Diffusion of Technology Generations: A Model of Adoption and Repeat Sales

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This paper explores multiple-generation demand dynamics of "fast-tech" products, which we define as durable technological products and technology-based services where repeat purchases are motivated by user-perceived functionality increases that trigger generational transitions. Examples of fast-tech products include: personal computers (PCs), DRAMs, printers and wireless telephone services. In management of fast-tech products, special attention must be paid to the different needs of adopters and repeaters, which may require different product, advertising and distribution-channel strategies. We develop a model of multiple-generation product diffusion in which sales are constructed as the sum of adoption sales and repeat sales thus, for the first time, separately identifying first-time purchases and repeat purchases. The model also identifies (1) the potential market for each generation, (2) total systems in use (subscribers if a service market) by time period and (3) systems-in-use (installed-base) mix by product/service generation for each time period. The model reduces to the basic Bass model (1969) in the case of a single generation. We use two sets of empirical data (eight DRAM generations and nine PC generations) to demonstrate that the model provides an excellent fit to historical data. We also provide support for the Norton-Bass Model by fitting it to these same data.

1. Introduction

Technological products come in generations. The time between generations may be long as was the case for sailing ships and ships powered with steam engines, or generations may follow one another in rapid-fire succession as is true of semiconductor chips and personal computers. In any case, generational progression is a fundamental trait of technology-based products and, in a broader sense, of all products. Generational boundaries are of great interest to management because the transitions are rife with opportunity as well as fraught with danger. It is therefore important to develop an understanding of the demand dynamics and interrelationships between product generations. The advancement of such understanding is the purpose of this paper.

How is a generation to be defined? Because the basic phenomena being analyzed are based on market observations of underlying buyer behavior, we believe that the appropriate definition should be based on evaluations of product functionality from the buyer's perspective and not alone on engineering characterizations of individual product features. We shall suggest a general definition and apply specific criteria for the product categories that we study.

There are two groups of buyers of a product generation: (1) adopters, who are first-time buyers of the product category, and (2) repeat buyers, who previously purchased earlier generation products. For a model to characterize inter-generational dynamics of product diffusion, it must capture the processes of adoption and repeat buying. Although other models such as Norton-Bass (1987) accurately model generation sales resulting from the underlying adoption and repeat-purchase processes, the model presented here, which we shall refer to as the BB-01 Generations model, is the first to explicitly model the internal structure of these processes, constructing the sales of a generation from its constitute adoption and repeat-purchase components.

Because we are especially interested in the diffusion of technology products and services, which have relatively short inter-generational times (e.g., a few years), our desire is to develop models that will stand the test of many generations. The greatest number of generations that have previously been modeled is four. To verify the model presented here as well as to provide support for the validity of the Norton-Bass model (1987) we use empirical data from eight DRAM generations (1974-2000) and nine PC generations (1975-2000).

2. Literature Review and Earlier Models

The earliest model of the demand relationship between one generation of a product and a successor generation is the Fisher-Pry model (1971). This model is a simple model of substitution over time of the later generation for the earlier expressed as a share of sales for each of the generations. The model is based on Pearle's Law: "The fractional rate of fractional substitution of new for old is proportional to the remaining amount of the old left to be substituted." The model is based on the assumption of constant proportionality k and is expressed as the differential equation $\frac{d}{dt}s(t) = k\ s(t)\left[1 - s(t)\right]$, where s(t) is fractional market share. The Fisher-Pry model has been shown to provide good fits to share data for two successive generations of products. Blackman (1971) modified and Perterka (1977) extended the Fisher-Pry model to allow share to be distributed among several generations. The Fisher-Pry model as well as its modifications deal with share only and do not account for sales of the generations, nor does it account for the components of sales such as first-time buyers and repeaters.

The first model of sales of multiple generations of products is the Norton-Bass model as described in Norton (1986) as well as Norton and Bass (1987, 1992). This model is an extension of the Bass model (1969) of the diffusion of a single-generation product. It deals with sales of successive generations of products in those cases where adopters continue buying the product at a constant rate and buyers of earlier generations gravitate to later generations according to the Bass model cumulative distribution. In this model, each generation may expand the market. Any incremental market adopts the newest generation or is usurped by a later generation in processes governed by Bass model cumulative distributions. The Norton-Bass model has been shown to provide very good fits to sales data for each product generation for several product categories. It has also been shown to dominate the Fisher-Pry model in fitting share data. The Norton-Bass model equations for three generations are:

$$s_1(t) = F(t_1)\,m_1\left[1 - F(t_2)\right], \tag{1}$$

$$s_2(t) = F(t_2)\left[m_2 + F(t_1)\,m_1\right]\left[1 - F(t_3)\right] \text{ and} \tag{2}$$

$$s_3(t) = F(t_3)\left[\, m_3 + F(t_2)\left[m_2 + F(t_1)m_1\right]\right], \tag{3}$$

where $S_g(t)$ is sales of generation g at time t, t_g is the time since the introduction of generation g, m_g represents the incremental market potential for generation g and $F(t_g)$ is the cumulative adoption function of the Bass model at time t_g. In Bass (1969), F(t) is shown to be

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \left(\dfrac{q}{p}\right) e^{-(p+q)t}}, \tag{4}$$

where p and q are model parameters to be estimated when the model is fit to observations data. In the Norton-Bass model m_g is conceptualized as

$$m_g = a_g M_g \,, \tag{5}$$

where M_g is the ultimate market potential measured as the number of ultimate applications, customers or sockets for generation g if there are no succeeding generations and a_g is the average buying rate per application per unit of time. Neither of these generational factors is observed or identified quantitatively, but m_g is a model parameter and is estimated.

In the model, sales of generation 1 will be $m_1F(t_1)$ until generation 2 arrives and then it will be this quantity minus what generation 2 steals. Migration from earlier generations to the latest generation is assumed to depend on the adoption rate for the latest generation and is the product of this adoption rate and the theoretical sales of the prior generation if the latest generation had not arrived. In other words, the Bass model diffusion process governs first-time sales as well as repeats. There are two components of first-time sales: (1) customers who entered the market potential pool only when the latest generation became available and who purchased the latest generation and (2) those customers who made a first–time purchase of the latest generation but were in the pool of possible adopters of the prior generation. The latter component was *usurped* from the prior generation by the latest or it could be said to be *leapfrogging* the prior generation. Similarly, either generation g repeaters consist of those who

(1) made an adoption purchase or a repeat purchase of the prior generation and made a purchase of generation g or (2) made a purchase of a generation earlier than g-1 and were usurped by generation g thus leapfrogging generation g-1. Therefore, the model involves the usurping of both adopters and of repeaters.

In equations (1), (2) and (3) for the Norton-Bass model the F functions do not have generational subscripts because Norton and Bass found that for several product categories the p and q parameters for the estimated F functions were the same across generations. A more general version of the model, which was explored by Norton (1986), designates generational subscripts for the F's and thus has p's and q's that vary by generation.

There have been numerous applications and several published papers applying the Norton-Bass model or some variation of it. Mahajan, Sharma and Buzzell (1991) used a similar model to estimate the extent of Kodak's infringement of Polaroid's instant photography patents. Islam and Mead

(1997) discuss use of the Norton-Bass model in which the p's and q's vary over generations as first described by Norton (1986). Johnson and Bhatia (1997) applied the Norton-Bass model to generations of mobile communications and report good results. Kim, Chang, and Shocker (2000) modified the Norton-Bass model to deal with inter-category effects as well as generational dynamics in a study of wireless telecommunications. Bayus, Kim and Shocker (2000) have provided an overview and literature review of models that treat the dynamics of multi-product interactions including successive product generations. Danaher, Hardie and Putsis (2001) have developed a model of a subscription service for two generations of analog wireless telephone. The model posits the basic Bass model as the process for adoptions of the first generation product prior to the entry of the second generation and posits usurping of the remaining market potential of the first generation by the second generation at a rate that is proportional to the basic Bass model adoption rate for the expanded market potential. They mistakenly conclude that the Norton Bass model (1987) does not allow *leapfrogging*, however as described above, this is not true. Mahajan and Muller (1996) have developed a model to describe the systems of IBM mainframe computers in use based on an extension of the basic Bass model and have developed normative guidelines for the introduction timing of a new generation based on the model. Lehmann and Pae (2000) have used the framework of the Norton-Bass model in a cross-sectional analysis of several product categories to study the effect of intergeneration time, the time between the introductions of successive generations, on the adoption rate for the new generation.

3. A Multiple-Generations Model of Adoptions and Repeat Sales

Prior models of diffusion of durable technological products and technology-based services have four significant shortcomings. First, they do not separately identify first-time purchases and repeat purchases. Second, they do not use the potential market as an identifiable quantity, which would be helpful in both estimating and forecasting. Third, they do not permit calculation of the installed base (products/services in use) at each time period. Fourth, they do not provide a way to quantify adopters in each time period by the product generation they own, which is the installed-base mix by product generation. Installed-base mix is often required; for example, PC software companies must track the PC installed base by generation to estimate the number of PCs capable of running their application. In the case of a subscription service (e.g., wireless telephone), the installed base is the number of subscribers and the installed-base mix quantifies the number of subscribers by generation of service (e.g., analog cellular, digital cellular, PCS) at each time period. To address these four shortcomings, a multiple-generations model of adoption and repeat sales is required.

Shortcomings of prior models are apparent in the modeling of "fast-tech" products. We define "fast-tech" products as the thousands of product categories that improve so rapidly that customers want a newer version long before the older one wears out or ceases to be capable of fulfilling previously defined needs. Fast-tech products include durable technology products (e.g., PCs, DRAMs, microprocessors, printers, video games, PDAs) and technology services (e.g., wireless voice, software, Web-based services, networks). When customers see the possibilities offered by a newer product, they redefine their needs in light of the new technology. Fast-tech products include virtually all products and services that are largely based on digital technology because the rapid changes in the foundation technologies (e.g., semiconductor equipment, semiconductors, microprocessors, hard-disk drives, telecommunications, software) enable rapid changes in products of which they are components.

In fast-tech product markets, repeat purchases are motivated by functionality increases that trigger generational transitions. Even in the early generations of fast-tech products and services, repeat purchases are a substantial component of sales. For some generations repeat purchases may be the largest group of purchases during the critical launch phase of a new product. A new generation may also cause market expansion so that customers who would not have purchased a prior generation product will adopt the new generation because of some combination of lower price, greater functionality, and greater ease of use.

Management of fast-tech products requires that special attention be paid to the different needs of adopters and repeaters. Repeaters may require different product, advertising and distribution-channel strategies. For example, repeaters may prefer higher-functionality, higher-priced products while adopters may prefer lower-functionality, lower-priced products. Repeaters usually require a high degree of operational compatibility with their old products while adopters might be more receptive to new capabilities that are incompatible with prior generations. Repeaters may be more self-sufficient than adopters and prefer not to pay for the expense of a high-support distribution channel. Massmedia advertising may be required to make new potential adopters aware of a new generation product, while repeaters may be reachable via more targeted media.

We will develop a general class of multiple-generation diffusion models in which we model repeat sales and adoption sales (first-time purchases) explicitly and identify the sources of repeating from earlier generations as well as repeat timing. We also model the sources and timing of adoption sales in terms of first-time purchases usurped from prior generations and those that come from market expansion. This class of models is the first to decompose sales into repeat sales and adoption sales. We will refer to the new model as the BB-01 Generations model (or just the BB-01) to distinguish it from other models.

3.1. "Generations" and Other Definitions

We define a product generation, or more exactly a product-category generation, as the set of product brands and models fitting the customer-perceived functionality characteristics of the generation. For example, 16-megabit (Mb) DRAM is a generation of the product category DRAM chips, which includes many chip brands and models from various manufacturers. The generation that followed was 64-Mb DRAM. We further require that a new generation of a product category be one triggered and identified by a functionality increase so great that adopters of all prior generations will eventually buy the new generation (or a later generation, if usurped). For example, the adopters of prior generations were among the first adopters of the seventh PC generation (Windows PCs).

The model we develop can be used for both (1) end-user products and (2) products that are components of end-user products. By definition for end-user products, each adoption (first-time purchase) is of exactly one product unit and the adopter makes no further purchases of the product generation that was adopted. Further, by definition, each adopter after having made the first purchase makes a repeat purchase of exactly one product unit in each successive generation except that a generation may be skipped by a portion of would-be repeaters when they leapfrog a generation (are usurped by a later generation).

When modeling end-user products, sales are naturally expressed in user-perceived units. When modeling products that are components of end-user products, however, the BB-01 definition of generation dictates that care be taken to express sales in user-perceived product units, not manufacturer-perceived units. For example, DRAM chips are components of PCs, but chips are manufacturer-perceived units. PC end-users desire that their PCs have a specific amount of DRAM expressed in megabytes (e.g., 64 MB) but do not generally know nor care how many DRAM chips are required.

Like the basic Bass model (1969), in the BB-01 model the maximum number of potential adopters M_g should be thought of as potential applications or potential "sockets" for the product, not the number of potential purchasing units (customers). For example, the buying entity for PCs may be a household, but the number of sockets might be best defined as the number of family members. Variously, the buying entity for PCs might be an office manager, but the sockets would be the number of employees. Extending this approach might define two sockets per person with one for a desktop computer and one for a notebook or one socket for a computer at home and one for a computer at the office. A single buying entity (e.g., person, business, household) might purchase more than one end-user product. To model such purchases, the units of the potential market M_g should be defined such that no multiple purchases exist.

3.2. Model Components

The major components of the model structure are adoption sales and repeat sales. The basic equation is

$$sales_g(t) = adoptionSales_g(t) + repeatSales_g(t) \tag{6}$$

or

$$s_g(t) = a_g(t) + r_g(t)\,, \tag{7}$$

where $s_g(t)$ is sales of product generation g, t is time relative to generation 1 starting at t=1, $a_g(t)$ is adoption sales (sales to first-time buyers) at time t, $r_g(t)$ is repeat sales (sales to buyers who have purchased a previous generation) at t.

3.2.1. The Adoption Function

In general terms a_g may be expressed as a function of basic components:

$$a_g(t) = aMf_g(t) - au_g(t) + au_{g-1}(t)\,, \tag{8}$$

where $aMf_g(t)$ is adoption sales that would have occurred if there had been no usurped sales, $au_g(t)$ is adoption sales that are usurped by generation g+1, and $au_{g-1}(t)$ is adoption sales usurped by generation g from generation g-1. Adoption sales, then, depend on the adoption process and the process of usurpation.

Adoption sales of generation g at time t that would have occurred if there had been no usurped sales is modeled as

$$aMf_g(t) = M_g f_g(t_g), \tag{9}$$

where M_g is the incremental market potential that is created by generation g, t is the starting time of generation 1 and $t_g = t - \tau_g + 1$, $1 \Updownarrow t_g \Updownarrow u_g$ with τ_g being the time t that generation g was introduced and u_g being the number of periods for which there are sales of generation g. f(t) is the adoption-time distribution of the basic Bass model as derived in Bass (1969) to be

$$f(t) = \frac{\frac{(p+q)^2}{p} e^{-(p+q)t}}{\left(1 + \left(\frac{q}{p}\right) e^{-(p+q)t}\right)^2}. \tag{10}$$

Notice that M_g has the same meaning as in the basic Bass model, i.e. the maximum number of adopters in the market potential. To accomplish this we used the adoption function f of the Bass model (1969) rather than the cumulative adoption function F that would have led us into the same difficulties as in the Norton-Bass model where m_g (see equation (5)) is a composite quantity that cannot be separated into its constituents to identify M_g. Using f enables the BB-01 model to track the flow of buyers from adoption to repeat purchasing.

The general usurped adoption sales function that we employ is:

$$au_g(t) = aMf_g(t)\; f_{g+1}(t_{g+1}), \tag{11}$$

where $au_g(t)$ is the number of adopters usurped by generation g+1, $aMf_g(t)$ is the number of adopters who would have adopted generation g if generation g+1 had not appeared and $f_{g+1}(t_{g+1})$ is the Bass model adoption distribution for generation g+1. Many different functions might be chosen to represent the timing of usurpation, but because the adoption distribution for generation g+1 will reflect the attractiveness of the new generation, one plausible assumption is that the usurpation distribution will be the same as the adoption distribution for the usurping generation. Substituting equation (11) in equation (8) we have

$$a_g(t) = aMf_g(t) - aMf_g(t)\ f_{g+1}(t_{g+1}) + aMf_{g-1}(t)\ f_g(t_g)\,. \tag{12}$$

3.2.2. The Repeat Function

In general terms the repeat function $r_g(t)$ may be expressed as:

$$r_g(t) = rpool_g(t)\ \phi_g(t_g) - ru_g(t) + ru_{g-1}(t)\,, \tag{13}$$

where $rpool_g(t)$ is the pool of buyers available to make a repeat purchase of generation g, $\phi_g(t_g)$ is the repeat timing distribution, $rpool_g(t)\ \phi_g(t_g)$ is repeat sales that would have been made at t_g if there had been no usurps, $ru_g(t)$ is repeat sales that are usurped from generation g, and $ru_{g+1}(t)$ is sales that are usurped by generation g+1. We have examined different definitions of the repeat pool and different specifications for the repeat timing distribution.

3.2.2.1. Repeat Pool Definition

For the repeat pool we considered the following definitions: (1) $rpoolCA_g(t)$, which is cumulative adopters who bought any prior generation through t-1 and (2) $rpoolCS_g(t)$, which is cumulative sales of the prior generation through t-1. We have explored other definitions of the repeat pool such as cumulative sales over all generations prior to generation g but discarded them because they involve double counting of buyers in the repeat pool. Consider repeat-pool definition (2), $rpoolCS_g(t) = \sum_{i=1}^{t-1} s_{g-1}(i)$, which is cumulative sales of the prior generation through t-1 and includes some, but not all, of the adopters and repeaters of generations prior to generation g-1. The appeal of (2) is that it ties repeating for the current generation to the buyers of the prior generation, but its weakness is that at any time t it excludes adopters from generations 1 through g-2 who have not yet purchased generation g-1. This exclusion produces a repeat pool that is too small, especially early in the product life cycle for later generations. We have experimented with this definition in fitting the model to observations of several product categories. We found that in models of products of only a few generations (e.g., 2-4) it was satisfactory. For a larger number of generations (e.g., 8-9), however, the effect was to cause repeat sales to appear too late in the product life cycle, resulting in a longer expected time-to-repeat that does not compare well with experience. Our preferred repeat pool definition is definition (1), $rpoolCA_g(t) = \sum_{j=1}^{g-1} \sum_{i=1}^{t-1} a_j(i)$, which is cumulative adopters who bought any prior generation through t-1. This definition is broader than (2) in that it includes adopters of all prior generations and after several generations is larger so it models repeats earlier in the product life cycle yielding an expected time-to-repeat that compares favorably with experience.

3.2.2.2. *Repeat Timing Distribution*

In considering the repeat timing distribution $\phi(t_g)$, we have examined the following specifications: (1) a Bass model adoption distribution $h_g(t_g)$ with additional parameters a_g and b_g to be estimated for each generation, (2) a Bass model adoption distribution $h(t_g)$ with parameters a and b the same for all generations and (3) the same Bass model adoption distribution $f_g(t_g)$ as used to model adoptions. Each of these employs a Bass model distribution because repeat purchasers like first-time purchasers are influenced by external factors (e.g., advertising and publicity) and internal factors (e.g., product recommendations by prior purchasers). After considering each of these alternatives including fitting a version of the model using each, we concluded that the advantages of simplicity and fewer parameters argued strongly for (3), the same distribution as used for adoptions, in spite of the potential advantage of (1) and (2) in modeling repeat timing independent of adoption timing. The repeat pool is thus given by

$$rpool_g(t) = rpoolCA_g(t) = \sum_{j=1}^{g-1} \sum_{i=1}^{t-1} a_j(i)\,. \tag{14}$$

The repeat function can now be expressed as

$$r_g(t) = rpool_g(t)\ f_g(t_g) - ru_g(t) + ru_{g-1}(t)\,, \tag{15}$$

which by using

$$rpoolf_g(t) = rpool_g(t)\ f_g(t_g) \tag{16}$$

to expand becomes

$$r_g(t) = rpoolf_g(t\ ) - ru_g(t) + ru_{g-1}(t)\,. \tag{17}$$

3.2.2.3. *Usurpation of Repeat Purchases*

Using equation (16) we specify the usurping function $ru_g(t)$ as

$$ru_g(t) = rpoolf_g(t\ ) f_{g+1}(t_{g+1})\,, \tag{18}$$

thus allowing repeat purchases to be usurped in the same manner as adoption purchases. Substituting in equation (15) we have the repeat function $r_g(t)$ as

$$r_g(t) = rpoolf_g(t) - rpoolf_g(t) f_{g+1}(t_{g+1}) + rpoolf_{g-1}(t) f_g(t_g)\,. \tag{19}$$

3.2.3. Equation to Be Estimated

From equation (7), we have $s_g(t) = a_g(t) + r_g(t)$. The components may be expanded using equations (8) and (15) to obtain

$$s_g(t) = aMf_g(t) - au_g(t) + au_{g-1}(t) + rpool_g(t)\ f_g(t_g) - ru_g(t) + ru_{g-1}(t), \tag{20}$$

which with (9), (11), (14), (16) and (18) expands to the equation to be estimated:

$$\begin{aligned} s_g(t) = a_g(t) &+ \left[\sum_{j=1}^{g-1}\sum_{i=1}^{t-1} a_j(i)\right] f_g(t_g) \\ &- \left[\sum_{j=1}^{g-1}\sum_{i=1}^{t-1} a_j(i)\right] f_g(t_g) f_{g+1}(t_{g+1}) + \left[\sum_{j=1}^{g-2}\sum_{i=1}^{t-1} a_j(i)\right] f_{g-1}(t_{g-1}) f_g(t_g), \end{aligned} \tag{21}$$

where $a_g(t)$ is defined by equation (12) expanded with equation (9):

$$a_g(t) = M_g f_g(t_g) - M_g f_g(t_g)\ f_{g+1}(t_{g+1}) + M_{g-1} f_{g-1}(t_{g-1})\ f_g(t_g)\,. \tag{22}$$

After estimation of p_g and q_g of f_g and M_g, the following components of sales can be derived for each generation: adoption purchases before and after usurps, repeat purchases before and after usurps, sales usurped from adoption purchases and sales usurped from repeat purchases.

3.2.4. Calculation of Installed Base and Installed-Base Generational Mix

Installed base IB(t) is used here as cumulative adopters and at time t is given

by
$$IB(t) = \sum_{g=1}^{G}\sum_{i=1}^{t} a_g(i) = \sum_{g=1}^{G} cumA_g(t)\,, \tag{23}$$

where G is the number of generations and $a_g(i)$ is the number of adopters whose first purchase was a generation g product at time i. Equation (23) counts adopters by the generation product they first purchased. There is another way of counting adopters that is especially useful: by the generation of product they own at time t, which if an adopter has made a repeat purchase, will be a later one than they originally purchased. Using equation (7), (23) can be rewritten

$$\sum_{g=1}^{G}\left[\left\{\left(\sum_{i=1}^{t} a_g(i)\right) + \left(\sum_{i=1}^{t} r_g(i)\right)\right\} - \left(\sum_{i=1}^{t} r_{g+1}(i)\right)\right] = \sum_{g=1}^{G}\left[\left(\sum_{i=1}^{t} s_g(i)\right) - \left(\sum_{i=1}^{t} r_{g+1}(i)\right)\right] = \sum_{g=1}^{G} IB_g(t)\,, \tag{24}$$

where
$$\left(\sum_{i=1}^{t} s_g(i)\right) - \left(\sum_{i=1}^{t} r_{g+1}(i)\right) = cumS_g(t) - CumR_g(t) = IB_g(t)\,. \tag{25}$$

In (25) $IB_g(t)$ is the number of adopters or repeaters who have purchased a generation g product by time t and have not yet purchased a later generation product; that is, at time t, $IB_g(t)$ adopters own a generation g product. At t, the installed-base mix is given by the series $IB_1(t)$, $IB_2(t)$ . . . $IB_G(t)$. In equations (23), (24) and (25) the quantities $a_g(t)$, $s_g(t)$ and $r_g(t)$ are net of usurps so no additional consideration of usurps need be given. If the available data are the number of subscribers by type of service (e.g., wireless telephone subscribers by generation of service), an alternative equation to be estimated is (25) rewritten as

$$IB_g(t) = \left(\sum_{i=1}^{t} s_g(i)\right) - \left(\sum_{i=1}^{t} r_{g+1}(i)\right). \tag{26}$$

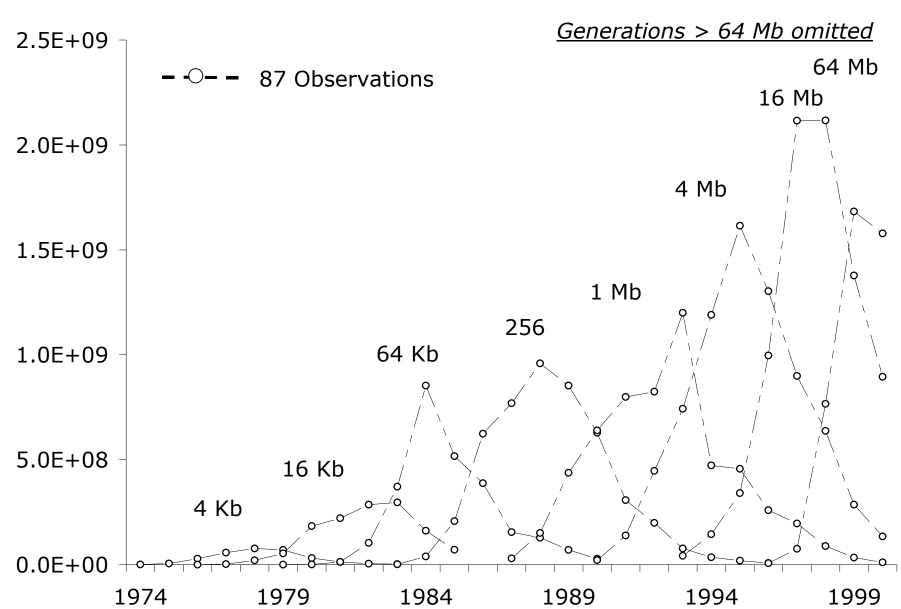
4. Models Fit to Empirical Data

The following sections describe the fit of the Norton-Bass model and the BB-01 model to eight generations of DRAM data and nine generations of PC data. In each case, the joint estimates of the parameters of the system of simultaneous nonlinear equations were developed utilizing SAS software.

4.1. Eight Generations of DRAM Data

The data employed are unit sales of dynamic random-access memory (DRAM) chips for eight generations sold between 1974 and 2000. The data are from Dataquest, the leading provider of DRAM shipment data. DRAM generations are commonly identified by the number of bits per chip. As shown in Figure 1, the chip generations modeled here are 4 Kb, 16 Kb, 64 Kb, 256 Kb, 1Mb, 4 Mb, 16 Mb and 64 Mb (Kb and Mb indicate Kilobits and megabits, respectively, where K is 1024 and M is 1024^2 = 1,048,576). Chip generations of configurations greater than 64 Mb were in their infancy at the time of this study and were not included. It is remarkable that Figure 1 is consistent with the previously observed em-

FIGURE 1: Worldwide DRAM Sales for 8 Generations

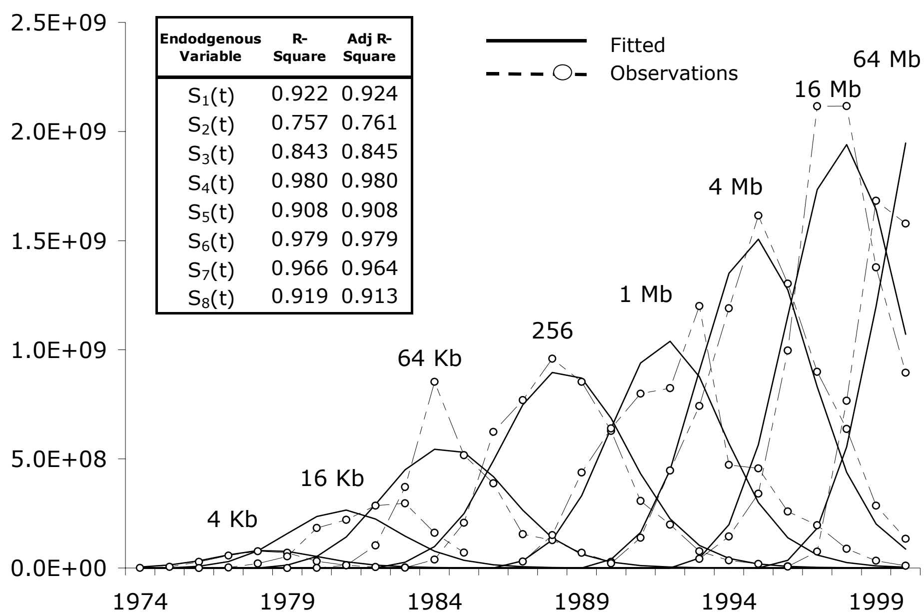


pirical generalization pattern (Bass 1995) for the rise and fall of generations and market expansion as generations increase. The generalization previously observed for four or fewer generations is seen here to apply to eight generations of DRAM.

4.1.1. Norton-Bass Model Fit to DRAM Data

Figure 2 shows the Norton-Bass model with same p and q fit to eight generations compared to the 87 observations. Fitting the model to eight generations requires that 10 parameters be estimated: m_g for each generation and p and q of F, the Bass cumulative distribution. Also in Figure 2 are the parameter estimates, standard errors and t-ratios as well as R-squares for each generation, which indicate that the model provides a good fit to each generation.

FIGURE 2. Norton-Bass Model Fit to DRAM Chip Sales



Endodgenous Variable	R-Square	Adj R-Square
$S_1(t)$	0.922	0.924
$S_2(t)$	0.757	0.761
$S_3(t)$	0.843	0.845
$S_4(t)$	0.980	0.980
$S_5(t)$	0.908	0.908
$S_6(t)$	0.979	0.979
$S_7(t)$	0.966	0.964
$S_8(t)$	0.919	0.913

Param	Estimate	Approx Std Err	t Ratio
m1	1.60E+08	6.83E+06	23.47
m2	2.61E+08	3.89E+07	6.73
m3	3.21E+08	6.63E+07	4.85
m4	4.74E+08	6.17E+07	7.69
m5	4.21E+08	8.83E+07	4.77
m6	7.50E+08	9.92E+07	7.56
m7	6.92E+08	1.17E+08	5.93
m8	8.85E+07	1.99E+08	0.44
p	0.0180	0.0020	9.18
q	0.8802	0.0321	27.45

4.1.2. BB-01 Model Fit of DRAM Observations

DRAMs are components in many types of end-user products such as PCs, printers, copiers and telecommunication switches. PCs consume most DRAM chips; for example, according to Dataquest, in 1995 PCs were two-thirds of the DRAM market. With respect to the characteristics described below the remainder of the DRAM market is thought to be similar to the PC market.

DRAM manufacturers identify DRAM generations as the number of bits per chip expressed in kilobits (Kb) or megabits (Mb), but end-users of the products in which DRAMs are parts typically specify only the amount of DRAM bits desired, not the chip configuration. Because the bit is the most convenient common factor for all chip configurations, a product socket is best though of as for a single bit when employing the BB-01 model to fit DRAM generations data.

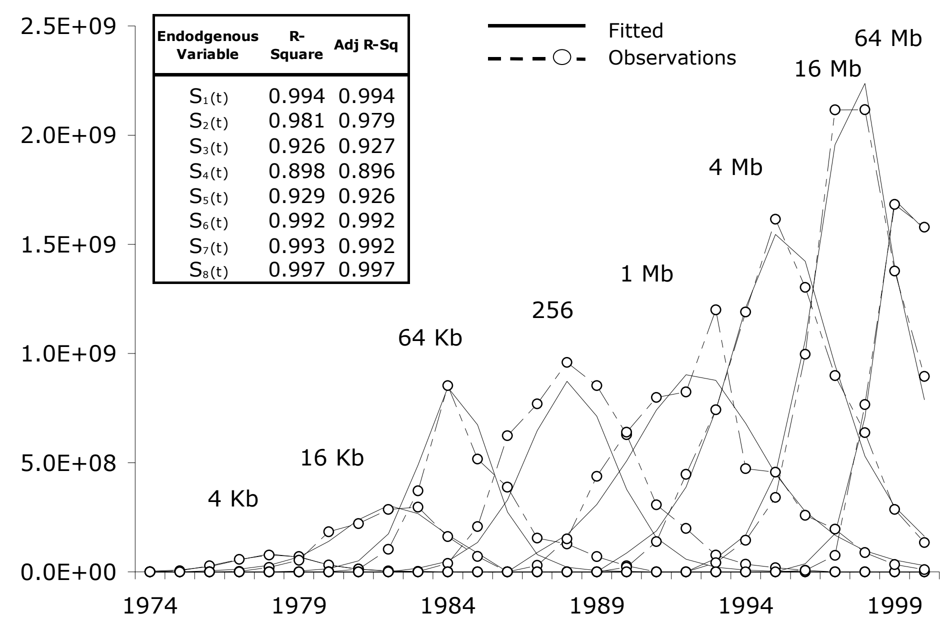
When an end-user makes a first-purchase of end-use equipment (e.g., PC), the component DRAM bits are first-time purchases (adoptions). End users upgrade DRAM by adding chips or by replacing chips with a later generation. The bits in added chips are also adoptions. The bits in replacement chips are repeat purchases up to the number of bits being replaced; over that the bits are adoptions. Similar rules apply when the end-use equipment is replaced: bits in the new equipment up to the number of bits in the equipment being replaced are repeats; others are adoptions. End-users of products using DRAMs tend to expand or upgrade DRAM with each new DRAM generation because (1) applications grow in memory requirement and (2) DRAM prices drop from generation to generation: typically a generation g bit costs one-fourth of a generation g-1 bit.

One might wonder whether DRAM satisfies the BB-01 model definition of a generation. Do users of end-use equipment with DRAM components virtually always replace and expand their DRAM bits with each new DRAM generation? Remember that PC users can replace their DRAM in two ways: (1) by replacing or adding DRAM chips or (2) by replacing the PC. There were eight generations of DRAM chips between 1975 and 2000 and nine generations of PCs. Clearly, the generations cycles of these two product categories are on the average about the same. The reason is simply that the other main drivers of PC generations (e.g., microprocessors, graphics controller, disk drive electronics) are on the same cycle as DRAMs because like DRAMs they are semiconductor products.

Because DRAM is on about the same generation cycle as its end-use products, the BB-01 model can be used to fit DRAM sales in a three-step process. First, DRAM chips are changed to bits by multiplying sales for each generation by the number of bits per chip for the generation. Second, the BB-01 model is fit to bits sold per generation. Finally, fitted bit sales, M_g for each generation and model components (e.g., adoptions, repeats, usurps) as well as the parameter standard errors are divided by generational bits per chip to convert back to chips. Figure 3 shows the result compared to the 87 observations. The model closely replicates the empirical generalization of the rise and fall of generations and market expansion as generations increase. The fit is better than that of the Norton-

Bass model with R-squares for four of the eight generations greater than .99 and with t-ratios quite high. The fit is also superior to the Norton-Bass model fit with generational p's and q's (not shown).

FIGURE 3. Bass-Bass Model Fit to DRAM Chip Sales

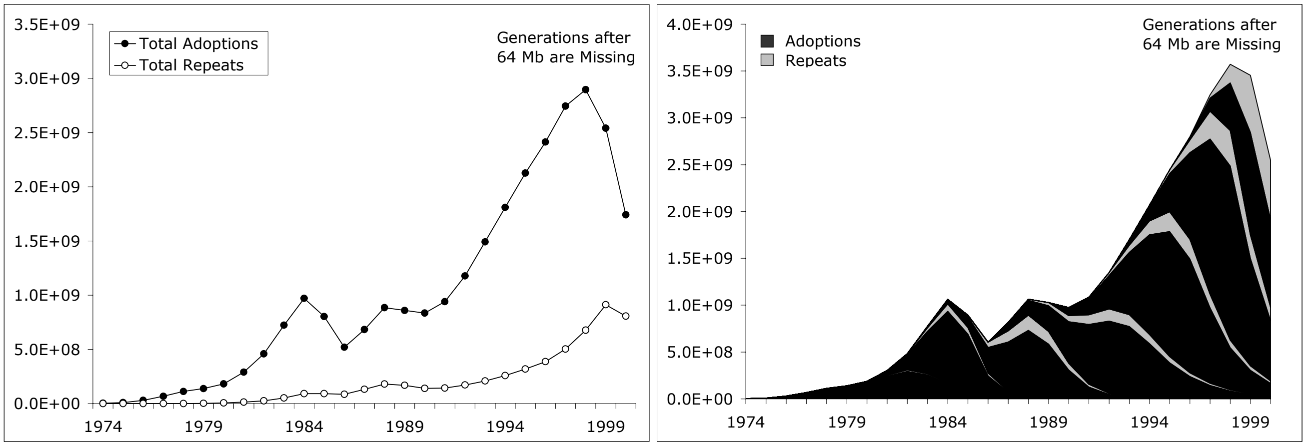


Endodgenous Variable	R-Square	Adj R-Sq
$S_1(t)$	0.994	0.994
$S_2(t)$	0.981	0.979
$S_3(t)$	0.926	0.927
$S_4(t)$	0.898	0.896
$S_5(t)$	0.929	0.926
$S_6(t)$	0.992	0.992
$S_7(t)$	0.993	0.992
$S_8(t)$	0.997	0.997

Param	Estimate	Approx Std Err	t Ratio
M1	3.07E+08	5.44E+06	56.45
M2	1.32E+09	4.63E+07	28.55
M3	2.45E+09	1.62E+08	15.17
M4	2.88E+09	3.18E+08	9.08
M5	5.05E+09	3.68E+08	13.70
M6	7.24E+09	1.84E+08	39.40
M7	8.59E+09	2.41E+08	35.66
M8	2.87E+09	1.07E+08	26.91
p1	0.0034	0.0004	9.31
p2	0.0017	0.0004	4.42
p3	0.0004	0.0002	1.96
p4	0.0020	0.0012	1.69
p5	0.0086	0.0023	3.70
p6	0.0053	0.0005	9.81
p7	0.0025	0.0003	7.76
p8	0.0025	0.0003	7.88
q1	1.1056	0.0248	44.59
q2	0.8723	0.0376	23.23
q3	1.2764	0.0929	13.74
q4	1.0135	0.1135	8.93
q5	0.6476	0.0535	12.10
q6	0.7694	0.0202	38.16
q7	0.9901	0.0275	36.04
q8	1.4409	0.0367	39.21

The fit of the BB-01 model is not the sole criterion for judging its usefulness. Rather, the information content that can be generated from the model should also be considered. For example, Figure 4 shows the totals for all generations of DRAM chip adoptions and separately of repeats while Figure 5 shows the layers of adoptions and repeat purchases. Remarkably, even after 27 years, adoptions are still by far the largest portion of sales. Bits per chip have increased so rapidly, quadrupling each generation, that repeat purchasers have recently bought fewer chips each generation and still increased the number of bits per end-use device (e.g., PC). The result has been that for DRAM manufacturers to achieve chip sales growth they have had to rely on market expansion.

Figure 4. DRAM Adoptions v. Repeats (Left)
Figure 5. DRAM Adoptions v. Repeats (Stacked) (Right)



4.2. Nine Generations of Personal Computers

Sales data for PCs by generation suitable for the BB-01 model are not available. Data categorizing PC sales by microprocessor bit-width (e.g, 8-bits, 16-bits, 32-bits) are sometimes used, but this definition of generations identifies only three for the entire 26-year history of PCs. We develop below the required generational definitions capturing all primary user-perceived PC generations.

Although PC data by generation are not available, total sales by year (see Figure 6) are, *albeit* not from a single source. We used publications and databases from Future Computing, StoreBoard, Computer Industry Almanac, BIS, Computer Industry Forecasts and eTForecasts as well as over a million articles to glean the data and supporting qualitative information. We used data for only the U.S. market because worldwide data are not as often based on reliable measurements. We included PCs sold to both consumers and businesses. We included all operating systems (e.g., Basic, CP/M, DOS, Apple II, Macintosh, Windows, Unix) and all PC forms (e.g., desktop computers, notebook computers, small servers) except handhelds. We used an all-inclusive approach because the various segments are so intricately intertwined that they are not separable. For example, a business user is a consumer at home so consumer and business PC diffusion are not separable. We also used estimates of installed base (see Figure 7) although we considered these estimates less reliable.

Figure 6. U.S. PC Unit Sales

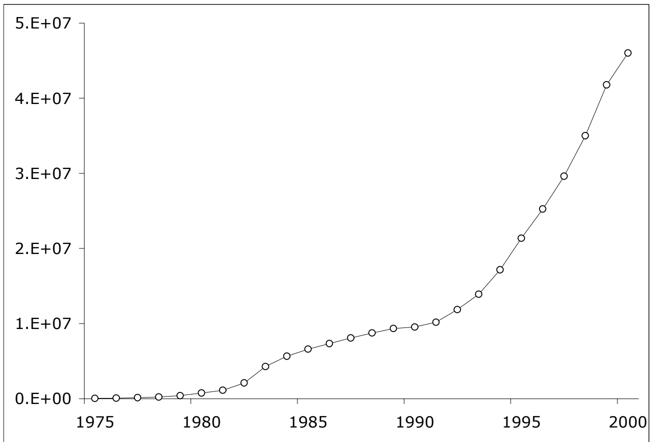
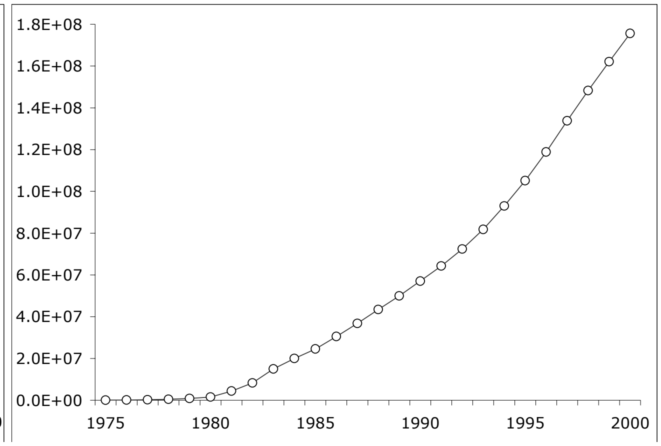
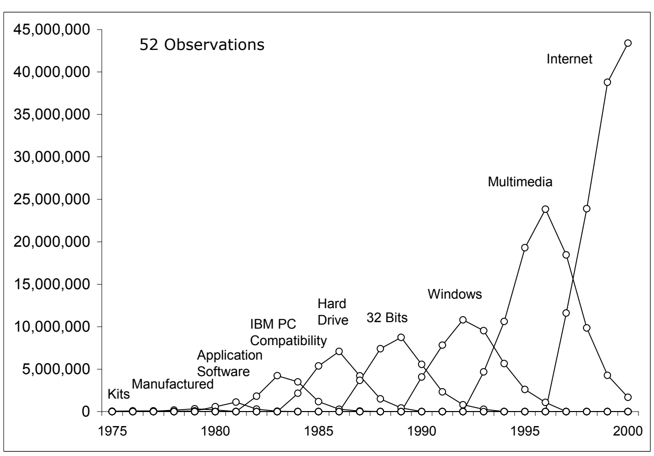


Figure 7. U.S. PC Installed Base



The Slicer model was used to decompose total sales into the constituent-generation sales shown in Figures 8 and 9 with generations named by the primary trigger (see Table 1). The Slicer model methodology has three key steps. First, user-perceived generations are identified by start and end dates by doing a thorough review of the category history with the goal of identifying all product changes that triggered massive repeat purchasing. We used more than a million articles about the PC market to glean

Figure 8. U.S. PC Unit Sales by Generation (Left)
Figure 9. U.S. PC Unit Sales by Generation (Stacked) (Right)



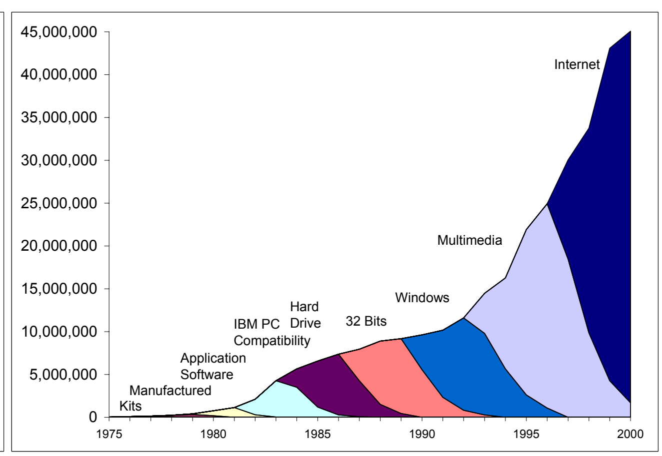


TABLE 1. U.S. PC Generations (1975-2000)

Generation	Main Trigger (Name)	Secondary Drivers	Start-End Years	Typical Configuration	Price	New Thing
1	**Kits**	Micro-processors, MS Basic	1975-1978	1-2 MHz 8080, 4-8KB RAM, Cassette Tape, Basic	\$500-\$800	Desktop PC Kits, Basic
2	**Manufactured PCs**	CP/M, Floppy	1977-1980	1-2 MHz Z80, 16-32KB DRAM, Floppy Disk, CP/M, Basic	\$1,500-\$2,500	Manufactured PCs, CP/M OS, Floppy, Games
3	**Application Software**	Home Computers	1979-1983	2-5 MHz Z80, 32-64KB DRAM, Hard Disk, Floppy, CP/M, Basic	\$100-\$300, \$2,000-\$3,500	Modem, VisiCalc WP, DB
4	**IBM PC Compatibility**	Complete PC Standard	1982-1987	5-10 MHz Intel 8088, 64-256KB DRAM, HD/Floppy, MS DOS	\$2,500-\$4,000	Complete PC Standard, Portable PC, B&W Monitor
5	**Hard Drive**	Mac, LaserJet, Desktop Publishing	1984-1989	6-12.5 MHz Intel 286, 256KB-1MB DRAM, 10-40MB HD, Floppy, MS DOS, Macintosh	\$2,000-\$4,000	Laptop, Color Monitor, LAN, Mouse
6	**32-Bits**	Larger Addressable RAM	1987-1993	16-33 MHz Intel 386, 1-4MB DRAM, 80-250MB HD, Floppy, MS DOS, Macintosh	\$2,000-\$5,000	Laser Printer, Desktop Publishing, Notebook PC
7	**Windows**	Notebooks	1990-1996	25-50 MHz Intel 486, 4-8MB DRAM, 300-600MB HD, Floppy, Windows 3.0	\$1,700-\$4,500	Client/Server, Color Printer,
8	**Multimedia**	Under \$1,000 PCs, CD ROM	1993-2000	60-150 MHz Intel 486-Pentium, 8-16MB DRAM, 800MB-6GB HD, Floppy, CD ROM, Windows 3.1-95-NT	\$1,000-\$4,000	Web Browser, CD ROM, Sound, Color Notebook
9	**Internet**	Low-Price PCs, Email, Web Content, 56K+ Modem	1997-	150MHz-1GHz Intel Pentium II-III, 16-128MB DRAM, 8-30GB HD, Floppy, CD ROM, Windows 98-2000, Linux	\$500-\$3,500	CD-R, DVD

the detailed generational history, a summary of which is shown in Table 1. In the second step of the Slicer methodology, installed-base estimates are used to calculate plausible upper and lower bounds on cumulative adopters for each generation. Estimates of the installed base exceed cumulative adopters by the number of systems that have been replaced but not discarded. Moreover, installed-base estimates are subject to error of unknown magnitude; therefore, the installed-base numbers imply uncertainty about the magnitude and increase in cumulative adopters. The Slicer algorithm employs the installed-base trajectory to define bounds that are used dynamically to limit the percentage change in cumulative adopters (cumulative M_g) from generation to generation. Using the bounds defined in step 2 in the third and final step, the Slicer model requires that

$$TotalSales(t) = \sum_{g=1}^{G} s_g(t_g)\,, \tag{27}$$

where TotalSales(t) is sum of sales of all generations of a product category (e.g., PCs), G is the number of generations, t is the starting time of generation 1 and $t_g = t - \tau_g + 1$, 1⇳ t_g ⇳ u_g with τ_g being the time t that generation g was introduced and u_g being the number of periods for which there are sales of generation g. In equation (27), sales of generation g at time t_g is specified by

$$s_g(t_g) = \left(\sum_{j=1}^{g} M_g \right) f_g(t_g)\,, \tag{28}$$

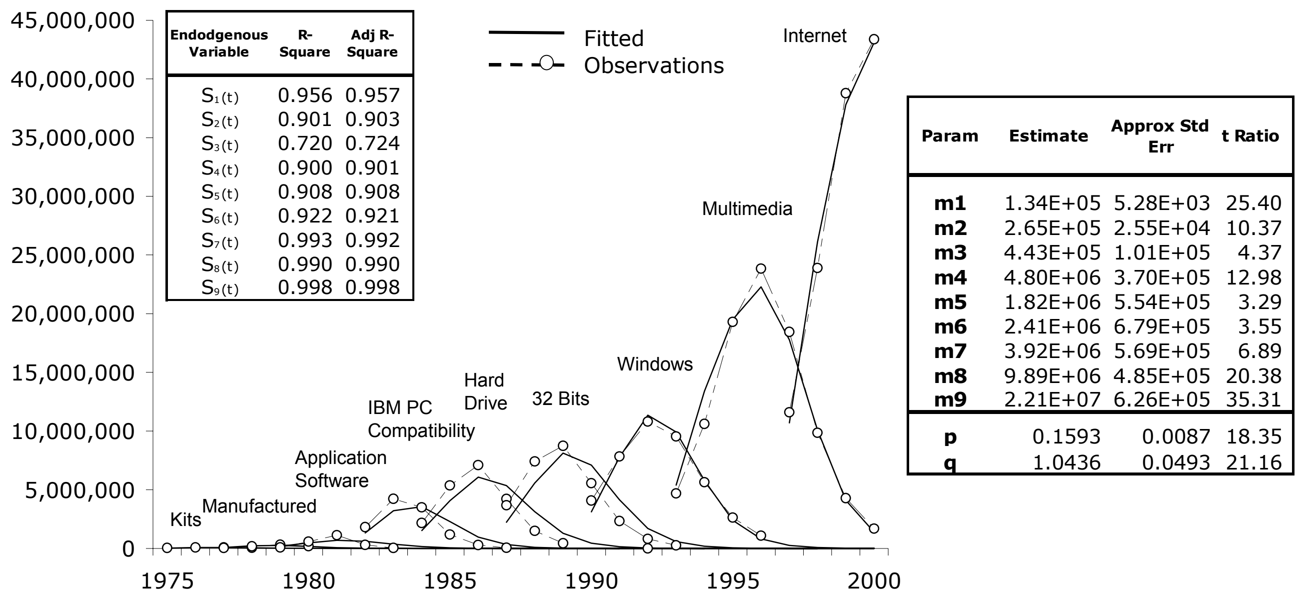
where M_g is the incremental market potential of generation g and f_g is the adoption distribution of the basic Bass model as specified in equation (10). The set of series $s_g(t_g)$, 1⇳ g ⇳ G, we refer to as the resulting *slice* of total sales. By using cumulative market potential $\sum_{j=1}^{g} M_g$ as the quantity that is multiplied by $f_g(t_g)$, the model dictates that the adopters of all prior generations as well as the adopters of the current generation will purchase the current generation according to the Bass adoption distribution.

The Slicer algorithm that we have developed estimates the underlying sales for each PC generation. The algorithm requires that the sum of the estimated generational sales for each time period closely approximate the known total sales for each time period. To generate the data shown in Figures 8 and 9, a combination of random and learning algorithms requiring intensive computing (ten PCs running in parallel over several days) were used. The plausibility of the final slice was judged by comparing known sales of a lead product (e.g., Windows) when available, to the generation sales estimated by the algorithm. For detailed information about the algorithm, see Bass and Bass (2001).

4.2.1. Norton-Bass Generations Model Fit to PC-Generations Data

Figure 10 shows the Norton-Bass model fit to nine generations of PC data compared to the 52 observations. Fitting the Norton-Bass model to nine generations requires that 11 parameters be estimated: m_g for each generation and

FIGURE 10. Norton-Bass Model Fit to PC Generations



Endodgenous Variable	R-Square	Adj R-Square
$S_1(t)$	0.956	0.957
$S_2(t)$	0.901	0.903
$S_3(t)$	0.720	0.724
$S_4(t)$	0.900	0.901
$S_5(t)$	0.908	0.908
$S_6(t)$	0.922	0.921
$S_7(t)$	0.993	0.992
$S_8(t)$	0.990	0.990
$S_9(t)$	0.998	0.998

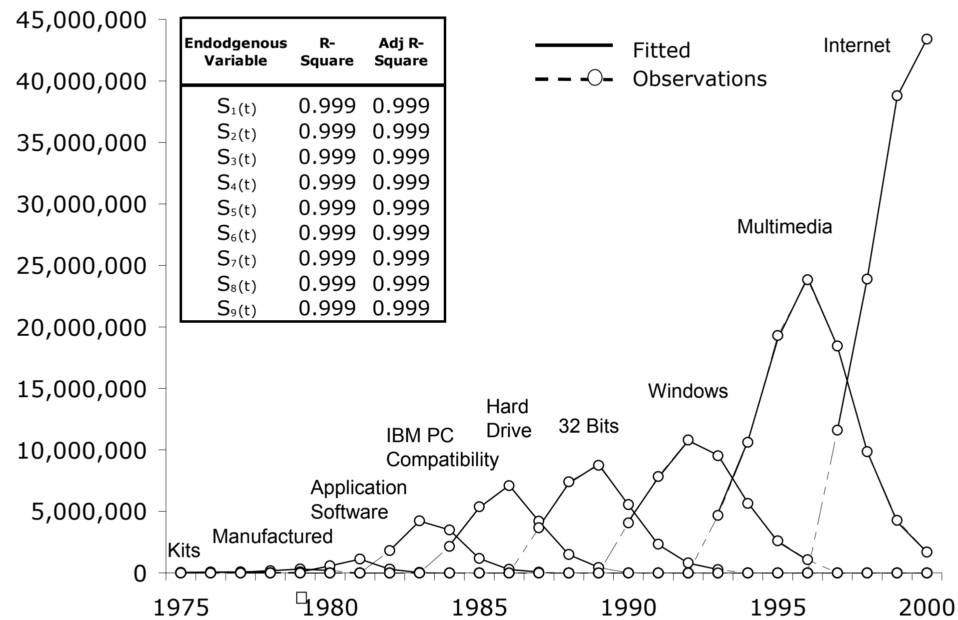
Param	Estimate	Approx Std Err	t Ratio
m1	1.34E+05	5.28E+03	25.40
m2	2.65E+05	2.55E+04	10.37
m3	4.43E+05	1.01E+05	4.37
m4	4.80E+06	3.70E+05	12.98
m5	1.82E+06	5.54E+05	3.29
m6	2.41E+06	6.79E+05	3.55
m7	3.92E+06	5.69E+05	6.89
m8	9.89E+06	4.85E+05	20.38
m9	2.21E+07	6.26E+05	35.31
p	0.1593	0.0087	18.35
q	1.0436	0.0493	21.16

p and q of F, the Bass cumulative distribution. Figure 10 also shows the parameter estimates with parameter standard errors and t-ratios as well as R-squares for each generation. It is clear that the Norton-Bass model provides an excellent fit to the nine generations of PCs. The t-ratios for all parameter estimates are very high and the R-squares for the last three generations are greater than .99.

4.2.2. BB-01 Generations Model Fit to PC-Generations Data

Figure 11 shows the BB-01 model fit to nine generations of PCs compared to the 52 observations. Fitting the BB-01 model to nine generations requires that 27 parameters be estimated: p_g and q_g of f_g and M_g for each generation. Also shown are the parameter estimates with standard errors and t-ratios as well as generational R-squares. The fit of the model is extraordinarily strong with R-squares for each generation of .999 or greater. The high R-squares from the BB-01 model fit to the Slicer output are not surprising since Slicer and the BB-01 model are based, *albeit* with different implementations, on the same key insight into "fast-tech" markets: each adopter purchases one product each generation. Both the Slicer output and the BB-01 model fit of it should be judged, not on the BB-01 R-squares, but on the plausibility of

FIGURE 11. Bass-Bass Model Fit to PC Generations



Endodgenous Variable	R-Square	Adj R-Square
$S_1(t)$	0.999	0.999
$S_2(t)$	0.999	0.999
$S_3(t)$	0.999	0.999
$S_4(t)$	0.999	0.999
$S_5(t)$	0.999	0.999
$S_6(t)$	0.999	0.999
$S_7(t)$	0.999	0.999
$S_8(t)$	0.999	0.999
$S_9(t)$	0.999	0.999

Param	Estimate	Approx Std Err	t Ratio
M1	3.41E+05	9.17E+02	372.3
M2	6.74E+05	1.28E+03	526.2
M3	1.36E+06	2.85E+03	477.8
M4	1.01E+07	2.00E+04	505.0
M5	1.13E+07	6.62E+04	170.6
M6	8.20E+06	1.23E+05	66.7
M7	1.41E+07	1.69E+05	83.1
M8	5.47E+07	3.38E+05	161.8
M9	8.78E+07	3.30E+05	266.4
p1	0.0504	0.0003	155.1
p2	0.0136	0.0001	191.4
p3	0.0050	0.0000	145.6
p4	0.0402	0.0002	164.6
p5	0.0333	0.0003	98.0
p6	0.0457	0.0005	87.0
p7	0.0386	0.0004	95.4
p8	0.0198	0.0002	79.7
p9	0.0273	0.0000	579.2
q1	0.9726	0.0043	228.4
q2	1.4443	0.0024	611.8
q3	2.1041	0.0032	664.0
q4	1.4311	0.0035	404.8
q5	1.1903	0.0050	240.0
q6	1.0520	0.0061	173.3
q7	0.8970	0.0051	175.7
q8	0.9268	0.0043	218.0
q9	0.8962	0.0012	762.5

the resulting decomposition into adoption and repeat purchases as well as other obtainable information. We considered and found highly plausible each of the following: (1) the evolution of repeat purchases and adoptions for each generation, (2) the trend in repeats as a percentage of sales, (3) the expected time-to-repeat trend, (4) the installed base over time, (5) the evolution of the installed-base mix and (6) the fit of the basic Bass model to BB-01 adopters.

FIGURE 12. Components of Sales of Personal Computer Generation Seven

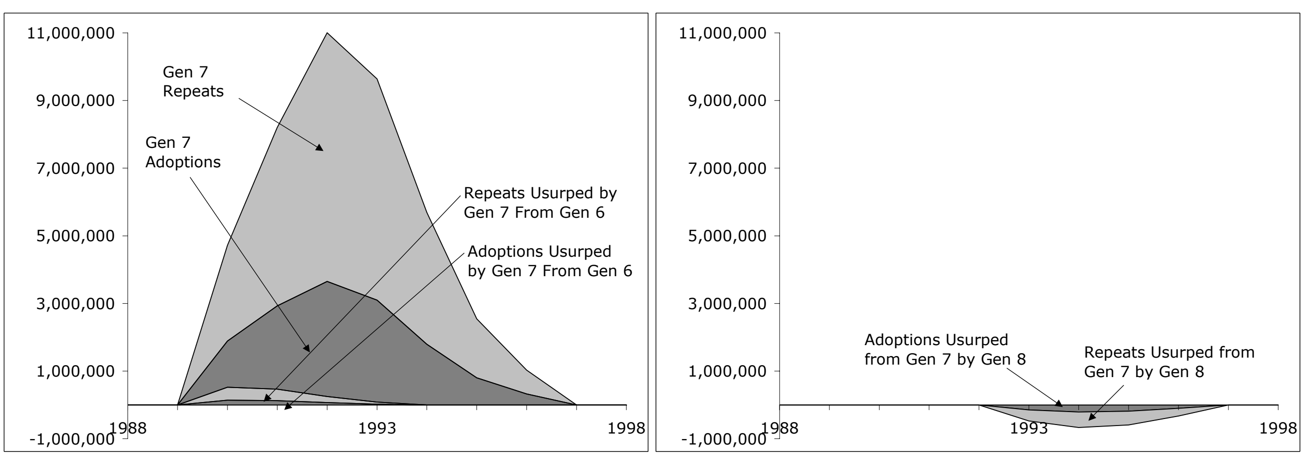


Figure 12 shows the constituents of generation seven sales. Since the market is substantially developed by generation seven, it is not surprising that repeat purchases are the largest component followed by adoptions. Repeat purchases, adoptions and usurps increase from the start of generation seven while adoptions and repeats usurped from generation seven start with eight.

In Figure 13, adoptions and repeats for each generation are shown. The upper line bounding the total area closely approximates total U.S. PC sales in Figure 6. The graph shows that repeat purchases contribute substantially to sales after the first few generations. Figure 14 and Figure 15 make clear that repeats are generally increasing with time except when the market has been substantially expanded by the appeal of a new generation. The first such market expansion occurred in 1982 when adoptions surged following the introduction of the IBM PC. In 1989 repeats peaked at 71% of sales after which repeat purchases decreased relative to adoptions each year because of a succession of new technologies that expanded the market; namely, Windows and notebook PCs in generation

FIGURE 13. BB-01 Estimate of PC Sales with Adoptions and Repeat Sales Separately Identified

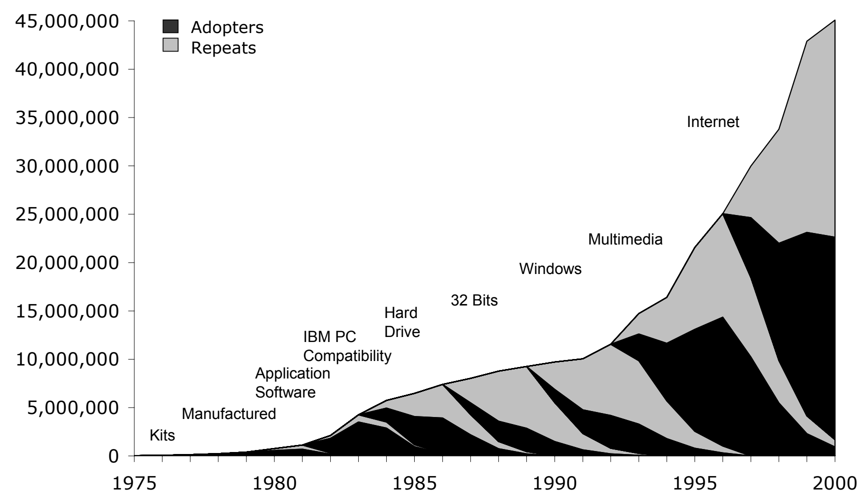
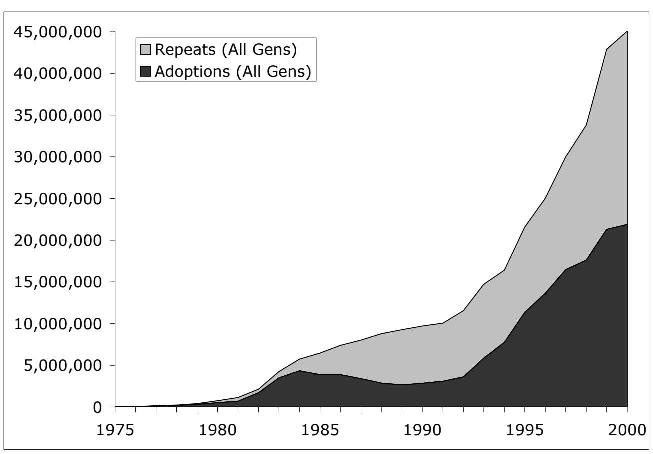
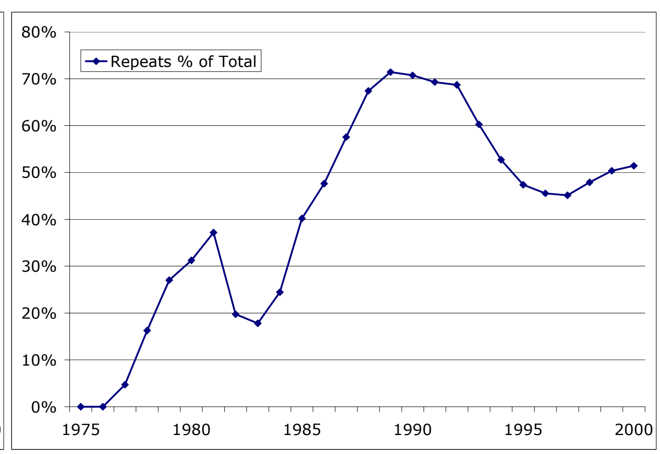


FIGURE 14. Repeats and Adoptions (Stacked) (Left)
FIGURE 15. Repeats as Percentage of Sales (Right)





seven, multimedia in generation eight and the Internet and under low-price PCs in generation nine. From a low of 50% in 1998, repeat purchases started gaining again on adoptions. The reversals as well as the percentages shown in Figure 15 are similar to those reported in the PC industry.

Another benchmark used to judge the plausibility of the BB-01 result is typical time between purchases, which has been reported at times for some PC market segments. Figure 16 compares reported typical time between purchases to calculated expected time-to-repeat (ETR). We calculated ETR by assuming that repeaters make repeat purchases of generation g in the same order that they purchased the prior generation. By simulating a first-in-first-out (FIFO) queue of generation g-1 purchasers, we are able to calculate at any time t the ETR for those leaving the FIFO queue by making a repeat purchase of generation g. The annual average ETR is a weighted average over all generations. Figure 16 shows bands of reported typical times between purchases for three time intervals as a background for average annual ETR, which together show plausibility of the expected time to repeat series. The 1981-82 ETR dip was due to the introduction of the IBM PC, which attracted repeat purchases earlier than they would have otherwise occurred.

FIGURE 16. BB-01 PC Expected Time-to-Repeat v. Typical Reported Time between Purchases

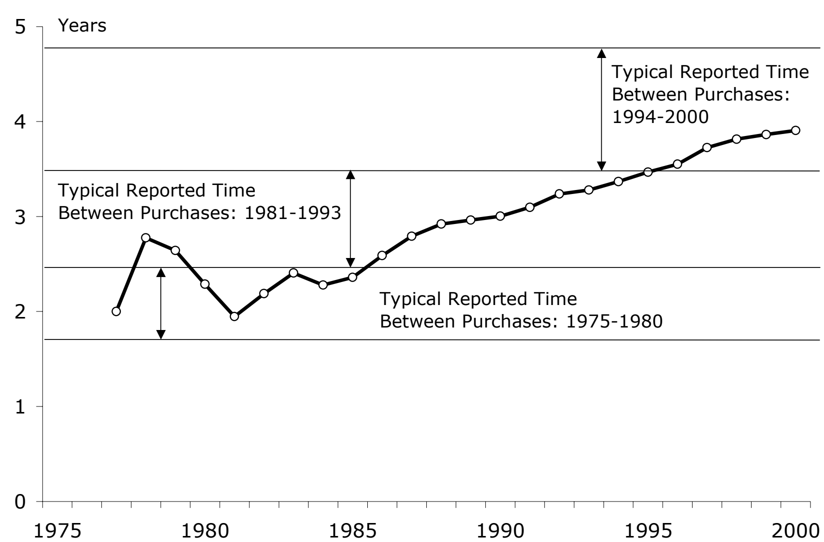
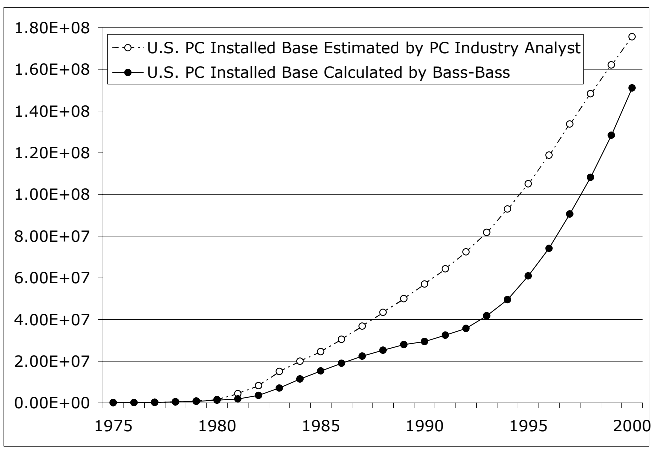
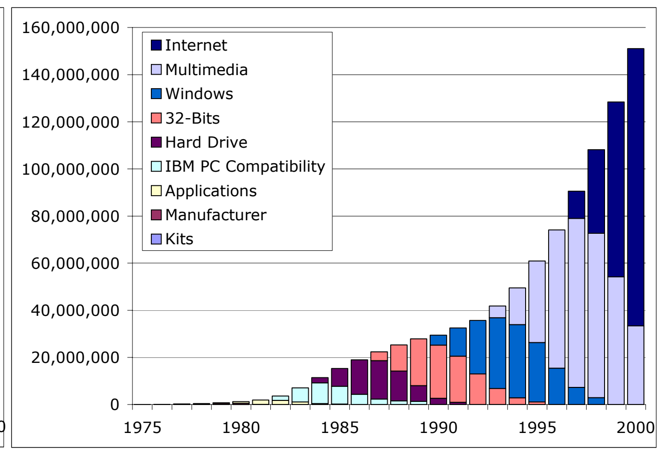


Figure 17 shows cumulative adopters calculated by the BB-01 model compared to industry estimates of installed base. Figure 18 shows the installed-base mix by year calculated by the BB-01 model, which quantifies PCs of a given vintage that are still in use.

The trends in Figure 17 are similar, both increasing with comparable slopes over much of the range. The BB-01 installed base is lower and lags industry estimates by a few of years. As previously explained, estimates of the installed base exceed cumulative adopters by the number of PCs that have been replaced but not discarded; that is, the BB-01 model counts only the purchase of new PCs as adoptions with the passing on of a used PC not considered an adoption. The fact that replaced PCs are kept a few years by the same or another owner accounts for much of the discrepancy between the model and industry estimates. Another contributing factor is that industry estimates are very rough, typically based on spotty penetration surveys measuring only one segment of the market (e.g., consumer). Industry measures of PC sales have been much more reliable than estimates of installed base since product flow (regardless of customer segment) through most distribution channels has been accurately measured most of the 26-year history of personal computers.

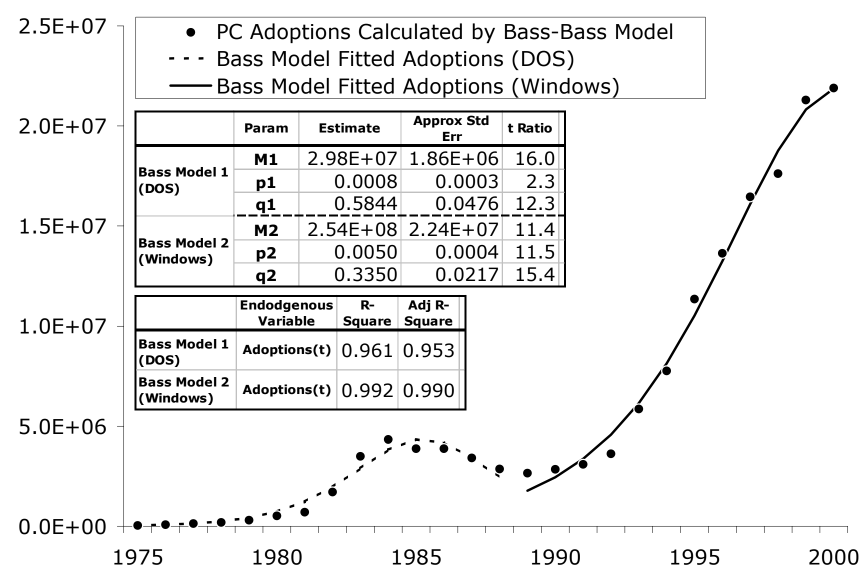
FIGURE 17. U.S. PC Installed-Base Observations v. Bass-Bass Output (Left)
FIGURE 18. U.S. PC Installed-Bass Generational Mix (Right)





As a final plausibility indicator, we used the basic Bass model (1969) to fit the adoptions series from the BB-01 model. We have long understood that the basic Bass model is not suitable for fitting long-run series of fast-tech product sales, such as PCs, because after the first few time periods repeats are such a large portion of sales that the series is contaminated: it does not embody the underlying adoption process. Our dream, and a primary motivation for this research, has been to accurately quantify the adoption series buried in measures of sales. The dots in Figure 19 are the BB-01 output adoptions summed over all nine PC generations. The peak in 1985 implies two adoption processes: the character-based user interface (DOS and predecessors) process starting in 1975 and peaking in 1985 followed by the graphical-user interface (GUI, e.g., Macintosh and Windows) process starting in 1989. The fits of both series are excellent with R-square above .95 for the first and above .99 for the second with very high t-ratios for all parameter estimates. The Bass model identifies 2000 as the peak in GUI adoptions and the two models predict a total U.S. market potential of 284 million. This prediction is consistent with the following facts: (1) the BB-01 model identified 154 million adopters at the end of 2000 and (2) when generations eight and nine are complete there will be 189 million adopters of generation nine and prior products. The higher potential market predicted by the basic Bass model is anticipating generations ten and later. When one considers that more than 50% of the members of the 138 million U.S. civilian workforce now have a computer at work, over 60% of the 106 U.S. households have at least one computer with 30% of households owning more than one PC, the market potential forecast by the Bass model seems quite reasonable. Another big change in user interface like GUI, change in form factor like notebooks or some other new big thing might be just the ticket for another enormous underlying wave in the PC market.

FIGURE 19. Basic Bass Model Fit of Total PC Adopters Calculated by BB-01 Model



	Param	Estimate	Approx Std Err	t Ratio
Bass Model 1 (DOS)	M1	2.98E+07	1.86E+06	16.0
	p1	0.0008	0.0003	2.3
	q1	0.5844	0.0476	12.3
Bass Model 2 (Windows)	M2	2.54E+08	2.24E+07	11.4
	p2	0.0050	0.0004	11.5
	q2	0.3350	0.0217	15.4

	Endodgenous Variable	R-Square	Adj R-Square
Bass Model 1 (DOS)	Adoptions(t)	0.961	0.953
Bass Model 2 (Windows)	Adoptions(t)	0.992	0.990

5. Summary and Conclusions

Fast-tech products are different: repeat purchasing is driven by user-perceived functionality increases. Although there are some earlier product markets (e.g., mainframe computers) that show signs of fast-tech behavior, there was an explosion in fast-tech categories spawned by semiconductor technology. Starting in the mid 1970s, semiconductors gave form to microprocessors, DRAMs, and PCs. Pioneering fast-tech categories were soon followed by cellular telephone, DVD, Internet and many others. Since 1974-75, the Moore's Law regularity of exponential change in semiconductor price/performance has been a drum beat signaling new capability in almost uncountable end-user products and services.

The rapid rates of functionality change in fast-tech products have resulted in (and been the result of) rapid market adaptation to change. Buyers of earlier generations migrate rapidly to newer generations and new buyers are brought into the market as higher functionality applications become available. To capture the dynamics of the underlying market structure of adoption, repeat buying, and usurping, a new model of generational interaction and market growth is required. We have developed such a model and applied it to data for all developed generations of two of the most important fast-tech products, one end-user product and one component product. In both cases the model fits the data exceptionally well and, more importantly, the model produces estimates of the internal structure of demand dynamics of adoption, repeating, usurpation, installed-base growth, installed-base mix evolution, and expected time-to-repeat that are highly plausible and consistent with independent estimates by industry experts.

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