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THE DIFFUSION OF NEW TECHNOLOGIES:
EVIDENCE FROM THE ELECTRIC UTILITY INDUSTRY

Nancy L. Rose

Paul L. Joskow

No. 501 July 1988

massachusetts
institute of
technology

50 memorial drive
cambridge, mass. 02139

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Nancy L. Rose
MIT School of Management
Cambridge, MA 02139

and

Paul L. Joskow
MIT Department of Economics
Cambridge, MA 02139

This paper investigates the effect of firm size and ownership structure on technology adoption decisions, using data on the electric utility industry. We argue that traditional models of technology diffusion are subject to sample selectivity biases that may overstate the effect of firm size on adoption probabilities. By extending conventional hazard rate models to use information on both adoption and non-adoption decisions, we differentiate between firms' opportunities for adoption and their underlying adoption propensities. The results suggest that large firms and investor-owned electric utilities are likely to adopt new technologies earlier than do their smaller and publicly-owned counterparts. Moreover, the selection biases from conventional statistical models can lead one to overstate size effects by a factor of two and to understate ownership structure and factor cost effects by two to four times.

Keywords: Technology diffusion, technology adoption, hazard rate models, selection bias.

1. Introduction

Economists have long been interested in understanding the determinants of technology diffusion across firms and industries.[1] An important set of questions in this area concerns "Schumpeterian" hypotheses of the influence of competition and firm size on innovation. Much of the theoretical and empirical work on process technology diffusion suggests that firm size may play an important role in decisions to adopt new technologies, perhaps as a proxy for such factors such as risk aversion, participation in research and development activities, or economies of scale in using the innovation. Recent empirical studies yield mixed results, however, on the question of whether larger firms are more or less innovative than are their smaller counterparts (see Oster, 1982, Hannan and McDowell, 1984, and Levin, Levin, and Meisel (hereafter LLM), 1987).

This paper uses data on steam-electric generating technology to analyze patterns of process technology diffusion across firms. By restricting the study to the electric utility industry, we abstract from competitive and market structure effects: virtually all firms operate as local monopolies subject either to rate of return regulation in the case of investor-owned utilities (IOUs) or to other forms of control in the case of most government and cooperatively-owned utilities.[2] This allows us to focus the analysis on the role of

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[1] See for example, Griliches (1957), Mansfield (1968), David (1969), and Nasbeth and Ray (1974).

[2] The existence of *de facto* exclusive retail franchises and rate-of-return regulation need not imply that firms have no incentives to undertake cost-reducing investments. For investor-owned utilities (IOUs), regulatory lag provides strong incentives to invest in cost saving technologies (Joskow, 1974). Other mechanisms through which investment incentives may operate include the threat of municipal condemnation (takeovers) and the possibility of wholesale power transactions with other utilities. All three of these mechanisms operated during our sample period and were particularly prominent during the 1950s and 1960s, when most of the generating units in our sample were planned.

firm size and two other determinants of technology diffusion suggested by the theoretical and empirical literature: factor cost differences that influence the expected cost savings from adopting an innovation and firms' ownership structures. The nature of our data also makes it possible for us to distinguish between measured size effects resulting only from differences in opportunities to adopt and those resulting from an underlying propensity to adopt new technologies quickly.

Two steam-electric generating technologies are analyzed in the paper: high pressure conventional units (2400 pounds per square inch (psi)) and very high pressure supercritical units (above 3206 psi).[3] The 2400 psi technology was first introduced in 1953 and began to diffuse fairly widely by 1958; the supercritical technology was first introduced in 1957 but diffused much more slowly. We use data on 144 utilities that built steam generating units between 1950 and 1980 to estimate the determinants of firms' decisions to adopt each of these technologies. Results from a broad range of statistical specifications suggest that larger firms and investor-owned utilities tend to adopt new technologies earlier than do small firms and municipal or cooperative utilities, conditional on equal factor prices. Our finding of positive correlations between firm size and the speed of technology adoption is similar to the conclusions reached by Sommers (1980) with respect to nuclear power, by Hannan and McDowell (1984) with respect to the banking industry, and by many of the case studies in Mansfield (1968) and Nasbeth and Ray (1974).[4] This result

[3] These technologies are discussed in Joskow and Rose (1985). We do not consider nuclear power technologies; see Sommers (1980) for a study of nuclear power technology choice.

[4] These studies do not, however, control for differential adoption opportunities. As discussed at greater length below, this may bias their results toward estimating positive relationships even when no relationship exists.

stands in contrast to Oster's (1982) conclusion that large firms were slower to adopt innovations in the steel industry and to LLM's (1987) conclusion that firm size does not affect technology adoption by grocery stores.

We also find that controlling for differential opportunities to adopt is critical to the results. Large firms have a higher probability of building a new generating unit of any kind in a given year, other things equal. Failing to account for these higher building probabilities leads one to overstate size effects on adoption propensities by a factor of two and to understate the effects of ownership structure and potential cost savings on adoption propensities for the 2400 psi technology.

The paper is structured as follows: In the next section we briefly discuss theoretical and empirical models of interfirm technology diffusion. Section 3 describes the particular innovations we study and the factors likely to affect their diffusion. Statistical models of adoption decisions are developed and compared in section 4 and estimates from these are reported in section 5. Conclusions are contained in the final section.

2. The Diffusion of New Technologies

Theoretical models of technology diffusion have attracted increasing attention in recent years; see Stoneman (1986) and David (1986) for overviews. Although the specific predictions depend upon the assumptions and focus of each model, a common set of factors that should influence the diffusion process tends to emerge. These include expected cost savings from adopting the innovation, competitive conditions and technological characteristics that affect the appropriability of gains, and characteristics that influence the expected profitability of the innovation or firms' "willingness to innovate," such as economies of scale or of learning in using the innovation, firm participation in complementary R&D activity, and discount rates. A diffusion path typically is generated by assuming that the cost of adopting the innovation declines through time. Firms' relative positions along this path are determined by their characteristics: firms with lower discount rates will adopt before firms with higher discount rates, larger firms will adopt sooner than smaller firms if economies of scale are important, firms with high factor costs will adopt innovations that increase input efficiency earlier than will firms with low factor costs.

Early theoretical work assumed that the costs and benefits of the innovation were known. More recent papers have relaxed these assumptions and emphasized the effects of uncertainty. In these models diffusion paths can be generated as uncertainty about the technology is resolved over time. Adoption decisions are influenced by firms' prior estimates of the mean and variance of the innovation's returns, their information updating processes and risk aversion, and the expected path of future technological change. These models suggest that more risk averse firms will be slower to adopt innovations, that firms may make mistakes (adopt technologies that are ex post unprofitable and fail to adopt those that are ex post profitable), and that interfirm diffusion will be slower when innovations are perceived to be riskier.

Institutional characteristics also may play an important role in determining the path of diffusion. Of these, the theoretical literature has been most concerned with possible vintage or "history" effects induced by the embodiment of technology in long-lived physical capital. As David (1986) notes, new technologies will be relatively disadvantaged when they are embodied in indivisible capital goods, particularly if capital costs of new plant are high relative to the operating cost of existing facilities. Not only will this tend to slow the diffusion of the new technology throughout the industry, it also suggests that the pattern of technology diffusion across firms will be dependent upon the history of capital investment. Firms that are equally likely to adopt a new technology, other things equal, may do so at different times if their initial capital configurations differ. It seems misleading, however, to characterize this as a difference in "innovativeness."

In this study, we distinguish between early use of technology that is observed only because opportunities for adoption are more frequent and early use that reflects an early decision to employ a new technology. In particular, large firms may adopt innovations sooner for reasons that have little to do with technological progressiveness, such as their more frequent capital additions to replace old (retired) capacity or to meet a given growth rate in demand.[5] We decompose the firm size effect into a component that influences a firm's opportunities to adopt an innovation and a component that affects its decision to exercise an opportunity to introduce the new technology.[6] This

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[5] Our notion of innovativeness is quite similar to Mansfield's (1968, p. 172) argument that large firms should be interpreted as being more progressive only if "the difference in the speed of response between large and small firms is greater than would be expected if a large firm acted as if it were simply the sum of an equivalent number of small, independent firms."

An example may clarify our distinction. Compare two utilities: a large firm with 1000 megawatts (Mw) of capacity and a small firm with 100 Mw of capacity, each growing at 10 percent per year. Assume that both will use the new technology at the first available opportunity; that is, they are equally "innovative." If new units come in 100 Mw increments, the large utility will build a unit next year, while the small utility may not build a new unit for 10 years. We attribute this gap to differences in opportunities, not to differences in the propensity to adopt new technologies.

[6] Our decomposition also can be interpreted as separating the factors that affect the probability of <u>observing</u> a firm's adoption decision from those that affect the adoption decision itself. In this sense, the decomposition is a correction for sample selection biases.

explicit distinction differentiates our work from most previous empirical (and theoretical) work on technology diffusion.[7]

Finally, a number of factors that have received relatively little theoretical attention also may influence interfirm diffusion patterns. These include the role of human capital investments and labor unions, regulatory distortions of technology choices, and deviations from pure profit-maximizing objectives (for example, by government-owned firms or non-profit entities).[8] The predicted effects of these are context-specific. For example, some forms of regulation may speed technology diffusion (Hannan and McDowell, 1984, on banking regulation); others may retard it (Oster and Quigley, 1977, on building codes). Government ownership might allow technology-oriented bureaucrats to adopt innovations sooner than would a profit-maximizing management; in other cases, the insulation from profit-maximizing pressures might permit management to lag in technology adoption (Wilson).

Given the breadth of theoretical predictions and their dependence on specific assumptions about the nature of the technology and the industry, it is useful to ask whether there are any generalizations that can be drawn from the empirical literature. Empirical tests of interfirm diffusion models have tended to focus on possible 'Schumpeterian' effects of firm size and market structure on technology adoption decisions. Early studies by Mansfield (1968), Romeo (1975), and some of the case studies in Nasbeth and Ray (1974) find that larger firms tend to adopt innovations sooner than do their smaller counter-

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[7] Oster (1982) captures this distinction by using plants rather than firms as her unit of analysis. She finds that steel plants owned by large firms tend to take longer to adopt innovations than do plants owned by small firms, other things equal.

[8] A number of these issues are raised by Nelson and Winter (1982) and Stoneman (1986).

parts, although this relation is not universal.[9] Much of the early literature was either largely qualitative or susceptible to considerable statistical and methodological criticism, however. Many of the statistical analyses suffer from selectivity problems (e.g., Romeo, 1975, uses data only on adopting firms in his time-to-adoption analysis) or from pooling across noncomparable innovations or industries (see the interindustry analysis in Romeo, 1975, and Benvignati, 1982, for examples).

Recent work, in an effort to address some of these concerns, has employed more sophisticated statistical models of the diffusion process. The results continue to be mixed, suggesting that no simple generalizations may apply in all industries. Oster (1982) examines the diffusion of the basic oxygen furnace (BOF) and continuous casting in the relatively concentrated U.S. steel industry. She finds a negative effect of firm size on adoption probabilities; large firms tend to adopt both innovations later than do smaller firms, although the effect is significant only for the BOF. LLM (1987) find negative effects of concentration on retail grocery stores' decisions to adopt optical scanner systems, but positive effects of market share. They report some evidence that the largest chains are not among the first adopters, but their reliance on a dummy variable for large average store size instead of measuring firm size makes it difficult to say much about firm size effects. In contrast, Hannan and McDowell (1984) find strong support for Schumpeterian models of innovation: they conclude that the probability of adopting automated teller machines (ATMs) rises with both firm size and market concentration. They also find significant regulatory effects (ATMs appear to be used to relax unit

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[9] For a number of innovations studied in Nasbeth and Ray (1974), small firms lead large firms in technology adoption.

banking and branching restrictions) and ownership effects (banks owned by bank holding companies are more likely to adopt ATMs). Sommers (1980) concludes that large utilities and members of power pools are more likely to try nuclear technologies, although he does not look explicitly at time to adoption and his econometric model creates some interpretation problems.[10]

We extend this body of empirical work in a number of dimensions. First, almost all of these studies mix "innovativeness" effects with "opportunity" effects; we explicitly differentiate between these. Second, we consider flexible forms for the time path of diffusion. Much of the empirical work to date has assumed that the "hazard rate," or probability of adopting an innovation conditional on not having already adopted it, is constant or monotonically increasing through time after conditioning on utility characteristics. Finally, adding evidence on the determinants of adoption decisions in the electric utility industry may help economists to better understand differential effects of factors like firm size across industries. To accomplish this, we first must describe how these factors are likely to influence the innovations we study.

3. Technological Innovation in Steam Electric Generating Technology, 1950-1980

In an earlier paper (Joskow and Rose, 1985), we argued that technological advances in fossil-fueled electricity generation over the past thirty years

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[10] Sommers uses a logit model to estimate the choice between coal and nuclear technologies conditional on building, but he uses only one observation per utility: the first adoption (for adopters) or last non-adoption (for non-adopters) decision. Utility characteristics are measured in the year of that decision, implicitly assuming that characteristics that affect adoption decisions vary through time but that the time path of characteristics prior to the adoption decision is irrelevant. These features make it difficult to compare his results to those of other studies.

have focused on improving the design thermal efficiency of generating units by increasing their steam operating pressures. Increases in thermal efficiency reduce operating costs by enabling utilities to generate more electricity from a given amount of fuel. Our 1985 study identified two significant steam generating technologies introduced after 1950: high pressure subcritical units operating at steam pressures around 2400 psi and very high pressure super-critical units operating above 3206 psi.[11] These technologies are the focus of the present analysis.

The previous theoretical and empirical literature on technology diffusion suggests at least five factors that are likely to affect the pattern of inter-utility adoption of these technologies. These include: the expected cost savings, uncertainty over the distribution of expected savings, utility size, utility ownership structure, and time.[12] We describe their anticipated effects below.

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[11] At pressures above the critical level of 3206 psi, water heated to 706^{2}F directly vaporizes to dry steam. Increasing steam pressure is one way to increase design thermal efficiency. This admittedly is only one dimension over which generating unit technology has been improved, however. Others include higher steam temperatures, the introduction of reheat cycles and multiple bleed point preheat cycles, and larger unit sizes. In our 1985 paper, we argue that technological progress in thermal efficiency over the last 25 years has focused on raising steam pressure conditions. This emphasis is maintained in our present study.

[12] We ignore potential differences in the regulatory environment across IOUs and focus instead on differences in ownership structures. Since municipal and cooperative utilities are not regulated in the same sense as are IOUs, any differences between the groups may reflect both organizational and regulatory effects. All investor-owned utilities face essentially the same general form of regulation. Within this general structure the regulatory environment of course varies over time and space. These differences are difficult to characterize empirically, however, and we do not believe that variables reflecting such differences are likely to be correlated with the independent variables that we use. It may be worthwhile to introduce measures of variations in the competitive and regulatory environment in future research. Absent this, our results should be interpreted as measuring the influence of the observed factors in the presence of regulated local monopoly markets.

We expect the speed of adoption to be increasing in average fuel costs. At their introduction, both technologies were expected to reduce operating costs by enhancing fuel efficiency. While the design efficiency gains were relatively modest (on the order of 2 to 5 percent), the significance of the ex ante cost savings depended on the utility's expected cost of fuel over the life of the generating unit. These costs vary considerably across utilities.[13] For the 144 utilities in our sample, the ratio of highest to lowest average fuel cost per million Btus was 325 percent in 1962 and 393 percent in 1972. Such differences in fuel costs should contribute to significant variation in the relative attractiveness of the new technologies.

Theoretical models suggest that greater uncertainty about a technology's potential will lead to a slower diffusion path, all else equal. Although data are not available to construct a direct test of the influence of uncertainty on adoption patterns, some insight may be gained by comparing diffusion paths across the two technologies. The 2400 psi units constitute a significant improvement over pre-existing subcritical technology although they were not a major departure from that technology; the supercritical units represent a more radical change from previous boiler technologies.[14] This dichotomy suggests that the uncertainty surrounding the ex ante costs and benefits of adopting the supercritical technology is likely to have been considerably larger than the uncertainty associated with adopting the 2400 psi subcritical technology. We

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[13] Transportation costs can account for a high fraction of delivered coal costs, implying that locations near high quality coal sources may face substantially lower costs.

[14] Operating at supercritical pressures eliminates the need for a substantial amount of equipment associated with saturated ("wet") steam, but requires more advanced materials and designs to handle the considerable increase in steam pressure.

would expect this to shrink the adoption probabilities for the supercritical technology and lead to a slower diffusion path.

The expected speed of diffusion also is dampened by the embodiment of generating technology in very long-lived capital equipment. Capital costs of powerplants are large relative to operating costs and plants are designed to have useful lives of thirty years or more. As power plants age their utilization patterns typically change, moving from base load to cycling to peaking operation. Additions of new generating capacity are driven primarily by increases in electrical load, rather than by opportunities to replace existing capacity with capacity that has significantly lower operating costs.[15] Although both 2400 psi and supercritical technologies were expected to lower the total cost of generating electricity, neither promised sufficient savings to warrant scrapping existing facilities and replacing them with new generating units.[16] This will tend to slow diffusion of both technologies and implies that we will observe a utility's decision to adopt one of these technologies only when the utility decides to add new baseload capacity.[17]

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[15] Obviously, generating capacity eventually is retired, so that retirements have some effect on the demand for additional capacity. During our sample period, however, capacity additions dwarf retirements. For example in 1970, 28,000 megawatts (Mw) of new generating capacity was added, while only 1,000 Mw was retired. Edison Electric Institute Statistical Yearbook of the Electric Utility Industry/1983, page 12.

[16] This is in sharp contrast to Oster's (1982) finding on the economics of replacing existing steel furnace technology with the basic oxygen furnace.

[17] We assume here and throughout the paper that a utility's decision to add new baseload capacity is independent of its technology choice. This corresponds to an assumption that utilities first decide their schedule of additions, based primarily on demand growth projections and unit retirement schedules, and then decide what type of units to build to meet their additions schedule. This assumption may not strictly hold; if new technologies are scale-augmenting, technology choice may have some effect on building schedules. Even in this case, the increase in efficient size is unlikely to be large relative to the size of the "average" generating unit. We therefore maintain the

There are a number of channels through which firm size might influence innovativeness. First, larger utilities are more likely to have internal engineering, design and maintenance staffs that are both interested in and capable of adopting new technologies before substantial experience has been gained with them (Joskow and Rose, 1985). Second, larger utilities are likely to be less averse to the risks of early adoption. For utilities with a large portfolio of generating units, the impact of a "mistake" on the cost of service and overall profitability will be modest.[18] Third, if there are economies that lead to lower costs when more plants of a given technology are operated by a single firm, larger firms may find early adoption more attractive. We find some evidence of this type of economy in our earlier work (Joskow and Rose, 1985): there appears to be modest learning-by-doing that may lower construction costs as a utility gains experience with a given technology. Finally, if new technologies are scale augmenting, they may be more attractive to larger utilities that can economically add capacity in large chunks.[19]

We also expect larger utilities to build new generating units of any kind more frequently than do smaller utilities, _ceteris paribus_. This will result from the relationship between size, growth rates, and the lumpiness of generating units. Thus, there may be a natural numerical relationship between size and speed of adoption that arises not from differences in the propensity to adopt new technologies but instead from differences in economic opportunities to add new capacity. As a result, failing to account for differential building

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independence assumption as approximately correct, and believe that accounting for potential correlations is unlikely to yield additional insight.

[18] If the cost impact is small relative to total costs, regulators are less likely to notice or penalize a utility in regulatory rate hearings.

[19] But see note 16, _supra_.

frequencies may induce a positive correlation between firm size and the estimated speed of adoption, even if the true relation is a positive effect of size on the probability of building but no effect of size on the probability of adoption conditional on building. Distinguishing between these two effects is critical to the interpretation of the results. We are not aware of any other work that controls for the opportunity to adopt as we do here.

Ownership structure may affect adoption probabilities although the direction of the predicted effect is ambiguous. There are three types of utilities in our sample: investor-owned (private) utilities, government-owned utilities (primarily municipal utilities) and cooperatives (primarily rural electric cooperatives). The largest group is the investor-owned utilities, which are most likely to behave as profit-maximizing firms.[20] Municipal utilities ("munis") and cooperatives ("coops") may have objectives other than profit-maximization that alter their behavior relative to that of investor-owned utilities. Munis and coops also appear to be less likely to be involved in R&D activities: 73% of investor-owned utilities belong to the Electric Power Research Institute (EPRI), as compared to only 37% of munis and 32% of coops (EPRI, 1987, p.1). We expect most of these differences to lower innovation probabilities for munis and coops. There could be offsetting considerations, however. If government-owned utilities are more responsive to the interests of power plant engineers, for example, we might expect greater pressures to adopt

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[20] Regulatory lag and opportunities to make wholesale transactions that are subject to relatively loose regulatory constraints (Joskow and Schmalensee, 1983) provide incentives to adopt cost-saving technologies. Since new generating technologies tend to be more capital-intensive than older generating technologies, rate of return regulation may provide additional incentives (Smith, 1974).

new technologies (Joskow, 1976). We expect this to be of potential significance only for the largest government- or cooperatively-owned utilities.

Finally, the expected pattern of diffusion through time is unlikely to be monotonic. While much of the literature posits constant or increasing hazard rates, we expect that adoption probabilities will increase initially and then decline for both of our innovations. The technologies we explore co-exist in time with each other and with older (lower pressure) technologies. Although the 2400 psi technology was developed before the supercritical technology, for a large part of the sample period the 2400 psi and supercritical technologies represent competing choices.[21] This suggests that the probability of adoption for 2400 psi units may decline after some date as utilities decide to "skip" a generation of technology and move immediately to the newer supercritical technology. Declines in the adoption probability for the supercritical technology are likely to arise not from the development of more advanced technologies but from unexpected problems with supercritical units. The development of substantial reliability problems and unexpectedly high maintenance costs for supercritical units during the mid-1970s appear to have reduced or eliminated the expected savings from this technology (Joskow and Rose, 1985, and Joskow and Schmalensee, 1987). Adoption probabilities for supercritical technologies should have decreased after these problems were realized.[22]

In summary, we expect adoption probabilities for each of the two technologies considered in this paper to be increasing in firm size and fuel

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[21] A number of utilities reverted to older technologies after building one or more units with the newer technology. For reasons discussed below, this result may be expected for the supercritical technology. Less explicable is its occurrence for the 2400 psi technology.

[22] One might expect this to increase the adoption probability for 2400 technologies, although there is little evidence of this in the data.

costs. The predicted effect of ownership structure is ambiguous, although it seems likely that the probability of adopting an innovation will be higher for investor-owned utilities than it is for government and cooperatively owned utilities. Finally, we expect that adoption probabilities will vary through time, initially rising as uncertainties about the technology are resolved and costs decline and ultimately falling as even newer technologies become available.

4. Statistical Models of Technology Adoption

The empirical literature has used a variety of approaches to estimate models of technology diffusion. We discuss below two of the most popular classes of models with the assumptions implicit in their use. These are models based on normal probability distributions, including probit and Tobit analyses, and those based on failure time or hazard rate specifications. We also describe a statistical model of technology adoption that we believe distinguishes firm size effects on "innovativeness" from firm size effects on adoption opportunities better than have most previous models.

Common to our paper and much of the literature on technology diffusion is a focus on time to transition or first use of a new technology, not on technology choice *per se*. In line with this, we characterize firms as being either in the "no adoption" state, prior to their first use of the new technology, or in the "adoption" state, once the technology has been used and forever after.[23] This emphasis is appropriate if one is concerned with how long it takes firms

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[23] As such, our paper belongs in the literature on interfirm diffusion patterns; see Hannan and McDowell (1984) and LLM (1987) for other recent examples of this type of study. Intrafirm diffusion patterns-- the penetration of innovations within firms-- have been subject to less empirical study.

in an industry to try a new technology rather than with how long it takes firms to convert their entire production lines to the new technology. This approach seems of particular interest for industries such as electric utilities, in which technology is embodied in long-lived capital.[24]

We also assume that a utility's probability of adoption is related to its characteristics, such as size and average fuel cost, as of some point in time; cross-sectional differences in these characteristics drive the differences in utility adoption dates. Variations in adoption rates through time are determined by forces common to all utilities, such as the number of other firms adopting the technology, improvements in the technology through time, or resolution of uncertainties about the technology's costs and benefits. Using this assumption, which typifies much of the empirical work in this area, we work with models that specify the adoption probability as: Pr(utility i adopting at time t) = $f(X_i, t)$, where X_i are utility i's characteristics measured at some time common to all utilities.

<u>Normal probability models</u>

A number of studies have used a normal probability distribution to analyze the time until adoption for firms or plants, measured from some initial date of availability.[25] This model was implicit in early studies that used OLS regressions to estimate the determinants of interfirm differences in adoption dates (c.f. Mansfield, 1968, and Romeo, 1975). A significant shortcoming in

[24] If capital is long-lived and operating costs are low relative to capital costs, replacement of capacity is likely to be slow even if firms are aware of technological advances and prepared to adopt them as soon as it is profitable to do so.

[25] One could as easily measure time since adoption, counting backward from the end-of-sample date (see Oster, 1982).

many early studies is the failure to account for sample selection or censoring problems: firms that had not adopted the new technology by the end of the sample period frequently were excluded from the analysis (Romeo, 1975) or treated as never adopting. These biases can be eliminated by including both adopters and non-adopters in the sample and using a Tobit model to treat end-of-sample censoring on adoption dates; see Oster (1982) for a study using this technique.

A second potential problem arises from the normal distribution's range over $(-\infty,+\infty)$. Presumably a technology cannot be adopted prior to some innovation date, implying that the time until adoption is distributed over $(0, +\infty)$, where time is set equal to 0 in the year that the technology first becomes available. The statistical analysis could account for this either by treating the distribution as a left-truncated normal or by transforming the model. We find the latter course most appealing and in our empirical work with the normal probability model assume that the log of the time to adoption is distributed as a normal random variable, with right censoring at the end-of-sample date.[26]

To derive the likelihood function based on this distributional assumption, define the set of exogenous variables that affect firm i's adoption decision as X_i, firm i's time until adoption as t_i, and the end-of-sample censoring date as T. We also define $\underline{X}_i = -X_i$ as a normalization to ease the comparison between this model and the other models discussed below, where the time to adoption is a decreasing function of $X_i\beta_n$ and β_n is the parameter vector from the normal probability model. Given these assumptions, the likelihood function is:

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[26] This follows from an assumption that the time to adoption is distributed as a log-normal random variable.

$$(1)\quad \Pr(\tilde{t}_1,\ldots,\tilde{t}_N) = \prod_{j=1}^{N_1} \{ \phi((\tilde{t}_j - \underline{X}_j\beta_n)/\sigma) /\sigma\} \prod_{k=1}^{N_2} \{1 - \Phi((\tilde{T}-\underline{X}_k\beta_n)/\sigma) \}$$

where ˜ denotes the natural log of the time variable, N_1 is the set of firms that adopt on or before the end-of-sample date, N_2 is the set of firms that have not adopted by time T, and $N = N_1 + N_2$. The parameters β_n and σ can be estimated by maximum likelihood methods.

This model does not assume any explicit time dependence in the adoption probability; systematic variations in adoption dates are attributable only to variations in firms' characteristics (X). The model does, however, assume that the "critical" level of $X\beta_n$, above which firms choose to adopt the technology, declines through time. This can be seen most easily by recognizing that the expected time to adoption is declining in $X\beta_n$: $E(\tilde{t}_i|X_i) = \underline{X}_i\beta_n + .5\sigma^2 = -X_i\beta_n + .5\sigma^2$. This feature of the model is consistent with the assumptions built into most theoretical models of technology diffusion that the cost of adoption or perceived riskiness of the technology declines over time.

Hazard rate models

A second class of models used to analyze technology diffusion is based on failure time or hazard rate specifications (Hannan and McDowell, 1984, and LLM, 1987). The hazard rate, $h_i(t)$, is defined as the probability that firm i will adopt an innovation at time t conditional on having not adopted the innovation before t. Because these models explicitly focus on transition probabilities, they seem particularly suited to study patterns of technology adoption across firms.[27]

Although particular distributional assumptions on the hazard rate vary across applications, the models share a common structure. The unconditional probability that firm i will adopt the innovation at time t (the density function) is equal to:

$$(2)\quad f_i(t) = h_i(t)\exp\left(-\int_{\tau=0}^{t} h_i(\tau)d\tau\right)$$

and the probability that firm i will not adopt the innovation prior to t (the "survivor" function) is equal to:

$$(2)\quad 1 - F(t) = \exp\left(-\int_{\tau=0}^{t} h_i(\tau)d\tau\right)$$

To estimate this model, the form of the hazard rate must be specified. In principle, virtually any function that satisfies the properties of a conditional probability could be used. For concreteness, we consider two specifications of the hazard rate.

The proportional hazards model is perhaps the most widely used specification; in the diffusion literature, LLM (1987) use this model to estimate the diffusion of optical scanners among retail grocery stores. The proportional hazards model assumes that the relative hazard rates for two firms are constant through time, allowing the hazard to be decomposed into separate firm and time

[27] See Kalbfleisch and Prentice (1980) for descriptions of failure time models and their applications. Hazard-rate models have been used extensively to model unemployment dynamics; see Lancaster (1979) and Nickell (1979) for early applications.

components. We can write this as $h_i(t) = h_0(t)\exp(X_i)$, where $h_0(t)$ specifies the evolution of the hazard rate over time and X_i are fixed firm characteristics. The time component can be estimated non-parametrically (see LLM, 1987) or parametrically by assuming some distribution for $h_0(t)$. Our estimates of the proportional hazard model parameterize $h_0(t)$ using the Weibull distribution: $h_0(t) = \alpha t^{\alpha-1}$. Under this assumption, the likelihood function for the data is:

$$(4)\quad \Pr(t_1,\ldots,t_N) = \prod_{j=1}^{N_1} \alpha_w \cdot t_j^{\alpha_w - 1} \exp(X_j\beta_w)\cdot\exp(-\exp(X_j\beta_w)t_j^{\alpha_w}) \cdot \prod_{k=1}^{N_2} \exp(-\exp(X_k\beta_w)T^{\alpha_w}$$

where N_1 and N_2 are as defined earlier and β_w and α_w are the parameters of the Weibull proportional hazards model. The adoption probability is increasing in $X\beta_w$; the hazard rate will be monotonically increasing, decreasing or constant through time as α is greater than, less than, or equal to one.

Alternatives to the proportional hazards model allow the relative probabilities of adoption across firms to change through time. This can be accomplished either by allowing time-varying firm characteristics to affect adoption probabilities (see Hannan and McDowell, 1984) or by interacting time and firm effects.[28] To allow us to compare results across different models, we choose the latter approach. We specify the hazard rate as following a log-logistic distribution:

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[28] Hannan and McDowell assume that the adoption probability conditional on X_i is constant through time, although changes in X_i over time may increase or decrease the adoption probability for a firm.

$$(5)\quad h_i(t) = \alpha_e t^{\alpha_e - 1} \exp(X_i\beta_e) \;/\; (1 + t^{\alpha_e} \exp(X_i\beta_c))$$

where subscript e denotes estimates from the log-logistic hazard model. This specification allows us to estimate the hazard as a function of the constant firm characteristics (X_i) used to estimate the Tobit and Weibull diffusion models discussed above. As in the Weibull hazard model, the adoption probability is increasing in X_i. The log-logistic specification implies a monotone decreasing hazard rate if $\alpha_c \leq 1$ and a hazard that is initially increasing then decreasing for $\alpha_c > 1$. This latter characteristic is particularly appealing for our data. The log-likelihood associated with this specification is:

$$(6)\quad LL_c = \sum_{i=1}^{N} \Big\{ (1-a_i)[\ln(\alpha_c) + (\alpha_c-1)\ln(t_i) + X_i\beta_c - 2\ln(1 + t_i^{\alpha_c} \exp(X_i\beta_c))] - a_i \ln(1 + T^{\alpha_e}\exp(X_i\beta_c)) \Big\}$$

where a_i is a dummy variable equal to one for utilities that do not adopt the new technology by T, zero otherwise.

<u>Models conditional on building (double-censored models)</u>

All of the models described above assume that date at which utilities would choose to adopt the new technology is known and that the variables included in X affect firms' adoption decisions but not their adoption opportunities. As described earlier, we think these assumptions are unlikely to be satisfied either in our data set or in most technology diffusion studies.[29]

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[29] Similar assumptions are implicit in many studies of unemployment transitions, in which job offers are assumed to arrive independently of variables included in X.

In particular, we expect large firms to build generating units more frequently than do small firms, generating spurious correlations between firm size and adoption probabilities in the earlier models.

This is illustrated in figure 1. Denote the latent (unobserved) adoption value for firm i at time t by $A(X_i, t)$. Firm i will adopt the new technology at the first opportunity after $A(X_i, t) \geq A^*$, where A^* is the "critical" level required for adoption. Each time we observe the utility building a new unit we learn one of two things. Either the utility uses an old technology, in which case we know $A(X_i, t) < A^*$, or the utility adopts the new technology, in which case we know $A(X_i, t) \geq A^*$.[30] Censoring occurs when a utility does not build each year. Let t^* be the date at which $A(X_i, t) \geq A^*$. We know that t^* lies somewhere between the date of the last old unit (t_0) and the date of the first new unit (t_1). For utilities that build frequently, the gap between t_0 and t_1 will tend to be small and t_1 will be quite close to t^* (see t_0^B and t_1^B in figure 1). For utilities that build infrequently, the gap between t_0 and t_1 may be large, suggesting that t_1 may greatly exceed t^* (see t_0^S and t_1^S in figure 1).

If we have data on the units built before the utility adopts the new technology, as well as the date at which the utility first uses the new technology, we can correct this censoring bias by estimating adoption probabilities conditional on building a new unit. Consider a panel data set with observations on each utility over time. For each year, we observe one of three outcomes: the utility builds a unit and adopts the new technology, the utility

[30] Since we are interested in time to first use, not in technology choice per se, we only need to observe building decisions until the first new technology unit is constructed.

builds a unit but does not adopt the new technology, or the utility does not build any unit.[31] This suggests a full likelihood function of the form:

$$(6)\quad \Pr(u_{11},\ldots u_{NT}) = \prod_{it\,\epsilon\,N_1} \text{pr(utility i builds at t)} \cdot \text{pr}(A(X_i,t) \geq A^*) \cdot$$
$$\prod_{it\,\epsilon\,N_2} \text{pr(utility i builds at t)} \cdot \text{pr}(A(X_i,t) < A^*) \cdot$$
$$\prod_{it\,\epsilon\,N_3} \text{pr(utility i does not build at t)}$$

where u_{it} is an observation on utility i's generating unit choice in year t, N_1 is the set of utility-year observations in which utilities build and adopt the new technology, N_2 is the set of utility-year observations in which utilities build but do not adopt the new technology, N_3 is the set of utility-year observations in which utilities do not build any units, and $N_1 + N_2 + N_3 = NT$.

We choose a probit specification to model building probabilities for each utility and a log-logistic hazard specification to model the evolution of the latent adoption probabilities.[32] We assume, as discussed in note 17, that utilities' building decisions are independent of their adoption decisions. This implies yields the log-likelihood for the double-censored model:

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[31] After a utility builds a unit with the new technology it is considered to be in the adoption state for the rest of the sample.

[32] Any of the other models could be used to model the adoption probability; we choose the log-logistic hazard because it is the most flexible of the models we consider.

$$(7)\quad LL_f = \sum_{i=1}^{N} \sum_{t=1}^{T} \Big\{ b_{it}a_{it}(\ln(\Phi(Z_{it}\Psi)) + \alpha_f\ln(t) + X_i\beta_f - \ln(1 + t^{\alpha_f}\exp(X_i\beta_f))) + b_{it}(1 - a_{it})\cdot (\ln(\Phi(Z_{it}\Psi)) - \ln(1 + t^{\alpha_f}\exp(X_i\beta_f))) + (1-b_{it})\cdot\ln(1 - \Phi(Z_{it}\Psi)) \Big\}$$

where b_{it} is a dummy variable equal to one if utility i builds a unit at time t, 0 otherwise; a_{it} is a dummy variable equal to zero before the utility adopts the new technology and one during all other years; Ψ are the parameters of the variables Z in the building probit; and the subscript f denotes estimates from the full-maximum likelihood, double-censored model.

Under the independence assumption, this likelihood function is separable in the building and adoption probabilities.[33] We can therefore estimate the parameters of the adoption decision by estimating the probability of adoption conditional on building. In this light, the biases of the conventional adoption models discussed above arise from sample selection biases: these models censor observations in which utilities decide to build but not adopt the new technology. While sophisticated applications of the conventional models recognize that the adoption date for non-adopters is right-censored at the end of the sample date, the applications generally fail to treat the left-censoring

[33] While the independence assumption may not be strictly true, we believe it is approximately correct for this industry and that little would be gained from the complexity introduced by allowing for correlated errors.

that arises because utilities' adoption decisions are not observed until they build a new unit.[34]

In the following section, we report results using each of the four specifications we have developed: Tobit, Weibull proportional hazards, log-logistic hazard, and hazard models conditional on building. We expect the first three specifications to yield qualitatively similar results, although the magnitude and interpretation of the coefficients will vary across the models, due primarily to their different implicit assumptions on the evolution of the hazard rate through time. The results from these models indicate what our estimates would be if we used the techniques common in the diffusion literature. We are most interested in comparing these estimates to those from the model that conditions on building decisions, which we consider to be a more correct specification for our problem. Differences between the first three sets of results and those of the double censored problem will provide information on the significance of the biases introduced by assuming that adoption (or observation) opportunities are randomly distributed across firms, independently of variables that affect adoption probabilities. While estimates of the building probability are not required to estimate the adoption parameters, we also report results from building probit equations to illustrate the influence of size on adoption opportunities.

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[34] An equivalent statistical treatment for the bias is to write the likelihood function as a left- and right-censored hazard model, in which we observe t0 and t1 for each utility, and estimate the likelihood function over N: Π Pr(t0 < t* ≤ t1).

5. Data and Results

The statistical models developed in the previous section are estimated using data on the building decisions and technology choices of 144 electric utilities over the 1950 through 1980 period. In this section, we first describe the data used in the analysis and present descriptive statistics on the patterns of technology adoption in the industry. We next report estimates of adoption patterns for the 2400 psi technology and compare the results across different statistical specifications; the corresponding results for the supercritical technology follow. The section concludes by discussing what we learn from the various statistical models.

Data and descriptive statistics

Our data set consists of information on a census of 144 electric utilities that built one or more fossil-fired steam turbine generating units between 1950 and 1980.[35] For these utilities, we collected information on the date and technology type of all fossil-fuel steam turbine capacity additions, firm size in megawatts of capacity, capacity growth rates, average fuel cost per million Btus, and type of ownership (investor, municipal, federal, or cooperative).

We define X, the set of exogenous variables that affect a utility's adoption decision, to include four variables: firm size, type of ownership, average fuel cost, and (perhaps) time. To allow for nonlinear effects of firm size, we include both size and size-squared in the equations. The building equation models a utility's decision to build zero versus one or more units in

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[35] Missing data forced us to exclude from the sample three utilities that built coal-fired generating units during this period. The utilities included in the sample constructed 1091 units between 1950 and 1980, which comprise virtually all fossil-fired steam turbine capacity added during the sample period.

a given year. We assume that Z, the set of variables that influence a utility's building decision, includes the utility's size, growth rate, ownership structure (perhaps), and time. The model allows for nonlinear size effects and time trends by including quadratic terms in both utility size and time.

As discussed earlier, the adoption models are based on a constant X_i for each firm, raising the question of when the characteristics should be measured.[36] We consider two dates: 1960 and 1970 (due to data collection requirements, fuel prices are observed two years after each of these dates).[37] The first of these allows us to measure firm characteristics part-way through the diffusion process for the 2400 psi technology and before the diffusion process really begins for the supercritical technology. If utilities are forward-looking, 1960 may be too myopic. We therefore consider 1970 as an alternative. As there is no strong theoretical basis for choosing between these, we allow the data to decide which is more appropriate.

Before presenting results from tightly parameterized statistical models of the diffusion process it may be instructive to examine some simple descriptive statistics on the data. Table 1 reports means and standard deviations for the variables used in the statistical analysis. As indicated, the 2400 psi technology had diffused quite widely through the industry by 1980, with 93 utilities (65 percent) adopting this technology by the end of the sample. The supercritical technology achieved much more limited diffusion, with only 39 utilities (27 percent) adopting the supercritical technology by 1980.

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[36] Building probabilities may be a function of constant or time-varying firm characteristics.

[37] The choice of dates is somewhat arbitrary; we were influenced by data availability in selecting these two candidates.

This pattern is amplified in table 2, which reports the distribution of technology type for the 1091 generating units included in our sample. The table highlights the co-existence of both old and new technologies over long periods: units continue to be built using old lower pressure technologies twenty or more years after newer technologies have been introduced. The relative dominance of different technologies does shift over time, however. The 2400 psi technology supplanted lower pressure technologies as the modal choice by the mid-1960s and was itself superceded by the supercritical technology during the early 1970s. As noted earlier, however, the 2400 psi technology re-emerged as the leading technology during the last part of the 1970s, most likely in response to increasing dissatisfaction with the operating performance of supercritical units.

The differences in the diffusion path of the 2400 psi and supercritical technologies may be illustrated best by a graph of the diffusion paths. Figure 2 plots nonparametric (Kaplan-Meier) estimates of the survivor function for each of the two technologies (see Kalbfleisch and Prentice, 1980). As indicated by the bottom curve, the probability of adopting the 2400 psi technology is quite small until after 1956. From 1957, the hazard rate (which is proportional to the slope of the curve) looks fairly constant and relatively large. Although it flattens somewhat in the mid-1970s, it returns to the previous rate by the end of the period, suggesting that continued penetration of the technology through the remaining 34 percent of the utilities is likely.

The picture is quite different for the supercritical technology. The hazard rates are small until the mid-1960s, increase substantially for a 5 year period, and then decline again in the early 1970s. Virtually no utilities adopted this technology after 1975 and it seems likely that the technology will never penetrate much beyond the 27 percent adoption level achieved by 1980.[38] With these diffusion patterns in mind, we now turn to parametric estimates of adoption probabilities, to determine whether systematic differences across utilities explain the positions of individual firms along the diffusion curves.

Results for the 2400 psi technology

In this section, we first examine Tobit, proportional hazards, and log-logistic hazard estimates for the diffusion of the 2400 psi technology.[39] These allow our results to be compared to those of other diffusion studies, most of which use a variant of one of these models. After discussing these results, we examine estimates from the hazard model conditional on building to determine the extent of biases introduced by the exclusion of adoption opportunity information from the first three models.

Table 3 reports results from the first three models. As discussed earlier, the exogenous variables in the models are utility size and its square, the utility's average fuel cost, ownership dummy variables for coops and government-owned utilities, and time. Because specifications that measure utility size by 1970 capacity outperform those that use 1960 measures of size, only the former are reported.[40] The first three columns report Tobit, Weibull

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[38] In future work, one might wish to modify the likelihood function to allow the cumulative probability of adopting this technology to asymptote over time to some level considerably less than one.

[39] All the likelihood functions used in this study were programmed in Fortran and estimated using a maximum likelihood routine based on the BHHH algorithm. We are grateful to Hank Farber for providing us with the code for his optimization routine.

[40] The results using 1960 size measures are quite similar, but the standard errors tend to be somewhat larger and the fit of the equation somewhat poorer than in the corresponding equations that use 1970 capacity.

proportional hazards, and log-logistic hazards results using 1962 average fuel prices. The second three columns report similar specifications using 1972 average fuel prices. Since the Tobit model implicitly assumes a constant hazard through time, time is not included in the Tobit specifications.

The results are quite similar across all six specifications. Firm size has a strong, significant, positive effect on adoption probabilities. Larger firms are likely to adopt the technology earlier than are smaller firms, although there are diminishing returns as indicated by the negative coefficient on the size-squared term. The quadratic peaks at 8,500 to 10,000 Mw of 1970 capacity, substantially above the sample mean of 1,900 Mw but not beyond the sample size range. This suggests that for a few large utilities, size has a net negative effect on adoption probabilities. The estimated magnitude of the size effect is virtually identical across the Tobit and Weibull specifications and is substantially larger in the log-logistic specification.

Fuel prices appear to have some positive impact on adoption probabilities, although the effect is statistically distinguishable from zero only in the hazard models that use 1972 fuel prices. The point estimates for coop and government ownership suggest negative effects on adoption probabilities, but these are imprecisely measured and cannot be statistically distinguished from zero. Finally, the hazard models suggest that adoption probabilities initially rise through time. The magnitude of the time coefficient in the log-logistic specification implies that the hazard diminishes within the sample period, suggesting that the Weibull's restriction on a monotonic hazard should be rejected.

To explore how much of the size effect in these results might be due to differences in adoption opportunities, we next estimated a model of utilities' building decisions. Table 4 reports estimates from probit models of the building equations.[41] The results indicate strong positive effects of size on building probabilities, although the quadratic terms indicate that the size effects peak sooner for the building models than they do for the adoption models (between 1600 and 6000 Mw). This implies that building probabilities decline with size over part of the sample of utilities. Capacity growth rates also have substantial positive effects on building probabilities. Building probabilities rise through time, but at a declining rate. Finally, coops and munis appear to build less frequently than do comparable investor-owned utilities, although the estimated effect is fairly unstable and imprecise across specifications.

These results suggest that at least part of the firm size effect in the adoption models may be due to differences in the frequency of building, which translate into differences in the frequency with which we observe technology choices of different types of firms. To treat this possible source of bias, we re-estimate the adoption probabilities using the full information structure of the problem. While we could in principle apply this technique to all three models, the Tobit and Weibull model impose restrictions on the time path of hazard rates that more flexible models reject, so we apply this technique only to the log-logistic hazard. This model is estimated on a panel of annual data on each utility over the 1950 through 1980 period.

Table 5 reports adoption probabilities conditional on building for a number of specifications of the 2400 psi technology log-logistic hazard. A comparison of table 5 with table 3 suggests quite substantive changes from the

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[41] The estimates assume serially uncorrelated independent errors. If these assumptions are violated--for example, by negative serial correlation in the errors--the reported standard errors will be inconsistent.

simple adoption model results. First, the estimated effect of firm size on adoption probabilities is halved. While larger firms appear to exercise their opportunities to adopt the 2400 psi technology earlier than do smaller firms, about half the effect of firm size on the simple adoption probabilities can be attributed to differential building rates. This suggests that models that fail to account for systematic differences in adoption or observation opportunities may significantly overstate size effects on innovativeness. The quadratic term suggests that size effects peak in the same range as estimated in table 3.

Moreover, after treating this source of bias, the effects of the other factors in the adoption model become much more pronounced. Average fuel costs have a much larger estimated effect on decisions to adopt the new technology and can be easily bounded away from zero. The ownership variables also have a significant effect in the full maximum likelihood model. Once differential building rates are accounted for, government-owned and cooperative utilities are less likely to adopt the 2400 psi technology than are investor-owned utilities. At least part of this effect may be due to the smaller effect of firm size. Since munis and coops tend to be smaller than are investor-owned utilities, firm size may have absorbed part of the ownership effects in the earlier results. When the effect of firm size is reduced, the differences among the ownership structures becomes more apparent.

Results for the supercritical technology

These same statistical models can be used to study the determinants of adoption probabilities for the supercritical technology. As we noted earlier, the greater uncertainty surrounding this technology is likely to have slowed its diffusion and the development of substantial reliability problems with early supercritical units appears to have almost halted its diffusion by the end of the 1970s. We are interested in exploring whether these factors also affected which firms are most likely to have adopted the technology.

Table 6 presents results from both simple adoption probability models and full maximum likelihood models. In columns 1 through 3, we report Tobit, Weibull proportional hazards, and log-logistic hazard results, using 1970 capacity and 1972 fuel prices. In general, these results are much noisier than were those for the 2400 psi technology. Utility size has a slightly larger effect on adoption probabilities for the supercritical technology, although the estimates are within a standard deviation of those for the 2400 psi technology. The quadratic in size continues to be important and adoption probabilities again peak in the 8,500 to 10,000 Mw range. Adoption probabilities rise through time ($\alpha > 1$ in both Weibull and log-logistic models), but eventually decline (in the log-logistic results). The time paths are statistically indistinguishable from those for the 2400 psi technology, but the point estimates suggest a somewhat slower diffusion rate for supercritical units. The fuel price and ownership variables have no clear effect in these equations; the point estimates are unstable and the standard errors are enormous relative to the coefficients.

We report estimates for the full maximum likelihood model in columns 4 and 5 of table 6. Correcting for building opportunities has much less impact on the results for the supercritical technology than it had for the 2400 psi technology. The firm size effect remains within 10 to 20 percent of the estimates from simple adoption probability models and are substantially larger than were the corrected size effects for the 2400 psi technology. The hazard rate rises more quickly in the full maximum likelihood model, though the difference in the coefficient from the simple log-logistic model does not appear statistically signficant. The estimated effects of fuel prices and ownership structures continue to be unstable and very poorly identified.

These results may be an artifact of the limited number of utilities that adopt this technology over the sample period (39 of 144). With only one-quarter of the sample ever adopting the technology, the data appear not to contain enough information to pin down distinctions among the adopters and non-adopters. Alternatively, the results may reflect the peculiarities of the supercritical technology itself.

6. Conclusions

The results presented in this paper provide strong evidence that large firms tend to lead the electric utility industry in adopting technological innovations. For both of the new technologies we analyze, large firms were significantly more likely to be among the early adopters. There does, however, appear to be an optimum size with respect to encouraging the diffusion of innovations: for the very largest firms in the industry, increasing size reduces the probability of early adoption. Our results also suggest that Oster's (1982) finding of a negative correlation between firm size and innovativeness in the steel industry does not generalize to all capital-intensive industries.

Our results also suggest that ownership structure can exert an important influence on innovative activity. Investor-owned utilities tended to adopt the 2400 psi technology earlier than did their municipally-owned and cooperatively-owned counterparts in the industry, leading to more rapid diffusion of the technology through the industry. This finding is consistent with the observation that investor-owned utilities also exhibit more involvement in industry research and development activities and organizations.

Finally, our analysis provides strong evidence on the need to control for differences in building opportunities when analyzing firms' decisions to adopt technologies embodied in long-lived capital. In most cases, we expect to observe more frequent capacity additions for larger firms in an industry. This can lead econometric results to overstate the correlation between firm size and adoption probabilities. We propose a methodology to correct this bias, and find that its application to the 2400 psi technology reduces estimated size effects by one-half. Moreover, we find that the effects of ownership structure and factor cost differentials are larger and more precisely estimated after controlling for the opportunity bias. These results suggest that future studies of technology diffusion, and other studies that employ hazard rate analysis, may benefit from application of this methodology.

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Table 1

SAMPLE DESCRIPTIVE STATISTICS
(144 Utilities)

Variable	Mean	Standard Deviation
Utility Size (hundred Mw)		
1960 capacity	9.91	14.75
1970 capacity	19.26	27.54
Utility Size^2 (hundred Mw)		
1960 capacity	314.45	1153.19
1970 capacity	1124.57	3505.59
Capacity growth rate (%)	3.27	4.95
Average fuel cost (cents/million Btu)		
1962	26.51	6.03
1972	39.48	11.81
Ownership (0,1)		
Investor	.70	
Government	.17	
Cooperative	.13	
2400 psi technology		
First adoption		1953
Percent utilities adopting by 1980		.65
Mean adoption date (for adopters)		1967.9
Supercritical technology		
First adoption		1957
Percent utilities adopting by 1980		.27
Mean adoption date (for adopters)		1968.1

Table 2

NUMBER OF UNITS BUILT
BY TECHNOLOGY CLASS AND TIME PERIOD

Time	≤ 2000 psi	2000 psi	2400 psi	3500 psi	Total
1950-1954	115	11	2	0	128
1955-1959	150	57	33	2	242
1960-1964	71	41	61	7	180
1965-1969	47	8	64	49	168
1970-1974	50	13	62	70	195
1975-1980	29	10	108	31	178
Total	462	140	330	159	1091

Table 3

ADOPTION PROBABILITY ESTIMATES, NOT CONDITIONED ON BUILDING:
2400 PSI TECHNOLOGY

	Adoption Probability Model					
Variable	Tobit	Weibull	Log-logistic	Tobit	Weibull	Log-logistic
Fuel price as of:	1972	1972	1972	1962	1962	1962
Constant	.264 (.499)	-11.408 (1.253)	-16.290 (1.581)	.840 (.639)	-10.917 (1.241)	-15.096 (1.548)
Size (1970)	.070 (.014)	.070 (.008)	.118 (.016)	.070 (.014)	.068 (.008)	.120 (.015)
$Size^2$ (1970)	-.00035 (.00009)	-.0004 (.00006)	-.0007 (.00009)	-.00035 (.00009)	-.0004 (.00006)	-.0007 (.00009)
Fuel Price	.003 (.011)	.015 (.008)	.029 (.013)	-.017 (.021)	.011 (.016)	.010 (.026)
Coop	-.574 (.429)	-.244 (.439)	-.263 (.583)	-.648 (.424)	-.323 (.427)	-.380 (.596)
Government	-.389 (.331)	-.413 (.284)	-.265 (.477)	-.412 (.331)	-.418 (.303)	-.263 (.484)
Time	--	2.990 (.310)	4.319 (.395)	--	2.947 (.295)	4.207 (.387)
Sigma	1.391 (.172)	--	--	1.384 (.168)	--	--
Log-likelihood	-235.52	-356.66	-350.92	-234.76	-358.05	-352.98
Number of Observations	144	144	144	144	144	144

Standard errors in parentheses.

Table 4

ESTIMATES OF BUILDING PROBABILITIES:
PROBIT MODELS

Variable	1970 Size	1960 Size	Time-Varying Size
Constant	-2.375 (.106)	-2.308 (.105)	-2.235 (.105)
Size	.020 (.003)	.024 (.005)	.004 (.004)
$Size^2$	-.0002 (.00002)	-.0004 (.00005)	-.0001 (.00003)
Growth	.112 (.011)	.119 (.010)	.136 (.008)
Time	.119 (.013)	.121 (.012)	.123 (.013)
$Time^2$	-.003 (.0004)	-.003 (.0004)	-.003 (.0004)
Coop	-.101 (.093)	-.153 (.093)	-.291 (.091)
Government	.015 (.077)	-.044 (.076)	-.183 (.075)
Sample proportion no build	.804	.804	.804
Proportion Correctly Predicted	.830	.831	.831
Log-likelihood	-1778.97	-1787.22	-1791.67
Number of Obs.	4464	4464	4464

Standard errors in parentheses

Table 5

ADOPTION PROBABILITY ESTIMATES, CONDITIONAL ON BUILDING: 2400 PSI TECHNOLOGY

Variable	1972 fuel price	1962 fuel price
Constant	-15.615 (1.157)	-13.296 (1.055)
Size (1970)	.051 (.009)	.051 (.008)
$Size^2$ (1970)	-.0002 (.00006)	-.0002 (.00005)
Fuel Price	.061 (.009)	.044 (.016)
Coop	-1.246 (.401)	-1.424 (.423)
Government	-1.056 (.326)	-1.092 (.331)
Time	4.386 (.305)	4.013 (.275)
Log-likelihood	-2557.87	-2578.71
Number of Observations	4464	4464

Standard errors in parentheses.

Table 6

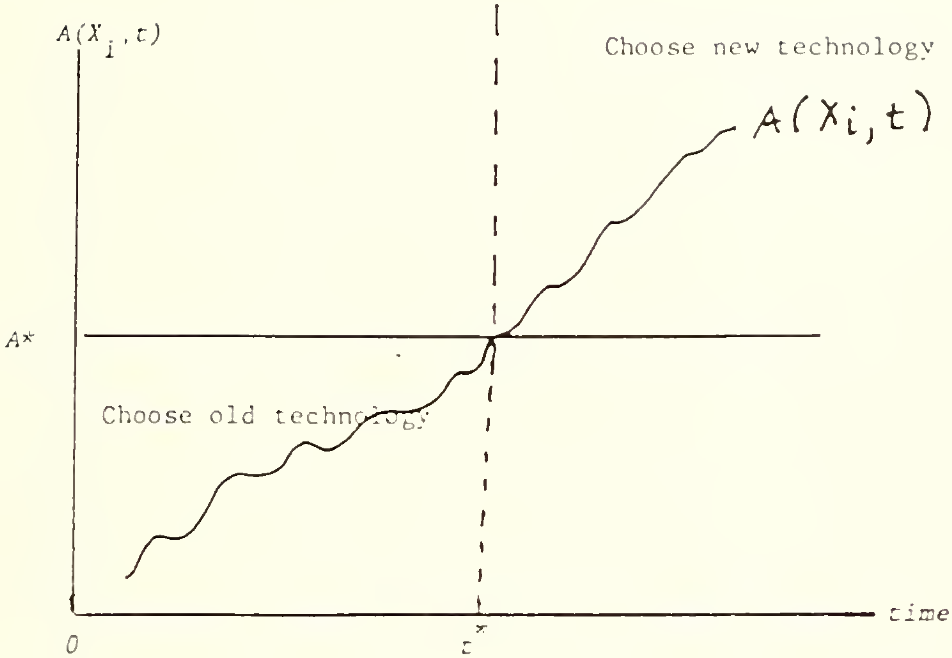
ADOPTION PROBABILITY ESTIMATES:
SUPERCRITICAL TECHNOLOGY

	Not Conditioned on Building			Conditioned on Building	
Variable	Tobit	Weibull	Log-logistic	Fuel 72	Fuel 62
Constant	-3.479 (1.625)	-11.315 (2.282)	-15.196 (2.392)	-16.766 (1.448)	-15.389 (1.429)
Size (1970)	.122 (.046)	.085 (.014)	.100 1.020	.090 (.010)	.092 (.011)
$Size^2$ (1970)	-.0006 (.00025)	-.0005 (.0001)	-.0005 (.001)	-.0005 (.00007)	-.0005 (.00007)
Fuel Price (1972)	.007 (.028)	-.009 (.016)	.005 (.021)	.004 (.011)	-.038 (.021)
Coop	.230 (.960)	.044 (.798)	.222 (.849)	-.603 (.657)	-.661 (.647)
Government	-.128 (1.019)	.104 (.741)	.073 (.838)	.257 (.463)	.311 (.453)
Time	--	2.675 (.629)	3.639 (.642)	4.468 (.407)	4.366 (.415)
Sigma	2.344 (.615)	--	--	--	--
Log-likelihood	-90.76	-183.39	-178.94	-2496.24	-2494.09
Number of Obs.	144	144	144	4464	4464

Standard errors in parentheses.

Figure 1

UNOBSERVED ADOPTION VALUES



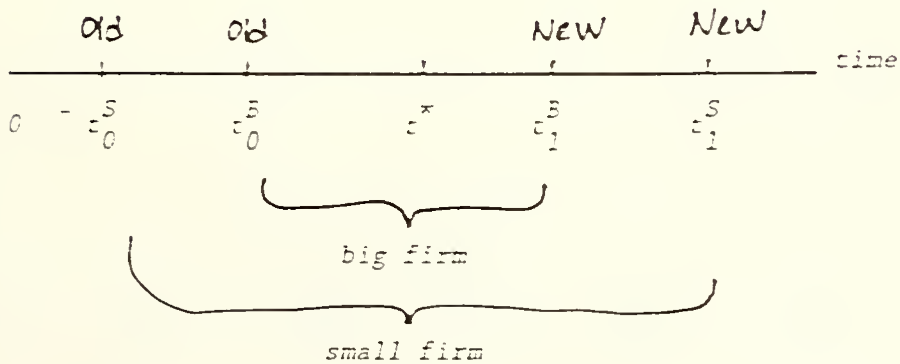
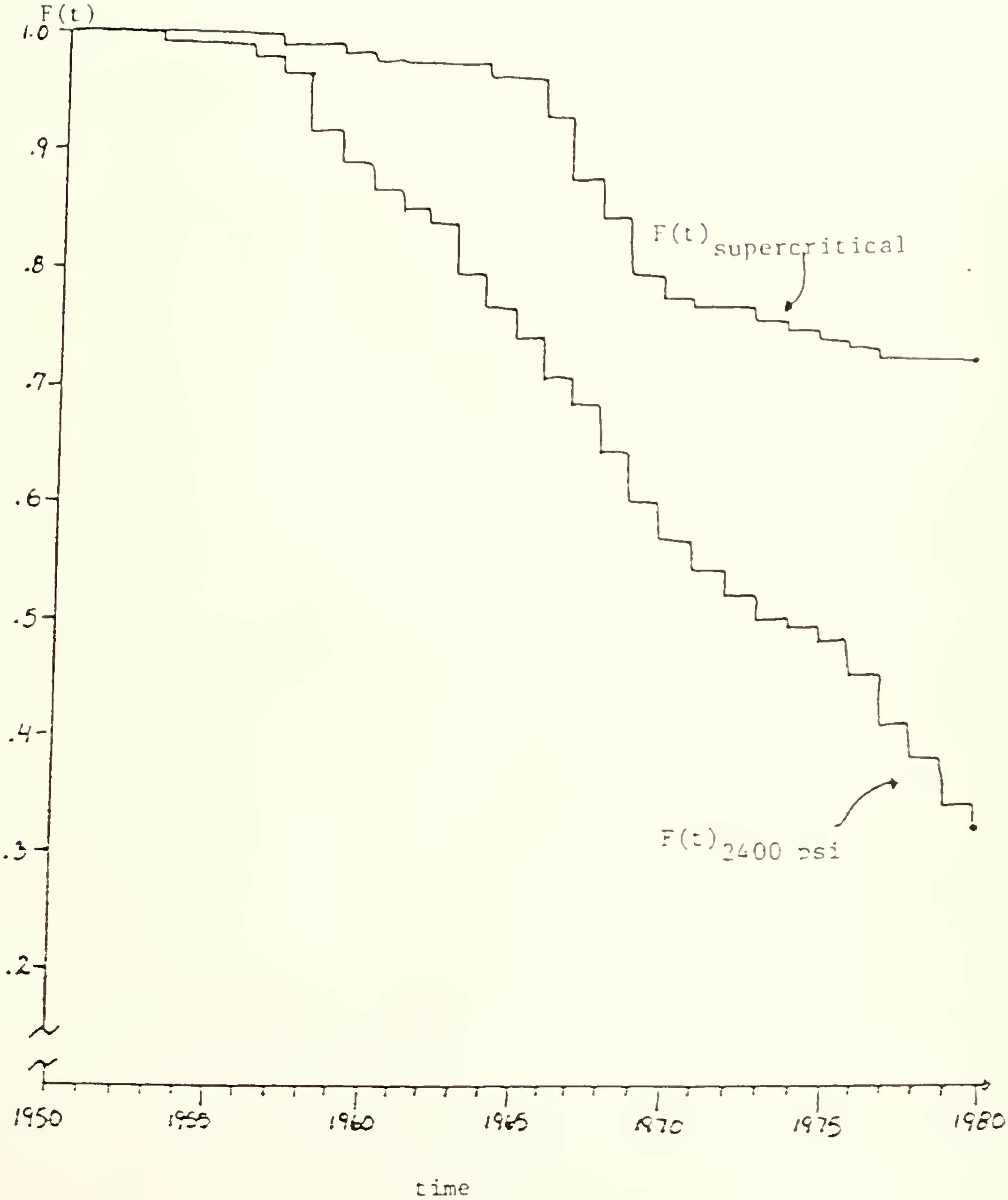


Figure 2

KAPLAN-MEIER ESTIMATES OF SURVIVOR FUNCTIONS



3-[illegible]