternative estimation algorithms that circumvent these biases. One possibility is to add the structure needed to derive exact expressions for the shutdown and input demand decisions. This would be computationally burdensome, and require a host of auxiliary assumptions. Instead, we develop a semiparametric estimator

[2] Related empirical work indicates that it is not uncommon to find entry, exit, and gross job flow rates similar to those in our data (this work dates back at least to Wedervang (1965); for more recent analyses see Baldwin and Gorecki (1989), Dunne, Roberts, and Samuelson (1988), and Davis and Haltiwanger (1992)).

[3] Productivity is defined here, as elsewhere, as the residual from a relationship between deflated sales and inputs; a definition which gives it a central role in policy debates. If the industry has a single product and the deflator is specific to that product, then productivity has the traditional interpretation of a production function residual. If not, measured productivity is a residual from a reduced form sales equation that is assumed to be stable over the period. Either way the productivity variable will generate the simultaneity and selection problems dealt with in this paper.

for the production function parameters. This estimator is consistent with a quite general version of the theoretical framework, and easy to use. It does rely on the assumption that there is only one *unobserved* state variable that causes differences in firm behavior at a given point in time (its productivity), and that, conditional on the values of all the observed state variables, investment is increasing in productivity (at least for a known subset of the sample). So, we provide some simple tests of whether a single firm specific unobservable is sufficient to account for the impact of simultaneity and selection on the parameter estimates.

We now summarize our empirical findings. A traditional way of accounting for entry and exit when using firm level data is to construct a "balanced" panel, keeping only those firms that operate the entire sample period, and then compute either an O.L.S., or "within," estimator of the production function coefficients. Under certain simplifying assumptions (Mundlak (1963)) the within estimator, which uses deviations from firm-specific means in O.L.S. estimation, controls for simultaneity caused by endogenous input demands. So, we compare our estimator to the within and O.L.S. estimators from the balanced panel constructed from our data, as well as the within and O.L.S. estimators from the full sample (constructed by keeping firms that eventually exit until the year prior to their exit and introducing new entrants as they appear).

We find that going from the balanced panel to the full sample more than doubles the capital coefficient, and decreases the labor coefficient by about 20%. The apparent signs of the biases in the balanced panel coefficients are exactly what theory predicts and explain anomalies in production function coefficients estimated from balanced panels. Moving from either the total or within estimators on the full sample to our estimator causes further, though less dramatic, movements of both coefficients in the predicted directions. In particular, our estimate of the capital coefficient is twice again as large as the within estimator from the full sample, and our estimate of the labor coefficient is almost 15% lower than the O.L.S. estimator from the full sample.

When we use our production function estimates to construct measures of aggregate productivity (constructed as an output share weighted average of the productivities of all active plants), we find that aggregate productivity increases sharply after each of the two periods in which the industry underwent changes that decreased regulation. One advantage of micro data is that we can disaggregate and delve deeper into this productivity growth. We introduce two measures. The first is a variable cost efficiency index. It measures the efficiency of labor allocation conditional on the extant joint distribution of capital and productivity. The second decomposes total productivity into the unweighted average of plant level productivities and the sample covariance between productivity and output share. The higher the covariance, the higher the share of output that goes to more productive firms, and the higher is industry productivity.

The variable cost efficiency index shows that aggregate productivity increases do not result from a more efficient allocation of variable factors of production *conditional* on the existing distribution of state variables among plants (the joint distribution of capital, productivity, and age). Thus, the increase in efficiency that followed the regulatory changes came from either a reallocation of fixed inputs to more productive enterprises, or from increases in average productivity growth of the plants. Our decomposition of industry productivity provides no evidence of an increase in the (unweighted) average productivity, but shows sharp jumps in the plant level covariance of output share and productivity after each of the regulatory changes.

The realized productivity gains, then, seem to result from a reallocation of output to more productive plants. Since there is no evidence of variable factors being reallocated to firms whose capital-productivity combinations warranted it, we look for evidence of a reallocation of *capital* towards more productive plants. A tabulation of the correlation of capital and productivity over the sample period, and the relationship between shutdown frequencies, on the one hand, and capital, age, and productivity, on the other, provides support for the capital reallocation explanation. That is, the productivity growth that followed regulatory change seemed to result from the downsizing (frequently the shutdown) of (often older) unproductive plants, and the disproportionate growth of productive establishments (often new entrants).

The next section provides a brief history of the telecommunications equipment industry and documents some changes in the regulatory structure. The data set is also described. Section 3 summarizes the theoretical model used to guide estimation. Section 4 provides the estimation algorithm, presents the parameter estimates and, in Section 4.1, examines their robustness to specification error. Section 5 uses our estimates to analyze the evolution of industry level productivity. The conclusion provides some caveats on the interpretation of our results and on the use of our estimation algorithm. The Appendix outlines how the data base was constructed.

2. OVERVIEW OF THE INDUSTRY

We begin with a brief review of recent developments in the telecommunications industry. This will illustrate the importance of the empirical phenomena which motivate the estimation strategy and provide some background for the empirical results.

Beginning in the early 1970's, the telecommunications industry entered into a period of rapid change. There were significant technological developments in telecommunications equipment and a gradual liberalization of the regulatory environment governing the provision of telecommunications services. Together these developments have led to a substantial restructuring of the U.S. telecommunications equipment industry. For the purposes of this study, we include in our definition of the industry practically all types of customer premise and network telecommunications equipment, with the exception of the various types of transmission media, such as copper wire, coaxial cable, and glass fiber (for details see the Appendix).

For most of the twentieth century, American Telephone and Telegraph (AT&T) maintained an exclusive monopoly in the provision of telecommunications services and, through their procurement practices, extended that dominant position into the equipment industry.[4] Initially, AT&T controlled the telephone patent, but AT&T's dominance in the equipment market was maintained by the requirement that any equipment attached to the Bell system network had to be supplied by AT&T itself. Prior to divestiture, Western Electric, AT&T's manufacturing subsidiary, supplied approximately 90% of AT&T's equipment purchases.[5] Given that AT&T was by far the largest purchaser of telecommunications equipment, entry into the equipment market was effectively prohibited.

At the manufacturing level, barriers to entry seemed to be no greater than in other electrical appliance industries.[6] The effective barrier to entry came from restrictions in the market for users of the equipment. An end-user could not legally attach a telephone set, or any other piece of terminal equipment, to the public network. This, together with AT&T purchasing equipment almost solely from Western Electric, meant that the only method of entry into the private equipment market was to establish a telephone company, a strategy that was generally prohibited by state regulatory authorities. As a result, Western Electric was relatively free from competitive pressures in the equipment market.

In recent years however, Western Electric's dominance in the equipment market has faded for two related reasons.[7] The transition from electromechanical to fully electronic technology in both the switching and transmission of signals opened up many new markets for telecommunications equipment (multiplexers, modems, facsimile machines,...). Also, changes in the telecommunications regulatory structure has provided new firms the opportunity to enter the equipment industry.

One of the first important decisions was the "Carterphone" decision of 1968. The Carter Electronics Company won an antitrust suit against AT&T after AT&T had prevented Carter from connecting a private two-way radio system to the network. The Carterphone decision, and subsequent rulings by the Federal Communications Commission (FCC) in support of the decision, paved the way for the interconnection of private equipment to the public network and entry into the equipment market.

The conditions restricting entry were further eroded in 1975 when the FCC established a registration and certification program to allow for the connection

[4] Brock (1981, p. 234).

[5] Office of Telecommunications (1986, p. 23). Also NTIA (1988, pp. 322–323).

[6] Brock (1981, p. 235). Temin (1987, p. 335) writes "there does not seem now nor has there been in the past an economic argument explaining why competition could not exist in the sale of telecommunications equipment."

[7] In 1982 the Census of Manufactures published for the first time the four-firm concentration ratio for SIC 3661, Telephone and Telegraph Apparatus. In previous years this number had been suppressed for disclosure purposes. See also NTIA (1988, pp. 305–350), and Temin (1987) for discussion of developments in the equipment industry.

TABLE I

CHARACTERISTICS OF THE DATA

Year	Plants	Firms	Shipments (billions 1982 $)	Employment
1963	133	104	5.865	136899
1967	164	131	8.179	162402
1972	302	240	11.173	192248
1977	405	333	13.468	192259
1982	473	375	20.319	222058
1987	584	481	22.413	184178

of private subscriber equipment to the network, in effect extending the Carterphone decision to all equipment that met FCC standards. By 1978, the program included PBX's, key telephone sets, and telephones. Thus the tie between the telephone service providers and the equipment industry had finally been broken.

The result of these changes was sustained entry into telecommunications equipment between 1967 and 1987.[8] A surge in entry began in the late 1960's and continued into the 1970's, as many small firms sought to take advantage of the Carterphone decision and the registration and certification program. Table I[9] documents this fact (for details on the construction of the database used in this paper, see Appendix 1 and Olley (1992)). Between 1967 and 1972 the number of plants and the number of firms in the industry almost doubled and there was substantial entry between all subsequent censuses.

Despite significant changes in the regulatory environment, in 1982 AT&T remained the largest service provider in the United States and, as a result, the largest purchaser of telecommunications equipment. As long as AT&T continued its practice of buying most of its equipment from its manufacturing subsidiary, Western Electric maintained a dominant position in the equipment industry, even in the face of the changes in the regulatory environment. The 1982 Consent Decree changed this situation dramatically. The agreement, signed in January 1982 and implemented in January 1984, called for the divestiture of AT&T's regional operating companies. The seven regional Bell operating companies (RBOC's) that were created from the Consent Decree are all very large companies in their own right. It is important to note that as a result of the divestiture the RBOC's are free to purchase equipment from any supplier and are prohibited from manufacturing equipment themselves. The effect of the Consent Decree on the fraction of Bell system companies' equipment purchases from Western Electric is illustrated in Table II.

[8] For example, there were only four PBX manufacturers in 1969, but more than thirty by 1980 (National Academy of Engineering (1984, p. 86)).

[9] Use of the LRD data is subject to the U.S. Bureau of the Census confidentiality rules which prohibit releasing any information that allows one to infer plant, or firm, level data.

TABLE II

BELL COMPANY EQUIPMENT PROCUREMENT
(PERCENT PURCHASED FROM WESTERN ELECTRIC)

1982	1983	1984	1985	1986[E]
92.0	80.0	71.8	64.2	57.6

[E] Estimated for 1986.
Source: NTIA (1988, p. 336, and discussion pp. 335–337).

TABLE III

ENTRANTS ACTIVE IN 1987

	Number	Share of Number Active in 1987 (%)	Share of 1987 Shipments (%)	Share of 1987 Employment (%)
Plants: New since 1972	463	79.0	32.8	36.0
Firms: New since 1972	419	87.0	30.0	41.4
Plants: New since 1982	306	52.0	12.0	13.5
Firms: New since 1982	299	60.1	19.4	27.5

Table I only tells part of the entry story. In addition to increased competition from U.S. manufacturers, the regulatory changes also induced competition from several large foreign producers. In 1972 and 1977 imports accounted for only 2% of new supply, and by 1982 that share only reached 4%. However, the share of imports rose steadily after 1982. By 1987 imports made up 14% of new supply.[10] This increase in the share of imports can account for a large part of the fall in domestic employment between 1982 and 1987 observed in Table I. Note that the import figures understate the share of the domestic market that the foreign suppliers captured, since many foreign suppliers have manufacturing facilities in the U.S.

Table III provides an indication of the importance of the entry process (in terms of domestic production). Almost 90% of the firms, and 80% of the plants, active in 1987 entered since 1972, and the new entities account for over 30% of shipments and 40% of employment. Many of the new entrants entered after 1982 (though the later entrants tended to be smaller as of 1987).[11]

Table IV provides an indication of the importance of the exit or liquidation process. 60% (70%) of the plants (firms) that were active in 1972 did not survive until 1987 and these plants (firms) accounted for 40.2% (13.8%) of 1972 employment and 39% (12.1%) of 1972 shipments. Over 40% of the plants that

[10] U.S. Industrial Outlook, various years.

[11] About 400 of the 419 new entrants were "de novo" new entrants; they enter by opening a new plant or transferring an existing plant into the industry. The others purchased a plant from an existing firm.

TABLE IV

INCUMBENTS EXITING BY 1987

	Number	Share of Number Active in Base Year (%)	Share of Shipments in Base Year (%)	Share of Employment in Base Year (%)
Plants active in 1972 but not in 1987	181	60.0	40.2	39.0
Firms active in 1972 but not in 1987	169	70.0	13.8	12.1
Plants active in 1982 but not in 1987	195	41.2	26.0	24.1
Firms active in 1982 but not in 1987	184	49.1	17.3	16.1

were active in 1982 did not survive until 1987, and these plants produced about 25% of 1982 output.[12]

3. THE BEHAVIORAL FRAMEWORK

Our empirical goal is to analyze changes in the distribution of productivity that accompanied the changes in the regulatory and technological environment outlined above. To do so, we need estimates of production function parameters. We noted that the changes in the environment were accompanied by a great deal of entry and exit, and as we show below, a major determinant of whether or not a plant exits is its productivity. There was also a great deal of productivity related change in the quantities of inputs used by the continuing establishments.

Given that a firm's productivity is not directly observable, the fact that exit and input demand decisions are based on it generates two problems in obtaining production function estimates. First, to the extent that differences in efficiency are known to firms when they choose their inputs, and we show below that the efficiency of a given firm is highly correlated over time, we face the classic simultaneity problem analyzed by Marschak and Andrews (1944).

Second, the entry and exit that accompanied the industry restructuring generates the issue of how to handle attrition from, and additions to, the data. Although researchers have drawn attention to the implications of entry and exit

[12] There is a question of whether there was more entry and exit than one would typically find in a manufacturing industry. Baldwin and Gorecki (1989) provide entry and exit figures for four digit Canadian manufacturing industries based on a plant level panel comparable to ours. Their figures are for a ten (rather than fifteen) year period, but when we multiply the figures they obtain as averages over all four digit industries by 3/2 to make them comparable to the figures in Tables III and IV, we obtain numbers for the share of employment in new plants and firms, and the shares of employment in plants and firms that eventually exit, that are very close to ours. On the other hand, their figures for the fraction of firms that are new, and the fraction of firms initially active that eventually exit, are smaller than the analogous numbers in our tables.

on production function estimates for some time,[13] there has been little formal analysis of their effects.

The traditional way of accounting for entry and exit restricts the analysis to a "balanced" panel, a data set that consists of only those firms that were present over the entire sample period.[14] If firms' exit decisions depend on their perceptions of their future productivity, and if their perceptions are partially determined by their current productivity, then a balanced panel sample will be selected, in part, on the basis of the unobserved productivity realizations. This will generate a selection bias of a particular form in the production function estimates. We illustrate this point by considering the balanced panel in the empirical section.

To analyze either the selection or the simultaneity problem we need a dynamic model of firm behavior that allows for firm-specific efficiency differences that exhibit idiosyncratic changes over time. To sort out the simultaneity problem, the model must specify the information available when input decisions are made. To control for the selection induced by liquidation decisions, the model must generate an exit rule.[15]

There are several models that allow for idiosyncratic uncertainty and entry and exit (Ericson and Pakes (1995), Hopenhayn and Rogerson (1993), Jovanovic (1982), and Lambson (1992)). The model used here combines features of the models in Ericson and Pakes, and in Hopenhayn and Rogerson. We now summarize aspects of the model needed for the input demand and the liquidation rules.

As in Ericson and Pakes, we assume that current profits are a function of the firm's own state variables, factor prices, and a vector which lists the state variables of the other firms active in the market. In our example the vector of firm specific state variables consists of a_t, the age of the firm, k_t, the firm's capital stock, and ω_t, an index of the firm's efficiency. A market structure consists of a list of these triples for all active firms. Factor prices are assumed to be common across firms and to evolve according to an exogenous first order Markov process.

At the beginning of every period an incumbent firm has three decisions to make. The first is to decide whether to exit or continue in operation. If it exits, it receives a sell-off value of Φ dollars and never reappears again. If it continues,

[13] For a recent example, see Davis, Gallman, and Hutchins (1991), who interpret the positive age effect in their analysis of the productivity of fishing vessels as resulting from a selection bias due to exit.

[14] Often fixed effects, or firm specific constants, are considered; see, e.g., Pakes and Griliches (1984). These authors note the possibility of biases from their sample selection procedure.

[15] Starting with Marschak and Andrews (1944), many articles have recognized the importance of having a behavioral model to evaluate alternative estimates of production function parameters. Griliches, for example, writes: "It is harder to make an adequate allowance for the simultaneity problem without constructing a complete production and input decision behavior model" (Griliches (1967, pp. 277–278)). Our approach differs from the previous literature in that our model is more detailed in its treatment of dynamics and industry equilibrium. We are particularly concerned with accounting for entry and exit.

it chooses variable factors (labor) and a level of investment, which together with the current capital value determine the capital stock at the beginning of the next period.

The accumulation equations for capital and age are given by

$$(1) \qquad k_{t+1} = (1-\delta)k_t + i_t \quad \text{and} \quad a_{t+1} = a_t + 1,$$

both of which hold with probability one. As in Hopenhayn and Rogerson (1993), the index of productivity, ω, is known to the firm and evolves over time according to an exogenous Markov process. The distribution of ω_{t+1} conditional on all information known at t is determined by the family of distribution functions

$$(2) \qquad F_\omega = \{F(\cdot|\omega), \omega \in \Omega\}.$$ [16]

The firm is assumed to maximize the expected discounted value of future net cash flows. Therefore, both the exit and the investment decisions will depend on the firm's perceptions of the distribution of future market structures given current information. The investment, entry, and exit decisions generated by these perceptions will, in turn, generate a distribution for the market structure in future years. Ericson and Pakes (1995) provide a formal definition for, and prove the existence of, a Markov perfect Nash equilibrium in investment strategies for a problem similar to ours—an equilibrium where firms' perceptions of the distribution of future market structures are consistent with the objective distribution of market structures that the firms' choices generate (Maskin and Tirole (1988)). Here we assume the existence of such an equilibrium and then use the investment and liquidation rules that result to structure estimation.

Both the profit and the value function in this equilibrium depend on the market structure and on factor prices. Since the values of these state variables do not differ across agents in a given period, we omit them from our notation and index the value and profit functions by time. This is a convenient way to note that the relationship of profits and value to the firm specific state variable depends on factor prices and market structure, and that these variables do not vary across agents in a given time period. The Bellman equation for an incumbent firm can then be written as

$$(3) \qquad V_t(\omega_t, a_t, k_t) = \max\Big\{\Phi, \sup_{i_t \geq 0} \pi_t(\omega_t, a_t, k_t) - c(i_t) + \beta E[V_{t+1}(\omega_{t+1}, a_{t+1}, k_{t+1})|J_t]\Big\}$$

[16] The Ericson-Pakes (1995) model has the distribution of ω_{t+1} conditional on past history dependent on the amount of investment in R&D, as well as on ω_t. Unfortunately we do not have the R&D data that would facilitate estimation of their model.

where $\pi_t(\cdot)$ is the restricted profit function giving current period profits as a function of the vector of state variables, $c(i_t)$ is the cost of current investment i_t, β is the firm's discount factor, and J_t represents information available at time t.

The max operator in (3) indicates that a firm compares the sell-off value of its plant (Φ) to the expected discounted returns of staying in business.[17] If the current state variables indicate continuing in operation is not worthwhile, the firm closes down the plant. If this is not the case the firm chooses an optimal investment level (constrained to be nonnegative). The solution to this control problem generates an exit rule and an investment demand function. If we define the indicator function χ_t to be equal to zero if the firm exits, then the exit rule and the investment demand equation are written, respectively, as

$$\chi_t = \begin{cases} 1 & \text{if } \omega_t \geq \underline{\omega}_t(a_t, k_t), \\ 0 & \text{otherwise}, \end{cases} \tag{4}$$

and

$$i_t = i_t(\omega_t, a_t, k_t). \tag{5}$$

The functions $\underline{\omega}_t(\cdot)$ and $i_t(\cdot)$ are determined as part of the Markov perfect Nash equilibrium, and will depend on all the parameters determining equilibrium behavior. In particular, these functions are indexed by t as they depend on the market structure and the factor prices prevalent when these decisions are made.

4. ESTIMATION

We assume that the industry produces a homogeneous product with Cobb-Douglas technology, and that the factors underlying profitability differences among firms are neutral efficiency differences.[18] The production function is

$$y_{it} = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + \beta_l l_{it} + \omega_{it} + \eta_{it}, \tag{6}$$

where y_{it} is the log of output (value added) from plant i at time t, a_{it} its age, k_{it} the log of its capital input, l_{it} the log of its labor input, ω_{it} its productivity, and η_{it} is either measurement error (which can be serially correlated) or a shock to productivity which is not forecastable during the period in which labor can be

[17] The assumption that Φ is independent of the firm's state variables is not necessary for our estimation strategy. However, if Φ is dependent on the state variables, then that dependence must satisfy certain regularity conditions for the analytic bias arguments developed in the next section to hold (see footnote 19).

[18] Though we maintain the assumption of the Cobb-Douglas technology in the empirical work in this paper, it is easy to generalize the estimation algorithm to allow for more general production technologies; translog with neutral efficiency differences across firms would do equally well (see Christensen, Jorgenson, and Lau (1973)). Our algorithm requires only that the production technology satisfies the invertibility condition used to go from equation (5) to (7) below (at least for some known subset of the data). This condition will be satisfied if the marginal productivity of capital is increasing in ω. See Pakes (1994, Section IV) for more detail.

adjusted. Here both ω and η are unobserved. The distinction is that ω is a state variable in the firm's decision problem, and hence a determinant of both liquidation and input demand decisions, while η is not.

We first consider the biases in the OLS estimates of (6) caused by endogeneity of input demands and by the self-selection induced by exit behavior. Endogeneity arises because input choices are determined (in part) by the firm's beliefs about ω_t when those inputs will be used. If there is serial correlation in ω_t inputs in period t will be positively correlated with it, and an OLS procedure that fails to take account of the unobserved productivity differences will tend to provide upwardly biased estimates of the input coefficients (moreover, we expect the more variable inputs to be more highly correlated with current values of ω_t; see Marschak and Andrews (1944) and Griliches (1957), for more detailed expositions).

Consider next the problem of self-selection induced by plant closings. Assuming, temporarily, that there are no variable factors (the estimation algorithm has a preliminary step which estimates their coefficients), the conditional expectation of y_t (conditional on current inputs, survival, and information available at $t-1$), includes the term

$$E[\omega_t | a_t, k_t, \omega_{t-1}, \chi_t = 1].$$

Recall that $\chi_t = 1$ if and only if $\omega_t > \underline{\omega}_t(a_t, k_t)$. Moreover, if the profit function is increasing in k, the value function must be increasing and $\underline{\omega}_t(\cdot)$ decreasing in k (see (3)). Firms with larger capital stocks can expect larger future returns for any given level of current productivity, and hence will continue in operation at lower ω realizations. Hence, the self-selection generated by exit behavior implies that $E[\omega_t | a_t, k_t, \omega_{t-1}, \chi_t = 1]$ will be decreasing in k, leading to a *negative* basis in the capital coefficient.[19]

We now describe our estimation algorithm. Labor is assumed to be the only variable factor (so its choice can be affected by the current value of ω_t). The other inputs, k_t and a_t, are fixed factors and are only affected by the distribution of ω_t conditional on information at time $t-1$ and past values of ω. In particular, the solution to the firm's optimization problem, (3), resulted in equation (5) for investment, i.e., $i_t = i_t(\omega_t, a_t, k_t)$. Provided $i_t > 0$, Pakes (1994, Theorem 27) shows that this equation is strictly increasing in ω (for every (a, k)). Consequently, for the subset of (i_t, a_t, k_t) values for which $i_t > 0$, we can invert (5) and write

$$\omega_t = h_t(i_t, a_t, k_t). \tag{7}$$

[19] Two further points should be noted. First, if older firms are less profitable conditional on their k and ω, then an analogous argument establishes that selection is associated with a positive bias in the age coefficient. We do not focus on age effects because the empirical results indicate that age effects on productivity are small. Second, the crucial part of the logic underlying the sign of these biases is that the difference between the value of continuing in operation and the sell-off value of the firm be increasing in ω and k (decreasing in a). If this condition is met, it does not matter whether the sell-off value is independent of k and a (which, for simplicity, was the specification in our behavioral model).

Equation (7) allows us to express the unobservable productivity variable, ω_t, as a function of observables, and hence to control for ω_t in estimation.

Note that (7) rests on there being only one unobserved firm specific state variable (ω or productivity) and on investment increasing in ω. Though these are strong assumptions, they have two advantages. First they generate a simple estimation algorithm for production function parameters which does not depend on the host of auxiliary assumptions necessary to fully specify equilibrium behavior. Second, the assumptions lead to an overidentified model and hence some direct tests of whether the restrictions have a significant impact on our estimates (see Section 4.1 below).

Substituting (7) into (6) we have

$$(8)\qquad y_{it} = \beta_l l_{it} + \phi_t(i_{it}, a_{it}, k_{it}) + \eta_{it},$$

where

$$(9)\qquad \phi_t(i_{it}, a_{it}, k_{it}) = \beta_0 + \beta_a a_{it} + \beta_k k_{it} + h_t(i_{it}, a_{it}, k_{it}).$$

The "partially linear" model in (8) is a semiparametric regression model (Engel, Granger, Rice, and Weiss (1986) and Robinson (1988)) which identifies β_l but not the production function coefficients of capital and age, β_a and β_k. That is, the equation does not allow us to separate the effect of capital and age on the investment decision from their effect on output. To identify β_a and β_k we use, in addition to the estimates of β_l and $\phi_t(\cdot)$ obtained from the partially linear model, estimates of the survival probabilities. These probabilities are given by

$$(10)\qquad \begin{aligned} &\Pr\{\chi_{t+1} = 1 | \underline{\omega}_{t+1}(k_{t+1}, a_{t+1}), J_t\} \\ &= \Pr\{\omega_{t+1} \geq \underline{\omega}_{t+1}(k_{t+1}, a_{t+1}) | \underline{\omega}_{t+1}(k_{t+1}, a_{t+1}), \omega_t\} \\ &= \wp_t\{\underline{\omega}_{t+1}(k_{t+1}, a_{t+1}), \omega_t\} \\ &= \wp_t(i_t, a_t, k_t) \\ &\equiv P_t \end{aligned}$$

where the third equality follows from (5) [i.e., $\omega_t = h_t(i_t, a_t, k_t)$], and (1) [which implies that a_{t+1} and k_{t+1} can be calculated from (i_t, a_t, and k_t)].

Now consider the expectation of $y_{t+1} - \beta_l l_{t+1}$ conditional on information at t and survival

$$(11)\qquad \begin{aligned} &E[y_{t+1} - \beta_l l_{t+1} | a_{t+1}, k_{t+1}, \chi_{t+1} = 1] \\ &= \beta_0 + \beta_a a_{t+1} + \beta_k k_{t+1} + E[\omega_{t+1} | \omega_t, \chi_{t+1} = 1] \\ &\equiv \beta_a a_{t+1} + \beta_k k_{t+1} + g(\underline{\omega}_{t+1}, \omega_t) \end{aligned}$$

where

$$g(\underline{\omega}_{t+1}, \omega_t) = \beta_0 + \int_{\underline{\omega}_{t+1}} \omega_{t+1} \frac{F(d\omega_{t+1}|\omega_t)}{\int_{\underline{\omega}_{t+1}} F(d\omega_{t+1}|\omega_t)}.$$

Note that the "bias" term in (11), $g(\cdot)$, is a function of *two* indices of firm specific state variables; ω_t and $\underline{\omega}_{t+1}[k_{t+1}(k_t, i_t), a_{t+1}(a_t)]$. To control for the impact of the unobservable on selection we need a measure of ω_t *and* a measure of the value of ω which makes the firm just indifferent between continuing in operation and selling off (i.e., $\underline{\omega}_{t+1}(\cdot)$). Most models used to correct for selection, and these date back to Gronau (1973) and Heckman (1974), have been single index models (for a good summary, see Ahn and Powell (1993, Section 2)).

Provided the density of ω_{t+1} conditional on ω_t is positive in a region about $\underline{\omega}_{t+1}$ (for every ω_t), the selection equation (10) can be inverted to express $\underline{\omega}_{t+1}$ as a function of P_t and ω_t. Then we can write $g(\cdot)$ as a function of P_t and ω_t. That is, by conditioning on the selection probability (or on the "propensity score") we can condition on the value of one of the two needed indices, a technique which has been used for single index models at least since Rosenbaum and Rubin (1983).[20] For given values of β_a and β_k we can condition on the second index by conditioning on the nonlinear term generated from the partially linear model in (8), that is by conditioning on $\phi_t = \beta_0 + \beta_a a_t + \beta_k k_t + \omega_t$ in (9).

Substituting P_t and ϕ_t into $g(\cdot)$, rewriting, and letting ξ_{t+1} be the innovation in ω_{t+1}, we have

$$(12) \qquad y_{t+1} - \beta_l l_{t+1} = \beta_a a_{t+1} + \beta_k k_{t+1} + g(P_t, \phi_t - \beta_a a_t - \beta_k k_t) + \xi_{t+1} + \eta_{t+1}$$

where

$$\xi_{t+1} = \omega_{t+1} - E[\omega_{t+1}|\omega_t, \chi_{t+1} = 1]$$

and from (9), (10), and (11),

$$g(\underline{\omega}_{t+1}, \omega_t) = g\left[\wp_t^{-1}(P_t, \phi_t - \beta_a a_t - \beta_k k_t), \phi_t - \beta_a a_t - \beta_k k_t\right] \equiv g(P_t, \phi_t - \beta_a a_t - \beta_k k_t).$$

Equation (12) clarifies the need for the first stage of the estimation algorithm. Since the capital in use in a given period is assumed to be known at the beginning of the period and ξ_{t+1} is mean independent of all variables known at

[20] We thank a referee for this reference. For further discussion, see Heckman and Robb (1986) and more recently Ahn and Powell (1993), who also base their suggestion for controlling for selection in single index models on the propensity score.

the beginning of the period, ξ_{t+1} is mean independent of k_{t+1} (and of a_{t+1}). On the other hand we want to allow for the possibility of some labor adjustment to realizations of ξ_{t+1}. This implies that l_{t+1} is not mean independent of the disturbance in (12) and clarifies the need for the first stage of the estimation algorithm.

We turn now to the details of estimating the system given by (8), (10), and (12). Readers not interested in these details can turn directly to the empirical results.

The econometric properties of the partially linear model in (8) have been analyzed using kernel (Robinson (1988)) and series (Andrews (1991) and Newey (1995)) estimators of $\phi_t(\cdot)$ and, subject to regularity conditions, the resulting estimators of β_l have the same limiting distribution. For simplicity, we use a polynomial series estimator for $\phi_t(\cdot)$. We project y_t and l_t and a polynomial in the triple (i_t, a_t, k_t). The empirical results presented here use a fourth order polynomial (with a full set of interactions) to approximate $\phi_t(\cdot)$, but there was almost no change in either the estimates of the coefficients of interest, or the minimand, in going from a third to a fourth order approximation. Also, since the investment function, and hence $\phi_t(\cdot)$, should differ with changes in market structure, we estimated different polynomials for each of the four regulatory periods (1974–77, 1978–80, 1981–83, and 1984–86).

Next consider estimation of the survival probability (10). Here we use both series and kernel estimators and compare the results. The series approximation was constructed by using a polynomial series in (i_t, a_t, k_t) as regressors in a probit estimation (the formula the computer uses to evaluate the normal is a series approximation to the true distribution; so this gives us a series composed with a series as our approximating function). Again we used a fourth order polynomial in (i_t, a_t, k_t) with a full set of interactions, and again there was no change in the fit in going from the third to the fourth order. The kernel results presented here use the bias reducing normal based kernels in Bierens (1987), though the parameter estimates were almost identical when we used a standard normal kernel.[21] The model implies that both the stopping rule and the investment equation change with market structure, and changes in either of these functions will change the form of the survival probability, so we ran both the kernel and the series estimator twice, once allowing for different selection equations in each of the four different regulatory periods, and once not.

Table V provides the correlation coefficients between the indicator variable for survival in period $t+1$ conditional on survival in period $t(\chi_{t+1})$, and the

[21] Whenever we use the bias reducing kernels in Bierens (1987) we use a diagonal Ω with the inverse of the variance of the regressors as the diagonal elements, choose a bandwidth by cross-validation, and use a degree of bias reduction of four. Standard normal kernels used a diagonal covariance matrix with the inverse of the variance of the regressors as the diagonal elements, and a bandwidth of one.

TABLE V

CORRELATION COEFFICIENTS BETWEEN VARIOUS PREDICTED SURVIVAL PROBABILITIES AND χ_{t+1}

	χ_{t+1}	PHAT1	PHAT2	PHAT3	PHAT4
χ_{t+1}	1.00	.285	.350	.102	.218
PHAT1	.285	1.00	.671	.398	.324
PHAT2	.350	.671	1.00	.215	.583
PHAT3	.102	.398	.215	1.00	.483
PHAT4	.218	.324	.583	.483	1.00

Notes: (1) χ_{t+1} is a 0, 1 random variable that takes the value 0 when a plant closes.
(2) PHAT1 and PHAT2 are the kernel estimates. PHAT1 is estimated over the entire data set, and PHAT2 is estimated separately for the four time periods 1974–1977, 1978–1980, 1981–1983, and 1984–1987.
(3) PHAT3 and PHAT4 are the probit estimates. PHAT3 has no time dummies, and PHAT4 is estimated with time period dummies corresponding to the periods in note (2), and these dummies are interacted with i_t, k_t, and a_t.

different estimates of the selection probabilities.[22] Two points emerge from the table. First, the kernel estimator provides predictions (PHAT1 and PHAT2) which fit better than the series estimator (PHAT3 and PHAT4). Second, the fits are better when we allow for different stopping rules and different investment functions in the four different regulatory regimes (compare PHAT2 to PHAT1, or in the series case, PHAT4 to PHAT3). Consequently we use PHAT2, the kernel estimates that allow for differences in the selection function in our different regulatory periods, in the analysis that follows.

The third (and final) step of the estimation procedure takes the estimates of β_l, ϕ_t, and P_t from the first two steps, substitutes them into equation (12) for the true β_l, ϕ_t, and P_t, and then obtains estimates of (β_a, β_k), by minimizing the sum of squared residuals in that equation. Here we try both a series and a kernel estimator of the unknown $g(P_t, h_t)$ function. Recall that we estimate ϕ_t and $h_t = \phi_t - \beta_a a_t - \beta_k k_t$, so the values of the regressors that determine $g(\cdot)$ depend upon the values of the parameters of interest.

For the series estimator we used a fourth order polynomial expansion in (P_t, h_t) (and again there was almost no difference in either the sum of squares, or in the coefficients of interest, between the third and the fourth order approximation). Thus the series estimator is obtained by running nonlinear least squares on the equation

$$y_{t+1} - b_l l_{t+1} = c + \beta_a a_{t+1} + \beta_k k_{t+1} + \sum_{j=0}^{4-m} \sum_{m=0}^{4} \beta_{mj} \hat{h}_t^m \hat{P}_t^j + e_t \tag{13}$$

[22] The unit of analysis for all the empirical results is the plant. This assumes that each plant of a multi-plant firm makes decisions independent of the other plants of the same firm. We did several runs which allowed for different exit and investment rules both for multi-plant firms and for the dominant firms in the industry. These modelling differences did not affect the empirical results of interest (see footnote 32). Note also that our treatment of plants as the unit of analysis means that we *do not* record the sale of a plant from one telecommunications equipment firm to another as exit followed by entry.

with

$$\hat{h}_t = \hat{\phi}_t - \beta_a a_t - \beta_k k_t.$$

Here $\hat{\phi}_t$ and b_l are taken from the estimates of the partially linear model in (8), and $\hat{P}_t$ is taken from the kernel estimates of the survival probability in (10).

The kernel estimator is obtained by forming a kernel estimator of the regression of

$$y_{t+1} - b_l l_{t+1} - \beta_a a_{t+1} - \beta_k k_{t+1}$$

on $\hat{P}_t$ and $\hat{h}_t = \hat{\phi}_t - \beta_a a_t - \beta_k k_t$ for different values of (β_a, β_k), and then using a nonlinear search routine to find that value of (β_a, β_k) that minimized the sum of squared residuals from this regression. Again the results are the bias reducing kernels in Bierens (1987) (though we also used a standard normal kernel with little difference in the resulting coefficient estimates).[23]

Finally, the results indicate that a linear trend (representing disembodied technical change) was significant, so we included a time trend in the production function in (10), and carried it through the estimation procedure.

A note on the properties of these estimators is in order. The estimator used here belongs to a class of semiparametric estimators whose properties are discussed in Pakes and Olley (1995). That paper extends semiparametric results in Newey (1994), and Andrews (1994, 1995) to cover problems which require estimates of nonparametric functions which are indexed either by other nonparametric functions, or by the parameters of interest (e.g., $g(\cdot)$ in (12)). Pakes and Olley provide a set of smoothness conditions on the primitive functions, conditions on the choice of kernels (bias reduction, bandwidth selection, and smoothness conditions), and trimming conditions, that together insure that the *kernel* estimator of $g(\cdot)$ in equation (12) provides $\sqrt{n}$ consistent and asymptotically normal estimators of the capital, age, and time coefficients. The asymptotic covariance matrix of the parameter estimates for this paper is developed as an example in Section III of Pakes and Olley (1995). We do not currently know of a theorem that insures $\sqrt{n}$ consistency and asymptotic normality when the series estimator is used for $g(\cdot)$, as in equation (13). However, we would be surprised if the series estimator did not have the same properties as the kernel estimator (especially in light of the results we are about to present) and it is *much* easier to compute.[24]

[23] Kernel estimation was computationally burdensome as the kernel had to be re-evaluated each time we needed to evaluate the objective function at a different parameter vector. As a result, we chose the bandwidth by cross validation at the estimate of the parameter vector obtained from the series estimation procedure, and held the bandwidth fixed at that value thereafter.

[24] Pakes and Olley (1995) also compute bootstrapped standard errors for the semiparametric production function estimates developed here (though on a smaller data set). The bootstrap estimates of the standard errors were consistently higher than estimates obtained from our analytical formula. However, as discussed in Pakes and Olley the bootstrap estimates of the standard errors are likely to be biased upwards due to computational problems.

The results of the two three step estimation procedures, together with some other estimates of the production function coefficients, are provided in Table VI. Columns 1 and 2 employ the subset of the data set that contains only those plants that were active throughout the sample period. That is, these columns use the "balanced panel." Column 1 provides the OLS estimates from the balanced panel, while Column 2 provides the within estimates (a fixed effects model which uses deviations from plant specific means in least squares estimation). Columns 3 to 9 use the "full" sample; this sample keeps plants that eventually drop out for all periods in which they are active, and introduces new entrants as they appear.[25]

The first point to note is that the full sample contains almost three times the number of observations in the balanced panel. Thus the selection criteria implicit in using a balanced panel throws out roughly 65 percent of the observations. This percentage, together with the theoretical discussion above, helps explain many of the anomalies generated by the balanced panel.

The estimates in columns (1) and (2) are what we have come to expect from production function estimates from balanced panels. The labor coefficient is higher than we would expect for the elasticity of output with respect to labor (certainly higher than the share of labor in total cost, about .65 in these data), while the capital coefficient is lower than we would expect (and almost disappears in the "within" dimension in column (2)). The age coefficient is close to zero in all specifications and we will ignore it in our discussion.

We have two reasons for worrying about biases in these estimates. First endogeneity of the input choices should lead to a positive correlation between the inputs and the unobserved productivity term (a problem which is likely to be more severe the easier it is to adjust the input to current realizations of productivity). This is the traditional reason for believing there is a positive bias in the O.L.S. estimate of the labor coefficient. The within estimator will only account for the bias if the plant's productivity is constant over time (and there was significant restructuring during the period under study). Second, even considering the 1972 cross section as the universe for the subsequent analysis, by taking the balanced panel we are only keeping those firms that did well enough to survive the entire period (Table IV indicates that this was under half of the plants active in 1972). Since firms with larger capital stocks will survive on the basis of lower productivity realizations, we expect selecting on survival to

[25]Our procedure does not generate an estimate of ω_t for either incumbents with $i_t = 0$ (see equation (7) above) or for entrants in the year prior to their entry, and we omit both entrants in their first year and firms with $i_t = 0$ from this analysis. Moreover because the data are a rotating five year panel we also omit some observations from the initial year of each rotation (see the footnote to the table, and our Appendix). These selection criteria are all functions of variables known in period t, and the moment conditions that generate our estimators are conditional on any values for period t variables, so the selection procedures *do not* change the consistency of our estimators. It is possible to use the information in the omitted observations to increase the efficiency of our estimators, but this would require additional assumptions and a significant increase in computational burden.

TABLE VI

ALTERNATIVE ESTIMATES OF PRODUCTION FUNCTION PARAMETERS[a]
(STANDARD ERRORS IN PARENTHESES)

Sample:	Balanced Panel		Full Sample[c, d]						
								Nonparametric F_ω	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Estimation Procedure	Total	Within	Total	Within	OLS	Only P	Only h	Series	Kernel
Labor	.851	.728	.693	.629	.628			.608	
	(.039)	(.049)	(.019)	(.026)	(.020)			(.027)	
Capital	.173	.067	.304	.150	.219	.355	.339	.342	.355
	(.034)	(.049)	(.018)	(.026)	(.018)	(.02)	(.03)	(.035)	(.058)
Age	.002	−.006	−.0046	−.008	−.001	−.003	.000	−.001	.010
	(.003)	(.016)	(.0026)	(.017)	(.002)	(.002)	(.004)	(.004)	(.013)
Time	.024	.042	.016	.026	.012	.034	.011	.044	.020
	(.006)	(.017)	(.004)	(.017)	(.004)	(.005)	(.01)	(.019)	(.046)
Investment	—	—	—	—	.13	—	—	—	—
					(.01)				
Other Variables	—	—	—	—	—	Powers of P	Powers of h	Full Polynomial in P and h	Kernel in P and h
# Obs.[b]	896	896	2592	2592	2592	1758	1758	1758	1758

[a]The dependent variable in columns (1) to (5) is the log of value added, while in columns (6) to (10), the dependent variable is the log of value added $-b_l * \log(\text{labor})$.

[b]The number of observations in the balanced panels of regressions 1 and 2 are the observations for those plants that have continuous data over the period, with zero investment observations removed. The 2592 observations used in columns (3), (4), and (5) are all observations in the full sample except those with zero investment. Approximately 8% of the full data set had observations with zero investment. Columns (6) to (10) have fewer observations because the sampling procedures for the Annual Survey of Manufactures forced us to drop observations in years 1978, 1983, and the last year, 1987. See note c.

[c]The number of observations in the last four columns decreases to 1758 because we needed lagged values of some of the independent variables in estimation. This rules out using the first observation on each plant and the first year of the rotating five-year panels that make up the Annual Survey of Manufactures. To check that the difference between the estimates in columns (6)–(9) and those in columns (3)–(5) are not due to the sample, we ran the estimating equations in columns (3)–(5) on the 1758 plant sample and got almost identical results.

[d]Consult the text for details of the estimation algorithm for columns (6) to (10).

generate a negative correlation between the disturbance term in the selected sample and capital.

By going to the full sample we expect to eliminate much of the selection problem, but not necessarily the problems generated by the endogeneity of the input choices. Columns (3) and (4) provide the OLS and within estimates on the full sample. The simple act of adding back in the plants that were active during only part of the sample period almost *doubles* the capital coefficient and pushes the labor coefficient down by about 20% (for both the total and the within columns). Of course, the column (3) and (4) coefficients should still be biased by selection and endogeneity. In particular since the within column uses only changes over time and has to discard those plant-year changes in productivity that induce the plant to close down, one might expect a large negative bias in the capital coefficient generated by selection, whereas the total column makes no attempt to control for firm specific differences in productivity, so we might expect a large positive bias in the labor coefficient.

To account for the positive bias in the labor coefficient in column (3), we should substitute a polynomial expansion in the triple (i_t, a_t, k_t) for ω_t in equation (6) and re-estimate that equation. Column (5) adds only investment to the list of regressors in column (3). If the polynomial needed for ω_t were both linear and did not require interactions with time for the different regulatory periods, the estimate of the labor coefficient in column (5) would be consistent. The capital and age coefficients, however, would confound the effect of capital and age on output with their effect on investment and hence have no direct interpretation. There are two points to note from column (5). The investment coefficient is highly significant, indicating that there is likely to be a simultaneity bias in the column (3) estimates. Second, as predicted the labor coefficient goes down (by another 10%).[26]

The labor coefficient from equation (8), which used a fourth order polynomial expansion in (i_t, a_t, k_t) whose coefficients were allowed to vary over the four regulatory periods to account for ω_t, was .608 (.027) (not too different from the column (5) estimate, and close to 15% lower than in column (3)). Columns (6) to (9) use this coefficient, the implied estimate of ω_t, and the estimate of P_t from the selection equation (10) to obtain estimates of the capital, age, and time coefficients.

Column (6) regresses $y_{t+1} - .608 l_{t+1}$ on age, capital, time, and a polynomial in the estimate of the selection probability. If there were no serial correlation in ω_t, our model would reduce to a single index selection model (that index being $\underline{\omega}_{t+1}$), and the bias term ($g(\cdot)$ in equation (12)) could be expressed as a function of P_t, making the estimates in column (6) consistent. On the other hand if ω is serially correlated, then we would expect k_{t+1} to be positively correlated with the now omitted ω_t, generating a positive bias in the capital coefficient in this column.

Column (7) regresses $y_{t+1} - .608 l_{t+1}$ on age, capital, time, and a polynomial in $\hat{h}_t$, the estimate of ω_t obtained from the first equation. If the probability of exit were zero, so that $E[\omega_{t+1} | \omega_t, \chi_{t+1} = 1] = E[\omega_{t+1} | \omega_t]$, then the bias term in (12) could be expressed as a function of ω_t, and the estimates in column (7) would be consistent. Since the transitions on the full panel are selected for survival (though this is only survival over a two, not fourteen, year period), and the now omitted P_t is declining in k_{t+1} given ω_t, we expect a negative bias in this capital coefficient.

The estimates of the upwardly biased capital coefficient from column (6), and the downwardly biased coefficient from (7) are surprisingly close to one another. If we were to ignore the variance in these estimates they would imply that the

[26] On the suggestion of a referee we also estimated the equations in columns (3) and (5) using capital constructed as $K_t = (1-\delta)K_{t-1} + I_t$ rather than $K_t = (1-\delta)K_{t-1} + I_{t-1}$. The results were virtually identical to those reported in Table VI.

true β_k lies between .33 and .36 (these bounds rule out the total and the within estimates from the balanced panel or the full sample).

Columns (8) and (9) provide the third stage of our estimation routine. Column (8) uses the series and column (9) the kernel estimate of $g(\cdot)$. The coefficient estimates, .342(.035) and .355(.058) are within the bounds generated by columns (6) and (7), and not significantly different from one another. Since we only know that the kernel estimate is $\sqrt{n}$ consistent and asymptotically normal, we use it in the analysis to follow.[27]

To summarize, both the total and within estimates from the balanced panel produce estimates of the labor and the capital coefficients with *large* biases in the directions predicted by the theory. Going to the full sample helps, but the within capital coefficient is under one half of, and the labor coefficient almost 15% larger than, the capital and labor coefficients from our estimation procedure (and there are smaller biases, with the predicted signs, in the other coefficients).[28]

However, there are two costs to our procedure. First, we obtain higher estimated standard errors than the total and within estimates from the full sample (especially for capital). Still our estimated variances are not "out of bounds" for micro estimates of labor and capital coefficients (compare them to the variances estimated from the balanced panel). Second, our procedure is more computationally demanding (from a programming and a required c.p.u. time point of view). In fact the estimates in columns (5) to (8) were obtained from standard nonlinear search routines (if one uses a polynomial estimate of the survival probability) and were not very c.p.u. time intensive (the consistent labor coefficient is easy to generate). The kernel estimates of column (9) were

[27]We have done more than reported above and this note summarizes some other results. The system was estimated: (i) assuming that F (the family of distributions for ω_{t+1} conditional on ω_t) was a normal family, (ii) using several different estimators for the nonparametric components, and (iii) adding a trimming step to account for low density regions of the data. When we assume that $\omega_{t+1} = \rho\omega_t + \xi_{t+1}$, with $\xi_{t+1} \sim N(0, \sigma^2)$, the model generates a correction term for the third equation which is $\rho\omega_t$ plus σ times the inverse of a Mill's ratio. This model resulted in a higher sum of squared residuals than in column 9 (670 vs. 635) and a capital coefficient of .23. However, when we allowed σ to be a linear function of ω_t, which produces an interaction term between ω_t and the Mill's ratio, the fit improved markedly and the capital coefficient increased to .30. Generalizing further and replacing $\rho\omega_t$ with $f(\omega_t)$ and letting σ be a polynomial in ω_t produced fits and estimates close to those in column (9). There was no noticeable difference between our estimates and those obtained using different estimators, for the nonparametric components, and/or after adding a trimming step, except for a few runs in which one or more of the estimated standard errors were significantly higher before outliers were trimmed away.

[28]At the request of a referee we conducted two Hausman tests to summarize the differences between the standard OLS and Fixed Effects production function coefficient estimates (columns (3) and (4)) and those obtained from our procedure (column (9)). The observed values of the $\chi^2(3)$ test statistics were respectively 45.38 and 58.91, which clearly reject either null hypothesis (i.e., that the OLS or the Fixed Effects models are correct).

much harder to generate, but they are similar to the series estimates in column (8), and will be easier to obtain with improvements in computer hardware and software.[29]

4.1. *Robustness Analysis*[30]

This section begins with simple tests of whether the simplifying assumptions used to derive our estimating equations have led to gross errors in our estimates of the production function coefficients. We then review results obtained when we disaggregate in various ways. Our ability to disaggregate was limited by both the size of the overall sample and by the Census' confidentiality requirements.

Table VI compares our 3-step estimator to those from simpler algorithms that could be obtained by constraining our model in various ways. Next we consider whether relaxing the simplifying assumptions in *our* model leads to changes in the coefficient estimates.

We are particularly concerned with the assumption that investment demand can be expressed as a function of age, capital, and productivity (equation (5)). This assumption leads directly to our estimate of the labor coefficient in (8). To test it we ask whether l_t belongs in the third estimating equation. If our estimate of the labor coefficient, b_l, differs from β_l, then equation (12) contains the error $(\beta_l - b_l)l_{t+1}$. Recall that the disturbance in (12) contains the error $\xi_{t+1} + \eta_{t+1}$, where $\xi_{t+1} \equiv \omega_{t+1} - E[\omega_{t+1} | J_t, \chi_{t+1} = 1]$ and we expect l_{t+1} to be determined in part by ξ_{t+1}. Thus l_{t+1} would be correlated with the error in (12) whether or not the labor coefficient is correctly estimated. However, if our model is correct ξ_{t+1} should be mean independent of l_t. Moreover since l_t and l_{t+1} are highly correlated, if there were an error in our first stage estimate of β_l we would expect a significant coefficient for l_t if l_t is added to the list of regressors in (12).

To test our assumption we used our 3-step kernel estimation procedure to estimate the model

$$y_{t+1} - b_l l_{t+1} = \beta_a a_{t+1} + \beta_k k_{t+1} + g(P_t, \phi_t - \beta_a a_t - \beta_k k_t) + \gamma_l l_t + \xi_{t+1} + \eta_{t+1}.$$

The results are presented in column (1) of Table VII. The estimate of γ_l is not significant and the other coefficients barely change from column (9) of Table VI.

In an analogous manner we can add a_t and k_t to equation (12). This tests whether the index restrictions in the bias term, $g(P_t, \phi_t - \beta_a a_t - \beta_k k_t)$, are

[29] The full three equation model with series estimates of the last equation usually took under one hour on the 486,33 Mhz computer used for most of this analysis. The kernel estimates often took a day on the 486,33 Mhz machine, in part because we had to make more intensive use of nonderivative search routines. Routines for doing kernel estimation are currently available in standard software packages.

[30] We thank the referees and an editor for comments that led to this section of the paper.

TABLE VII

SPECIFICATION TESTS[a]
(STANDARD ERRORS IN PARENTHESES)

	Test 1	Test 2
b_l^{b}	.608	.608
b_a	.01 (.01)	.01 (.01)
b_k	.36 (.06)	.36 (.06)
b_t	.02 (.05)	.02 (.05)
γ_l	−.01 (.03)	—
γ_a	—	.00 (.02)
γ_k	—	−.01 (.04)

[a]See text for details.
[b]The labor coefficient is taken from the first equation, and is the same in both tests.

consistent with the data. The test uses our 3-step kernel estimation procedure to estimate the model

$$y_{t+1} - b_l l_{t+1} = \beta_a a_{t+1} + \beta_k k_{t+1} + g(P_t, \phi_t - \beta_a a_t - \beta_k k_t) + \gamma_k k_t + \gamma_a a_t + \xi_{t+1} + \eta_{t+1}.$$

If the assumptions underlying the estimators of column (9) in Table VI are correct, the estimates of γ_k and γ_a should be near zero. Column (2) of Table VII provides the results. The estimates of γ_k and γ_a are neither individually, nor jointly, significant, and the rest of the parameters do not change.

We now summarize the results from disaggregating and analyzing different subsamples of the data separately. We tried disaggregating by both time period and firm characteristics. In the time dimension the most telling results were obtained when we split the sample into three periods and did the analysis separately on the first and the last of them (1974/78 and 1982/87).[31] We present the results from OLS and the three step kernel estimation procedure in these two subperiods in the first four columns of Table VIII.

Note first that, as theory predicts, the three step estimator of the labor coefficient is lower, and that of the capital coefficient is higher, than the OLS estimates in both subsamples. As expected, the difference in the capital coefficient is larger in the later period (the period with markedly higher exit rates; see Table XII below). We note that there is some evidence the later period is less labor and more capital intensive than the earlier period. Unfortunately our estimators for the subsamples, particularly for capital in the later period, are too imprecise to put much confidence in this statement.

[31]We also allowed both the investment and the stopping rule to differ each year of the panel (not just the four subperiods reported in the text), and we separately analyzed plants that began operation after divestiture. Allowing for year effects in the investment and stopping rules did not cause a noticeable change in any of the coefficients of interest. There were not enough post divestiture plants to run the three stage estimation procedure separately for them, but the OLS results from this subsample of plants were not very different from the results for the 1982–87 period reported in the text.

TABLE VIII

PRODUCTION FUNCTION PARAMETER ESTIMATES
(STANDARD ERRORS IN PARENTHESES)

	Labor	Capital	Age	Time	# Obs.
1974–1978					
OLS	.78	.27	−.00	.03	832
	(.03)	(.03)	(.003)	(.01)	
3-Step Procedure[a]	.71	.29	.01	.10	578[b]
	(.05)	(.05)	(.03)	(.19)	
1982–1987					
OLS	.62	.33	−.01	−.02	1212
	(.03)	(.03)	(.002)	(.010)	
3-Step Procedure	.55	.40	.01	−.01	729
	(.05)	(.13)	(.02)	(.11)	
Switch Makers[c]					
OLS	.79	.25	−.01	.03	562
	(.05)	(.05)	(.003)	(.01)	
3-Step Procedure	.66	.31	.01	.01	387
	(.07)	(.16)	(.04)	(.16)	
Non-Switch Makers					
OLS	.67	.32	−.00	.01	2030
	(.02)	(.02)	(.002)	(.004)	
3-Step Procedure	.59	.37	.01	.04	1433
	(.03)	(.05)	(.03)	(.03)	

[a]The 3-step estimation procedure is described in detail in the text. The labor coefficient is obtained in the first step using a fourth order polynomial series estimator, the second stage uses a bias reducing kernel to estimate the survival probability, and third stage uses a bias reducing kernel estimator.
[b]The number of observations in the 3-step procedure is the number of observations in the third step of the estimation procedure in which the age and capital coefficient estimates are obtained.
[c]Switch makers are plants that primarily produce switching equipment, and nonswitch makers include all other plants.

Of the samples we created based on firm characteristics the most telling results were obtained when we divided the sample into switchmakers and nonswitchmakers by the plurality of their sales.[32] The results from the OLS and the three-stage kernel estimation procedure for these two subsamples are provided in the last four rows of Table VIII. Again both coefficients move in the expected direction in both subsamples as we move from the OLS to the 3-step estimator. There is also some indication that the coefficients are different in the

[32] We also estimated models in which plants belonging to multiplant firms had different stopping and investment rules (different from single plant firms, and different by the number of plants), and a model in which only plants belonging to the dominant firm in the industry had different stopping and investment rules. The results were not noticeably different than the results provided in Table VI. As noted in the Appendix plants producing fiber optic and microwave equipment are classified in a separate four digit industry than the rest of the plants in our data. There were not enough of these plants for a separate three stage estimation procedure, but we compared O.L.S. estimates from this subsample to those from the overall sample and there was not much difference.

two subsamples (switchmakers being less capital intensive), but a χ^2 test for the differences in the coefficients between the subsamples is below its expected value.

5. THE IMPLICATIONS FOR PRODUCTIVITY

We now use our production function estimates to construct measures of plant level productivity and analyze changes in its distribution between 1974 and 1987. Our plant level productivity measure is calculated as

$$p_{it} = \exp(y_{it} - b_l l_{it} - b_k k_{it} - b_a a_{it}),$$

where the parameter estimates b_l, b_k, and b_a, are taken from column (9) in Table VI.[33] Aggregate industry productivity is calculated annually as the share-weighted average of the plant-level productivity measure, using plant-level output shares as weights.

The annual productivity growth rates presented in column (1) of Table IX are calculated as the percentage change in the aggregate productivity index. These growth rates use the full sample and the parameter estimates from column (9) of Table VI. Column (2) of Table IX provides the productivity growth rates derived from the balanced panel and the coefficients estimated from that panel (from column (1) in Table VI).

There was a sharp drop in productivity between 1974 and 1975.[34] If we exclude that year the average annual growth rate in aggregate productivity in the full sample was 3.2%. There were important differences in the productivity growth rates between the four subperiods and these differences are not reflective of productivity growth in manufacturing as a whole. The correlation between the annual productivity growth rate for telecommunication equipment and that for manufacturing (obtained from the Bureau of Labor Statistics) was essentially zero. It seems that the factors underlying productivity growth in telecommunications equipment during this period are specific to the industry, and not related to trends in overall manufacturing productivity.

The movements in column (1) *can* be accounted for by changes in the regulatory environment. The two periods of high productivity growth are the

[33] The advantage of this estimate, rather than $\exp(\phi_{it} - b_k k_{it} - b_a a_{it})$, is that there are data available on p_{it} for all plants active in period t, whereas we cannot construct ϕ_{it} for the 8% of the plants with zero investment. We shall primarily be concerned with weighted averages of p_{it} and omitting plants with zero investment would tend to omit plants with low and declining productivities, thus biasing our aggregate results. If our parameter estimates are exact $p_{it} = \exp(\omega_{it} + \eta_{it})$, so that our measures of productivity include the impact of $\{\eta_{it}\}$. We have also used sales weighted averages of $\log(p_{it})$. In those calculations the impact of $\{\eta_{it}\}$ tends to average out. These results were similar (actually somewhat sharper) than those given below. We present the results using p_{it} because, as noted by a referee, they are closer to the usual notion of productivity.

[34] We have not been able to find a satisfactory explanation for this fall. Crandall (1991, p. 83) finds an 11% drop in sales between 1974 and 1975 in a period of substantial growth, and begins his productivity analysis in 1975.

TABLE IX

INDUSTRY PRODUCTIVITY GROWTH RATES[a]

Time Period	(1) Full Sample	(2) Balanced Panel
1974–1975	−.279	−.174
1975–1977	.020	−.015
1978–1980	.146	.102
1981–1983	−.087	−.038
1984–1987	.041	.069
1974–1987	.008	.020
1975–1987	.032	.036
1978–1987	.034	.047

[a]The numbers in Table IX are annual averages over the various subperiods.

periods following the registration and certification program in 1977 and 1978, and following divestiture in 1984. The growth rate in productivity is negative from 1981 to 1983. The Consent Decree announcing divestiture was signed in January 1982 so this was undoubtedly a time of reorganization and restructuring, and the negative productivity growth probably reflects the costs of this process.

Now compare our productivity figures to those obtained from the balanced panel. First, and perhaps most important, the time series for productivity obtained from the balanced panel is significantly different from that from the full sample.

There are several reasons for these differences. Both theory and our empirical results suggest that plants that eventually exit had low productivity growth. The balanced panel's exclusion of these plants should generate an upward bias in its productivity index. Second, new entrants tended to be smaller and have lower productivity than the average productivity of continuing establishments (but higher productivity than those which exit). At least in the year they enter, the difference in the treatment of new entrants also tends to bias the productivity index from the balanced panel upward. In contrast, the new entrants who survive had greater average productivity growth than the average incumbent, tending to make the full sample have higher productivity growth than the balanced panel.

The overall effect of omitting exiting and entering firms is to bias the productivity figures derived from the balanced panel upwards (see Table IX). Moreover, the bias is particularly large (on the order of thirty percent) in the post 1978 period, the period of restructuring induced by the certification and registration program and divestiture.

We now delve deeper into the determinants of industry productivity. We first ask about the efficiency of the output allocation among plants. One can ask this question either conditional on the extant distribution of fixed factors (age, capital, and productivity), or unconditionally. We begin with the efficiency of the allocation conditional on the distribution of fixed factors. To analyze this issue we introduce a variable cost efficiency index. The index is defined as the ratio of the minimum variable cost of producing industry output, given the current distribution of fixed factors (age, capital, and productivity), to the actual variable cost of producing industry output. Firms are assumed to minimize variable cost given their fixed factors, so their actual variable cost of production is calculated as

$$(14) \qquad C(Y_i, K_i, a_i, p_i, w_i) = \min_{L_i} w_i L_i \quad \text{subject to}$$

$$Y_i \leq L_i^{\beta_l} K_i^{\beta_k} e^{\beta_a a_i} e^{p_i}$$

where p_i is productivity as defined at the beginning of this section. The minimum total variable cost of producing industry output is calculated as the solution to

$$(15) \qquad \min_{Y_1, \dots, Y_N} \sum_{i=1}^{N} C(Y_i, K_i, a_i, p_i, w_i) \quad \text{subject to}$$

$$\sum_{i=1}^{N} Y_i = Y.$$

The static efficiency index is calculated as the ratio of (15) to the sum of (14) across plants. Results are presented in Table X where we have averaged the annual static cost efficiency index over four subperiods.

Table X goes one step further. It decomposes the static variable cost index into two terms; a measure of the efficiency of allocation of output among plants within a firm (the intrafirm index), and a measure of the efficiency of the allocation of output between firms (the interfirm index). Specifically the intrafirm index is the ratio of the variable cost of production one would obtain if one allocated the *actual* firms' output efficiently among their own plants to the actual cost of production (from (14)). The interfirm component is the ratio of the minimum cost of production obtained from (15) to the cost of production obtained from efficiently allocating the existing firm distribution of output

TABLE X

VARIABLE COST EFFICIENCY[a]

(MINIMUM COST OF PRODUCTION DIVIDED BY ACTUAL COST OF PRODUCTION)

Years	Total	Interfirm	Intrafirm
1974–1977	.77	.84	.91
1978–1980	.69	.76	.91
1981–1983	.65	.72	.91
1984–1987	.72	.80	.89

[a]See text for details.

among the plants of the firms (the numerator of the intrafirm index). Thus the product of the interfirm and intrafirm indices equals the total index.

All movements in the static efficiency index are caused by movements in the interfirm component of the index; the intrafirm component was essentially constant at .9 throughout the period. The interfirm index declined in 1978–1983 when the industry was undergoing restructuring induced by regulatory changes. It increased after deregulation, but not to the level prior to 1978.

As of 1987, the more competitive structure that emerged after deregulation generated an interfirm allocation of output that was less efficient, *conditional* on total output produced and on the existing joint distribution of fixed factors, than the output allocation prior to deregulation. Perhaps this finding is not surprising. More concentrated industry structures may well allocate output among existing plants in a more cost effective manner; a multiplant monopolist allocates output efficiently. This implies that the increases in aggregate productivity that followed the registration and certification program and divestiture were either a result of a reallocation of fixed factors towards more productive enterprises, or increases in average productivity growth. We now investigate these possibilities.[35]

To distinguish between these two sources of productivity growth it is helpful to decompose the productivity figures in a different way. Our measure of industry productivity is a weighted average of plant-level productivity, with shares of industry output as weights,

$$p_t = \sum_{i=1}^{N_t} s_{it} p_{it},$$

where p_t is industry productivity at time t, p_{it} is plant level productivity, and s_{it} is plant i's share of output at time t. Now decompose p_t into two terms as follows:

$$(16) \qquad \begin{aligned} p_t &= \sum_{i=1}^{N_t} (\bar{s}_t + \Delta s_{it})(\bar{p}_t + \Delta p_{it}) \\ &= N_t \bar{s}_t \bar{p}_t + \sum_{i=1}^{N_t} \Delta s_{it}\, \Delta p_{it} \\ &= \bar{p}_t + \sum_{i=1}^{N_t} \Delta s_{it}\, \Delta p_{it} \end{aligned}$$

where

$$\Delta s_{it} = s_{it} - \bar{s}_t \quad \text{and} \quad \Delta p_{it} = p_{it} - \bar{p}_t,$$

and $\bar{p}_t$ and $\bar{s}_t$ represent unweighted mean productivity and unweighted mean share, respectively.

[35] Deregulation is also likely to generate benefits from less restrictive output policies. We do not attempt to measure these benefits.

Table XI presents the three terms from equation (16). Column (1) is industry productivity constructed as a weighted average of plant-level productivities. Column (2) is the *unweighted* average of plant-level productivity, and column (3) is the sample covariance between productivity and output. The larger this covariance, the higher the share of output that goes to more productive firms and the higher is industry productivity. Finally, the fourth column of Table XI gives the correlation coefficient between plant-level capital and plant-level productivity.

Unweighted average productivity has not changed much since 1975, but there has been a reållocation of output from less productive to more productive plants. This reallocation of output, and not an increase in average productivity, is behind the increase in productivity at the industry level. Moreover the allocation of output seems to have improved dramatically following the certification and registration program, and then again following divestiture.

From the static cost efficiency index, we know that this reallocation of output to more productive plants is not a result of a more efficient allocation of variable factors of production conditional on the existing distribution of fixed factors. So it should be a result of a reallocation of capital towards more productive plants. A complete analysis of this reallocation process requires the details of the dynamic general equilibrium model behind the adjustment process —a task beyond the scope of this paper. All we provide is reduced form evidence on the extent of the capital reallocation process.

Column (4) of Table XI provides the correlation between capital and productivity. It has increased since the Consent Decree, and it increased following earlier regulatory changes also. The only two years in which there was a

TABLE XI
DECOMPOSITION OF PRODUCTIVITY[a]
(EQUATION (16))

Year	p_t	$\bar{p}_t$	$\Sigma_t\, \Delta s_{it}\, \Delta p_{it}$	$\rho(p_t, k_t)$
1974	1.00	0.90	0.01	−0.07
1975	0.72	0.66	0.06	−0.11
1976	0.77	0.69	0.07	−0.12
1977	0.75	0.72	0.03	−0.09
1978	0.92	0.80	0.12	−0.05
1979	0.95	0.84	0.12	−0.05
1980	1.12	0.84	0.28	−0.02
1981	1.11	0.76	0.35	0.02
1982	1.08	0.77	0.31	−0.01
1983	0.84	0.76	0.08	−0.07
1984	0.90	0.83	0.07	−0.09
1985	0.99	0.72	0.26	0.02
1986	0.92	0.72	0.20	0.03
1987	0.97	0.66	0.32	0.10

[a] See text for details.

perceptible drop in the capital-productivity correlation were 1983–84, when the adjustment to deregulation must have been greatest.

The importance of the reallocation of capital towards more productive plants is also evident in exit behavior. The stopping rule from the behavioral model (equation (5)) implies that whether a firm shuts down depends on its productivity, capital stock, and age. The nonparametric estimation procedure derives survival probabilities, but treats these probabilities as nuisance parameters. Table XII provides a simple probit analysis of survival probabilities with our estimates of productivity, capital, and age, as well as time dummies, as right-hand side variables. As theory predicts, the exit probability is negatively related to the firm's capital stock and its productivity, with productivity having the larger effect. As in the production function, age is insignificant and sometimes the wrong sign. Also, there seems to be an effect of deregulation on the probability of exit. Conditional on any triple for the state vector, the exit probability seems to have gone up sharply after 1984. One mechanism for the reallocation of capital that facilitated the increase in aggregate productivity seems to have been the shutdown of unproductive plants.

Our results indicate that the changes in the telecommunications industry improved performance by inducing a reallocation of capital to more productive plants. This reallocation process seems to be facilitated by entry and exit, phenomena which would not be picked up from the analysis of balanced panels (much less aggregate data). Nevertheless, it is the reallocation of capital, rather than an increase in the efficiency of the allocation of variable inputs or in average productivity, that seems to underlie the increase in productivity that followed the deregulation of the telecommunications equipment industry.

TABLE XII

PROBIT MODELS OF EXIT PROBABILITIES[a]

(STANDARD ERRORS IN PARENTHESES)

	1	2	3
Intercept	−1.39 (.11)	−0.69 (.25)	−0.63 (.25)
Productivity	−0.16 (.06)	−0.15 (.06)	−0.16 (.06)
Age		0.00 (.01)	−0.00 (.01)
Capital		−0.09 (.03)	−0.10 (.03)
D2			−0.37 (.20)
D3			0.10 (.14)
D4			0.47 (.12)
# Obs.	2098	2098	2098
Log Likelihood	−392.2	−387.1	−372.1

[a]The dummy variables are defined as follows: Base period is 1974–1977; D2 = 1 for years 1978 to 1980, 0 otherwise; D3 = 1 for years 1981 to 1983, 0 otherwise; D4 = 1 for years 1984 to 1987, 0 otherwise.

6. CONCLUDING CAVEATS

We conclude with two caveats. First, we would like to emphasize that it is too early to assess the full impact of deregulation on productivity in the telecommunications equipment industry. Our analysis suggests that changes in the regulatory structure were followed by an increase in industry productivity generated by a reallocation of capital and a shift in production towards more productive plants. However, the long term effect of divestiture on productivity will depend on its effect on R&D activity. Partly because of Bell Labs, AT&T's research subsidiary, the telecommunications network in the United States is the most sophisticated in the world. Our estimates indicate that there has not been an increase in average productivity since divestiture. However, any change in productivity resulting from a change in the structure of R&D after deregulation would probably not be apparent in the data until after 1987. We know that when we take the RBOC's together with AT&T their joint R&D expenditures and employment after divestiture are not lower than the predivestiture levels of AT&T (Noll (1987)). However, it is still too early to know whether the changes in industry structure have affected the efficiency of those R&D expenditures.

The second point is related. The data indicate that certain plants appear to generate more sales for given amounts of capital and labor expenditures than others, and that these differences in sales generating ability (which we will call productivity) among plants are highly serially correlated over time. This implies that there is an unobserved, serially correlated, state variable that is a determinant of both survival probabilities and input choices.

We deal with this unobserved serially correlated state variable by assuming that there is a one-to-one relationship between it and investment conditional on the observed state variables (at least on the subset of the data with $i_t > 0$). A more general model, say one that allowed for a separate effect of an R&D process on profits, and hence on investment, would be unlikely to generate an invertibility condition without incorporating information on additional observables. Alternatively, we could have allowed for errors in the investment equation (equation (5)). We stopped where we did for three reasons. First, our tests indicate that one unobserved state variable was sufficient to capture the effects of unobservables (through exit behavior and input demands) on the production function estimates. Second, we did not have detailed R&D data. Third, an error in the investment equation would lead us to a semiparametric errors-in-variables problem which is beyond current econometric knowledge. We do not doubt, however, that extensions to (or modifications of) our techniques may be necessary for different questions or different data sets.

The conceptual point we would like to emphasize is not that our solution need always be used. Rather, it is that the solution that *is* used to study changes in the performance of an industry should take into account the differential efficiency of enterprises in producing sales, and the serial correlation in these efficiency differences over time. Because of this serial correlation, the efficiency differences are determinants of the rates of expansion (or contraction) of plants.

This makes the efficiency differences an integral part of the process by which markets adjust to changes in their environment. In our case differences in adjustments before and after deregulation were the major determinant of the pre- and post-deregulation differences in industry performance.

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APPENDIX 1: THE DATA

The data are an extract drawn from the Longitudinal Research Database (LRD) maintained at the Center for Economic Studies at the Bureau of the Census and described in McGuckin and Pascoe (1988). The LRD contains the data for manufacturing establishments collected by the Census of Manufactures in 1963, 1967, 1972, 1977, 1982, and 1987, and by the Annual Survey of Manufactures for non-Census years from 1973 to 1986. The data are collected at the establishment level and include detailed information on inputs and outputs that characterize the production process. A more detailed description of the data and variable construction can be found in Olley (1992).

Telecommunications networks are composed of three broad categories of equipment. Terminal equipment terminates a telephone wire at a customer's premises and includes telephone sets, key telephone sets, facsimile machines, and modems. Transmission equipment, which carries the signal between terminal stations and switching centers, includes coaxial cable, microwave radio equipment, optical fiber, and communications satellites. Finally, switching equipment, the heart of the network, links the terminals of the telecommunications system. The main types of switching equipment are private branch exchanges (PBX) and central office switching centers. This study focuses on all three types of equipment with the exception of transmission cable. Thus we do not include plants that produce transmission media such as copper wire, coaxial cable, or glass fibers.

In terms of the classification system used by the U.S. Bureau of the Census, the telecommunications equipment industry is made up primarily of those plants that are classified in SIC industry 3661, Telephone and Telegraph Apparatus. The three 5-digit product classes within SIC 3661 are 36611, switching and switchboard equipment, 36613, carrier line equipment, and 36614, other telephone and telegraph wire apparatus. This last 5-digit product class includes such products as telephone sets, key telephone sets, and telephone answering devices. In addition, a subset of the plants from SIC 3663, Radio and Television Communications Equipment, are included in the analysis.

The subset of plants added from industry 3663 are plants that produce products within the 5-digit product class 36631, communications systems and equipment, except broadcast. The Bureau of the Census classifies fiber optics communication equipment, microwave communication equipment, facsimile communication equipment, and carrier line equipment, n.e.c. (not elsewhere classified) in the product class 36631, but we include these plants. However, the product class 36631 also includes military space satellites, amateur radio communications equipment, and other products that we felt should be excluded. Therefore, we tried to eliminate from the data set those plants that primarily produce products outside our definition of the industry.

Though our choice of product classes is as close to the desired definition of the product market as possible, we have pulled together data for plants in different four-digit SIC industries and comparison with published aggregates will be limited.

We now describe the variables used. Unless otherwise specified, all variables are measured at the plant level and are taken from the LRD.

Value added is total shipments, adjusted for changes in inventories, minus the cost of materials. Real value added is constructed by deflating output by a 4-digit industry output deflator and deflating the cost of materials by a 4-digit materials deflator. The deflators are taken from the productivity database described in Gray (1989). The *labor* variable is an hours variable constructed by taking the total compensation for labor, including all supplemental labor costs, and dividing by the production worker wage rate at the given plant.

The *capital* measure is constructed using a perpetual inventory method, $K_{t+1} = (1 - \delta)K_t + I_t$. Since the capital data in the LRD distinguish between buildings and equipment, all calculations of the capital stock are done separately for buildings and equipment. Real capital is obtained by deflating investment by a 4-digit industry new investment deflator taken from the extended PCS data set. As suggested by Hulten and Wykoff (1981) buildings are depreciated at a rate of .0361, and equipment at .1179.

In order to construct the capital series using the perpetual inventory method, we had to address two other issues. We need an initial capital stock, and we want to utilize LRD data on rentals and used equipment expenditures. The method of dealing with the initial condition problem differed with the information available on the plant. If the plant is first observed in an ASM year we treated the plant as a new entry, and assumed the entire book value of capital was put in place in the previous year. If a plant is first observed in a census year, it could have opened any time between the previous census and the first observed census. As a result we calculated two estimates of capital; the first assumes that the plant is new in the first observed census year, and the second assumes that the entire book value was put in place in the previous census year. The initial capital stock used in the analysis was a simple average of these two estimates. For plants first observed in the first year of the LRD (1963) we took the book value in that year to be correct.

If a plant rented capital, the rental value is capitalized and added to current year capital stock. The rental data are capitalized using rental rates for all manufacturing supplied by the Bureau of Labor Statistics. Rentals seem to be more important for smaller plants than they are for large plants. Many small plants do not have any buildings on their books and rent their factory. Many plants also report purchases of used equipment. In the calculation of the capital stock, used equipment is deflated using the new investment deflator and added to current capital. Finally, partly because of the sampling design, there were often missing years on the plants. We imputed the missing investment data by averaging reported investment in the year just before the missing data with investment in the year immediately following the gap. This allowed us to keep the historical information on the plant's capital.

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