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Forecasting the Adoption of a New Product

The art of prophecy is very difficult – especially with respect to the future.

— Mark Twain

The development and launch of a new product into the marketplace can be a very exciting time for all of those involved in the process, especially when it is a novel product that serves a previously unmet consumer need. If, for example, one is a member of a team preparing for the launch of a new portable engine that is not only more powerful than current combustion engines but also uses one-tenth of the natural resources, then it is understandable to feel great pride in the thought of bringing this product to market. For marketing managers, however, the anticipation and excitement of launching a new product should be quickly tempered by the task of forecasting its demand or, put another way, predicting both the adoption of the product by consumers immediately following its launch as well as the path of this adoption over the expected lifetime of the product. The quotation above by Mark Twain humorously describes the difficulty of making predictions in general, but one could argue that the same is true in forecasting the demand of new products.

Despite the challenges involved in creating reliable forecasts, there is no question that demand forecasts for new products guide many critical decisions faced by a company. One such decision is how much of the new product to produce in order to meet demand at launch and in the months and years ahead. Another decision is how much to offer in promotional discounts or price cuts and the effect this will have in speeding the adoption of the new product. Clearly there is an expectation that consumer adoption will be better if the firm spends more on promotion or advertising, but how much will it affect the adoption curve?

An analytical framework for modeling the first-purchase growth of a new product was first presented by Frank Bass in 1969.[1] In the years since its introduction, it has come to be called a new-product *diffusion* model, given its premise of how information about a product is communicated between members of a social system, but more simply it is just called "the Bass model." At a high level, the Bass model is used to determine the shape of the curve representing cumulative adoption of the new product. However, as an analytical framework, it can also be used to address many pre-launch, launch, and post-launch strategic decisions about a new product such as those mentioned in the previous paragraph.

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[1] Frank M. Bass, "A New Product Growth Model for Consumer Durables," *Management Science* 15:5 (1969): 215–227.

Professor Elie Ofek and Research Associate Peter Wickersham prepared this note as the basis for class discussion.

The purpose of this note is to review several key concepts of the Bass model and to illustrate these concepts through a case example. Some extensions of the Bass model, including the incorporation of marketing-mix variables, are then discussed as well as issues of competition between firms. Finally, the Bass model is compared with models that use historical data of the product to forecast next-period sales.

Overview of the Bass Model

The Bass model is both intuitive and simple, which could be one reason why it is so widely used today. The model in its basic form usually assumes that a consumer can adopt the new product only once; as a result, the model is typically applied to durable products such as appliances, televisions, or other products that are only purchased once every few years.[2] The model is also relevant for modeling the first time an individual begins using a new product or service. The general theory behind the Bass model makes assertions of how information about a new product is passed between individuals in a social system and how this affects their timing of adoption. It is believed that some individuals decide to adopt an innovation independently of the actions of others; these individuals are dubbed *innovators*. As Bass describes in his 1969 paper, "innovators are described as being venturesome and daring." Other individuals in the system are influenced to adopt a new product when they observe that more and more people have already done so. That is, they respond to the influences of the social system and obtain information about a new product from those that have already adopted the product; these individuals are called *imitators*.

At this point, before we examine the key parameters of the Bass model, it is necessary to define some basic terms that will be used to describe the Bass model in equation form. Since the model describes the adoption curve of a new product, we require a set of variables to represent those consumers who have adopted the new product by a particular time point as well as a way to represent those who have *not* adopted the new product. Thus, let's define the following:

- $N(t)$ is the total or cumulative number of consumers who have already adopted the new product through period t.
- $N(t - 1)$ is the cumulative number of adopters for the new product through the previous time period (i.e., $t - 1$).
- $S(t)$ is the number of new adopters for the product *during* the time period t and can be expressed as $N(t) - N(t - 1)$.

Having defined these terms, we now move to the three key parameters in the Bass model—usually called m, p, and q. In forecasting the demand of a new product, it is first necessary to determine the total market size, m. The parameter m provides the *scale* of the demand forecast, a total consumer base or terminal value of total adopters that will not be exceeded. Total market size can take several units of measurement such as the total number of relevant consumers or the total number of households that could adopt the new product. The other parameters in the model, p and q, are critical in determining the particular *shape* of the adoption curve. That is, together p and q specify how fast or slow the adoption of a new product is expected to proceed. So the adoption of a

[2] If the new product is truly durable, which means it is only purchased once, then the Bass model reflects the unit demand equivalent to the first adoption of the new product. Otherwise, if repeat purchases are expected to occur by the same individual, then it is necessary to account for the product's average frequency of purchase or duration of use, which is not covered in this note.

new product can either proceed at a fast or slow pace (specified by p and q) but can also be on a small scale or a large scale (specified by m).

With this in mind, the Bass model asserts that the likelihood of an initial purchase being made at time t, given that a purchase has not been made before, is a linear function of the number of the previous adopters, as shown in expression (1):

$$p + (q/m)\, N(t-1) = \text{likelihood of purchase by a new adopter in time period } t \qquad (1)$$

In the expression above, p is called the *coefficient of innovation* and represents the rate or probability that an *innovator* will adopt at time t. Notice that this rate does not change over time and reflects the intrinsic tendency of innovators to adopt the new product. This parameter also accounts for external factors that may influence the innovators such as the effects of advertising and other mass media. By contrast, q is called the *coefficient of imitation* and accounts for the "word of mouth" or "social contagion" effects that result from interpersonal communications between adopters and non-adopters. Imitators are influenced by the number of previous buyers and "learn" from those who have already bought. Note in equation (1) that q is multiplied by the proportion of consumers who have adopted the new product at the start of time t (i.e., $N(t-1)/m$). Thus, and in line with the theoretical framework of the Bass model, the likelihood of an imitator adopting the new product is a function of those who have already adopted. Consistent with our above notation:

- $m - N(t-1)$ is the number of consumers who have *not* previously adopted by the start of time period t; this is the pool from which new adoptions in the current period can occur.

Since expression (1) defines the rate of new adopters (i.e., likelihood of an initial purchase by a new adopter in time period t) and $m - N(t-1)$ represents the number of consumers who have yet to adopt, multiplying these two expressions provides the number of adoptions occurring during time period t. This equation (see below) is the Bass model in its simplest form:

$$S(t) = [p + (q/m)\, N(t-1)]\, [m - N(t-1)] = \text{number of new adopters during time } t \qquad (2)$$

The model is straightforward to implement in a spreadsheet such as Microsoft Excel®. **Figure A1** provides the cumulative adoption curves for several values of p and q. In this plot, market penetration was defined as the cumulative number of adopters at time t, $N(t)$, divided by m. Consider the curves presented in **Figure A1**. A new product with a high coefficient of innovation (e.g., 0.5) is adopted very quickly, even if it has a relatively low coefficient of imitation (e.g., 0.0001); thus, the adoption curve for this product immediately starts to increase following launch and then levels off as the market becomes saturated and there are fewer and fewer consumers left who have not already adopted the new product. Alternatively, a new product with a low coefficient of innovation (e.g., 0.001) is adopted very slowly at first, even if it has a relatively high coefficient of imitation (e.g., 0.5). This is because there are so few innovators from whom the imitators can seek information about the product; as a result, new adoptions are slow until a critical mass of adopters is achieved, and then new-product adoptions really take off (before ultimately saturating). This particular phenomenon, slow growth at the beginning followed by rapid growth followed by market saturation, is why adoption curves for new products are often called S-curves.[3] Before continuing on, can you think of a product that might be represented by each one of these curves?

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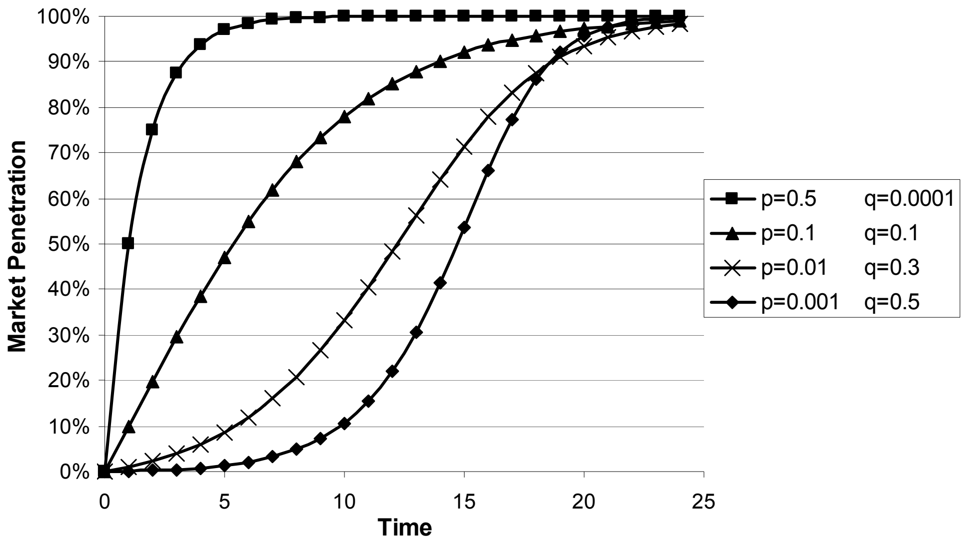
[3] However, we will avoid using the term S-curve in this note since not all adoption curves follow this shape, as shown in **Figure A1**. We also note that it is possible to construct a continuous-time version of the Bass model and solve it using differential equation techniques (see Frank M. Bass, Dipak Jain, and Trichy Krishnan, "Modeling the Marketing-Mix Influence in New-Product Diffusion," chapter in Mahajan, Muller, and Wind, eds., *New-Product Diffusion Models* (New York: Springer Science & Business Media, 2000).

Figure A1 Bass Models with Various Levels of Innovation (p) and Imitation (q)



Source: Casewriter.

Figure A2 Numerical Example with m = 30 (in millions), p = 0.0112, and q = 0.5

***t* (years)**	***N*(*t*)**	***S*(*t*)**	***N*(*t*)/*m***	***S*(*t*)/*m***
1	0.336	**0.336**	1.12%	1.12%
2	0.834	0.498	2.78%	1.66%
3	1.567	0.732	5.22%	2.44%
4	2.627	1.061	8.76%	3.54%
5	4.133	1.505	13.78%	5.02%
6	6.204	2.071	20.68%	6.90%
7	8.931	2.727	29.77%	9.09%
8	12.303	3.372	41.01%	11.24%
9	16.130	3.827	53.77%	12.76%
10	**20.014**	**3.884**	**66.71%**	**12.95%**
11	23.457	3.443	78.19%	11.48%
12	26.088	2.631	86.96%	8.77%
13	27.833	1.745	92.78%	5.82%
14	28.862	1.030	96.21%	3.43%
15	29.422	0.560	98.07%	1.87%
16	29.712	0.290	99.04%	0.97%
17	29.858	0.146	99.53%	0.49%
18	29.930	0.072	99.77%	0.24%
19	29.966	0.036	99.89%	0.12%
20	29.983	0.017	99.94%	0.06%
21	29.992	0.009	99.97%	0.03%
22	29.996	0.004	99.99%	0.01%
23	29.998	0.002	99.99%	0.01%
24	29.999	0.001	100.00%	0.00%

Source: Casewriter.

Now, in order to see how the Bass model comes together in greater detail, **Figure A2** shows the numerical values of cumulative adopters at time t, $N(t)$, and new adopters, $S(t)$, for satellite radio, a case example to be discussed in the next section (for now, take the values for m, p, and q at face value). Before examining the particular values in the table, note that at the start of period $t = 1$, $N(t - 1) = 0$, and the only term left in the model of equation (2) is pm, or approximately 336,000 consumers (i.e., 0.0112 × 30 million) in our case example. Also note in **Figure A2** that the number of new adopters increases in each successive time period to a peak of 3.884 million in year 10. This indicates the inflection point in the cumulative adoption curve, after which new adoptions of the product will continue but at a diminishing rate, as shown by $S(t)$ decreasing in years 11 through 24.

Estimation of Parameters

Since firms often require a demand forecast for a new product well before it is launched into the marketplace, it is necessary to develop estimates of the parameters in the Bass model based on our understanding of the potential market for the new product in combination with a knowledge of previously launched products that can serve as an analogy to our new product. In the case of the parameter m, it may sometimes be very easy to determine the total market size for a new product. For a new drug therapy that targets a particular disease, there is often a well-known estimate of the number of people afflicted with the disease. However, for some products, especially for technology products where it may not be readily apparent who the potential users are, estimation of m may take much more effort. Market research surveys that quantify consumer interest or assess the likelihood of purchase for particular segments of the population are one way to gauge the total market size, but it should be noted that these surveys can sometimes be too optimistic in estimating m.

We now turn our attention to the selection of p and q. Prior to the launch of the new product, one approach to determine p and q is through the analysis of previously launched analogous products. **Figure B** lists the p's and q's of several different products based on their actual historical annual sales.[4] More specifically, by retrospectively fitting a separate Bass model to each product's historical sales curve, a catalog of p's and q's was established for a variety of products. It is possible to use the p and q from a previously launched analogous product to create a Bass model for a new product.

Importantly, in determining the appropriate values for p and q, it is advised that the selection of analogous products should be based on product and market characteristics, rather than "simply mirroring the path managers hope their new product will follow." Taking this concept a step further, Thomas (1985) recommends the analysis of the following factors in assessing the appropriateness of a particular analog: environmental factors, market structure, buyer behavior, marketing-mix strategies of the firm, and characteristics of the innovation.[5,6] Often it may be appropriate to consider several analogous products and to use a weighted average of their p and q values with each weight acting as a hypothesized probability that the product will exhibit that level of innovation and/or imitation.

In the event that you want to use an analogous product for which there are no published values of p and q, there are well-documented methods for deriving p and q from actual unit sales data.

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[4] Gary Lilien, Arvind Rangaswamy, and Christophe Van den Bulte, "Diffusion models: Managerial applications and software," chapter in Mahajan, Muller, and Wind, eds., *New-Product Diffusion Models*.

[5] R. J. Thomas, "Estimating Market Growth for New Products: An Analogical Diffusion Models Approach," *Journal of Product Innovation Management*, 2 (March 1985): 45–55.

[6] Several alternative approaches for assessing the appropriateness of a particular analog have been suggested. For example, one could use Everett Rogers, "Five factors of perceived attributes of an innovation" (see chapter 6 of Everett Rogers, *Diffusion of Innovations* [New York: The Free Press, 1962]).

Although beyond the scope of this note, in most cases a type of nonlinear-least-squares (NLLS) regression model is used to fit past unit sales data of an analogous product or early unit sales data of the new product itself (i.e., actual sales data from several time periods following launch). Using this approach, one can essentially derive values of p and q to populate your own version of **Figure B**. Two notable websites contain software to facilitate the estimation process (www.basseconomics.com and www.mktgeng.com/products). In addition, the **Appendix** contains a less precise but simpler method based on ordinary-least-squares (OLS) regression.

Figure B Bass Model Parameter Estimates for Several Products/Technologies

Product (Period of Analysis)	p	q
Refrigerator (1926–1979)	0.025	0.126
Calculator (1973–1979)	0.143	0.520
CD player (1986–1996)	0.055	0.378
Cable television (1981–1994)	0.100	0.060
Power leaf blower—gas or electric (1986–1996)	0.013	0.315
Home personal computer (1982–1988)	0.121	0.281
Cellular telephone (1986–1996)	0.008	0.421

Source: Adapted from Lilien, Rangaswamy, and Van den Bulte (2000).

Case Example—Satellite Radio

In the late 1990s, significant development efforts were being made by two start-up companies—XM and SIRIUS—to launch new satellite radio services. Within several years, XM and SIRIUS planned to deliver 50 or more high-quality, digital radio channels to the car and/or home via satellite, similar to the way satellite television had a few years earlier. Although both services have since launched and are now operational, in 1997, no one had ever developed a system to deliver satellite radio directly to mobile consumers anywhere in the continental U.S. There were huge technical challenges to overcome, and the up-front capital investment required to launch each service was in excess of $1 billion. In short, these companies faced a host of challenges in bringing satellite radio from a concept to a reality.

With this as background, it is not hard to see why the development of reliable estimates of the market size of satellite radio and its rate of adoption, as well as a justification of the revenue model selected (advertising supported and/or subscription based), was critical for both XM and SIRIUS in early discussions with investment banks, radio manufacturers, and satellite companies. Undoubtedly, each of these potential partners wanted to see realistic demand forecasts for satellite radio before investing in the new technology. The following case example uses the Bass model to forecast the demand of satellite radio. Further background and discussion of the questions surrounding the launch of XM can be found in "XM Satellite Radio (A)" (HBS Case No. 504-009).

Determination of Total Market Size (m)

In order to estimate the total market size (m) for satellite radio, in July 1997, XM commissioned a national telephone survey to identify target markets. The survey consisted of 80 questions designed to estimate market size and sensitivities as well as to identify key market segments, service attributes, and the strengths and weaknesses of terrestrial AM/FM radio offerings. Over 6,000 surveys were completed by more than 4,000 participants residing in urban areas and over 2,000 participants from rural areas.

Overall, the study projected that there were about 160 million listeners interested in the new XM service. Of these, over 96 million projected listeners would be willing to pay for the radio only without a subscription fee, and over 38 million of those listeners would be willing to pay a $12 per month subscription fee and $200 for a new XM-compatible radio. **Figure C** summarizes the findings regarding the demand for satellite car radios at various hardware and subscription prices. As noted in the tabular findings, the study confirmed that as the cost of the radio and/or monthly subscription fee was lowered, the size of the potential target market increased.

Figure C Cumulative Projected Demand at Various Car Radio and Subscription Price Levels

	Subscription Price				
Radio Price	**$12**	**$10**	**$8**	**$5**	**$2**
$400	23,682,641	27,404,662	27,484,190	27,590,767	27,714,837
$300	24,781,778	28,526,070	28,685,126	28,898,280	29,146,420
$250	26,552,125	30,698,835	31,225,323	31,840,895	32,637,794
$200	31,470,304	36,515,712	37,829,543	40,490,651	42,806,598
$150	35,626,570	41,580,232	44,098,158	49,110,199	52,965,846
$100	45,726,942	54,026,759	58,682,464	68,262,745	77,771,435

Source: Adapted from a market research study commissioned by XM Satellite Radio in 1997. See "XM Satellite Radio (A)," HBS Case No. 504-009, for further details.

From a pedagogical perspective, **Figure C** demonstrates that even if one conducts extensive market research to find an appropriate m, there may still be a great deal of uncertainty in estimating this parameter. In this case, XM investigated market size primarily along two dimensions—radio price and subscription price. Note that given its current plans XM would only have direct control over one of these two dimensions—subscription price (including $0 subscription). Unless some arrangement was made with radio manufacturers as part of agreements to build and market radios for XM, the retail prices of satellite radios would be beyond their direct control. In addition, at this point in 1997, XM had yet to decide whether to pursue the market for home radios, especially since most industry observers saw satellite radio mainly as a product for the car. Taken together, these factors underscore the importance of performing sensitivity analysis around the determination of m. For this example, we will assume an m of 30 million potential adopters of satellite radio. This market size was based on a subscription price of $10 per month and radio price of $250 when focusing on car radios only. However, since radio price was highly uncertain at the time, varying m for several levels of radio price and seeing the resulting impact on new adopters during the first several years following the launch of satellite radio would be highly recommended in this case.

It is also useful to note that, since satellite radio was primarily a product for the automobile, some industry analysts in 1997 used the total number of vehicles in the United States as the total market size for satellite radio (i.e., about 200 million vehicles). Before going on to the selection of p and q, can you think of some advantages and disadvantages to taking this approach in selecting m?

Selection of Coefficients of Innovation (p) and Imitation (q) by Analogy

The selection of an analogous product or set of products on which to base one's estimates of p and q is a critical step in the creation of a Bass-model forecast for a new product. It is so critical, in fact, that many companies use external experts or consultants to develop estimates of these parameters. It is undoubtedly a *subjective* process, but it should be given careful thought and attention nevertheless. In 1998–1999, with its launch still several years away, satellite radio could potentially draw analogies from several existing products, either in terms of direct physical characteristics or other external factors such as market structure. As a result, in this example we will aim to utilize several analogous products to develop p and q for satellite radio as opposed to just one product. First, and perhaps most obvious, since satellite radio was considered to be the "next generation" of car radio, the past adoption of AM/FM automobile radios would certainly be an analogous product to consider. In addition, the portable CD player could be considered as another analogy since it was a recent innovation in audio products providing digital sound quality, reflective of what satellite radio was attempting to provide over analog AM/FM radio (SIRIUS was initially named CD Radio). Lastly, other subscription services that utilize satellite signals to carry information/content, such as cellular phones or satellite television (e.g., DIRECTV®), would also be of interest. From here, one must search the literature for published estimates of p and q for these products or derive them from the past sales data of these products (see the **Appendix** for more details).

The first two columns of **Figure D** contain estimates of p and q for three of the products discussed above—the portable CD player, automobile radio, and cellular phone. The next task is to "average" these values of p and q into a single set of values for satellite radio. Taking the arithmetic mean could be one way to find such an average, but that would assume that each product is *equally* similar to satellite radio as to one another. Clearly, some aspects of these products are more similar to satellite radio than others. As a result, it is recommended to develop a set of criteria on which to judge the similarity of each product to satellite radio. For simplicity, we will only examine two criteria: 1) market structure and 2) characteristics of the product. Each of these criteria can be weighted in its importance or predicted impact on consumer adoption. For instance, we may believe that the product characteristics of satellite radio (e.g., its physical features, programming content) may be of more importance than the structure of the market for satellite radio (e.g., original equipment manufacturer [OEM] versus aftermarket, subscription-based revenue model). As a result, for this example, a weighting factor of 0.4 was given to market structure, while a weighting factor of 0.6 was given to product characteristics.

Figure D Bass Model Parameter Estimates for Analogous Products

			Criteria / Numerical Score		Weighted Numerical Score
Product	p	q	**Market Structure (w_a=0.4)**	**Product Characteristics (w_b=0.6)**	
Portable CD player	0.00605	0.66	4	7	5.8/18.2 = 0.319
Automobile radio	0.0161	0.41	8	9	8.6/18.2 = 0.473
Cellular phone	0.008	0.421	8	1	3.8/18.2 = 0.208
Weighted Average for Satellite Radio:	**0.0112**	**0.5**			18.2/18.2 = 1.0

Source: Casewriter.

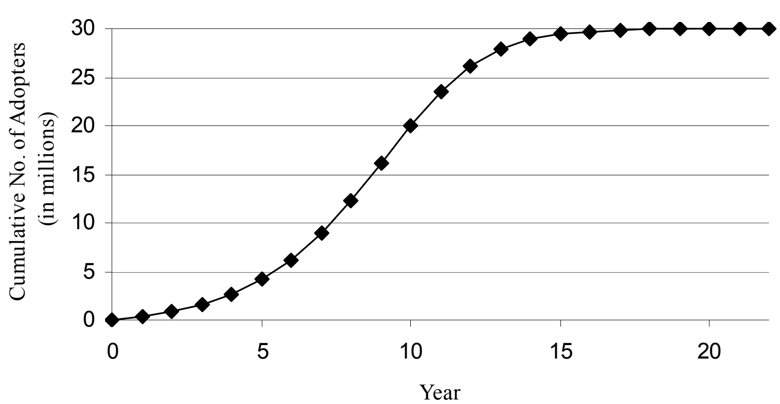
Notes: Wt. numerical score for CD player = (4*0.4) + (7*0.6) = 5.8 / (5.8 + 8.6 + 3.8) = 0.319.
Wt. avg. p for satellite radio = (0.319*0.00605) + (0.473*0.0161) + (0.208*0.008) = 0.0112.

Figure D shows the weights given to each criterion (w_a and w_b) as well as the numerical scores measuring the similarity of each analogous product to satellite radio. The numerical scores were given on a scale of 1 to 10 and were based on the author's subjective knowledge of satellite radio. For example, the cellular phone was given a score of 8 for market structure because revenue model is subscription based with an initial cash outlay for the phone, an approach that was expected to be used with satellite radio. Conversely, a score of 1 was given to the product characteristics of the cell phone because it is substantially different in its form and function to satellite radio.

Evaluation of the Demand Forecast

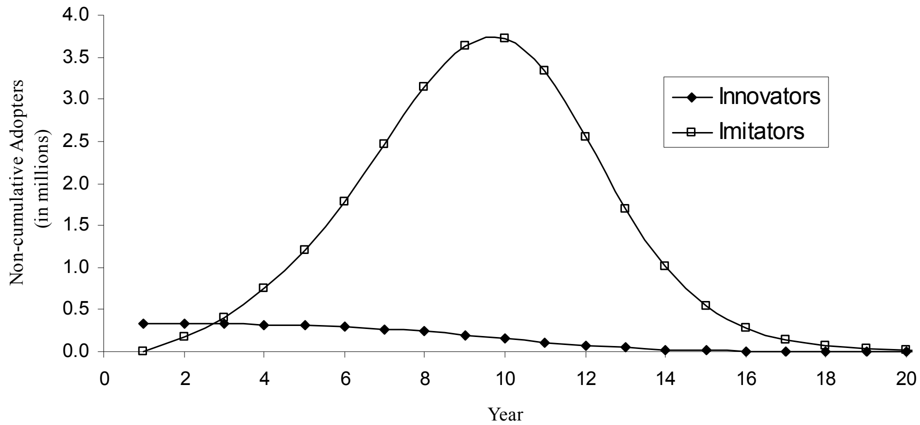
Using our estimates of *m*, *p*, and *q*, we are now able to construct a forecast for the demand of satellite radio over time (see **Figure E1**). In particular, given our analysis of analogous products, we expect that satellite radio will get off to somewhat of a slow start in its first five years following launch and then will accelerate rapidly between years 5 and 12. This is due to the fact that the model is dominated more by imitators than innovators, as shown in **Figure E2**. Since the coefficient of innovation, *p*, is small relative to the coefficient of imitation, *q*, it is expected that it will take several time periods before there will be a sufficient number of innovators from whom the imitators will seek information about satellite radio. However, once a "critical mass" is reached by year 5, the strong imitative effects will take over and the number of new innovators to adopt the product will slowly diminish over time.

Figure E1 Demand Forecast for Satellite Radio Based on the Bass Model



Source: Casewriter.

Figure E2 Adoptions of Satellite Radio by Innovators as Compared with those by Imitators

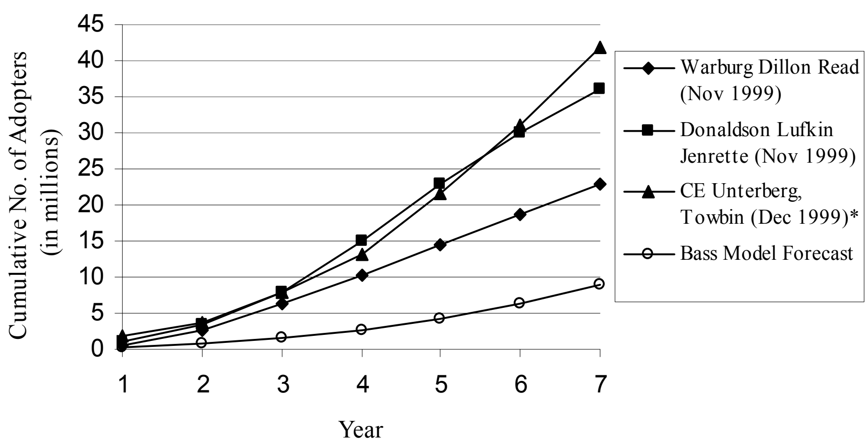


Source: Casewriter.

Figure E1 presents a potential adoption curve for satellite radio, but now the task is to verify if this curve makes sense. As a reality check, the shape of the adoption appears plausible given the current market situation with satellite radio. In 1999, it was expected that satellite radio would not be immediately available as OEM equipment in all new cars. Rather, it appeared that satellite radio would first be available as an aftermarket product and then more gradually as OEM equipment. Thus, the need to *replace* one's car radio in order to get the service, in a sense, might erect such a high barrier that adoption early on is primarily driven by innovators. And later, as more consumers purchase new cars with satellite radio available as OEM equipment, this barrier to adoption may be lowered considerably. In addition, paying a subscription for radio will be a considerable change for consumers; it will be a cost that they are not used to bearing each month. Potential adopters may need to see that others are freely willing to pay for radio before they become more open to the idea, thus contributing to a high degree of imitation.

Now that we have gained some confidence in our initial demand forecast of satellite radio, it is (of course!) tempting to compare our estimates with those of other industry analysts. **Figure F** contains several adoption curves developed by equity research analysts of several financial services firms.

Figure F Comparison with Other Published Forecasts for Satellite Radio



Source: Casewriter.

*Includes home radios.

At first, it may be disconcerting to see that our forecast is the most conservative of the group by far. Examination of some of the models used to develop the more aggressive demand forecasts identified that most of them modeled the growth in adoption as a percent penetration in the number of vehicles in the United States. For instance, in one model it was believed that satellite radio would reach 3% market penetration in U.S. vehicles by the third year following product launch, 7.5% by the fifth year, and almost 15% by the seventh year. In addition, none of the analysts' forecasts shown in **Figure F** explicitly estimated the total market size of satellite radio.

So what can be learned from these comparisons? An understanding of the Bass model provides a nice framework in which to assess the quality of our forecast in relation to other forecasts. In this case, we can internally debate whether our assumption of using a small coefficient of innovation for satellite radio makes sense, given that the analysts forecast a much faster uptake by consumers in the first several years. Knowledge of the Bass model also stimulates one to ask a number of "what if" scenarios. For example, what if we could assess the sensitivity in our year-to-year demand forecasts given a change in the overall market size, m, based on the research in **Figure C**? By varying the estimate of m, the Bass model allows one to develop a range of cumulative adopters at each time point for the first several years and then reexamine based on actual sales data after the satellite radio service is on the market for a few years.

A final note on forecasting the demand of satellite radio using the Bass model is that the forecast represents predicted adoptions for satellite radio as a technology and does not predict the expected market share of the individual firms (e.g., XM, SIRIUS) or any impact of their marketing activity. The next section on incorporating marketing-mix variables discusses one way to model the impact of the marketing actions of the firm on the overall adoption rate of the product. The subsequent section provides a perspective that incorporates competition into a forecasting framework.[7]

Incorporating Marketing-Mix Variables

Although the demand forecast for satellite radio that we have developed based on the Bass model is a simple way to demonstrate the speed at which the product may penetrate the market, the observant marketer may offer a claim to affect this penetration through either decreases in price or increases in advertising. To this end, one can use a generalized form of the Bass model that takes into account these two types of marketing-mix variables.[8] In its functional form, the generalized Bass model (GBM) is just the standard Bass model from equation (2) multiplied by a time-dependent term, $Z(t)$, that is a function of marketing activity. For example, to incorporate a change in price in period t:

$$S(t) = [p + (q/m)\, N(t-1)]\, [m - N(t-1)]\, Z(t),$$

$$\text{where} \quad Z(t) = 1 + \alpha[P(t) - P(t-1)]/P(t-1) \tag{3}$$

The parameters in $Z(t)$ are interpreted as follows:

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[7] Readers interested in learning more about these topics, as well as understanding how to combine the diffusion pattern of an innovation (as presented in this note) with the expected profits from each new adopter (through customer lifetime value analysis), are referred to *Innovation Equity: Assessing and Managing the Monetary Value of New Products and Services* (Ofek, Muller and Libai, 2016, University of Chicago Press).

[8] Frank M. Bass, Trichy V. Krishnan, and Dipak Jain, "Why the Bass Model Fits Without Decision Variables," *Marketing Science* 13 (Summer 1994): 204–223.

- α is a coefficient that indicates the percentage change in the speed of diffusion that results from a 1% change in price. (α is usually negative so that $\alpha[P(t) - P(t-1)]/P(t-1)$ is positive when the price is dropped).
- $P(t)$ is price in period t.

In reviewing equation (3) above, note the following characteristics of the GBM. First, a price decrease is assumed to affect the number of adoptions in that period only. That is, there is no carryover effect to the next time period. Second, it assumes that the actions of the firm through its marketing mix affects everyone the same, even though we have previously hypothesized that the imitators behave differently from the innovators. Although these may be perceived as shortcomings or too limited of an approach to model the effect of marketing-mix variables, the GBM can be useful in practice.

Going back to the example of satellite radio, perhaps we are currently considering a promotion to subsidize retailers up to $50 off the best-selling aftermarket satellite radio to lower the average retail price from $250 to $200 (i.e., a drop of 20%). What effect will this promotion have on increasing new subscriptions (i.e., new-product adoptions) for this year?[9] From **Figure C**, we can see that expected demand increases from about 30 million subscribers to 36 million subscribers if the satellite radio price is permanently lowered from $250 to $200 (at a $10 per month subscription fee). Using this as a crude proxy for the sensitivity of adoption rate, this corresponds to an α of -1 (20% increase in demand/20% decrease in price). Since in this promotional campaign we are considering a 20% decrease in price, $Z(t)$ is equal to $1 + (-1 \times -0.2)$, or 1.2. Multiplying $Z(t)$ by our previous Bass model forecast for year 3 (1.6 million subscribers), we find that the promotional campaign could speed adoption for the year by 320,000 additional subscribers and bring the total to 1.92 million subscribers for the year (**Figure G**).

Although, in hindsight, our forecast based on the GBM was off by about 1.25 million subscribers in year 3 when compared to actual sales data, it is good to note that other forecasts from other sources in 1999 were off by 5 million subscribers or more.

Figure G Bass Model Forecast for Satellite Radio (in millions) When Adjusted for a $50 Price Decrease in Year 3 and a Comparison to Actual Subscribers

Year	Bass Model Forecast	Actual Subscribers
1	0.3	0.2
2	0.8	1.1
3	1.92[a]	3.2

Source: Casewriter.

[a]Forecast was 1.6 million without the effect of the $100 price decrease.

[9] Assume we are entering the third year following launch of satellite radio in 2001.

Competitive Considerations

It has been noted previously that the Bass model forecasts the adoption of a new product or technology over time—satellite radio, for example. However, if multiple firms are planning to offer competing models of satellite radio, then it is important to assess the relative adoption of different models offered by competing firms in addition to satellite radio as a whole. Or, put another way, what piece of the total pie for satellite radio in 1999 was expected to go to XM as compared with that for SIRIUS? Even if the Bass model provides an understanding of the "total pie," the more specific forecast of each product offering would presumably be of greater interest to each individual firm as they make a pitch for investment in *their* company as opposed to the competition. Thus, in general, how can one consider competition when developing a forecast based on the Bass model?

The answer to this last question depends in part on whether the Bass model is being created while the new product is still in development or whether the new product is already on the market. If the launch of the new product is still months or even years away, as was the case with satellite radio in 1999, then there is very little known about what might differentiate one company's model of the product from a competitor's model. As a result, expected market shares are often assigned arbitrarily. For example, since the launch of satellite radio was not expected until 2001, several investment analysts in their financial valuations of XM and SIRIUS in 1999 assumed a 50/50 split in market share between the two firms.

If two or more versions of the new product are already competing with each other in the marketplace or if prototypes or descriptions of these competing models are available before launch, then it is possible to assess the current set of attributes for each product and to estimate the likelihood that a consumer would choose one product over another by creating a discrete-choice model. The important step in developing such an analysis is to develop a set of key attributes by which to compare the different competing versions of the product. In the case of satellite radio, attributes to consider might include programming content, subscription price, radio price, as well as physical features of each radio model. Then, specific levels of each attribute are defined in order to test the preference of individual consumers using a methodology like conjoint analysis.[10] For example, the company might decide to test three levels of subscription price: $10 per month, $12 per month, and $14 per month. To assess preferences for different types of content, one could include specific types of programming choices: a channel for kids, a reggae channel, a radio talk personality such as Howard Stern, or sports programming such as NFL football.

Using these attributes, the preference structure of each individual is estimated as well as the likelihood that each individual would prefer the profile of one competing alternative over another. Aggregating these likelihoods across all individuals in the sample then provides estimated market shares for each product. As a result, a company might expect to gain a certain market share if a specific radio program is introduced or if their monthly subscription fee is lower compared with that of the competition, since it increases the likelihood that an individual would prefer that alternative. The exact timing of the market share gain or loss is not specified in the resulting discrete-choice model, but one can apply these market shares to a particular time *(t)* of the Bass model to estimate the number of adopters (or the cumulative adoption) for each competing model of the product or technology.[11]

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[10] For more information on conjoint analysis, see "Analyzing Consumer Preferences," HBS Case No. 599-112.

[11] Though not discussed here, one could alternatively augment the Bass model itself to incorporate aspects of competition. In addition to the same parameters specified in the standard Bass model, this extension requires one to define m_i, the size of

Data-Driven Demand Forecasts

Although much of the material in this note has focused on the Bass model, it is worth discussing at least one of the many other forecasting models used in business today. Before doing so, at the risk of being repetitive, let's recall the main attributes of the Bass model. In short, it is useful in forecasting the *adoption* of *new products* for which there may be *little or no* previous sales data. The term *adoption* is used because, in its simplest form, the Bass model forecasts the *first* purchase of a product. The model uses three parameters—m, p, and q—and it does not require previous unit sales data of the product of interest in order to compute a demand forecast.[12]

This last point is one attribute of the Bass model that separates it from the majority of other methods used to forecast. Although the Bass model describes the first adoption of a new product, most forecasting models use historical sales data of a product in order to forecast future demand—including repeat purchases if the product is not a durable product. Thus, the more general term of *data-driven demand forecasts* is used to describe these methods. Implicit in this explanation is that, unlike the Bass model, data-driven forecasts cannot be used to construct demand forecasts for products that are still in development or that have just been launched. Despite this drawback, data-driven models can nevertheless be utilized to one's advantage in a variety of situations. Moreover, entire textbooks have been devoted to the explanation of these methods.[13] For illustration purposes of data-driven forecasts, we will focus on moving averages and smoothing methods, which are applied to the satellite radio example to provide a comparison to the Bass model.

A simple method used to forecast unit sales in future time periods from historical data is to calculate a *moving average* of the unit sales from some number of previous time periods. For instance, one could decide to forecast the unit sales of a particular product for the next week as just the average of the past 15 weeks (i.e., a 15-week moving average). This method may prove to be a very reliable way to forecast some products, especially mature ones. However, let's say that a dramatic shift in the marketplace has occurred in the past six weeks due to a new market entrant, and there is a need to rely more heavily on recent data when constructing the forecast for future time periods. *Exponential smoothing methods* provide an exponentially weighted moving average of all previously observed values. Forecasts are determined by averaging (i.e., smoothing) previous time periods in an exponentially decreasing manner. Put another way, a weighted average is calculated in which more recent observations are weighted more than older ones. Specifically, a weight of β (defined as a constant between 0 and 1) is used for the most recent observation, $\beta(1 - \beta)$ for the next most recent, $\beta(1 - \beta)^2$ for the next, and so on. As an example, if β is 0.8, then the weighting factor for the most recent observation would be 0.8; the weighting for the next most recent observation would be 0.8×0.2, or 0.16; and the one after that would be $0.8 \times 0.2 \times 0.2$, or 0.032. Since the sum of the weighting factors is 1, when β is 0.8, one should note that all other previous observations have a combined weighting factor of no more than 0.008 ($0.8 + 0.16 + 0.032 + 0.008 = 1$). As a result, in this example, much weight was given to more recent observations when β was 0.8 than if it was something less, say, 0.3. More

Brand i''s potential market, and an additional coefficient, γ_{ij}, which describes the intensity of the imitative effect of Brand j's potential market that in turn contributes to Brand i's growth. For more information, see Rabikar Chatterjee, Jehoshua Eliashberg, and Vithala R. Rao, "Dynamic Models Incorporating Competition," chapter in Mahajan, Muller, and Wind, eds., *New-Product Diffusion Models*.

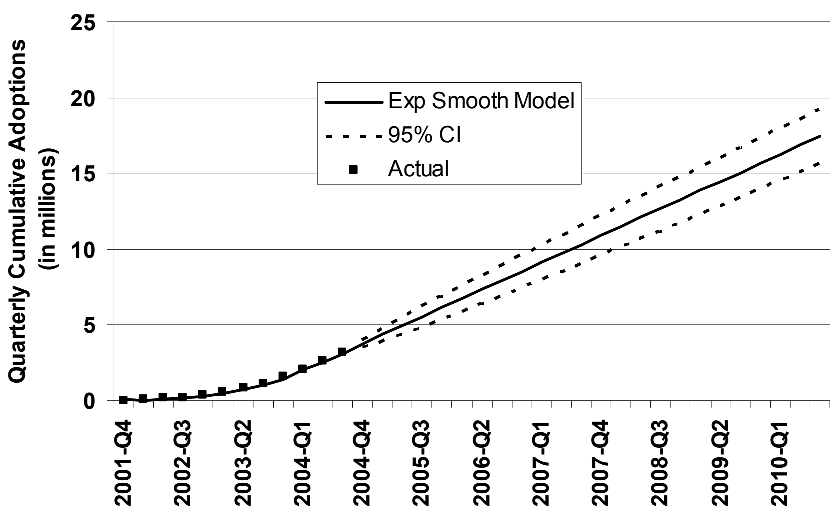
[12] Although it does not require previous unit sales data, such data (when it becomes available) can be used in order to calculate an estimate of p and q via nonlinear regression.

[13] J. E. Hanke, D. Wichern, and A. Reitsch, *Business Forecasting* (Upper Saddle River, NJ: Prentice-Hall, 2001). Such texts also contain more advanced data-driven techniques not covered here.

generally, since smaller β's provide more weight to a greater number of historical observations, their forecasts are more "smooth" and less susceptible to recent changes in the data. Knowing this, one can decide upon β beforehand. Or, commercially available forecasting software packages often automatically determine an appropriate value for β, and one could then examine this value to see if it makes sense to use.[14]

To show this method in practice, exponential smoothing was applied to the satellite radio case example. Based on the first 12 quarters of actual subscription data for satellite radio (4Q01 to 3Q04), a quarterly forecast was computed for the next 10 years using the exponential smooth method in Forecast Pro™, a commercially available forecasting tool. **Figure H1** shows how the exponential smooth model fits the actual historical data for satellite radio during the first three years; it then provides a forecasted trend along with 95% confidence limits. For comparison, **Figure H2** puts the exponential smooth model on the same plot as our previous Bass-model forecast. A notable difference is that, unless the exponential smooth model is adjusted for seasonality, it will always show a forecast that is linear, since it uses the same combined exponential weighting factor to forecast each successive time point into the future. By contrast, the Bass model is nonlinear and in this case is S-shaped as previously noted in an earlier section. As shown in **Figure H2**, the forecast using the Bass model starts out more slowly in terms of sales (adoptions) than the exponential smooth forecast but then accelerates and increases past the exponential smooth forecast.

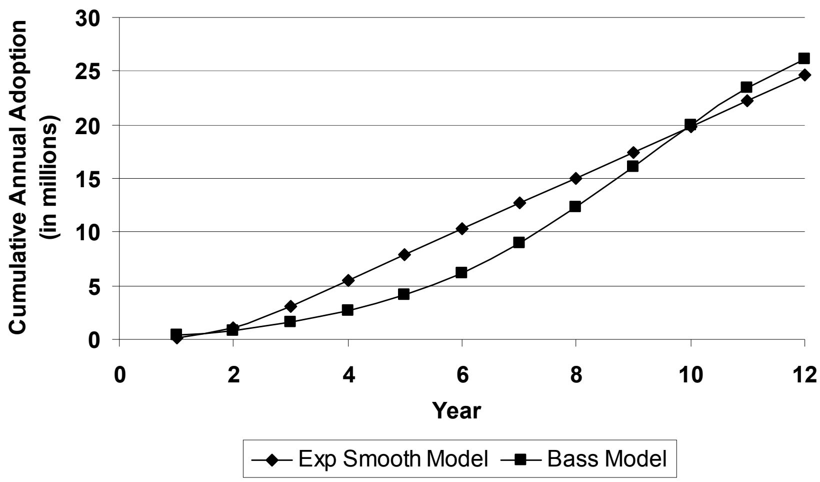
Figure H1 Satellite Radio Forecast Using an Exponential Smoothing Method



Source: Casewriter.

[14] It is also important to note that there are extensions of exponential smoothing that include Holt's method, which adjusts for an overall linear trend in the historical data, as well as Winters's method, which further adjusts for seasonality.

Figure H2 Comparison of Forecasts: Bass Model vs. Exponential Smooth



Source: Casewriter.

One additional note is that the Bass model has a terminal value of *m* for its forecast, the total market size. If one forecasts far enough in the future, the exponential smooth method will continue *ad infinitum* and, thus, exceed all realistic sales estimates! This is an inherent danger of extrapolating too far using exponential smoothing methods. In practice, to avoid this trap, exponential smoothing methods are sometimes applied as a rolling forecast of the next several (say, five) time periods. When actual sales data become available at each time period, these actual data are typically recorded and the exponential smoothing method is used to recalculate a forecast for the next five time periods in the future. For example, let's assume we have three years of historical monthly sales data through January 2005, and we have used an exponential smoothing method to forecast sales for the next five months (i.e., February 2005 through June 2005). When actual sales data for February 2005 become available, we can use these data and the exponential smoothing method to recalculate a five-month forecast for March 2005 through July 2005. Thus, we limit the extrapolation of exponential smoothing and re-calculate our forecasts as more data become available.

Summary

The overarching goal of this note was to provide you with tools and methodologies for forecasting the demand of innovative new products. **Figure I** provides a tabular summary to help in distinguishing the major concepts and methodologies discussed in this note; each has its own place in the toolbox of the marketer in business today. Our focus on the Bass model reflects our belief that it should be a central part of developing estimates for the adoption of new products. It is the only method that addresses the diffusion of an innovation in terms of how information about the product is shared among the pool of potential adopters of the product, and it can be applied early in a product's development. And, to be sure, the Bass model provides more than just a number or a curve over time—it facilitates a greater understanding of the market for the new product so that, ultimately, better decisions about its marketing and promotion can be made.

Figure I Relevant Concepts and Methodologies for Demand Forecasting

Methodology	Models Sales/Adoption over Time	Requires Previous Sales Data of the Product	Includes Marketing-Mix Variables	Models Underlying Behavior or Consumer Preferences	Estimates Market Share
Bass model	X			X	
Generalized Bass Model (GBM)	X		X	X	
Discrete-choice model (market-share model)			X	X	X
Exponential smoothing method	X	X			

Source: Casewriter.

Appendix
Estimating Bass Model Parameters from Past Sales Data[14]

Background

A method of estimating the parameters of the Bass model via ordinary-least-squares (OLS) regression was also offered in Bass's seminal paper in 1969. The approach first re-expresses the Bass model as the following:

$S(t) = [p + (q/m)\,N(t-1)]\,[m - N(t-1)] = pm + (q-p)\,N(t-1) - (q/m)\,N(t-1)^2$

Or, more simply:

$S(t) = \mathrm{a} + \mathrm{b}\,N(t-1) + \mathrm{c}\,N(t-1)^2$

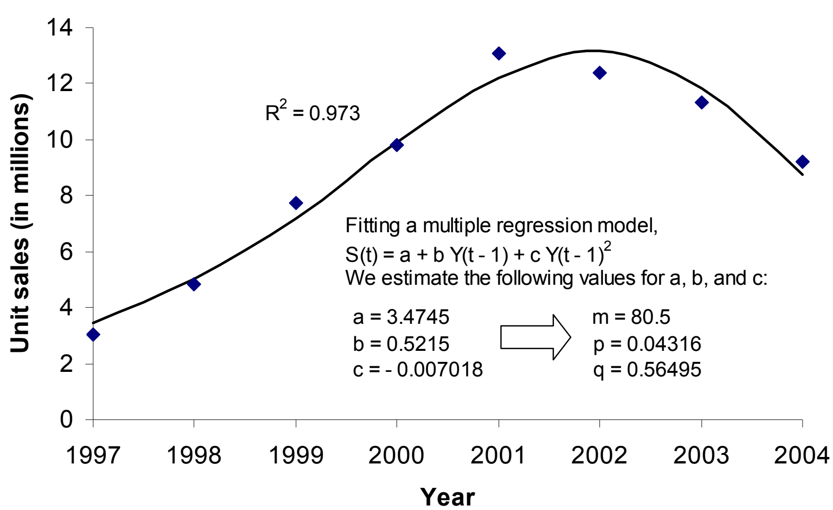
Parameters a, b, and c are then estimated via OLS regression using almost any statistical software package. The parameters m, p, and q are then determined by:

1. $m = -\mathrm{b} \pm (\mathrm{b}^2 - 4\mathrm{ac})^{1/2}/2\mathrm{c}$
2. $p = \mathrm{a}/m$
3. $q = -m\mathrm{c}$

[14]In general, stable and robust estimates of the Bass model parameters are obtained only if the data under consideration include the peak of the noncumulative adoption curve. Several methods have been proposed for updating parameter estimates as more data become available. For a more complete discussion of estimation procedures for the Bass model, the reader is referred to: Vijay Mahajan, Eitan Muller, and Frank M. Bass, "New Product Diffusion Models in Marketing: A Review and Directions for Research," *Journal of Marketing,* 54 (January 1990): 1–26; and William P. Putsis, Jr. and V. Srinivasan, "Estimation Techniques for Macro Diffusion Models," Chapter 11 in Mahajan, Muller, and Wind, eds., *New-Product Diffusion Models*.

Case Example—Handheld Organizers (1997–2004)

Handheld organizers provide an excellent case example for demonstration of this method. Note that what we call a handheld organizer was also called a personal digital assistant (PDA) in the late 1990s. At the time, these products were used as an extension of the PC—a way to take notes, keep track of personal contacts, and write e-mails offline. Of these models, the Palm Pilot was the undisputed market leader. Once handheld devices became wireless and Web-enabled communication tools, the term "smart phones" was introduced, and the old models like the Palm Pilot began to be described as "handheld organizers." The introduction of wireless PDAs/smart phones hastened the end of the adoption curve of handheld organizers. **Figure J** shows the approach to the OLS regression analysis.



Source: Casewriter.