Empirical Determinants of Product Obsolescence and the Product Cycle: An Application to the Commercial Mainframe Computer Market

James B. Wade
Rutgers University
111 Washington Street
Newark, NJ 07102
(973) 353-1066
jwade@rbsmail.rutgers.edu

Shane M. Greenstein
Northwestern University
2001 Sheridan Road
Evanston IL 60208
(847) 467-5672
s-greenstein1@kellogg.northwestern.edu

David Barth
Bates White, LLC
(202) 747-2101
david.barth@bateswhite.com

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Abstract

We investigate the determinants of product obsolescence and the product cycle in the computer mainframe market. We use hazard models with time-varying covariates to estimate how long a product remains for sale and the rate at which a product's installed base declines to a low level after sales cease. We interpret these as measures of the determinants of success or failure in sales and support activities, respectively. We find that cannibalization and product vintage have strong effects on both of these activities. Interestingly, however, measures of competition influence post-sales support of these products differently than they affect the likelihood that the product will remain for sale. We also find that the duration that a product remains for sale has positive effects on its post-sale support, a finding that suggests that this variable may be a proxy for unmeasured quality and network attributes of the product.

Key works: Computing; hazard models; product cycle; cannibalization; sales and support.

JEL: M31, L10, L63

Introduction

Rapid product cycles characterize many high technology markets. Product cycles comprise of a series of sequentially related phases – design and testing, sales and marketing, after-sale support, servicing and upgrading. Many case studies describe and analyze the processes leading from birth to obsolescence, emphasizing how important all phases of these activities are to the strategic behavior of firms, and to competitive outcomes. Yet, little statistical research has measured the determinants of these phases, nor identified the empirical relationships between them. What determines which new products grow and prosper? How do these factors relate to the growth and servicing of installations after sales? These are key questions for forecasting, marketing and strategic management. We bring advanced statistical methods and extensive data to bear on them.

In this study we investigate the product life cycle of commercial mainframe computer systems during an especially dynamic period, from the late 1960s to the early 1980s. We use this period and this market for three reasons. First, we have relatively complete documentation of pertinent activity over an extended period. Data this complete is quite rare. Second, this market is one of the earliest precursors for many of the patterns that appeared later across a wide array of high technology equipment markets. This is a market in which best practice technology in equipment advanced at a rapid rate and user installations changed frequently. In this setting users buy new goods and retire old installations in an almost continuous upgrade cycle. Third, older systems do not lose their usefulness when a system or product line is no longer sold. Users of existing installations may still operate their system or perform incremental upgrades by purchasing complementary components. Hence, the installed base of systems may decline very slowly. This pattern arises in many high technology markets, and involves considerable business activity, but its empirical determinants are rarely, if ever, studied.

We develop an approach for measuring how market structure and other factors shape product sales and support, investigating two related measurement questions. First, which factors of market structure influence the sales of new products as well as the post-sale use of installations? Second, do these factors influence product sales and installation retirement in the same or opposite directions?

We use duration models to measure the determinants of product cycles. Specifically, every product goes through stages of birth, growth, and eventual decline. As a practical matter, it is possible to break this cycle into distinct stages, summarizing the life cycle of a product by examining the factors that influence the length of time associated with each phase. That is, different products sell for different lengths of time. We hypothesize the time a product remains for sale relates to features of the product and market environment in which it competes. Similarly, products vary in their usefulness after they are sold, depending in large part on how extensively vendors and third parties support them. The time associated with the decline of an installed base of products provides information about the after-sale service and support networks keeping these products in use. We hypothesize that the rate of decline of installations is explained, once again, by these same features.

We cannot directly test between the many theoretical approaches to understanding these phenomena, as many theories do not generate mutually exclusive hypotheses. However, we do develop a measurement approach that reflects the concerns of the literature on product obsolescence and on installed base. For example, our approach accounts for firm effects, vintage effects and cannibalization. It also accounts for competitive pressures within and between market niches and quality differences across goods, while staying within the practical bounds of the type of data available to most researchers.

We report several findings. We find that cannibalization and product vintage strongly influence how long a product remains for sale and the rate at which a product's installed base declines after sales cease. Interestingly, however, measures of competition influence post-sales support of these products differently than they affect the likelihood that the product will remain for sale. We also find that the duration that a product remains for sale has positive effects on its post-sale support, a finding that suggests that this variable may be a proxy for unmeasured quality and network attributes of the product. We conclude that sales and support are strongly related, though not precisely so, and discuss some interpretations below for why they differ from each other.

Our study builds on prior statistical determinants of product entry and sales. For example, many marketing studies seek to understand the product life cycle of pioneering products. These papers compare product life cycles across markets, primarily focusing on measuring whether there are any first or late mover advantages.[1] While this literature does shed light on the determinants of the life cycle after birth, it tends not to focus on the many other factors that also shape post-entry life cycles much later. It also does not focus on markets where there are competitive pressures from the continuous introduction of new products. These studies also compare very heterogeneous markets with one another, which introduces much variance into the picture at the cost of less robust inferences. As a result, these studies tend not to focus on post-sales support for durable goods, as our study will do.

We build on several papers that have studied one market over time. As with prior work, we compare experiences across segments within one market, examining the determinant of product entry and/or sales within a segment.[2] As with others, we exploit differences in market structure between product niches (at any point in time and over time) to identify the role of market structure in product turnover. We use time-varying covariates in our analysis to estimate hazard rates (Tuma, 1980). We show that this modeling approach yields results that are not difficult to estimate or interpret, and offers a potentially useful method for research of technology diffusion at the product level. Unlike others, we examine the entire product cycle after birth until retirement. This yields insights about the determinants of post-sales experience. Relatedly, we also investigate whether the determinants of the sales life and the post-sales life are similar. There are a few reasons to expect them to differ, since the competitive environment can change considerable over the life or a product.

We certainly are not the first researchers to use hazard models. However, we depart from most studies done by organizational ecologists who have primarily focused on predicting entry and exit at the organizational level (For review see Carroll, 1984; Hannan and Freeman, 1989; Singh and Lumsdon, 1990).[3] Our unit of analysis is the product, its sales and installations.[4] Unlike most previous empirical research on the product life cycle in computing, here the identities of leading products (instead of firms) receive attention. We think this is appropriate for trying to understand the micro-determinants of the diffusion of technology. In addition, our approach is appropriate for the mainframe market because firms did not turn over rapidly, but products did. There would be no sense in examining firm entry/exit, as the prior literature does. In this setting, the product is a much more interesting unit of analysis.

1. The commercial mainframe industry and the product life cycle

In this section, we first review what is known about the product cycle in computing and its relationship to sales and installed base. We then discuss variables that are likely to affect these processes and that lend themselves to measurement.

1.1 The product life cycle in computing, sales and installed base

From the late 1960s to early 1980s only a small number of firms marketed products in the large scale commercial computing industry and only a few firms entered or exited the industry, Mancke and McKie, 1983). During this period, however, there was frequent turnover of products, accompanied by rapid technical improvement. The term "product life cycle" became short-hand for regular and repeated turnover of products.[5]

From the buyer's perspective, the "product life cycle" consisted of upgrading, retrofitting, and improving existing systems or installing new systems. As customers discovered new technological opportunities and learned about new needs, they reevaluated their current systems. Buyers then often modified the memory and speed of their existing CPU, but kept other durable investments in software and peripherals. Alternatively, they kept their existing CPU but upgraded their particular software programs or peripheral components. This type of upgrading behavior could continue well past the time in which the product still sold. Peripheral and software upgrading could continue as long as users found it more expedient to work with existing systems than install new systems. Since installing new systems involved considerable setup expenses, many users continued to support and use their old systems well after a design ceased to sell. Because older systems with large installed bases were likely to have a large variety of peripheral products available (e.g. software, input output peripherals, etc.), users might be reluctant to upgrade to new systems. Essentially, large installed bases of successful older products create incentives for the product seller and third parties to support a wide number and variety of supporting products (Katz and Shapiro, 1985, Farrell and Saloner, 1986).

From the vendor's perspective, the "product life cycle" consisted of design, sales or leasing, and after-sale support. Some customers upgraded existing systems, while others compared the technical capabilities of all new systems and purchased new systems. With the passage of time, the entry of more competitors, the expansion of technical possibilities, and the expansion of buyers' needs, old product designs became technically obsolete. When a new design met with initial commercial success, then later parts of that product's "cycle" involved sales of complementary components to installations and potential upgrades. Often these later parts of the cycle continued well after a particular product design ceased to sell. All parts of this product cycle – designing, prototyping, manufacturing, initial rolling out, selling systems, servicing, support of existing installations, and customer upgrading – involved substantial technical and commercial risks.

Figure 1 shows the typical pattern for adoption of products at installations across the US. The number of installations using the product typically grows then falls. Growth occurs while the product is for sale. The number of installations declines as users retire their system or replace it with another. After a typical product ceases to be for sale, the installed base of users declines slowly, sometimes at a rate that is slower than the rate at which it grew. Though it is not shown, it is well known that extensive marketing and economic activity continues to support installed systems well after sales cease. Because the product is durable, continues to deliver useful services, and cannot be changed easily, use of older design can continue for quite a long time after purchase (Ito, 1995).

[Insert Figure 1 About Here]

1.2 Definitions

Our definition of a product focuses on the bundles of attributes embedded within a product. By "product," we mean a typical configuration of computer components associated with different capabilities and prices. The term “different products” refers to arrangements with significantly different attributes associated with different capabilities. A user typically buys a product, configures it with standard and customized peripherals, and adds standard and customized software applications onto it.

This definition is easier to implement in practice than one might first imagine. In practice, market surveyors decide whether different products, as labeled by vendors, correspond with different designs or bundles of attributes. As a practical matter, our definition of a product is quite similar to what hedonic researchers have used (with a few exceptions noted below). That is another reason for this benchmark.

We standardize on a few terms. To guard against falsely measuring the exit of phantom systems (or "vaporware"), we do not analyze models that, while listed in the data source or discussed in the trade press as a hypothetical possibility, ultimately have no sales. Our definitions of exit will correspond with industry practice to distinguish between a product still for sale and not. After a key event for tracking the end of sales, which we define and measure with hindsight, we say that sales of a product have stopped, and sometimes we say that the product has died. For another key event, the end of product support, which we also measure and define with hindsight, we will say that support for an installed base has ceased. We also will examine different definitions for when this support ends.

1.3 The determinants of the product cycle

This study examines a newly assembled set of data on products and installations; we are hesitant to presume very much about the specific features of firm behavior and market equilibrium, particularly for purposes of estimating product exit as a function of structural parameters of learning, costs, demand and substitution. We stay close to the issues found in the literature on product pioneering (e.g., Urban et al, 1986), though in our setting the notion of "first mover" is not as cleanly defined. We take further inspiration from the economics literature in dynamic growth and turnover (e.g., see Jovanovic and McDonald, 1994a,b), and the literature on installed base (Katz and Shapiro, 1985; Farrell and Saloner, 1986), though this theoretical literature does not provide specific predictions about what factors influence the end of sales and the decline of installed base. Rather, we attempt to estimate a model using reduced form statistical methods and borrow several common themes from the discussions of prior work.

In this study, we emphasize two themes. First, we hypothesize that market environment influences different aspects of the product cycle, in this case, sales and support. Second, we posit a relationship between sales of products and post-sale support of installed base. That is, market environment should influence both the anticipated value of (dis)continuing sales and also (dis)continuing support for existing installations. The first theme arises in previous work, but has not been empirically developed and applied to the later stages of the product cycle. The second theme has not been explored in any previous work we are aware of. These themes translate into several practical key issues:

- **Vintage, age and timing:** Much of the contemporary business press seems to claim that life cycles have shortened in later years of our sample. Does the age of a product have any relationship to exit and installed base? Sales of old products end as they fall technically behind; leaving only better products to survive (e.g., see Berndt and Griliches, 1993, or Stavins, 1996 about personal computers, or Requena-Silvente and Walker, 2005, about cars in the UK, or Khessina and Carroll, 2006 about optical disk drives). Is the same true for support of installed products? One might think so; vendors differ in their cost structure, distribution networks, efficiencies, and other firm-specific product-line strategies.

- **Niche markets and localized competition:** Does market niche predict exit? Possibly, since different niches have been associated with different customer bases, different applications and possibly different upgrade and replacement cycles.[6] How does the number of competing products influence exit? Competition from direct substitutes will be expected to be more constraining than competition from distant substitutes.[7] Similarly, competition from newly introduced and presumably more technologically advanced products is likely to have a greater impact than older less advanced products (DeFigueiredo and Kyle, 2006; Khessina and Carroll, 2006). Does intra-firm cannibalization affect product turnover? Cannibalization behavior by a firm may coincide with the obsolescence of an old product, particularly in markets where firms can anticipate the post-entry life cycle of a product.[8]

• **Persistence of success across stages of a life cycle:** Does the marketing success of a given product influence its post-sales viability? Products that have been actively sold for longer periods and those whose sales have generated a higher installed base may have greater post-sales success. Because such products are likely to have a large number variety of supporting products, externalities may be created that reduce the rate at which their installed base declines after sales have ceased. Brands may also convey information to users about the support network, raising the value of all products from the same company, even when these are quite far behind the frontier (See e.g., discussions in Robinson, 1988, or Shanker et al, 1998).

2. Estimation of the Model

We adopt a flexible estimation framework that measures the influence of time-invariant and time-varying determinants of product's sales and support. The former includes factors such as vendor, market segment, vintage, and system size. The latter includes factors such as cannibalization from close and distant substitutes, degree of competition from close and distant substitutes, and age of a product. Below, we first describe the various definitions that we use to define key events. After this, we describe our methodology for predicting the different types of events.

2.1 Pragmatic Definitions of Product Sales and Support

In all of our analyses of model exit, we use the individual model as the unit of analysis. We first must define the duration that a product is for sale and the duration that its installed base is supported after sales cease. A model is said to be for sale (or "alive") from the year in which the product is first produced to the year in which the product's installed base reaches its peak. More formally, let t define the age of a product, where t = 0 at the year in which a product first enters the market. Then t* is defined as the t associated with the year in which a product's maximum installed base (Ib_t) is recorded. For simplicity we drop any subscript for different products until the econometric section.[9]

This approach has several advantages. It is a reasonable measure of the length of sales since this is the first year in which retirements of the product are greater than the number of units sold. In practice, retirements do not exceed sales until sales cease -- i.e., once a product's installed base starts to decline it never increases again. Also, while the timing of activity is a much more coarse measure of change in status than a direct measure of market share, it is, accordingly, much less likely to be inaccurate. Hence, this approach is relatively insensitive to the types of minor measurement errors that naturally arise with 16 years of data for one market.

It is not as obvious how to precisely define the decline in after-sale support that accompanies a user's retirement of installations. Installations decline at very different rates and for a wide variety of reasons only loosely connected to their support networks. Thus, we want a definition that looks for large changes and correlates with the state of support.

Our definition has several advantages. First, they are easy to apply regardless of the scale of sales. This is important since many large (and expensive) systems retain support even though the total number of installations remains small. Second, as with the definition of sales, we have only relatively coarse information about decline in support. A good definition is reasonably insensitive to small measurement errors. Third, and perhaps most importantly, we want something that is available for all known systems, removing subjective guesses about when support ceased for some relatively obscure or comparatively unpopular systems.

We will define the end of support in two different ways, later testing the sensitivity or our inferences to these different definitions. The first definition of the end of installed base is the year in which the product's installed base drops to one quarter of what it was at its peak. The second definition extends to the year in which the product's installed base drops to a half of what it was at its peak. More formally, t^h is defined as the lowest t for which $Ib_t < 0.5(Ib_{t*})$ and, t^q is the lowest t for which $Ib_t < 0.25(Ib_{t*})$. It must be the case that $t^* < t^h \leq t^q$, and in the data the second inequality strictly holds for all but a few products.

Because our data source took censuses annually (generally at the beginning of the year), we assume t^*, t^h, and t^q occur at the midpoint between the last year the model did not meet the criteria given and the first year it does. In practice we add half a year to a product's sales life, and subtract half a year from its post-sales support. "True" peaks likely follow the observed peak, and threshold crossings will generally happen months before they show up in annual figures. This follows Petersen (1991) who suggests that when the exact time of an event is not known, time aggregation bias can be minimized by assuming the event occurred at the midpoint of the time period.

We illustrate our definitions of product exit with the following example. If our data source reported a peak installed base of 4000 units as of the beginning of 1978 for a product, we assumed that sales ceased in 1978.5. We assume that after sales support begins in 1978.5. If this models installed base drops to 1000 or below in 1980, we assume that t^q (the end of sales support) ends in 1979.5.

Related, as a practical matter another problem arises in setting the start time for after sales support for products that are only on sale for one year. Imagine, for instance that the above product's installed base dropped to 1000 units or below by 1979. In this instance, after sales support for this product would end at exactly the same time it began (e.g. 1978.5) and the observation would effectively be dropped from the analysis. Because it is unlikely that after-sales support in the form of complementary products and technical support would end at exactly the same point as sales cease, such an approach would lead to the under representation of products with short periods of after-sales support. In addition, because we only have annual observations, the "true" duration of sales support, while short, may well be greater than zero. Hence, for products following this pattern, we assume that after sales support begins at the beginning of the year in which the maximum installed base was reported. Thus, in the above example, after sales support would begin in 1978 and end in 1978.5.

Using these definitions of product sale and support we define three separate time periods that represent three definitions of the length of sales and support:

1) "Product sales" = t^*.

2) "After sale support" = $t^q - t^*$,

or

3) "After sale support" = $t^h - t^*$.

In other words, for a product we can extract two types of information for each model, the state occupied and the time spent in the state. Because we measure duration in three different ways, we will perform three separate analyses, the latter two providing similar information about the same sales support process. Notice that because not all states are completed by the time our data ends, we will also need to control for right censoring. We will also consider different approaches to left censoring.

2.2 Method

In order to control for the age of the product, we considered a variety of approaches. One approach is to use age dummies. Another approach 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 six years and the maximum age was 9.6 years old), the loss of degrees of freedom from using dummies is low in the sales data. However, this is not so far the support data. The number of non-truncated observations on the decline of installed base is low in practice, so the lost degrees of freedom become a concern. Thus, we prefer a less flexible modeling framework and estimated a model with continuous age, testing for differences between approaches where possible.

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, and 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. Again, the duration (t_i) will vary depending on which definition of duration that we are using. As we noted above, we assume that the hazard rate for a product increases with duration and use the Gompertz distribution. The following specification is used:

$$\mu(t) = exp[\boldsymbol{X}(t)\boldsymbol{\beta}(t)]exp[\gamma t]$$

where $\mu(t)$ is the instantaneous hazard rate for a system at time t, $\boldsymbol{X(t)}$ is a vector of time-varying independent variables and t is the duration. We expect that the hazard rate will increase with duration (age). Therefore, the coefficient γ should be positive. Each $exp[\boldsymbol{X(t)\beta}]$ can be thought of as multipliers of the rate and β and γ can be estimated by using maximum likelihood. For more details on this methodology, see Tuma (1980) and Carroll (1983).

Each model's life history was broken up 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 product. We then estimate a model-specific failure rate assuming that the failure rate is influenced by a set of independent variables.

One issue with our data is that it only extends back to 1968. A system that sold before 1968 has a left censored life cycle. The correct likelihood that would take account for left censored observations is very difficult to estimate when age is included as a covariate. One possible estimation strategy is to exclude all models that are left censored from the analysis. This approach effectively discards useful information. An second alternative is to use the whole sample, but include a dummy variable that takes on a value of one for models that are left censored and zero otherwise. Because of our limited degrees of freedom, we chose to use all of the available information and include a left censoring dummy that is coded one for left censored observations and zero, otherwise.

2.3 Trading off complete data with other limitations

There is one important limitation to our statistical approach, 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 compiled somewhat incomplete data on the era's product characteristics and prices.[10] Incomplete data sets, however, are not as useful for models of product sales and installed base. The attributes of products typically found in hedonic studies of the computer market – prices, speed and memory – are only available for the most popular products in this market. Yet, the most popular products live longest and are supported more vigorously. To focus solely on popular products imparts a selection bias into any study of product sales and installed base, missing less successful products with smaller sales.

In this study, we use information we can gather for all products. As we discuss in the following section, we are able to compile a complete census of products, their market niche, their age, their firm and degree of competition in market niche. We cannot, on the basis of data now available to us, determine whether the addition of additional information about a select set of popular models alters our conclusions. This is an open issue for future work.

3. Data

This paper's data on computer quantities and vintages comes from industry censuses compiled from International Data Corporation's (IDC) EDP Industry Reports (EDP/IR). We rely upon 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.[11] The data in this paper begin with the December 31, 1968 report and ends with the January 1, 1983 report. The first year that 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 the data incomparable with earlier years. Over the entire sixteen-year period, this data include the installed base of over 350 different computer systems, with over half introduced after 1968. From these we will follow the sales and support of 235 for whom we can assemble reasonably complete data. We explain these procedures below. These data are clearly the best available on the size of installed base of large computer systems in the United States.

3.1 The sample of systems

IDC's definition of a mainframe suffers from two biases. First, its definition of a mainframe in 1968 and 1969 is too broad. It includes some models that IDC reclassified as "Digital Dedicated Application" in 1970. These systems are actually minicomputers, like the DEC PDP-8, not general-purpose mainframe systems. Second, redefinition problems occur once IDC establishes several on-going 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) there previously.[12] IDC also revised its survey scope twice, once between 1969 and 1970, and once between 1976 and 1977. In both of these cases, IDC reduced the number of systems covered. Our approach was to construct a sample for installed base prior to the end of sales, then further develop as large a sub-sample as possible about user installations after sales cease. This makes the data set comparable to Greenstein and Wade (1998), which also estimates models on the duration of sales, but tailors the dataset for several novel questions that prior work could not address.

We define the market consistently across different years of the sample. In this paper 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 problematic sampling issues pertain to smaller systems, which we exclude. Finally, by the end of the sampling period, the difference between mainframes and some large general-purpose minicomputers (a.k.a. "superminis") becomes blurred, which raises questions about the survey's completeness. The primary issue is whether IDC included in the mainframe category all the super-minicomputer systems that were close substitutes for general-purpose mainframes. A reasonable case could be made that IDC included most of the relevant systems,[13] and a reasonable case could also be made that it did not.[14] Ending the sample in 1983 and excluding small systems minimizes this problem.

[Insert Table 1 About Here]

IDC tracks installed base data even after the model is obsolete.[15] Yet, there is occasionally some difficulty using this data when it comes to estimating installations after sales. In a number of cases, IDC chooses to aggregate similar same-age and size models after the models' installed bases start to fall. We disaggregate this data using linear interpolation based on the relative market shares at the last observation where the models are separate. For example, Table 1 shows the IDC data for the Honeywell 2020 and 2030 installed bases. IDC tracked these systems separately until 1978 and together thereafter. Our imputed values for 1979 to 1983 are italicized. In this case this procedure imputes similar t^h and t^q to these models. In general it does not.[16] Of the 235 models we track 53 become aggregated with another model at some point. While we believe the imputation method leads to accurate values for t^q and t^h, we place less confidence in exact values for installed bases. Since we need to disaggregate the IDC data to discuss after-sale support, this reinforced our inclination to estimate hazard rates rather than models where the endogenous variable is the cardinal quantitative value of the installed base, a number with much measurement error. Our procedure, in practice, will be less sensitive to such error.

3.2 Definition of events and independent variables

We need to define starting and ending events, when models enter and exit our duration model. We follow the definitions used above. This specification matches the IDC data nicely, because IDC usually begins tracking each product the year after its introduction. Since not all models exit by 1983, many specifications are right censored

The definition of support requires explanation. As noted, this event is defined as the first year that a product's installed base falls below some percentage threshold of its peak value. More specifically, we assume that the event occurs halfway between the last year the installed base exceeds this threshold value and the next year, when it falls below the threshold for the first time. We report estimates for both 50% and 25% thresholds.[17] Table 2 shows how products fall into these classifications in our data and the increasing severity of right truncation as the threshold value falls.

[Insert Table 2 About Here]

Finally, we note that we test a variety of specifications to insure that our results are not sensitive to a small accounting error in IDC's data. While Phister (1979) warns about several potential problems that could influence calculations using these data, he clearly believes that IDC's estimates of installed base are the best available. Dulberger also has some concerns about IDC's estimates of installed base, but concedes that they are the best publicly available.[18] Given these concerns, we tested the data for internal consistency by examining the history of each new system. Did the development of a system's installed base contain several years of growth followed by several years of decline? The presence of this pattern in the data makes it plausible. In any event, no alternative is completely satisfactory.[19]

For predicting changes to sales and after-sales status we define the following independent variables:

Year of Introduction (vintage): IDC data provides the year and month of introduction for each system. Our vintage variable is measured in years, with zero corresponding to 1968. Vintages prior to 1968 have negative numbers while those after 1968 are represented by positive numbers.

System Age: The IDC reports were taken at regular times, usually early in the year. Based on the year and month of introduction, we calculate system age at the time of the report.[20]

Brand Dummy Variables: We constructed firm dummy variables for IBM, NCR, Univac, Burroughs, CDC, General Electric (GEL), Honeywell, and RCA. The omitted category is for the

Japanese firms and a few smaller mainframe suppliers.

Numbers of Systems in Market Niches: IDC's censuses identify each system's size, with size ranging from 2 to 7. This measure is categorical, not continuous, and is correlated with memory and MIPS. It provides us with a measure of a market niche, as the size categories range from the highest and lowest ends of the computing spectrum. In this study, we analyze classes 4 through 7.[21] Previous analysis shows that the average system got larger over time (Greenstein, 1994). We analyze the market structure underlying each market niche by calculating the number of substitutes 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 non-adjacent size classes.

Cannibalization: This variable is incremented by one each time the firm introduces another newer product in an existing system's size class. 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.

Average Competitor Age: The number of systems variable captures the quantity of substitutes available to buyers, but says nothing about the technological quality of those models. If substitutes are far from the technological frontier they should present less effective competition. Essentially, this argument is similar to Barnett's (1996) argument at the population level that increasing fitness or competitive intensity exhibited by competitors should increase failure rates[22]. To control for the strength of substitutes, we calculate the average age of living competitors in a size class for each model as well as in adjacent and non-adjacent size classes. We expect that younger models will generate more intense competition than older ones[23].

Life Span: For the models that begin with product exit, we include a measure of the model's success in the marketplace. Life span is a natural candidate. This variable equals the time from product introduction to product exit, or the time the installed base grew.

Time Since Sales Cease: In our analyses of sales support, we include the time since sales of the product were discontinued. As this duration increases we expect that support of a product's installed base will be more likely to end as the product becomes increasingly technically obsolete.

4. Results

In this section we investigate the factors which lead to the end of sales and the end of post-sales support. Table 3 shows the means and standard deviations of the variables used in our analyses.

[Insert Table 3 About Here]

4.1 End of Sales: Alternative specifications

Greenstein and Wade (1998) have used similar data to investigate the probability that sales of a system will end. As a starting point for our analyses, we first present a model that is comparable to the preferred specification from that paper[24]. Model 1 of table 4 shows that cannibalization, age, and the number of products in a focal system's size class and in its adjacent lower size class have strong effects on the likelihood that a product will be taken off the market. Product vintage (year of introduction) has a negative impact suggesting that products introduced in later periods tend to stay on the market longer. All of these effects are consistent with previous findings.[25]

[Insert Table 4 About Here]

In model 2, we go beyond previous analyses and add the average age of other products in a system's size class as well as the average age of products in surrounding size classes. We do this to facilitate comparisons with the factors influencing support, which we will estimate below.

As it turns out, no significant effects are found except in the average age of the lower size class, a finding with no ready interpretation. All previous estimates remain qualitatively similar. We conclude that a number of new specifications contribute little; hence, the duration of sales are determined by vintage, firm effects, age, cannibalization activity, with differences arising due to competitive conditions across niches.

Finally, we note that some of the differences between these results and Greenstein and Wade (1998) – such as in the precise specification of age and vintage and the addition of average age – are there for convenience. These enable us to limit degrees of freedom so we can compare similar specifications across all estimates, both those about sales and those for support. In the latter case the data limitations are particularly binding, so a parsimonious specification has value.

4.2 Post-sales Support: Alternative specifications

In table 5, we explore the factors that influence a product's post-sales viability. We first estimate models in which post-sales support is assumed to extend from a product's last sale to the year in which the product's installed base drops to one-quarter of its peak value. We specify these models in ways that facilitate comparisons between the factors that drive post-sales viability (in Table 5) and those that influence the length of time that the product is actively sold on the market (in Table 4). We first estimate a model that is comparable to model 1 in Table 4.

[Insert Table 5 about Here]

The effects of age, cannibalization, and the number of products in a system's size class are consistent with those found for the length of time that the product is offered for sale.[26] The vintage effects, in contrast, are weak. The comparative ranking of firm effects has many similarities -- those firms whose systems sell for long (short) periods also tend to be those firms for whom the support comparatively last longest (shortest) as well. Burroughs is the only exception; they sell products that last comparatively long, but the installed base declines relatively faster. Surprisingly, non local density is negative, suggesting that as the number of products in nonadjacent size classes rises, the length of post sales support increases. This anomalous effect and the positive effect of local density disappear, however, in models 2 and 3, respectively.

Model 2 adds a product's lifespan and model 3 adds the average age of other products in its size class. Both have strong negative effects on the exit rate. The direction of a product's lifespan -- longer life span slows the decline of support -- suggests that this variable may be a proxy for unmeasured quality attributes of a system or the presence of complementary products that reinforce post-sales viability. We have more to say about this below. The direction of the effect for average age -- older competitor's slows the decline of support -- suggests that this variable may be a proxy for unmeasured quality attribute of new models.

Most other coefficients remain qualitatively similar except one. The effects of the number of products on the market disappear once lifespan and the average age of other products in a system's size class are included in model 3. Indeed, none of the density measures are significant, suggesting that these measures of competition have little effect on the length of post-sales support.

The models in Table 5 have many right-censored observations, so there is considerable benefit to conserving degrees of freedom.[27] For model 4 we drop the insignificant variables reflecting the number of competing products in and around a product's size class. All results remain substantively the same. In other models not shown here we included a product's peak installed base as a measure of product quality. Because no significant effects were found for this variable it appears that lifespan is a superior measure of this construct.[28]

In models 5 and 6 we perform a sensitivity analysis by using a different definition of when a product's post-sale use effectively ends. Here, we use the definition that post-sales support ends when a system's installed base drops to one-half of its peak value. This alternative definition of support we find that the results do not change substantively, except on the average age of products in a system's size class. In addition, the effect of cannibalization is weaker and only marginally significant (p<.06, one-tailed test). Both of these variables proxy for the influence of competitive substitutes from inside (cannibalization) or outside (average age of products) the firms, suggesting that their influence is stronger when a support network is older.

Overall, defining the end of post sales support as occurring when a product's installed base drops to one-quarter of its peak value seems to yield more information. Consequently, we settled on model 4 as our preferred specification. In this specification support for installations is sensitive to time since sales ended, vintage, firm effects, cannibalization activity, lifespan and also competition within niche.

4.3 Discussion of results

Table 6 measures of the importance of different exogenous variables for our two preferred specifications. This table summarizes the relationship between the factors that influence product sales and support. Three conclusions follow from this table. First, many of the factors that influence sales also influence support in the same direction. Second, the sales experience for a product, even controlling for all these other determinants, helps predict support for installations after sales end. Third, firms display different experiences in their comparative sales and support experience. We explain these findings in detail.

Vintage effects are moderately strong and significant in our preferred specifications for sales and support. Later vintages are not likely to discontinue sales sooner. Remarkably, even after controlling for quality of products and other factors, later vintages also do not reduce support sooner than earlier vintages. Table 6 shows that vintages which were approximately 4.5 years older (one standard deviation) are less than half as likely to have sales discontinued. Similar results are found for the end of sales support. This runs counter to the standard view that product cycles sped up over time.

Both sales and support display strong firm effects, and these are positively correlated (approximately .5). IBM has both higher probability of ending sales and shorter support for their products. Along with the frequent entry documented in Greenstein and Wade (1998), this pattern is consistent with faster upgrade cycles and faster replacement for the users of IBM products, consistent with IBM's reputation as the commercial and innovative leader during this time. General Electric also displays this pattern of faster ending of sales and support, though the interpretation is much different. This resulted from the well-known difficulties in bringing successful products to market and the eventual discontinuation of new sales after sale of the division to Honeywell (Fisher, Mickie and McGowan, 1983). RCA also displays a sales pattern consistent with its commercial difficulties, but the decline in support is not as strong as with General Electric. This contrast is consistent with the sales of RCA's product line to Univac, who continued to support it with further product upgrades after the acquisition. We find it reassuring that our statistical method easily aligns with historical/journalistic accounts of these events, but we also note the coefficients alone do not provide a unambiguous interpretation. It is necessary to understand them in context.

No consistent pattern characterizes the remaining firms. NCR displays a mildly weaker version of the pattern with faster sales turnover and faster use of products. Both CDC's and Univac's products stay for sale longer (moderately) and in use longer. This is consistent with their focus on making products for scientific and computationally intensive users. Interestingly, Table 6 shows that with the exception of Burroughs, all of the firm effects found in the end of sales analysis are amplified in the results for sales support. For instance, General Electric's multiplier of the rate increases from 1.69 in the end of sales analysis to 5.23 in our analyses of sales support. To the extent that these firm effects reflect stable firm strategies, they suggest that strategic decisions may have lasting effects on the processes studied here.

Sales and support display similar sensitivities to duration in our preferred specifications. In the end of sales analysis, an additional 1.91 years (one standard deviation) increases the probability of an event by 1.92 times as compared to only 1.64 times in the sales support analysis for 2.99 years (again, one standard deviation). This contrast likely arises for several reasons. First, the obsolescence of a new product is quite sensitive to the benchmarks against which it is compared. In contrast, existing installations can remain useful, as long as there is ample commercial support for them, even if they are not on the technological frontier. Second, age may stand for unmeasured quality of products for sale. Our specification for support has other controls for quality of the product, such as lifespan. The coefficient on lifespan is negative and strong, as expected – i.e., products that sell for longer periods also stay in use longer. A one standard deviation increase in lifespan decreases the probability of exit by almost 50%.

In both specifications, cannibalization influences the sales and support for products. More competition from a firms' products leads to shorter life span for sales and support. Introducing a newer product increases the probability of sales ending by almost 1.25 times, while a new product increases the probability of support ending by a similar amount.

Two interpretations are consistent with these findings. On the one hand, products from the same firm share sales organizations, brand names and other factors that influence buyer decisions. The presence of one naturally competes with the other, cutting into sales of an old product from the same firm and inducing retirements of similar products from the same firm. On the other hand, the competitive strength of a firm's offering and its installations can be anticipated. Firms may be introducing new products in anticipation of buyer announcements about intentions to retire their installations or stop purchasing old products. The former interpretation suggests that cannibalization represents competitive effects; the latter interpretation suggests that cannibalization represents unmeasured obsolescence, particularly of installations.

Sales and support are also sensitive to competitive conditions within a niche, though the effects are somewhat different in the two specifications. Number of competitors influences sales but not sales support. In contrast, the average age of competitors has weak effects on both sales and support..

Overall, we conclude that sale and support are positively and strongly related, a finding that complements Greenstein and Wade (1998), where entry and sales were positively but only weakly related. In particular, the strong relationship is observed in the results for vintage, duration, firm effects, lifespan, niche effects and cannibalization. These findings are consistent with the literature on installed base where optimal seller behavior anticipates relationships between product design and activities associated with supporting or upgrading those products. At the same time, our findings also emphasize that product sales and support have many related features and dependencies, insights that are largely missing from most theoretical discussions about the relationship between installed base and sales.

5. Summary

In this study, we measure the determinants of product sales and support. We measure the importance of different features of market structure as it changes over time or varies across product niches. Our findings illustrate the gains from analyzing the separate components of product life cycles – here, product sales and support. Previous research has generally not analyzed the factors linking the length of time a product remains for sale and in use. Further work might establish more theoretical and empirical links between different aspects of the product life cycle – entry, growth, market share, exit from sales, and user retirement.

Future work also should try to develop models of firm behavior that will increase our understanding of product line strategies, different racing behavior in different niches, and technical and marketing uncertainty prior to the introduction of a new design (e.g., see Hintsch, 2006). Such models can aid in developing the links between product entry and survival as new markets mature. One limitation of our study is that we do not jointly estimate firm decisions to offer sales and support, but simply infer their interaction through common independent variables, interpreting coefficients in light of historical accounts. That said, until such models are further developed, we find it insightful and useful to develop statistical methods at the product level, investigate the long run patterns, and interpret these patterns in light of well-known behavioral questions.

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Figure 1

Growth and Decline of Installed Base for a Typical Product

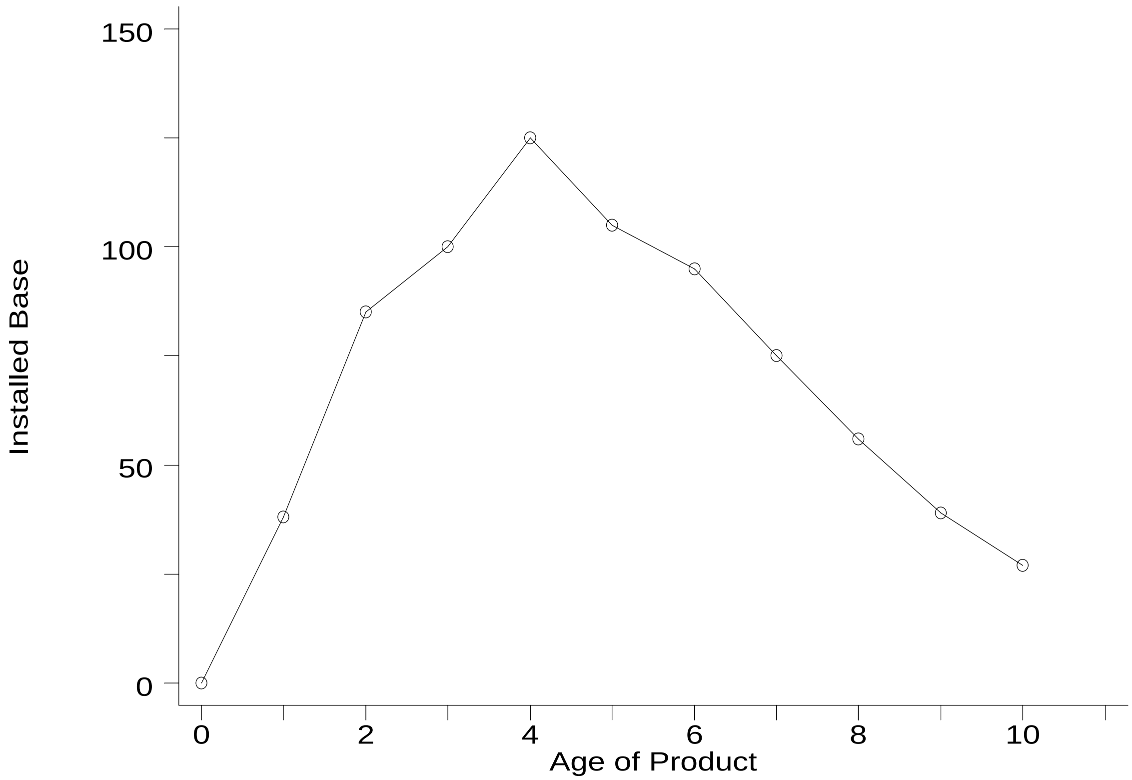

Table 1: Installed Base Figures for Two Honeywell Systems: an illustration

	Year	73	74	75	76	77	78	79*	80*	81*	82*	83*
Model	**2020**	0	215	440	510	560	455	*410*	*325*	*244*	*170*	*118*
	2030	0	38	85	100	125	105	*95*	*75*	*56*	*39*	*27*
	2020/2030							505	400	300	209	145

* *Italicized* numbers are imputed values. Non-italicized are the reported values.

Table 2: Number of Models in Different Threshold Categories

Threshold		Born Before 1968, Peak Before 1983	Born and Peak in 1968 to 1983	Born in 1968 to 1983, Peak after 1983	Total
50% Peak	Not Truncated	35	59		94
	Right Truncated	5	57	79	141
25% Peak	Not Truncated	29	30		59
	Right Truncated	11	86	79	176
10% Peak	Not Truncated	12	13		25
	Right Truncated	28	103	79	210
Total		40	116	79	235

Table 3: Means and Standard Deviations

End of Sales	Mean	Standard Deviation	End of Support[a]	Mean	Standard Deviation
End of Sales	.204	.404	**End of Sales**	.0653	.247
Year of Birth[b]	5.34	4.58	**Year of Birth**	1.60	4.05
Product Age	2.67	1.91	**Duration of Sales Support**	3.95	2.99
Density in Size Class	17.93	5.60	**Density in Size Class**	19.32	5.44
Density of Adjacent Lower Size Class	16.64	5.18	**Density of Adjacent Lower Size Class**	17.18	5.37
Density of Adjacent Higher Size Class	11.75	7.07	**Density of Adjacent Higher Size Class**	13.51	6.77
Density of Non Adjacent Size Classes	34.77	12.14	**Density of Non Adjacent Size Classes**	35.04	11.12
Number of Cannibalizations	.919	1.13	**Number of Cannibalizations**	2.60	2.35
Average Age	2.65	.503	**Average Age**	2.57	.489
Average Age of Adjacent lower Size Class	2.56	.473	**Average Age of Adjacent lower Size Class**	2.49	.453
Average Age of Higher Adjacent Size Class	2.17	1.19	**Average Age of Higher Adjacent Size Class**	2.35	1.10
Average Age of Non adjacent Size Classes	2.59	.327	**Average Age of Non Adjacent Size Classes**	2.60	.375
			Lifespan	4.94	1.80

[a] End of Support Defined as when Installed base drops to one quarter of peak installed Base.
[b] 1968 is defined as year zero.

Table 4: Models of Sales Cycle

	Model 1	Model 2
Product Age	0.3404** (.0597)	0.3432** (.0620)
Year of Introduction	-0.180** (0.060)	-0.187** (0.064)
IBM	0.879** (0.305)	0.844** (0.307)
NCR	0.110 (0.412)	0.148 (0.414)
UNI	-0.380 (0.337)	-0.316 (0.338)
HON	-0.419 (0.327)	-0.410 (0.329)
BUR	-0.655** (0.330)	-0.565* (0.333)
CDC	-0.250 (0.302)	-0.257 (0.303)
GEL	0.579 (0.386)	0.524 (0.398)
RCA	0.658* (0.404)	0.771* (0.413)
Number of Times Cannibalized	0.217** (0.070)	0.218** (0.072)
Density in Size Class	0.105** (0.024)	0.105** (0.026)
Density of Adjacent Higher Size Class	0.041 (0.025)	0.040 (0.030)
Density of Adjacent Lower Size Class	0.070** (0.018)	0.054** (0.021)
Density of Nonadjacent Size Classes	0.025 (0.016)	0.045** (0.020)
Average Age in Size Class		0.308 (0.215)
Average Age of Adjacent Lower Size Class		-0.470** (0.224)
Average Age of Adjacent Higher Size Class		0.160 (0.161)
Average Age of Nonadjacent Size Classes		-0.000 (0.312)
Left Censored	-0.662** (0.326)	-0.553* (0.336)
Constant	-6.481** (0.848)	-6.880** (2.016)
N **Log-Likelihood**	761 -64.61	761 -60.55

Standard errors in parentheses,,,
* significant at 10% level; ** significant at 5% level

Table 5: Model of Sales' Support Cycle

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Time Since Sales Ceased	0.328** (.0812)	0.189** (0.096)	0.261** (0.111)	0.166** (0.058)	0.137 (0.0497)	0.119** (.0479)
Year of Introduction	-0.032 (0.108)	-0.193 (0.124)	-0.132 (0.136)	-0.215** (0.092)	-0.087 (0.094)	-0.100* (0.056)
IBM	1.144** (0.593)	1.166* (0.607)	1.250** (0.618)	1.097* (0.602)	0.228 (0.418)	0.213 (0.404)
NCR	0.638 (0.822)	0.831 (0.842)	0.874 (0.848)	0.848 (0.841)	0.220 (0.563)	0.162 (0.561)
UNI	-1.121 (0.865)	-0.953 (0.870)	-0.934 (0.871)	-0.910 (0.867)	-0.523 (0.498)	-0.510 (0.497)
HON	-0.875 (0.905)	-0.830 (0.925)	-0.780 (0.933)	-0.726 (0.912)	-0.068 (0.504)	-0.134 (0.502)
BUR	1.123* (0.683)	1.454** (0.714)	1.490** (0.718)	1.421** (0.700)	0.741 (0.474)	0.606 (0.462)
CDC	-0.839 (0.764)	-0.738 (0.783)	-0.736 (0.788)	-0.899 (0.763)	-0.998* (0.566)	-1.044* (0.557)
GEL	1.693** (0.626)	1.767** (0.635)	1.808** (0.638)	1.655** (0.626)	0.864* (0.455)	0.931** (0.444)
RCA	1.400** (0.622)	1.345** (0.624)	1.418** (0.629)	1.262** (0.611)	0.152 (0.472)	0.143 (0.467)
Number of Times Cannibalized	0.249** (0.094)	0.257** (0.094)	0.257** (0.094)	0.244** (0.091)	0.121 (0.080)	0.146* (0.077)
Density in Size Class	0.080** (0.039)	0.076** (0.038)	-0.015 (0.051)		-0.020 (0.039)	
Density of Adjacent Higher Size Class	-0.024 (0.037)	0.029 (0.044)	0.006 (0.053)		-0.006 (0.037)	
Density of Adjacent Lower Size Class	-0.032 (0.029)	-0.017 (0.031)	-0.055 (0.042)		-0.029 (0.031)	
Density of Nonadjacent Size Classes	-0.050** (0.025)	-0.012 (0.029)	-0.043 (0.044)		0.015 (0.032)	
Average Age in Size Class			-1.355** (0.545)	-1.560** (0.393)	-0.490 (0.325)	-0.371 (0.249)
Lifespan		-.358** (.152)	-0.284** (0.162)	-0.369** (0.125)	-0.255** (0.117)	-0.254** (0.084)
Average Age of Adjacent Lower Size Class			-0.700 (0.518)	-0.523 (0.396)	-0.715** (0.325)	-0.448* (0.247)
Average Age of Adjacent Higher Size Class			-0.192 (0.298)	0.076 (0.175)	0.227 (0.203)	0.097 (0.128)
Average Age of Nonadjacent Size Classes			-0.571 (0.581)	-0.211 (0.429)	-0.184 (0.394)	-0.135 (0.296)
Left Censored	-1.156* (0.604)	-0.939 (0.610)	-1.008* (0.603)	-0.913 (0.593)	-0.576 (0.407)	-0.650* (0.399)
Constant	3.874** (1.197)	-3.819** (1.218)	6.356 (4.368)	3.193 (2.259)	2.520 (3.127)	1.370 (1.552)
N	888	888	888	888	657	657
Log-Likelihood	-70.69	-67.88	-63.64	-65.34	-138.08	-139.03

Standard errors in parentheses * significant at 10% level; ** significant at 5% level

Table 6: Multipliers of the Rate for End of Sales and End of Sales Support

Variables	Multiplier of the Rate End of Sales (Table 4, Model 2)	Multiplier of the Rate End of Support (Table 5, Model 4)[a]
Time since product birth/time since sales ceased[ce]	1.92	1.64
Year of Birth[bc]	0.43	0.42
IBM[d]	2.33	2.97
NCR[d]	1.16	2.33
UNI[d]	0.73	0.40
HON[d]	0.66	0.48
BUR[d]	0.57	4.13
CDC[d]	0.77	0.41
GEL[d]	1.69	5.23
RCA[d]	2.16	3.53
Density in Size Class[c]	1.80	
Density of Adjacent Lower Size Class[c]	1.32	
Density of Adjacent Higher Size Class[c]	1.33	
Density of Non Adjacent Size Classes[c]	1.72	
Number of Cannibalizations[d]	1.24	1.27
Average Age[c]	1.16	0.47
Average Age of Adjacent lower Size Class[c]	0.80	0.79
Average Age of Higher Adjacent Size Class[c]	1.20	1.09
Average Age of Non adjacent Size Classes[c]	1.00	0.92
Lifespan[c]		0.51

[a] End of Support Defined as when Installed base drops to one quarter of peak installed Base.
[b] 1968 is defined as year zero.
[c] Multiplier results from a one standard deviation increase in the variable
[d] Multiplier results from a one unit increase in the variable
[e] Duration is defined as age of the product for the end of sales analysis and time since sales end for the end of sales support analysis.

Endnotes

[1] Empirical research in this vein includes papers by Robinson and Fornell (1985), Urban et al (1986), Kalyanaram and Urban (1992), Golder and Tellis (1993) and Shankar et al (1998). For a description of a variety of new products, see Gort and Klepper (1982).

[2] This literature has a variety of antecedents. For one product at a time, see e.g., Stavins (1995) on PCs, Greenstein and Wade (1998) on mainframes, Asplund and Sandin (1999) on beer in Sweden, Chisholm and Norman (2005) on movies in the US, Requena-Silvente and Walker (2005) on automobiles in the UK, Defigueiredo and Kyle (2006) and Defigueiredo and Silverman (2006) on laser printers, Hitsch (2006) on breakfast cereals, or Khessina and Carroll (2006) on optical disk drives.

[3] A notable exception is a recent study by Khessina and Carroll (2006) who investigate the turnover of products in the optical disk industry using an ecological perspective.

[4] Research using the product as the unit of observation includes Stavins (1996), who examines entry and exit within the PC industry using information obtained from hedonic estimation. Khanna (1994) and Michaels (1979) examine heterogeneity in firm strategies within the large scale computer industry. Hartman and Teece (1990) examine introduction strategies and hedonic pricing in the minicomputer industry. Oliner (1992) examines retirement patterns and values among IBM mainframes at the product level, while Ito (1995) examines retirement decisions within business establishments. Khessina and Carroll (2006) investigate the determinants of product exit in the optical disk drive industry and find important differences in these exit rates depending on if the products are from startup firms or those entering the market from different industries.

[5] Different parts of the computer trade press and computer consulting industry used the phrase, "product life cycle," for very different purposes. See Inmon, 1985, Phister, 1979, Friedman and Cornford, 1989, Fisher, McGowan, and Greenwood, 1983, or Fisher, McKie and Mancke, 1983. When economists measure events associated with product turnover, it is usually to measure the rate of technical change and improvement in economic welfare. Of the many analyses, well known studies of mainframes include Chow (1967), Cole et al (1986), Dulberger (1989), Gordon (1989), Oliner (1993) Trajtenberg (1990), and Triplett (1989).

[6] For instance, 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 (1994) analysis of large scale computing. Racing behavior might result in shorter product cycles and more frequent product introductions.

[7] According to several perspectives, 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 failure rates (See Hannan and Freeman (1977; 1989) and Carroll (1984)).

[8] While product obsolescence in a technical sense is exogenous, 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 where the firm already has an existing product.

[9] In practice, in the rare case when the peak value for installed base is the same in two contiguous years, we choose the earlier year.

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

[11] Phister identifies several years in which IDC revised the reported number of installations in previous years, particularly for IBM models in 1967-1972. In those cases, we use Phister's reported updates. This makes this paper's estimates comparable with Phister's (1979) and Flamm's (1987a,b) description of the diffusion of computing equipment, which used more aggregate IDC data.

[12] The most important case is IDC's decision to include the IBM System 36 in the mainframe sample in 1976

(estimated installed base at 5000 units) and exclude it from mainframes after that (but include it in "small business systems").

[13] According to the 1983 IDC census for minicomputers and mainframes, the value of installed base associated with super-minicomputers was roughly half that of all minicomputers, or roughly 15 percent of the value of the installed base of mainframes. IDC's census differs from the other censuses, particularly CBMEA's (1992), because IDC includes several systems as mainframes which others classify as super-minicomputers. This makes IDC's census more complete by the early 1980s.

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

[15] There are six models that we delete from the sample because they appear to be obsolete at the time of introduction. All but one of these models has a maximum installed base of five or less. IDC stops tracking these models within a year or two of introduction.

[16] While IDC constructs product aggregates from similar products, they do not necessarily all have the same year of birth or peak year. Indeed, most often they do not.

[17] While other threshold values are possible, ones below 25% contain too much right censoring (due to the sample's end in 1983) to estimate significant results. For example, Table 2 shows that a 10% threshold yields only 25 events out of 235 models.

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

[19] Sales data are not available for this market.

[20] We initially estimated a specification where dummy variables controlled for vintage and system age. This specification required too many degrees of freedom; most estimates were insignificant. Consequently, we adopt a continuous specification for these variables.

[21] We omit size class 2 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. Consequently, we do not include size class 3 systems in the analysis because could not compute the number of systems in the lower adjacent size class for these systems.

[22] Barnett proposed that older organizations generate more intense competition because of their experience. In contrast, at the product level we propose that younger products generate more intense competition because they are more likely to be on the technological frontier.

[23] Calculating values for the average competitor age in the next highest size class was problematic for models in size class seven since this is the highest size class. We assigned a value of zero for this variable for products in size class seven. To check and see if this affected the results we performed a supplementary analysis in which we included a size class seven dummy variable. All effects remained robust and the size class dummy was not significant.

[24] There are certain differences between model 1 and the preferred specification presented by Greenstein and Wade (1998). Greenstein and Wade used one year increments in age in defining their age dummy variables rather than the continuous measure used here. They also used dummy variables to measure vintage while we used a continuous measure. Finally, we included models that were left censored (born before the beginning of the study period (1968). These changes were made because the number of non-truncated observations in the post-sales analysis is relatively low, so the loss of degrees of freedom became a concern. In order to minimize this and maintain comparability in the sales and post-sales analysis, we estimated models in which fewer degrees of freedom would be lost. This does not qualitatively alter the other estimates in the sales specification.

[25] One difference between these results and those reported by Greenstein and Wade (1998) is that the number of

products in higher adjacent size classes and those in nonadjacent size classes in that were positive and significant while here they barely miss significance ($p<.06$ – one tailed test). As we reported above, however, we use the entire sample (including products introduced prior to 1968) and a slightly different model specification in order to conserve degrees of freedom.

[26] For our models of post-sales support, the "age" variables measure time since the peak of sales. With the introduction of lifespan in the next model, these variables will capture the same influences as product age, since product age = lifespan + time since peak of sales.

[27] This is also one of the reasons we continue to specify age as a continuous variable instead of a series of discrete dummy variables.

[28] In other analyses not shown here, we added dummy variables indicating a model's size class to our preferred specifications for end of sales and support. The dummy variables were not significant, nor did the findings change.