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The product life cycle in the commercial mainframe computer market, 1968–1982

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We investigate product life cycles in the commercial mainframe computer market. We use hazard models with time-varying covariates to estimate the probability of product exit and Poisson models to estimate the probability of introduction. We measure the importance of different aspects of market structure, such as the degree of competitiveness, cannibalization, vintage, product niche, and firm effects. We find evidence of a relationship between the determinants of product exit and product entry.

1. Introduction

■ Innovation is rampant in adolescent industries. Old products die or evolve and new products replace them. Each generation of products offers new features, extends the range of existing features, or lowers their cost. Vendors quickly imitate each other's products, turning a novelty into a standard feature. Innovative leadership may change rapidly among firms or competing product lines. These events are referred to as the "product life cycle."

This article empirically investigates the product life cycle of commercial mainframe computer systems during an especially dynamic period, from the late 1960s to the early 1980s. In this period, best-practice technology in new computer systems advanced at a rapid rate. Each new product embodied new capabilities at lower prices.[1]

What determined the rate at which products turned over? We measure how market structure and other economic factors shape product introduction and turnover in the

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[1] Hedonic studies show that each new generation of products embodied dramatic declines in the price of basic functionality. See, for example, Dulberger (1989), Gordon (1989), and Triplett (1989). See Greenstein (1994) for evidence that the technical sophistication of the average system in use advanced at a rate not far from best practice.

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context of the commercial mainframe industry, emphasizing two related themes. First, many theories predict that market structure should influence the introduction of new products as well as their postentry survival. Second, many models predict that the same economic factors influence entry and exit in the same direction.

We estimate the rate at which a firm introduces a new system, and we also estimate the instantaneous probability of an existing system exiting the market. Unlike most previous empirical research on the product life cycle, here the identities of leading products (instead of firms) affect structural change and the diffusion of technology.[2] We depart from studies done by organizational ecologists who have focused on predicting entry and exit at the organizational level (for a review, see Carroll (1984), Hannan and Freeman (1989), and Singh and Lumsden (1990)). Our unit of analysis is the product.[3] This approach is natural for the mainframe market because firms did not turn over rapidly, but products did. We exploit historical differences in market structure between product niches to identify the role of market structure in product turnover.

Our measurement goals necessitate the use of time-varying covariates in our analysis of exit and entry. We estimate hazard rates (Tuma, 1980) and Poisson models (Cameron and Trivedi, 1986). We show that time-varying covariates are not difficult to estimate or interpret in these models, and we offer a potentially useful method for research on technology diffusion at the product level.

We document several findings. First, several features of market structure predict product introductions and exit; no simple explanation will be satisfactory. Entry also weakly increases over time. Next, there are important differences between firms and between niches in observed product life cycle behavior with respect to both entry and exit. There is not a strong relationship between the determinants of entry and exit behavior. Some of the economic factors shaping product life postentry have a similar influence on product entry, but some do not. Our most surprising finding is that, contrary to conventional wisdom, later-vintage products do not have shorter lives. We offer several interpretations for these findings.

2. The commercial mainframe industry and the product life cycle

■ This section first reviews what is known about the product cycle in computing. We then discuss empirical hypotheses that lend themselves to measurement.

□ **The product life cycle in computing.** By the late 1960s, a small number of firms marketed products in the large-scale commercial computing industry, and only a few highly publicized entry and exit episodes marked changes in the identity of the firms (Fisher, McKie, and Mancke, 1983). In the late 1960s and 1970s there was frequent turnover of products, accompanied by unabated technical improvement. The phrase "product life cycle" became shorthand for regular and repeated turnover of products.[4]

Figure 1 shows that many products entered and exited the market over the time period of our study. We explain the data sources below. Typically, each firm carried

[2] For previous work on the product cycle, see Gort and Klepper (1982) and Klepper and Graddy (1990). See Klepper (1996) for a review and theoretical synthesis of the life-cycle literature.

[3] Research using the product as the unit of observation includes Stavins (1995) in the PC industry, Khanna (1995), Michaels (1979), and Oliner (1993) in the large-scale computer industry, and Hartman and Teece (1990) in the minicomputer industry.

[4] The phrase "product life cycle" is used for many different purposes. See Inmon (1986), Phister (1979), Friedman and Cornford (1989), Fisher, McGowan, and Greenwood (1983), or Fisher, McKie, and Mancke (1983). Of the many hedonic analyses, well-known studies of mainframes include Chow (1967), Cole et al. (1986), Dulberger (1989), Gordon (1989), Oliner (1993), Trajtenberg (1990), and Triplett (1989).

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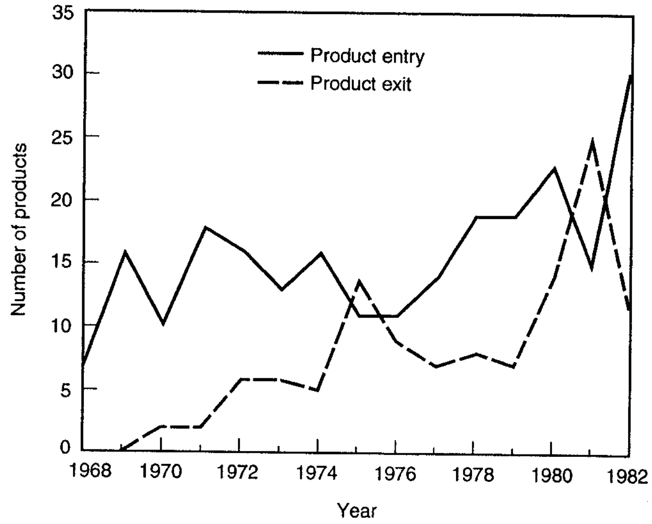
FIGURE 1

PRODUCTS ENTERING AND EXITING THE MARKET



one or more product lines, where each line consisted of many fully or partially compatible computer systems. Several firms marketed systems that were backward compatible with previous generations of systems. The industry's revenues grew steadily over time, and IBM consistently garnered a large share of overall sales, particularly for general-purpose mainframes.

From the buyer's perspective, the product life cycle involved either installing new systems or upgrading, retrofitting, and improving existing systems. As customers learned about new needs and discovered new technological opportunities, they reevaluated their situations. Buyers then modified their CPU memory and speed but kept other durable investments in software or peripherals. Alternatively, they enhanced particular software programs or peripheral components but not the CPU. This type of upgrading behavior could feed on itself. Peripheral and software upgrading could induce bottlenecks in CPUs, which induced further CPU upgrading, which in turn induced further peripheral and software enhancements.

From the vendor's perspective, the product life cycle concerned design, sales, and marketing. Some customers desired upgrades of existing systems, while others compared the technical capabilities of all new systems. Old product designs became technically obsolete with the passage of time, the entry of more competitors, the expansion of technical possibilities, and the expansion of buyers' needs. If a new design met with initial commercial success, then later parts of that product's "cycle" involved potential upgrades and sales of complementary components. All parts of this cycle—designing, prototyping, manufacturing, initial rolling out, selling systems, servicing, and customer upgrading—involved technical and commercial risks.

□ **Definitions.** Our definition of a product will focus on the bundles of attributes embedded within a product. When we say "product," we mean a typical arrangement of computer components associated with different capabilities and prices. "Different products" refers to arrangements with significantly different attributes. A user typically buys a product, configures it with standard and customized peripherals, and overlays standard and customized software applications onto it.

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This definition is easier to implement in practice than one might first conjecture. For all practical purposes, market surveyors decide whether different products, as labelled by vendors, correspond to different designs or bundles of attributes. Our definition of a product is similar to what hedonic research has used (with a few exceptions noted below).

To guard against falsely measuring the entry of phantom systems (or "vaporware"), we do not include models that, though listed in the data source, ultimately have no sales. After the last sale, which we measure with hindsight, we say that a product has exited. This definition corresponds with industry practice to distinguish between a product still for sale and not.

□ **The determinants of the product cycle.** At this stage in our empirical research with a newly assembled set of data, we are hesitant to presume very much about the specific features of firm behavior and market equilibrium, particularly for purposes of estimating product turnover as a function of structural parameters of learning, costs, demand, and substitution. We stay close to the issues found in the literature (e.g., see Jovanovic and McDonald, 1994a, 1994b or Pakes and McGuire, 1994), but we attempt to estimate a more modest model using reduced-form statistical methods.

We emphasize two themes. First, market structure should influence entry and exit in predictable ways. The same economic factors may be common to all products and result in similar economic tradeoffs for all products, resulting in similar entry/exit behavior. Second, it is possible for entry and exit decisions to be closely related. In models with little postentry uncertainty, there is a relationship between market structure, entry behavior, and exit behavior. When little postentry uncertainty influences forecasts about postentry profitability, then market structure influences the anticipated value of entering a new market and also influences the realized value associated with exiting.

These themes translate into several practical issues. Does entry or exit differ across years? Much of the business press presumes that life cycles have shortened in later years. Does the age of a product have any relationship to entry and exit? Old products exit as they fall technically behind, leaving only better products to survive (Berndt and Griliches, 1993; Stavins, 1995). New entry may become more likely in market niches where existing products are more distant from the technical frontier. Does entry or exit differ across firms? Firms differ in their cost structure, distribution networks, efficiencies, and other firm-specific product-line strategies. Furthermore, does market niche predict entry or exit? Different niches have been associated with different customer bases, different applications, and possibly different upgrade and replacement cycles.[5] How does the number of competitors influence entry and exit? Competition from direct substitutes will be more constraining than competition from distant substitutes.[6] Does intrafirm cannibalization influence product turnover? Cannibalization behavior by a firm may correspond with the obsolescence of an old product, particularly in markets where firms can anticipate the postentry life cycle of a product.[7]

[5] For example, many high-end computers are sold to scientific users who favor new computing architectures, inducing "racing" by high-end designers to stretch the technical frontier. See Khanna's (1995) analysis of large-scale computing. Racing behavior might induce shorter product cycles and more-frequent product introductions.

[6] Under many theories the intensity of competition between firms increases as the number of firms increases. In the context of research into firm entry and exit, more competitive environments are found to ultimately result in lower firm-founding rates and higher mortality rates. See Hannan and Freeman (1977, 1989) and Carroll (1984).

[7] Product obsolescence in a technical sense is exogenous, but the timing of cannibalization is an endogenous market event. Unmeasured error (in product obsolescence) might correlate with the decision to introduce a new product in a niche in which the firm has an existing product.

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3. Estimation of the model

■ We adopt a flexible estimation framework that measures the influence of time-invariant and time-varying determinants of product life. The former include factors such as market segment, system size, vendor, and vintage. The latter include factors such as degree of competition from close and distant substitutes, cannibalization from close and distant substitutes, and age of a product. First we describe our methodology for measuring exit. Then we discuss the measurement of entry.

□ **Exit.** In our analyses of model exits, we use the individual model as the unit of analysis. A model is said to fail in a given year if there is no further increase in the installed base. Each observation provides two types of information, the state occupied (alive or dead) and the time spent in the state. Following Tuma (1980), the likelihood function for any observation i can be written as

$$L_i = G_i(t_i)[\mu_i(t)]^{\phi},$$

where $G_i(t)$ is the survivor function, $\mu_i(t)$ is the hazard rate, ϕ is a variable that is one for uncensored cases and zero otherwise, and t_i is the number of periods that product i is alive in the sample. We begin by assuming a constant hazard rate $\mu(t) = \gamma$ (i.e., the exponential distribution). The survivor function is then $G(t) = \exp[-\gamma t]$. The following specification is used:

$$\mu(t) = \exp[\mathbf{X(t)}\beta(t)],$$

where $\mu(t)$ is the instantaneous hazard rate for a system at time t and $\mathbf{X(t)}$ is a vector of time-varying independent variables. Each $\exp[\mathbf{X(t)}\beta]$ can be thought of as multipliers of the rate, and β can be estimated by using maximum likelihood. For more details, see Tuma (1980) and Carroll (1983).

To control for the age of the product, we employ a series of age dummies. Another approach, which we considered, employs a specific functional form for changing hazard rates over time. For instance, the Gompertz function assumes that the hazard rate is an exponential function of duration (in this case product age). One advantage of using a continuous-time model such as the Gompertz is that only one degree of freedom is sacrificed. In contrast, a constant-rate model with age dummies controls for nonlinearities in age. Because the range of age in our sample is relatively small (only 24 models out of 175 lived over 6 years, and the maximum age was 9.6 years), the loss of degrees of freedom from using dummies is low. Thus, we prefer a more flexible modelling framework and estimate a constant-rate model.

One problem with our data is that it only extends back to 1968. Thus, a system that was alive before 1968 would be left censored. The likelihood function specified above is not correct if the entire event history of a case is not included. Unfortunately, the correct likelihood that would take account of left-censored observations is very difficult to estimate when age is included as a covariate. To minimize this problem, we include in our analysis only models for which the entire event history is known (i.e., those founded in 1968 or later).

To analyze model failure, we broke up each model's life history into yearly spells, with all but the last cell being censored on the right. Time-varying covariates are updated at the beginning of the year for each system. We estimate a model-specific failure rate assuming that the failure rate is influenced by a set of independent variables.

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□ **Model introductions.** To estimate the rate at which firms introduce new products in a given market niche, we use Poisson regression. More specifically, we assume that the number of product introductions by firm in a given size class at time t (Y_t) follows a Poisson process and is conditional on a set of time-varying covariates $\mathbf{X(t)}$. This implies that

$$\Pr(Y_t = y_t | t) = (e^{-\lambda_t}\lambda_t^{y_t})/y_t!.$$

The parameter λ_t, the mean of the number of product introductions by a firm in a size class in year t, is assumed to take the form

$$\lambda(t) = \exp[\mathbf{X(t)}\alpha],$$

where $\mathbf{X(t)}$ is a vector of independent variables. Each of the parameters $\exp[\mathbf{X(t)}\alpha]$ can be thought of as multipliers of the rate. The parameters are estimated by minimizing the following log-likelihood function:

$$\mathcal{L} = \sum_t [-\exp[\mathbf{X(t)}\alpha] + y_t\mathbf{X(t)}\alpha - \ln y_t!].$$

Use of Poisson regression has one serious limitation. A Poisson model assumes that the mean of the expected event counts equals its variance. Often, however, count data is overdispersed, i.e., the variance of the expected event exceeds the mean. Using the Poisson model in this instance can lead to erroneously small standard errors. To test whether the Poisson model is appropriate for these data, we use a regression-based test suggested by Cameron and Trivedi (1986). As we will show below, this test cannot reject the hypothesis that our data are distributed Poisson.

Finally, we adopt one convention. If a firm has never previously had products in a size class and has a product in that size class for the first time that year, no observation is recorded for that firm in that year in that size class. We do this for two reasons. First, the decision to participate in a size class is distinct from the decision to introduce new products in a size class that the firm has already entered. Second, firms rarely enter a new size class; thus, we can only identify behavior associated with introducing products to familiar market niches.

□ **Trading off complete data with other limitations.** Our statistical approach has one important limitation, which is best illustrated in comparison to the existing hedonic estimates for this era's computer market. Previous hedonic research on the computing industry has helped economists compile somewhat incomplete data on the era's product prices and product characteristics.[8] Incomplete datasets are not as useful for models of product turnover, unfortunately. The features of products typically found in hedonic studies of computers—prices, speed, and memory—are available only for the most popular products in this market. Yet the most popular products live longest. To focus solely on popular products imparts a selection bias into any study of product birth and turnover, missing products with smaller sales.

We instead use the information we can gather for all products. As we describe below, we are able to compile a complete census of products, their market niche, their

[8] Since features of the most popular models reflect the technical trends in the overall computer market, incomplete data are adequate for purposes of estimating changes in hedonic surfaces over time. See Triplett (1989) for a survey.

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age, their firm, and the degree of competition in market niche. We cannot, on the basis of data now available to us, tell whether the addition of more information about a select set of popular models alters our conclusions. We hope to make progress on this issue in future work.

4. Data

■ This article's data on computer prices, quantities, and vintages comes from industry censuses from International Data Corporation's (IDC) EDP Industry Reports (EDP/IR). We rely on IDC's definition of a system, always utilizing the first definition they use if there is any ambiguity. IDC estimated the number of installations of each type of computer system and, until 1981, estimated the monthly rental at which an average type of system leased.[9] The data in this article begin with the December 31, 1968, report and end with the January 1, 1983, report. The first year in which IDC distinguished between the number of installations inside and outside the United States was 1968. After 1983, the survey was reorganized in a manner that made it incomparable with earlier years. Over the entire sixteen-year period, these data concern the installed base of over 350 different computer systems, with over half introduced after 1968. These are clearly the best data available on the size of installed base of large computer systems in the United States.

□ **The sample of systems.** IDC's definition of a mainframe contains two biases. First, the 1968 and 1969 definition of a mainframe is too broad. It includes some systems that IDC reclassified as "Digital Dedicated Application" in 1970. These systems are actually minicomputers, like the DEC PDP-8, not general-purpose systems. Second, redefinition problems arise once IDC establishes several ongoing databases for systems other than mainframes (i.e., minicomputers, small business systems, desktop). Its researchers occasionally move a system out of (into) the mainframe category that was (not) previously there.[10] In addition, IDC revised its survey scope twice, once between 1969 and 1970 and once between 1976 and 1977. In both cases, IDC reduced the number of models covered.

The solution is to define the market consistently across different years of the sample. In this article the boundary is set by a very small mainframe, something the size of an IBM 360/20. All systems smaller than what IDC calls size "2" are excluded. Fortunately, most of the artificial sampling issues pertain to smaller systems, which we exclude.

Finally, by the end of the sample, the difference between mainframes and some large general-purpose minicomputers (also known as "superminis") becomes blurred, which raises questions about the survey's completeness. The main issue is whether IDC included in the mainframe category all the superminicomputer systems that were close substitutes for general-purpose mainframes. A reasonable case could be made that IDC included most relevant systems,[11] and a reasonable case could also be made

[9] Phister identifies several years in which IDC revised the reported number of installations, particularly for IBM models in 1967–1972. We use Phister's reported updates. Our data are comparable to Phister's (1979) and Flamm's (1987, 1988) description of the diffusion of computing equipment, which used more aggregate IDC data.

[10] The most important case is IDC's decision to include the IBM System 36 in the sample in 1976 (estimated installed base at 5,000 units) and exclude it from mainframes after that (but include it in "small business systems").

[11] According to the 1983 IDC census for minicomputers and mainframes, the value of installed base associated with superminicomputers came to roughly half the value of all minicomputers, or roughly 15% of the value of the installed base of mainframes. IDC's census is more complete than CBEMA's (1992), because IDC includes several systems as mainframes that others typically classify as superminicomputers.

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that it did not.[12] Ending the sample in 1983 and excluding small systems minimizes the problem.

□ **Definition of model failure and independent variables.** In this study we use the installed base of systems to estimate the timing of product exit. Product exit is defined as the first year that a product's installed base does not increase. More specifically, we assume that exit occurs during the midpoint of this year. This is a reasonable measure of product obsolescence, since this will be the first year in which retirements of the product are greater than the units sold. In addition, once a product's installed base begins to decline, the process never reverses itself. IDC usually begins tracking each product the year after its introduction. Following IDC, a model contributes an observation to our analysis in the first year that its installed base is above zero. Prior to that its installed base is zero.

While Phister (1979) clearly believes that IDC's estimates of installed base are the best available, he also warns about several potential problems that could influence calculations using these data.[13] Dulberger also questions the accuracy of IDC's estimates of installed base, while conceding that they are the best publicly available.[14] Given these concerns, the data were tested for internal consistency by examining the history of each new system. Did the development of its installed base contain several years of growth followed by several years of decline? The presence of such a pattern makes the data plausible. In any event, no alternative is satisfactory.[15]

In our analyses of model failure rates, we included the following independent variables:

Year of Introduction (vintage): IDC provides the year and month of introduction for each system. The year is a product's vintage.

System Age: We also construct dummy variables for a system's age. Each dummy variable covers a one-year increment with all products older than six years lumped together.

Firm Dummy Variables: We included firm dummy variables for IBM, NCR, Univac, Burroughs, CDC, General Electric (GEL), Honeywell, and RCA. We omit the Japanese firms and a few smaller mainframe suppliers.

System Size Class: IDC's censuses categorize every system by size, with size ranging from 2 to 7. This measure is categorical, not continuous, and it is correlated with MIPS and memory. It provides our measure of a market niche, as the categories range from the highest and lowest ends of the computing spectrum. In our analysis, we analyze classes 4 through 7.[16] Previous analysis of these data shows that the average system in this sample got larger over time (Greenstein, 1994). In some specifications

[12] The most questionable omissions in IDC's mainframe tables are those regarding the VAX 11-780 models from DEC and similar models from other firms such as Prime and Data General.

[13] He states, "It is my opinion that IDC's staff, files, and data sources make that organization's published statistics the best available" (p. 250). Yet Phister is not convinced that IDC's estimates of the size of installed base are precise, though he seems to believe that IDC got the general order of magnitude correct. Where available, this article uses Phister's corrections.

[14] One especially difficult problem is that IDC may underestimate the number of users who upgrade their systems (Dulberger, private communication).

[15] Sales data are not available. It is not possible to estimate sales from the change in installed base from year to year, because IDC's estimates become an increasingly poor estimate of shipments of systems when systems become more than a few years old.

[16] Size class 2 is omitted because IDC changed its definition of who was included in size class 2 in 1976, making reliable counts of systems in that size class difficult to obtain. Thus, we could not obtain estimates of the number of systems in the lower adjacent size class for size class 3 systems. Size class 3 systems were not included as endogenous variables.

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we include dummy variables for size classes 5, 6, and 7, omitting 4 (also see Greenstein and Wade, 1997).

Numbers of Systems: We analyze the market structure underlying each market niche by calculating the substitutions available to buyers in that niche. For each system, we computed the number of systems for sale in its size class as well as in adjacent and nonadjacent size classes.

Cannibalization: This variable is one after the firm introduces another newer product in an existing system's size class. Two other dummy variables, called cannibalization in an adjacent lower size class and cannibalization in an adjacent higher size class, are one when a firm introduced a newer system in an adjacent lower or higher size class, respectively. If two systems are introduced in the same year we do not label this cannibalization because we seek to measure when a firm replaces an existing model with a new design in the same product category.

□ **Definition of product introductions and independent variables.** In our analysis of introductions, a product introduction takes place when IDC records it. We count the number of product introductions for each firm for each size class for each year, except, as noted above, in the rare instance when a firm enters an entirely new size class for the first time. Also, in rare cases, a firm initially entered a size class but later is no longer selling systems in that size class. In that case, observations are still recorded for the firm in that size class, but we include a dummy variable indicating that the firm currently has no active products in the size class. We include a firm as long as at least one of the firm's products (or its decedents) sells.

Comparing Market Structure for Entry and Exit: We use many of the same variables as in the analysis of product exit, such as the number of systems in the focal size class, the number of systems in adjacent and nonadjacent size classes, size-class dummy variables for sizes 5 through 7, and firm dummy variables for IBM, NCR, Univac, Honeywell, Burroughs, CDC, GEL and RCA. To control for any time trend, we also include dummy variables spaced every two years as covariates. The omitted years were 1969 and 1970.

In addition, in some specifications we included the following variables:

Time Since Last Innovation in Size Class: This variable is simply the time elapsed since a firm last introduced a new model in the size class. This may indicate how far the firm's product line in this size class is from the technical frontier.

No Models in Size Class: This is included as a control variable in the product introduction analysis. It is a dummy variable that is one if a firm has no sales in a size class in which it had previously introduced a product. It is zero otherwise. If a firm no longer has products in a size class, it may have decided not to compete further in that niche. This controls for the possibility that the decision to reenter a size class (in which a firm is no longer active) differs from the decision to introduce products in a class in which the firm is currently active.

5. Results

■ In this section we investigate the determinants of product exit and entry using hazard rate and event count models, respectively. We present our preferred specifications. A more complete set of specifications can be found in Greenstein and Wade (1997). Table 1 shows the means and standard deviations for the variables in our analyses of product entry and exit.

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TABLE 1 Means and Standard Deviations for Mainframe Product Failure and Entry Analyses

Product Failure Variables[a]	Mean	Standard Deviation	Product Entry Variables[b]	Mean	Standard Deviation
Product Failure	.19	.39	*Product Entry*	.37	.68
Year of Birth	74.76	3.60	*Year*	75.91	3.93
Product Age	2.26	1.74	*No Models in Size Class*	.09	.28
Density in Size Class	18.47	5.50	*Time Since Last Product Introduction*	3.02	2.32
Density of Adjacent Lower Size Class	17.05	5.34	*Density in Size Class*	17.67	5.67
Density of Adjacent Higher Size Class	12.09	7.14	*Density of Adjacent Lower Size Class*	16.76	5.25
Density of Nonlocal Non-adjacent Size Classes	36.12	11.59	*Density of Adjacent Higher Size Class*	11.72	6.58
Cannibalization	.51	.50	*Density of Nonlocal Non-adjacent Size Classes*	34.34	11.56
Cannibalization Adjacent Lower Size Class	.51	.50			
Cannibalization Adjacent Higher Size Class	.42	.49			
$N = 649$			$N = 465$		

[a] Unit of observation is the product year.
[b] Unit of observation is firm size class year.

□ **Product failure.** Figure 2 shows the proportion of surviving systems in each size class over time. Few systems survive over six years. Size class 7 systems seem to have a survival advantage; a higher proportion of these systems survive over most of the age range. This is consistent with our earlier speculation that different market niches may have different product life cycles. Our more detailed multivariate analyses below will determine if this is the case.

Model 1 of Table 2 presents our preferred specification for our basic model of product life based on log-likelihood ratio tests. Surprisingly, contrary to many analysts' predictions, product life cycles do not seem to be shortening over time. Systems introduced in 1974 through 1981 have significantly lower chances of exit than those introduced earlier. These results provide limited evidence that product life cycles may be lengthening.

We also see considerable variation in the firm dummies, though not all these differences are significant. Interestingly, IBM's products, as well as those of RCA, have the second-highest rates of failure. Burroughs and CDC have the lowest product failure rates. Since these two firms had very different marketing strategies in this period (one focused on mainstream business computing, the other on scientific computing), it is difficult to interpret this finding.

Consistent with our expectations, systems are more likely to die as they get older. The positive effect of age increases sharply up until systems are three years old, then it stays relatively constant until an age of five years. After five years the hazard rate continues to increase. While the effects of age do not appear to be linear, a log-likelihood ratio test between this specification and one that included a continuous measure

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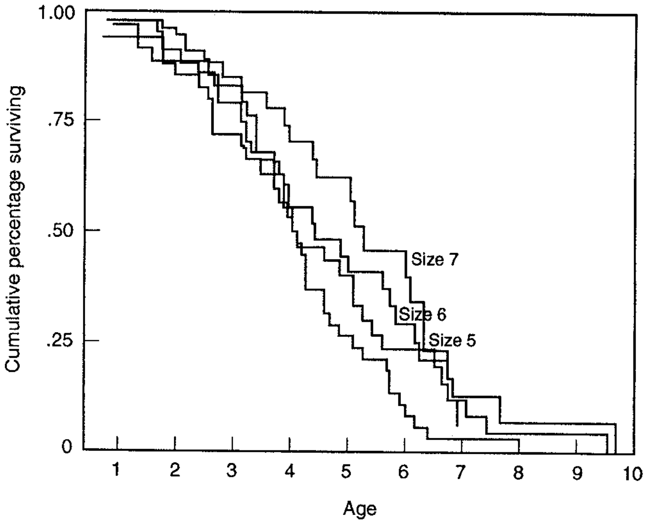
FIGURE 2

KAPLAN MEIER SURVIVAL ESTIMATES



of age revealed no significant difference in fit. Nonetheless, we feel that assuming no specific functional form is the more conservative modelling approach.[17]

We also investigate the role of market structure in each niche. In an initial specification not shown here, we found that systems in the largest size class were less likely to fail. These effects, however, disappeared once cannibalization and density in size class were included. More important, a comparison of the log-likelihoods revealed that including the size-class dummies did not significantly improve the model. Consequently, we did not include them in our preferred specification.

Model 1 shows that both cannibalization and density in size class have their expected positive effects on the failure rate. The effect of cannibalization is particularly notable in that cannibalization of a system increases the probability of failure by over 2.5 times. This seems to suggest that different cannibalization patterns in different market niches result in many of the differences between market niches. In another specification not shown here, we found that cannibalization in adjacent size classes had no significant impact on the failure rate.

The number of models in the adjacent size classes to the analysis all have their expected positive effect on the failure rate. Interestingly, the coefficients for the number of systems in the adjacent size classes approximately equal the coefficient on the number of systems in a system's own size class. Thus, these estimates indicate that products faced substantial competition from products in surrounding size classes.[18]

Model 2 in Table 2 translates our preferred specification for product life into a few simple summary statistics. Since the model is multiplicative, one can calculate the multiplier of the hazard rate for a system under different conditions. For example, we

[17] We also found that all our findings were robust to other functional forms, including the Gompertz and the piecerate model.

[18] As noted earlier, we dealt with the problem of left censoring by omitting systems born before 1968. Another approach included those observations and included a dummy variable indicating left-censored observations. We reran our model using a constant-rate model, a piece-rate model, and a Gompertz model. The results remained substantively the same except that nonlocal density and the density of the adjacent higher size class narrowly missed significance in the piece-rate model.

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can compare the hazard rate for a new system (zero years old) compared with a system that is between three and four years old. The older system is five times more likely to exit the market.[19] Similarly, a model that is over six years old is 12.7 times as likely to fail as a newly introduced model. By comparison, a model introduced in 1968 or 1969 is almost seven times more likely to exit than a model introduced from 1978 to 1979.

We also compare this to the multiplier effect for continuous variables by assuming a one-standard-deviation change in the continuous variable. The model identifies the most important covariates for product life. As can be seen, density of substitute products also has an important effect. Since density of competition gradually grows over time, this effect increases in our data (see Figure 3). Cannibalization and firm effects will also induce product failure, but we note that these effects are relatively similar in magnitude to the effects from less-extreme variation in our continuous variables—age, year, density, and so on.

□ **Product introductions.** To determine the appropriate model, we first plot the frequency distribution of the endogenous variable in a histogram. Figure 4 shows that the data appear to fit a Poisson distribution. We use a regression-based test suggested by Cameron and Trivedi (1986) to test the null hypothesis, H_0: var[y_i] $= \mu_i$, against the alternative H_1: var[yi] $= \mu_i + \alpha g(\mu_i)$, where $g(\mu_i) = \mu_i^2$. We followed the procedures as described by Cameron and Trivedi. We found no evidence of overdispersion of a linear or quadratic form. We also tested our model against a negative binomial model and did not find strong evidence that this was an improvement over the Poisson.

Model 3 of Table 2 presents our preferred specification of the rate at which firms introduced new products in each size class. Firms are slightly more likely to introduce new models between 1979 and 1982 than they are at the beginning of the period. While the estimates monotonically increase over time after 1972, the general lack of significant differences between the dummies provides only weak evidence, at best, that product introductions accelerated over time.

GEL and RCA, both of whom sold off their product lines to other firms after exiting in the early 1970s, have the lowest rate of entry. The low entry of products associated with GEL and RCA reflects the unwillingness of the new owners (Honeywell and Univac, respectively) to invest in those product lines after their purchase.[20] IBM, NCR, Honeywell, and CDC have relatively higher entry rates, a result that is consistent with the industry's perception that each of them was reasonably profitable during this period (albeit it is a very long leap from product entry rates at the firm level to firm profitability).

Again, we use size-class dummies to examine the role of a product's market niche. Size class 4 is the source of more product introductions. The effect of the number of models in a size class is negative and significant, suggesting that increased competition from substitutes deterred entry. Model 3 also shows that the time since the last product introduction and a control for having no current models active in a size class have no effect. Finally, in another specification not shown here, we found that the number of

[19] The effect of any covariate on the hazard rate can be expressed in terms of a multiplier of the baseline rate as follows: *Multiplier* $= \exp(\mathbf{X(t)}\beta_1(t)/\mu_b)$, where $\mathbf{X(t)}$ is the value of the covariate of interest, β_1 is its coefficient, and μ_b is the baseline hazard rate. In the case of comparing the hazard rate of a system that is between three and four years old to one that is less than one year old, the multiplier of the rate is five (or $e^{1.61}/e^0$).

[20] In our analyses we assumed that there was a risk of introducing an RCA or General Electric product until the last such product exited the market. The fact that the new owners introduced very few such products is largely responsible for the negative RCA and General Electric firm effects on entry.

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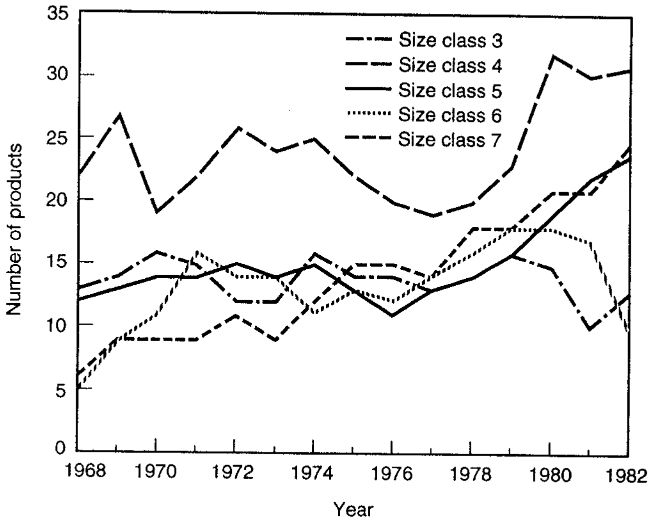
FIGURE 3

NUMBER OF PRODUCTS BY SIZE CLASS



over time in the mainframe market.[21] In fact, once time-varying covariates are controlled for, products that were introduced more recently tend to have longer expected life spans. There is limited evidence that after 1973 the rate of product introductions increases. These two results together suggest a gradual improvement in anticipated and *realized* postentry conditions across all market niches, from either secular declines in costs or secular increases in demand.

We find evidence that product life cycles differ across vendors. There is a small negative correlation (−.41) between the firm coefficients from the two preferred specifications. That is, the firms that enter with more products, all other things equal, also exit less often. The correlation is stronger (−.55) among the non-IBM firms.

Our statistical methods can only identify that these differences between firms exist, not why they occurred. Thus, we are very hesitant to attribute these differences to specific features of these firms, their efficiencies, or their stated strategies. For example, our sample ends before the Japanese firms fully developed their product lines in the 1980s. That said, the two known commercial failures, GEL and RCA, display patterns in line with their historical reputation. In addition, the result for IBM is suggestive that IBM could and did use its preeminent position to have a distinct product-line strategy—more new products and more experimentation (or less cautious product entry), inviting a mix of some successes and more failures. In addition, there are considerable differences among the non-IBM firms; CDC, Honeywell, and NCR appear to display the patterns of relatively successful firms, even after controlling for other factors.

We find evidence that product exit differs across market niches and mixed evidence that product entry differs across niches. Controlling only for age and firm, it appears that the larger the size class, the lower the rate of exit. On further investigation, much of this seems attributable to cross-niche differences in cannibalization and competition densities. Entry behavior seems to differ across niches, but the only robust inference

[21] We suspect that some of this belief comes from comparing product life cycles across classes of computers. In other words, product life cycles are almost certainly shorter in minicomputers and shorter still in microcomputers. That, however, does not mean that mainframes changed their patterns over time.

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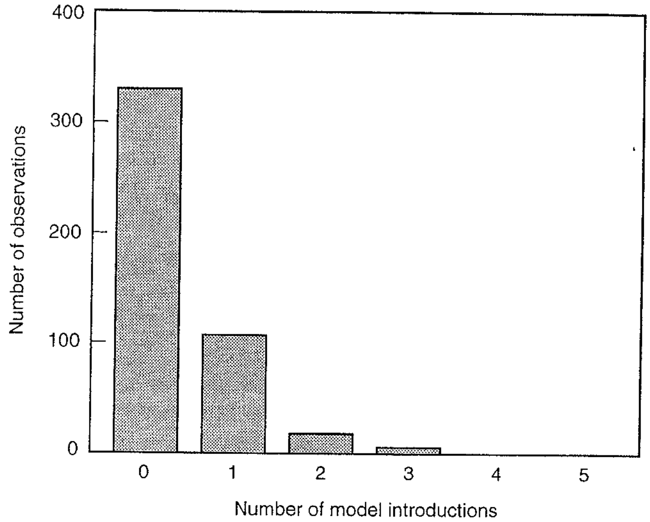
FIGURE 4

FREQUENCIES OF MODEL INTRODUCTIONS



is that the smallest niche has higher rates of entry. Putting the findings for entry and exit together, there is simply not sufficient evidence in favor or against the view that racing behavior was more severe at the technological frontier at the highest end of the computing market. Nor is there sufficient evidence to conclude that competition from even smaller systems had an appreciable effect on small-system entry and exit.

Once a firm introduces a new product in a size class, other products from that firm in that niche are more likely to exit. We offer two interpretations. If entry is random, then cannibalization tells us about competition between two products from the same firm. Those two products probably share many similar features, so the cannibalization coefficient measures these otherwise unmeasured similar features. It would not be surprising to see competition between similar products lead to the exit of the older one. If entry is not random at all, as in a market in which firms can reasonably predict obsolescence of existing products, the timing of obsolescence will be endogenous. Firms will try to cannibalize when their existing products are close to losing commercial viability. In that case, the coefficient on cannibalization measures otherwise unmeasured obsolescence. Available evidence as yet does not allow us to distinguish between these two interpretations. Finding a way to do so is a key issue for future research on product life cycles.

Finally, the evidence does not point toward a strong relationship between the factors that predict entry and exit, but it also does not suggest that there is no relationship. There is weak evidence that the year of introduction influences both entry and exit. The importance of cannibalization also points toward a more systemic relationship between entry and exit, but this interpretation has unresolvable ambiguities. There is some evidence that there are differences in entry and exit across niches, but we cannot attribute all these differences to market structure within a niche. While competition within a niche impacts both entry and exit, competition from surrounding niches only affects the exit rate. Finally, it is not possible to interpret all the firm effects in the entry/exit equations, but the coefficients do suggest there are some persistent differences in firm behavior toward entry and exit at the product level.

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These findings together do not suggest a strong relationship (but not the complete absence of one, either) between the determinants of entry and exit. On the one hand, if managers of firms are aware of the factors that lead to longer product survival rates, they should attempt to strategically introduce their products to take advantage of extended life cycles. On the other hand, it is plausible for the variables that influence product survival to have only a weak relationship with product introductions.[22]

6. Conclusion

■ In mainframe computing between the late 1960s and 1970s, products turned over frequently and new technical improvements diffused capabilities to users in new designs.

In this article we measure the determinants of entry and exit of new products. We move beyond standard hedonic methods. We measure the importance of different features of market structure for product entry and exit, especially as that structure changes over time or varies across product niches. Our findings illustrate the gains from analyzing the separate components of product life cycles—here, rates of product introduction and exit. Further work might establish links between different aspects of the product life cycle—entry, growth, market share, exit from sales, and user retirement.

Future work should try to develop structural models of firm behavior to account for product-line strategies, different racing behavior in different niches, and technical and marketing uncertainty prior to the introduction of a new design. Such models can help develop the links between product entry and survival as new markets mature. One limitation of our study is that we do not jointly estimate entry and exit processes but simply infer their interaction through common independent variables. Until interactive models are further developed, we find it useful to develop statistical methods at the product level, characterize the long-run patterns, and interpret these patterns in light of well-known questions.

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[22] Many researchers have suggested that there are substantial barriers to purposeful actions by firms in technology-intensive industries (e.g., Hannan and Freeman, 1977, 1984) due to bounded rationality, prediction error, difficulties in managing the timing of production innovation, and resolving other technical problems.

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