Which Stage of the Consumer's New Product Adoption Process Follows the Bass Model? An Empirical Exploration

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Abstract

The Bass Model, an elegant and powerful statistical model for new product sales forecasting, is founded on the behavioral premise of "innovation" and "imitation." In this paper, we try to understand at which stage of the new product adoption process – (1) awareness, (2) purchase, or (3) usage – does this behavioral premise of innovation and imitation apply. In other words, is it possible that innovation (i.e., independent decision-making) and imitation (i.e., following the lead of others) are behavioral concepts that actually apply at the stage of consumers becoming *aware* of the new product (i.e., prior to actual adoption) rather than at the time of actual adoption? Alternatively, could these concepts apply at the stage when consumers *use* the purchased product (i.e., after actual adoption)? Using adoption data from 48 product categories, we shed light on the answers to these questions. We are able to identify these effects by overlaying an additional parameter, called the *skew* parameter, in the Bass Model, and then exploiting the observed asymmetries around the mode in the adoption data to empirically identify its value. When the estimated skew parameter is equal to 1, our proposed model reduces to the traditional Bass Model, which says that the behavioral premise of innovation and imitation directly applies to the purchase stage in consumers' new product adoption processes. Values smaller and larger than 1, however, imply that the premise of innovation and imitation applies to the awareness and usage stages, respectively, rather than to the purchase stage. We find that the Bass Model applies (1) at the awareness stage for 37 product categories, (2) at the purchase stage (as is assumed in traditional applications of the Bass Model) for 10 product categories, and (3) at the usage stage for 1 product category. We show that the empirical performance of our proposed model is superior to that of the Nonuniform Influence (NUI) Model of Easingwood, Mahajan and Muller (1983) – which also allows for skewed adoption patterns – for 46 out of 48 product categories.

Keywords: New Product Adoption, Bass Model, Stages in New Product Adoption, Skewness.

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1 Introduction

There is an extensive amount of academic research in marketing on the development and applications of new product adoption models. The most influential model in this stream of research, that, in fact, pioneered a long subsequent line of research inquiry over four decades, is the Bass Model (Bass 1969). The attractive feature of the Bass Model (BM, henceforth) is that it allows the hazard function characterizing new product adoption at a point of time to be a linear function of the cumulative distribution function of the adoption process. Such a formulation is based on the following behavioral premise: Some consumers, called *innovators*, adopt the new product for reasons that represent their independent decision-making ability. Such reasons may arise, for example, due to (1) their being better informed about the new product from reading technology magazines, (2) their adventurous needs for novelty etc. Other consumers, called *imitators*, adopt the new product on account of social learning effects, influenced by previous adopters, either by observation or through explicit word of mouth. Such learning may lead these consumers to conclude, for example, that (1) the new product must be of good quality since other consumers have been adopting it, (2) they must adopt the new product lest they "miss out "on the consumption benefits already being reaped by other people. This behavioral premise of innovation and imitation not only makes intuitive sense but also is consistent with an extensive amount of behavioral research that has documented such bases for individuals' adoption practices with regard to new products (see Rogers 1995).

The purpose of this study is to understand at what stage of the consumer's new product adoption process does this behavioral premise of innovation and imitation manifest itself. For example, the literature has discussed the existence of distinct behavioral stages in consumers' new product adoption processes (see Mahajan, Muller and Kerin 1984, Sawhney and Eliashberg 1996, Eliashberg, Jonker, Sawhney and Wierenga 2000). We look at the following three broad stages of the consumer's new product adoption process: (1) awareness, (2) purchase and (3) usage.[1] We posit that the behavioral premise of BM, i.e., innovation and imitation, may specifically characterize *one* of the three stages, and as to which stage this is may not be the same across product categories. Using product penetration data from 48 product categories,

[1] These stages are referred to as (1) knowledge, (2) decision, and (3) implementation, respectively,by Rogers (1995).

we empirically prove this assertion. For this purpose, we first embellish the BM with an additional parameter, called the *skew* parameter. This parameter, depending on whether its value is smaller than, equal to, or larger than 1, captures the fact that innovation and imitation may be relevant descriptors of the awareness, purchase and usage stages respectively.[2] We find that the behavioral premise of the BM, i.e., innovation and imitation, characterizes (1) the awareness stage for 37 out of 48 product categories, (2) the purchase stage for 10 out of 48 product categories, and (3) the usage stage for 1 out of the 48 product categories.

The remainder of the paper is organized as follows. In section 2 we develop our proposed modification of BM, called Modified Bass Model (MBM henceforth). We also show how to embed the effects of marketing variables within this model, which yields the Generalized Modified Bass Model (GMBM), and provide estimation details. In section 3 we describe our data and present the empirical results. Concluding remarks are made in Section 4.

2 Modified Bass Model (MBM)

We present this section in two parts. First, we develop the MBM. Second, we provide estimation details.

2.1 Model Development

An individual is assumed to pass through three stages in his new product adoption process: (1) awareness, (2) purchase, and (3) usage. These stages are sequential in the sense that the individual would have to be be aware of the new product before he purchases it, and he would have to purchase the new product before he can use it. Given this structure, one can write down the following relationship between the cumulative distribution functions, at time t, characterizing the awareness, purchase and usage stages of the individual, respectively.

$$F_a(t) \geq F_p(t) \geq F_u(t). \tag{1}$$

In other words, at any point of time t, the individual's cumulative probability of being aware of the new product must be no less than his cumulative probability of purchasing the product, which in turn must be no less than his cumulative probability of using the product. Said

[2]In fact, when the skew parameter is equal to 1, our modified BM reduces to the traditional BM.

differently, within a population of consumers, at any point of time t, the cumulative number of consumers who are aware of the new product must be no less than the cumulative number who have purchased the product, who in turn must be no less than the cumulative number who have used the product.

We can represent the dependence between $F_a(t)$, $F_p(t)$ and $F_u(t)$ as shown below, that preserves the inequality shown in equation (1), without any loss of generality.

$$F_a(t)^{\frac{1}{\alpha_1}} = F_p(t) = F_u(t)^{\alpha_2}, \tag{2}$$

where $\alpha_1 \in [0,1]$ and $\alpha_2 \in [0,1]$ are parameters that relate the individual's cumulative probability of awareness and the cumulative probability of usage, respectively, to the individual's cumulative probability of purchase.[3]

Using new product adoption data, one can estimate $F_p(t)$. The traditional assumption is that $F_p(t)$ follows the BM, as shown below.

$$h_p(t) = p + qF_p(t), \tag{3}$$

where $h_p(t)$ is the hazard function corresponding to $F_p(t)$. This equation – a first-order differential equation – can be solved to obtain the following expression.

$$F_p(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}} \tag{4}$$

This cumulative distribution function implies a density function characterizing new product adoption that is *symmetric* about its mode. However, it has been empirically observed in many cases that new product adoption patterns are asymmetric about their mode, or, in other words, *skewed* (both left-skewed and right-skewed). We propose one behavioral explanation for these "seemingly anomalous "(in reference to the BM) adoption patterns below.

Suppose a consumer's awareness stage, rather than his purchase stage (or the usage stage), follows the BM. In other words,

$$F_a(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}. \tag{5}$$

Taken together with equation (2), this implies the following.

$$F_p(t) = [\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p}e^{-(p+q)t}}]^{\frac{1}{\alpha_1}}, \tag{6}$$

[3] It is easy to show that if F is a proper cdf, $F^{\alpha} (\alpha > 0)$ is also a proper cdf.

where $\alpha_1 \in [0, 1]$. This implies a right-skewed, rather than a symmetric, pattern for new product adoption (see Figures 1 and 2, curves corresponding to $\alpha < 1$).

Suppose a consumer's usage stage, rather than his purchase stage (or the awareness stage), follows the BM. In other words,

$$F_u(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}. \tag{7}$$

Taken together with equation (2), this implies the following.

$$F_p(t) = [\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}]^{\alpha_2}, \tag{8}$$

where $\alpha_2 \in [0, 1]$. This implies a left-skewed, rather than a symmetric, pattern for new product adoption (see Figures 1 and 2, curves corresponding to $\alpha > 1$).

Equations (6) and (8) can be combined to obtain the following MBM, which is our proposed model.

$$F_p(t) = [\frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}]^{\frac{1}{\alpha}}, \tag{9}$$

where $\alpha \in [0, \infty]$. We will refer to the parameter α as the *skew parameter* henceforth. If $\alpha = 1$, the MBM reduces to the traditional BM. This implies that innovation and imitation effects, as postulated by the BM, directly apply to the purchase stage of the consumer's adoption process. If $\alpha < 1$, the innovation and imitation effects inherent in the BM apply to the awareness stage of adoption, and if $\alpha > 1$, the effects apply to the usage stage of adoption. Figures 1, 2 and 3 illustrate the effects of varying α on the distribution $(F_p(t))$, density $(f_p(t))$ and hazard $(h_p(t))$ functions respectively. The case of the symmetric density in Figure 2 corresponds to $\alpha = 1$. The hazard function $(h_p(t))$ associated with the MBM can take a variety of flexible shapes (including declining and U-shaped), for various values of the skew parameter α, as shown in Figure 3. One can notice in Figure 3 that the increasing, S-shaped hazard that is associated with the BM corresponds to $\alpha = 1$. This makes the MBM a highly flexible diffusion model for new product adoption, while still preserving the core behavioral premise, and therefore theoretical elegance, of the BM.

We can incorporate marketing variables in the MBM, in the same manner as proposed by Bass, Krishnan and Jain (1994) for the BM, as shown below.

$$F_p(t) = [\frac{1 - e^{-(p+q)\{t + \beta_P lnP_t + \beta_A lnA_t\}}}{1 + \frac{q}{p} e^{-(p+q)\{t + \beta_P lnP_t + \beta_A lnA_t\}}}]^{\frac{1}{\alpha}}, \tag{10}$$

where P_t stands for the price of the product at time t (relative to its price in period 1), β_P is the corresponding price coefficient, A_t stands for the advertising expenditure associated with the product at time t (relative to the advertising expenditure at time 1), and β_A is the corresponding advertising coefficient. One would expect the price coefficient, β_P, to be negative, and the advertising coefficient, β_A, to be positive. In the spirit of the Bass, Krishnan and Jain (1994) model being called the Generalized Bass Model (GBM), we call this version of our proposed MBM as the Generalized Modified Bass Model (GMBM). Just as the GBM nests the BM as a special case – when (i) $\beta_P = \beta_A = 0$ or (ii) $\frac{P_t}{P_{t-1}} = constant\ \forall t$ and $\frac{A_t}{A_{t-1}} = constant\ \forall t$ – the GMBM nests the MBM as a special case under the same conditions.

Figures 1-3 summarize the effects of the skew parameter α on the stochastic process governing new product adoption. For example, in Figure 2, it is observed that as α decreases from 1, the density curve shifts to the right, and peaks later, which is consistent with consumers' purchase propensities lagging behind their awareness propensities (as also evidenced by the distribution curve shifting to the right in Figure 1). It is also observed in Figure 2 that as α increases from 1, the density curve shifts to the left, and peaks earlier, which is consistent with consumers' purchase propensities leading ahead of their usage propensities (as also evidenced by the distribution curve shifting to the left in Figure 1). Figure 3 reveals a range of flexible shapes – increasing, decreasing and U-shaped – for the implied hazard, with the increasing S-shaped hazard of the BM observed when $\alpha = 1$.

2.2 Estimation

The parameters of our proposed MBM can be estimated using the non-linear least squares (NLS) technique that was proposed by Jain and Rao (1990) to estimate the BM.[4] The following estimation equation characterizes this NLS estimation procedure.

$$n_t = [m - N_{t-1}]\frac{[F_p(t) - F_p(t-1)]}{[1 - F_p(t-1)]} + \epsilon_t, \tag{11}$$

where n_t refers to the observed number of adoptions for the product in year t, N_{t-1} refers to the cumulative number of adoptions for the product until (and including) year $t-1$, m is an estimable parameter that refers to the market potential for the product, $F_p(t)$ is given by

[4] An alternative estimation technique is that proposed by Srinivasan and Mason (1986). We found that the Jain and Rao (1990) technique fit the observed diffusion data better than the Srinivasan and Mason (1986) technique for all product categories. Therefore, the reported results are based on the Jain and Rao (1990) technique.

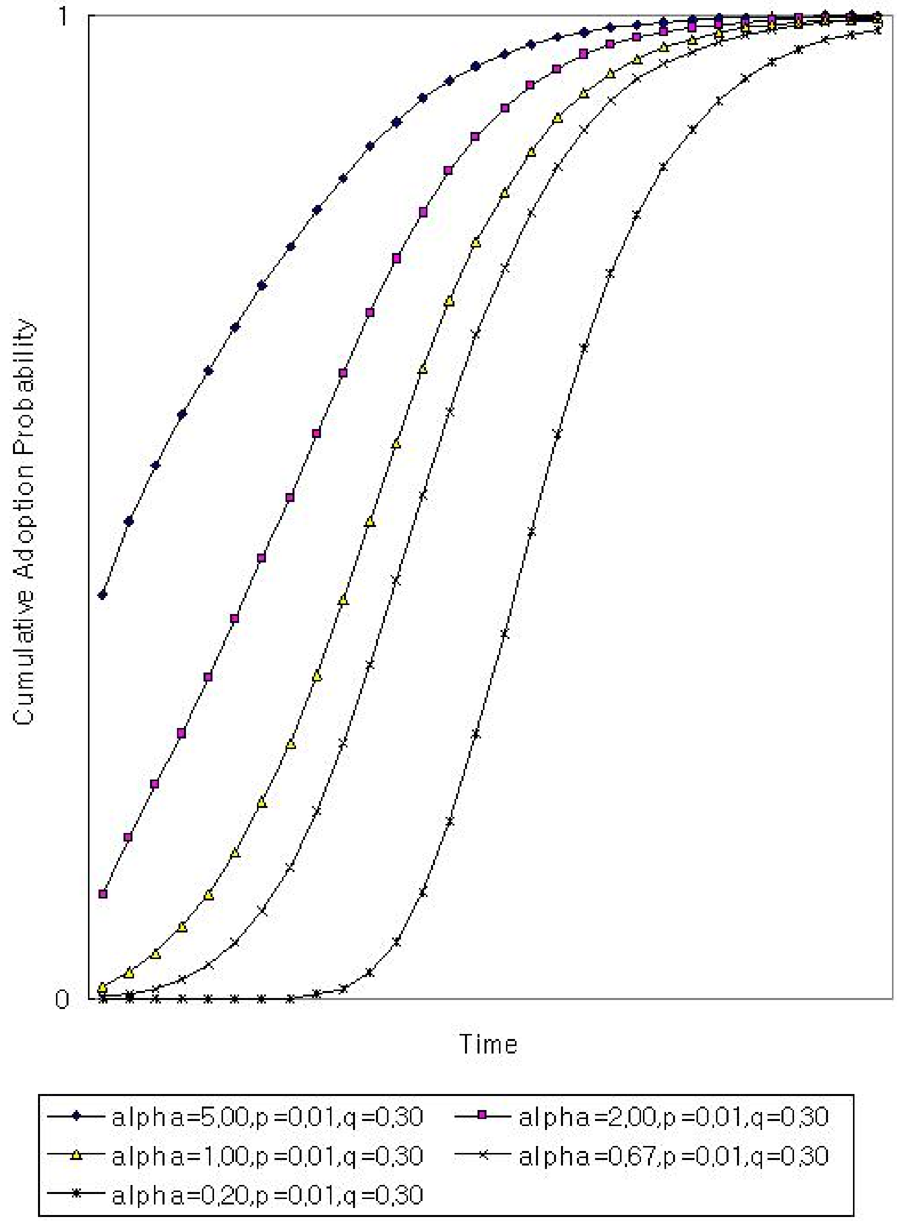

Figure 1: Probability Distribution Functions Implied by the MBM

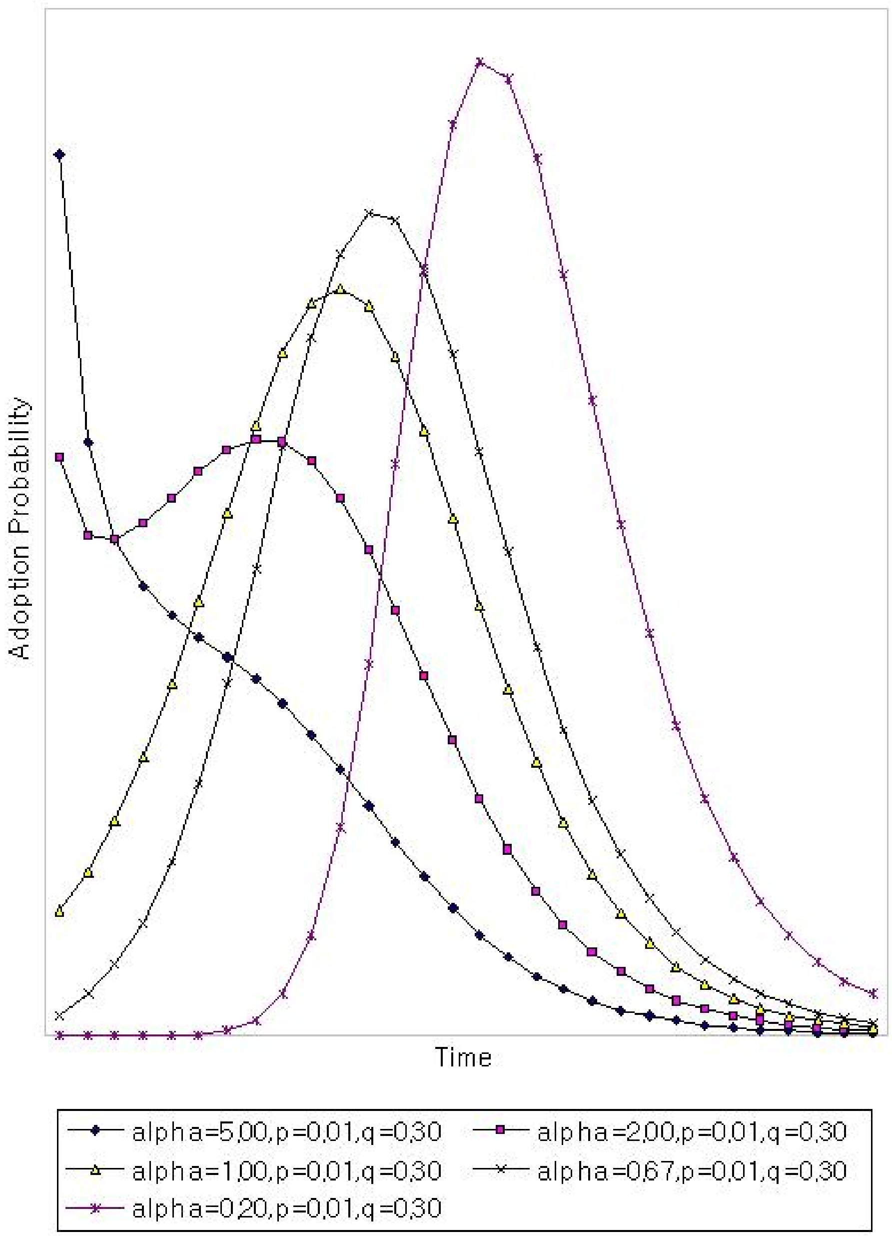

Figure 2: Probability Density Functions Implied by the MBM

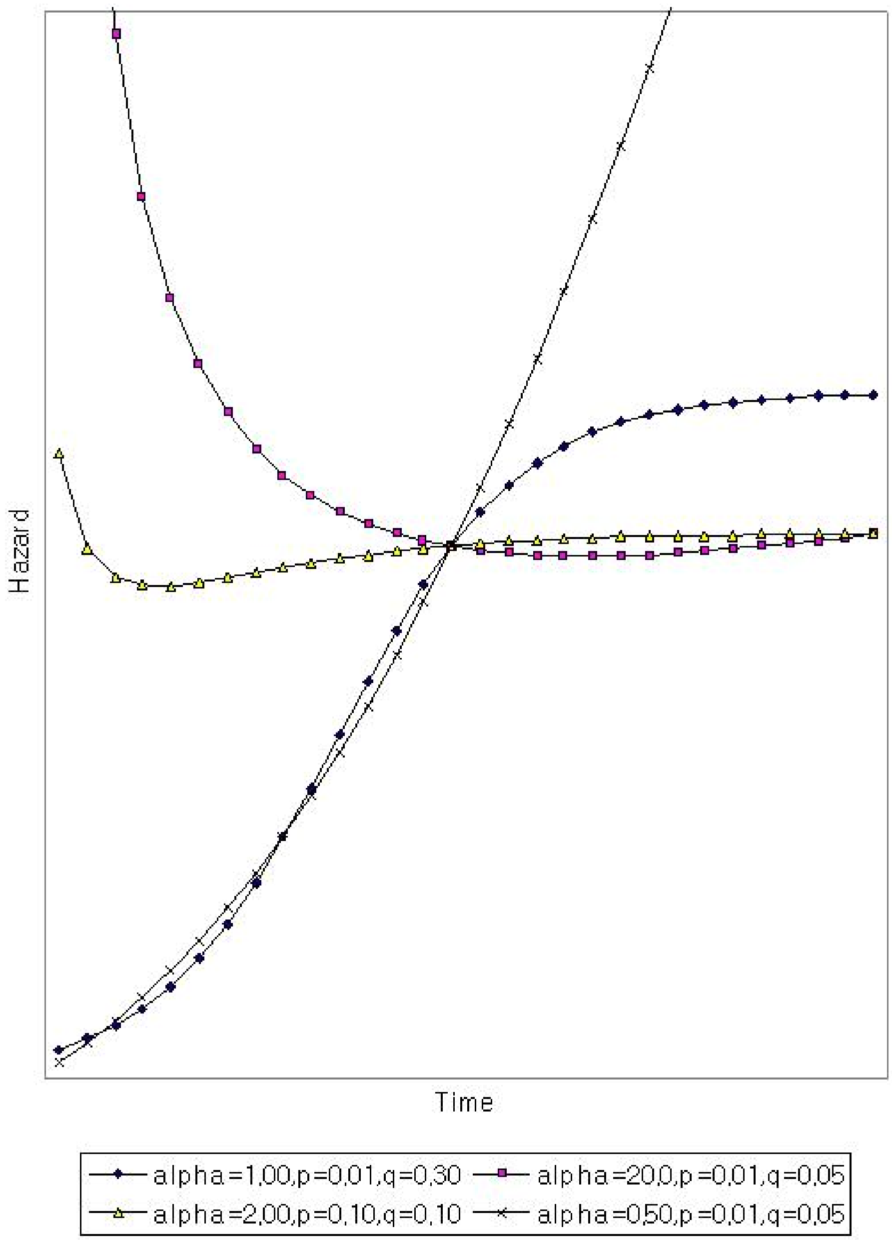

Figure 3: Hazard Functions Implied by the MBM

equation (9), and ϵ_t is the estimation error with mean zero. It is useful to note here that the MBM involves just one additional parameter – α – compared to the three parameters – p, q, m – of the BM. This appears to be a minor modeling cost considering the considerable additional flexibility afforded by the MBM in explaining observed adoption patterns.

The Non-Uniform Influence (NUI) Model, proposed by Easingwood, Mahajan and Muller (1983), also allows for skewed adoption patterns for new products, using just one additional parameter compared to the BM, also nesting the BM as a special case (when $\delta = 1$), as shown below.

$$h_p(t) = p + qF_p(t)^{\delta}, \tag{12}$$

where δ can be interpreted as the skew parameter of the NUI model. The theoretical disadvantage of the NUI model, compared to our proposed MBM, is that it does not have a closed-form representation for $F_p(t)$.[5] This makes the direct interpretation of the model parameters difficult. Further, Lilien, Kotler, and Moorthy (1992) observe that although the NUI model is empirically more flexible than the BM, "there is no causal or behavioral theory to help predict what the value of the extra (skew) coefficient should be." Since our MBM is derived using the behavioral premise of sequential stages in consumer decision-making, it does not suffer from this limitation. However, regardless of these relative theoretical and substantive advantages, *a priori*, of our proposed MBM over the NUI, whether the NUI model or our proposed MBM better explains observed adoption patterns of new products, and the asymmetries / skews inherent in them, is still an important empirical question. For this reason, we use the NUI model as a benchmark model while empirically estimating our proposed MBM using adoption data.

3 Empirical Results

3.1 Comparing MBM versus NUI and BM

We use publicly available penetration data on 48 different new products spanning the following industries: agricultural equipment, medical equipment, production technology, electrical appliances and consumer electronics (see Mahajan, Muller and Wind 2000). We estimate the proposed model of new product diffusion, i.e., MBM, as well as the two benchmark models, i.e.,

[5] In other words, the first-order differential equation represented by equation (11) cannot be solved to obtain a closed-form solution for $F_p(t)$.

NUI and BM, in each product category, and compare the three models in terms of the minimized least-squares criterion in order to identify the best-fitting model for each product.[6] The results of this fit comparison are presented in Tables 1 and 2.

Interestingly, the proposed MBM is found to be the best-fitting model for 46 out of 48 products, and the second-best model for 2 out of 46 products (i.e., mixers and black-and-white television).[7] We report the estimates of the MBM for the 48 products in Tables 3 and 4.

We find that the estimated value of α is not significantly different from one[8], as is assumed under the traditional Bass Model, for 10 out of 48 products in the data (Oxygen Steel-France, Scanning Stores-FRG, Ultrasound, Hybrid Corn, Blender, Dishwasher, Disposers, Microwave, Cordless Telephone, Leaf Blower). Among the remaining 38 products, the estimated value of α is significantly larger than one for 1 product (Tractors), and significantly less than one for 37 products. This implies that innovation and imitation effects, as embodied in the mathematical structure of the Bass Model, characterize the (1) awareness stage for 37 out of 48 products, (2) purchase stage for 10 out of 48 products, and (3) usage stage for 1 out of 48 products.

3.2 Comparing GMBM versus GBM

Bass, Krishnan and Jain (1994) derived a behaviorally appealing extension of the BM, called the GBM, where price and advertising were included in the BM by changing the time variable, t, to a composite variable of time and marketing variables, $t + \beta_P P_t + \beta_A A_t$. The appeal of the GBM lies in its ability to easily explain why the BM fits new product adoption data so well even though it ignores the influence of marketing variables. The reason is that prices and advertising expenditures for most new products approximately satisfy the condition $\frac{P_t}{P_{t-1}} = constant\ \forall t$ and $\frac{A_t}{A_{t-1}} = constant\ \forall t$. Since our GMBM extends the MBM by changing the time variable, t, to a composite variable of time and marketing variables, $t + \beta_P P_t + \beta_A A_t$, it retains the appealing behavioral premise of the GBM. In order to test whether the GMBM fits new product adoption data better than the GBM, we use the same new product penetration data used by Bass, Krishnan and Jain (1994) to demonstrate the empirical performance of the GBM. These

[6] In order to keep this model comparison meaningful, we use the same estimation technique, that proposed by Jain and Rao (1990), to estimate the three models.

[7] Among the 2 exceptions, for the mixers category, the MBM does almost as well as the best-fitting NUI.

[8] We use the two-sided 95% confidence interval around the estimated α to see whether or not it includes the value 1.

Product	*MBM*	*NUI*	*BM*
Tractors	451706	455414	629252
Oxygen Steel (*USA*)	64.63	161.6	335.1
Oxygen Steel (*Japan*)	62.72	94.19	565.1
Oxygen Steel (*France*)	86.97	112.2	97.53
Plastic Milk Containers(1*G*)	40.15	55.02	401.2
Merchant Ships	56.44	143.9	397.8
Scanning Stores (*FRG*)	151505	259945	152435
Scanning Stores (*DK*)	32487	58588	101859
CT Scanners ($<$ 100*beds*)	65.35	123.6	218.1
CT Scanners ($>$ 100*beds*)	149.10	193.6	503
Ultrasound	11.66	17.23	14.42
Mammography	19.96	40.08	28.82
Hybrid Corn	53.04	130.4	55.49
Artificial Insemination	54.73	81.53	276
Bale Hay	40.62	90.31	231.3
Room AC	33.84	45.06	51.19
Bed Cover	30.93	31.41	71.91
Blender	136.30	172.9	138.1
Can Opener	35.51	44.7	249.6
Elec. Coffeemaker	35.09	40.76	159.2
Coffeemaker ADC	4.80	17.17	20.59
Curling Irons	4.94	8.36	10.28
Dishwasher	11.26	13.73	13.73
Disposers	39.55	43.15	42.47

Table 1: *Fit Results: Minimized Sums of Squares for Alternative Models of New Product Diffusion.*

data span 3 different new products: Room AC, Color TV and Clothes Dryer.[9]

We estimate the GMBM and GBM in each product category, and compare the two models in terms of the minimized least-squares criterion in order to identify the best-fitting model for each product. The results of this fit comparison are presented in Table 5, and the corresponding plots of fitted sales are given in Figure 4. Interestingly, the GMBM is found to be the better-fitting model for all three products, which lends further credibility to the model as being well suited to handling the effects of marketing variables. We report the estimates of the GMBM for the 3 products in Tables 6 and 7.

For all three products, we find that the estimated value of α is significantly less than one.

[9] We do undertake this exercise for the product categories represented in section 3.1 since those datasets do not contain marketing variables.

Product	*MBM*	*NUI*	*BM*
Clothes Dryers	77.20	97.74	107.5
Electric Fondue	0.01	0.12	0.38
Hair Dryers	1.69	3.93	14.44
Hotplates	44.50	45.32	52.51
Steam Iron	38.57	61.7	785.2
Microwave	15.68	22.73	16.86
Mixers	90.79	89.3	110.8
Ranges	201.4	206	275.2
$Ranges\ Built - In$	4.11	5.06	12.9
Refrigerators	549.9	593.3	2632
Slow Cookers	4.79	9.13	9.65
Clothes Washer	311.2	312.1	743.6
Cable TV	16.23	22.81	70.66
Calculator	1.04	2.51	178.6
CD Player	35.56	40.71	60.12
Home PC	2.07	8.61	11.98
Answering Machine	23.58	31.29	74.29
B&W TV	601.1	418.7	3003.7
Color TV	55.57	67.59	277.5
VCR	68.81	203.8	412.6
Cordless Telephone	36.36	45.27	40.88
Electric Toothbrush	2.39	3.19	4.17
Leaf Blower	5.01	5.73	6.69
Radio	86.08	123.1	153.3

Table 2: *Fit Results: Minimized Sums of Squares for Alternative Models of New Product Diffusion.*

This implies that innovation and imitation effects, as embodied in the mathematical structure of the Bass Model, characterize the awareness stage for these three products, which is consistent with what we found for the majority of products in section 3.1. For comparison purposes, we report the estimates of the GBM for the 3 products in Table 8.

Firstoff, our results for the GBM mirror those obtained by Bass, Krishnan and Jain (1994) using the same data. Comparing the results in Table 8 with those in Tables 6 and 7, we obtain the following findings about the basic diffusion parameters, i.e., p, q, m.

1. The estimated p is always smaller under the GBM than under the GMBM. This implies that the estimated level of innovation in the awareness stage (i.e., desire to read technology magazines to become aware of new technologies) is larger than the degree of innovation

Product	p	q	m	α
Tractors	0.0005 (0.0002)	0.1238 (0.0078)	171220 (5536)	1.3482 (0.1095)
Oxygen Steel (USA)	0.0921 (0.0039)	1e-8 (0.0000)	1717.5 (67.4)	0.1159 (0.0072)
Oxygen Steel (Japan)	0.0735 (0.0047)	1e-8 (0.0000)	2560.2 (157.5)	0.2904 (0.0130)
Oxygen Steel (France)	0.0046 (0.0028)	0.1754 (0.0348)	1640.9 (222.1)	0.7423 (0.1671)
Plastic Milk Containers(1G)	0.0261 (0.0039)	0.0703 (0.0115)	2992.2 (158.0)	0.4098 (0.0345)
Merchant Ships	0.0634 (0.0023)	1e-8 (0.0000)	3390.1 (138.2)	0.1324 (0.0056)
Scanning Stores (FRG)	0.0001 (0.0003)	0.5113 (0.1645)	114080.8 (32688.8)	1.1121 (0.4445)
Scanning Stores (DK)	0.1503 (0.0366)	1e-8 (0.0000)	32678.7 (9704.1)	0.2219 (0.0387)
CT Scanners ($< 100beds$)	0.0999 (0.0141)	1e-8 (0.0000)	1370.0 (216.5)	0.1992 (0.0244)
CT Scanners ($> 100beds$)	0.0328 (0.0115)	0.0790 (0.0308)	2398.2 (263.2)	0.3934 (0.0783)
Ultrasound	0.0005 (0.0004)	0.4593 (0.0581)	760.0 (50.6)	1.2950 (0.2280)
Mammography	0.0060 (0.0047)	0.3331 (0.0562)	592.6 (49.0)	0.5930 (0.1748)
Hybrid Corn	0.0006 (0.0008)	0.4585 (0.0774)	841.7 (69.1)	0.8257 (0.2510)
Artificial Insemination	0.0638 (0.0058)	1e-8 (0.0000)	2642.3 (263.5)	0.2872 (0.0161)
Bale Hay	0.0639 (0.0318)	0.0666 (0.0564)	1893.6 (256.4)	0.2130 (0.0682)
Room AC	0.0050 (0.0015)	0.1070 (0.0124)	1734.0 (128.2)	0.6536 (0.0799)
Bed Cover	0.0074 (0.0012)	0.0760 (0.0086)	2504.6 (188.3)	0.6495 (0.0500)
Blender	0.0003 (0.0005)	0.1998 (0.0457)	1073.3 (129.2)	1.1680 (0.3846)
Can Opener	0.0378 (0.0042)	1e-8 (0.0000)	3564.2 (452.6)	0.3926 (0.0163)
Electric Coffeemaker	0.0134 (0.0006)	0.0450 (0.0062)	5296.4 (456.3)	0.7494 (0.0244)
Coffeemaker ADC	0.2372 (0.3650)	0.0502 (0.5126)	299.2 (96.6)	0.1629 (0.1773)
Curling Irons	0.0691 (0.0750)	0.2894 (0.2276)	253.0 (66.7)	0.4187 (0.2439)
Dishwasher	0.0003 (0.0001)	0.1960 (0.0172)	933.5 (46.7)	1.2916 (0.1519)
Disposers	0.0004 (0.0003)	0.1770 (0.0301)	1102.7 (126.1)	1.3766 (0.2831)

Table 3: *Parameter Estimates for the MBM (standard errors within parentheses).*

that one would infer at the purchase stage of adoption (i.e., adventure-seeking by buying new products) if one ignored the awareness stage of adoption.

2. The estimated q is always larger under the GBM than under the GMBM. This implies that the estimated level of imitation in the awareness stage (i.e., talking to friends and becoming aware of new technologies) is smaller than the degree of imitation that one would infer at the purchase stage of adoption (i.e., observing previous adoptions and then adopting the product oneself) if one ignored the awareness stage of adoption.

3. The estimated m is always smaller under the GBM than under the GMBM. In other words, the GBM under-estimates the market potential for the new product as long as α is *smaller* than 1.

Product	p	q	m	α
Clothes Dryers	0.0063 (0.0023)	0.0836 (0.0164)	2353.6 (329.4)	0.6090 (0.0969)
Electric Fondue	0.1142 (0.0104)	0.0369 (0.0276)	73.0 (4.7)	0.3906 (0.0237)
Hair Dryers	0.0743 (0.0239)	0.0444 (0.1038)	1160.4 (787.8)	0.3003 (0.0723)
Hotplates	0.0050 (0.0013)	0.0155 (0.0071)	4032.3 (1769.7)	0.8739 (0.0424)
Steam Iron	0.0233 (0.0009)	0.0029 (0.0081)	8426.6 (1763.5)	0.4373 (0.0188)
Microwave	0.0013 (0.0009)	0.2542 (0.0359)	1172.6 (124.2)	0.8225 (0.1597)
Mixers	0.0072 (0.0007)	0.0743 (0.0062)	3975.2 (196.6)	0.8891 (0.0427)
Ranges	0.0033 (0.0020)	0.0151 (0.0164)	18676.6 (38673.9)	0.5204 (0.0890)
Ranges Built − In	0.0176 (0.0025)	0.0511 (0.0163)	881.8 (157.1)	0.5695 (0.0524)
Refrigerators	0.0263 (0.0019)	1e-8 (0.0000)	8402.5 (599.3)	0.3432 (0.0139)
Slow Cookers	0.0449 (0.0397)	0.4019 (0.1585)	258.2 (36.7)	0.5109 (0.2214)
Clothes Washer	0.0074 (0.0005)	0.0166 (0.0060)	11235.2 (2673.2)	0.6777 (0.0345)
Cable TV	0.0163 (0.0045)	1e-8 (0.0000)	7850.2 (2553.9)	0.6091 (0.0184)
Calculator	0.1666 (0.0030)	1e-8 (0.0000)	1416.4 (25.3)	0.2542 (0.0035)
CD Player	0.0529 (0.0303)	1e-8 (0.0000)	1397.0 (1047.8)	0.3666 (0.0687)
Home PC	0.1361 (0.0250)	1e-8 (0.0000)	397.9 (89.0)	0.2490 (0.0290)
Answering Machine	0.0310 (0.0121)	0.1440 (0.0444)	1180.6 (160.0)	0.4467 (0.0912)
B&W TV	0.0469 (0.0047)	1e-8 (0.0000)	4523.5 (377.7)	0.4117 (0.0228)
Color TV	0.0442 (0.0065)	1e-8 (0.0000)	4732.8 (865.0)	0.3672 (0.0194)
VCR	0.1412 (0.0097)	1e-8 (0.0000)	1386.0 (91.1)	0.1375 (0.0122)
Cordless Telephone	0.0109 (0.0060)	0.1939 (0.0576)	1084.4 (232.3)	0.7783 (0.1832)
Electric Toothbrush	0.0983 (0.0398)	1e-8 (0.0000)	320.7 (134.8)	0.4359 (0.0649)
Leaf Blower	0.0208 (0.0069)	0.1133 (0.0824)	630.9 (397.0)	0.6801 (0.1649)
Radio	0.0315 (0.0226)	0.1376 (0.0890)	1857.6 (651.5)	0.4079 (0.1548)

Table 4: *Parameter Estimates for the MBM (standard errors within parentheses).*

Of course, for all three product categories used in the above analyses, the estimated value of α is smaller than 1. In order to understand the nature of the above-mentioned distortions in the parameter estimates in a more general manner, we classify the 48 product categories represented in Tables 3 and 4 into two classes: (1) those for which the estimated $\alpha < 1$, and (2) those for which the estimated $\alpha > 1$ (regardless of statistical significance). We then compare the estimated values of p, q and m between the BM and the MBM. We obtain the following findings.

1. The estimated p is always smaller (larger) under the BM than under the MBM when the estimated α is smaller (larger) than 1. In fact, the estimated p under the MBM is always insignificant when the estimated α is larger than 1, which implies that innovation effects

typically do not characterize the usage stage of adoption.

2. The estimated q is always larger (smaller) under the BM than under the MBM when the estimated α is smaller (larger) than 1. This implies that the estimated level of imitation in the usage stage (i.e., talking to friends and becoming aware of their usage experiences) is larger than the degree of imitation that one would infer at the purchase stage of adoption (i.e., observing previous adoptions and then adopting the product oneself) if one ignored the usage stage of adoption.

3. The estimated m is always smaller under the BM than under the MBM when the estimated α is smaller (larger) than 1. This implies that the bias in the estimated market potential is systematically smaller or larger than the true m (i.e., that implied by the MBM) depending on whether α is smaller or larger than 1 respectively.

In order to compare the GMBM and the GBM in terms of their estimated effectiveness of the marketing mix, we plot the price elasticities and advertising elasticities, when they are significantly different from zero (computed at the observed values of price and advertising for each product), under each model as a function of time. These are shown in Figures 5 and 6. In Figure 6, which plots the estimated price elasticities for Room AC and Color TV, we see that the GBM significantly under-estimates the magnitude of the price elasticity (-1.625 and -8 for Room AC and Color TV respectively) compared to the GMBM (-2.75 and -12, respectively) during the first year of adoption. To the extent that these price elasticities inform the manufacturers about the optimal introductory pricing for their new products, the GBM may lead the product manager to price higher than what would be profitable when launching the product (assuming, of course, that fitted adoption curves for analogous products – that resemble our estimated adoption curves – are available to the product manager). An interesting cross-over pattern is observed for the price-elasticity curves yielded by the two models. In other words, the GBM under-estimates the price elasticities for early years, and over-estimates the price elasticities for later years of new product adoption.

As regards the advertising elasticities, a similar pattern is observed for Room AC. Except for year 1, when the advertising elasticity is under-estimated (0.7 versus 0.8), the GBM consistently over-estimates the magnitude of the advertising elasticity compared to the GMBM (0.6

versus 0.35 in year 7). Again, to the extent that the product manager employs the GBM-based advertising elasticity for advertising planning, it may lead him to under-advertise the product during launch.

Product	*MBM*	*GBM*
Room AC	96360.2	129735
Color TV	148926	350981
Clothes Dryer	50910.9	101141

Table 5: *Fit Results: Minimized Sums of Squares for GMBM and GBM.*

Product	p	q	m	α
Room AC	0.0314 (0.0385)	0.1954 (0.1025)	22563.3 (3116.8)	0.4296 (0.2601)
Color TV	0.0141 (0.0100)	0.4507 (0.0656)	43017.4 (1925.9)	0.5103 (0.1623)
Clothes Dryer	0.0453 (0.0345)	0.1354 (0.0917)	21641.5 (3924.1)	0.4102 (0.1752)

Table 6: *Parameter Estimates for the GMBM (standard errors within parentheses).*

Product	β_P	β_A
Room AC	-1.1257 (0.5856)	0.3707 (0.2427)
Color TV	-3.8691 (1.468)	-0.0189 (0.0943)
Clothes Dryer	0.6790 (0.6803)	0.6674 (0.2201)

Table 7: *Parameter Estimates for the GMBM (standard errors within parentheses).*

4 Conclusions

In this paper, we investigate whether the behavioral premise inherent in the Bass Model (BM) – innovation and imitation effects that drive new product adoption – applies to the (1) awareness stage, (2) purchase stage, or (3) usage stage of the consumer's new product adoption process. For this purpose, we modify the BM using an additional parameter, called the *skew parameter*, and estimate the modified BM (MBM) using adoption data on 48 new products. We find that the behavioral premise of innovation and imitation effects apply to the (1) awareness stage for 37 out of 48 products, (2) purchase stage for 10 products, and (3) usage stage for 1 product. We compare the empirical performance of our proposed MBM to that of an alternative model –

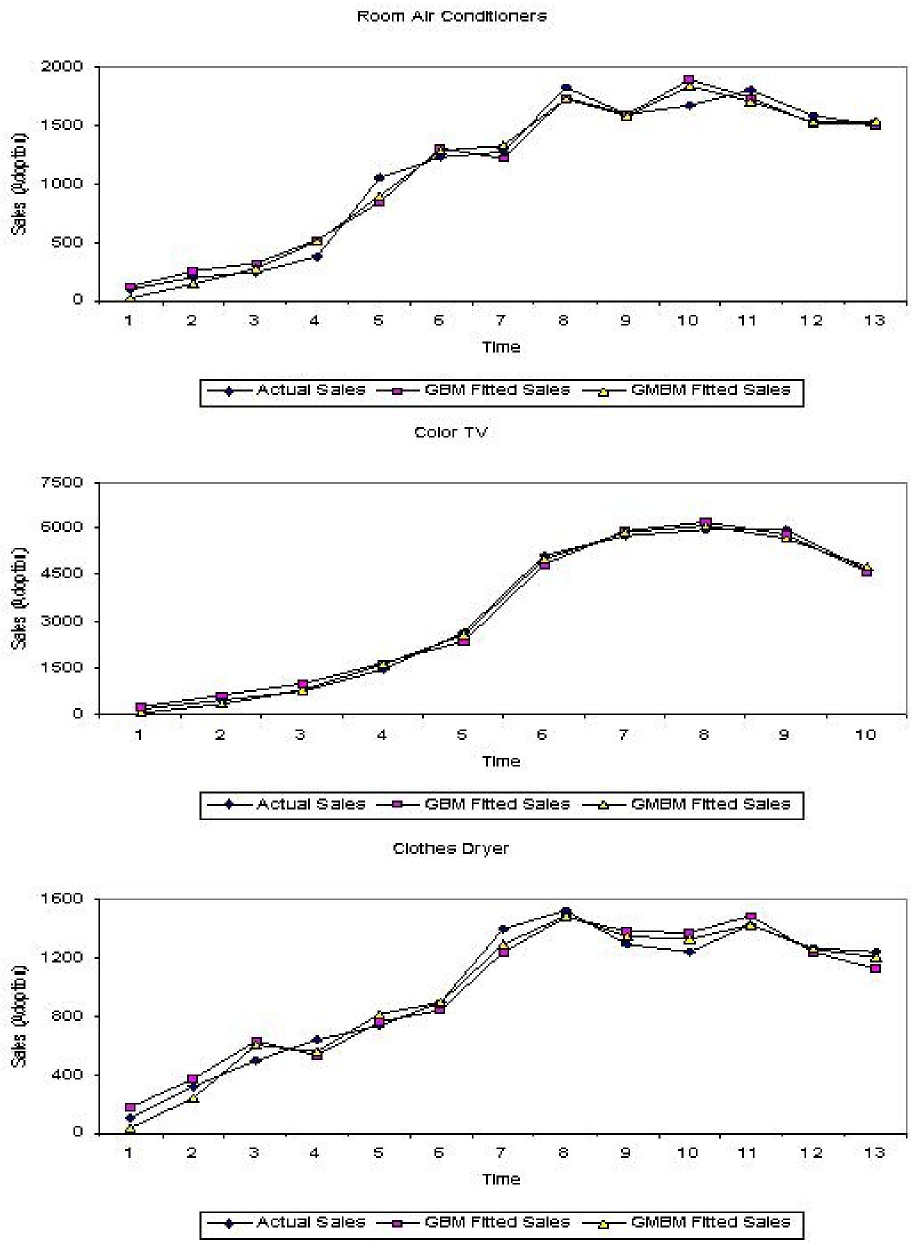

Figure 4: Plots of Fitted and Actual Sales

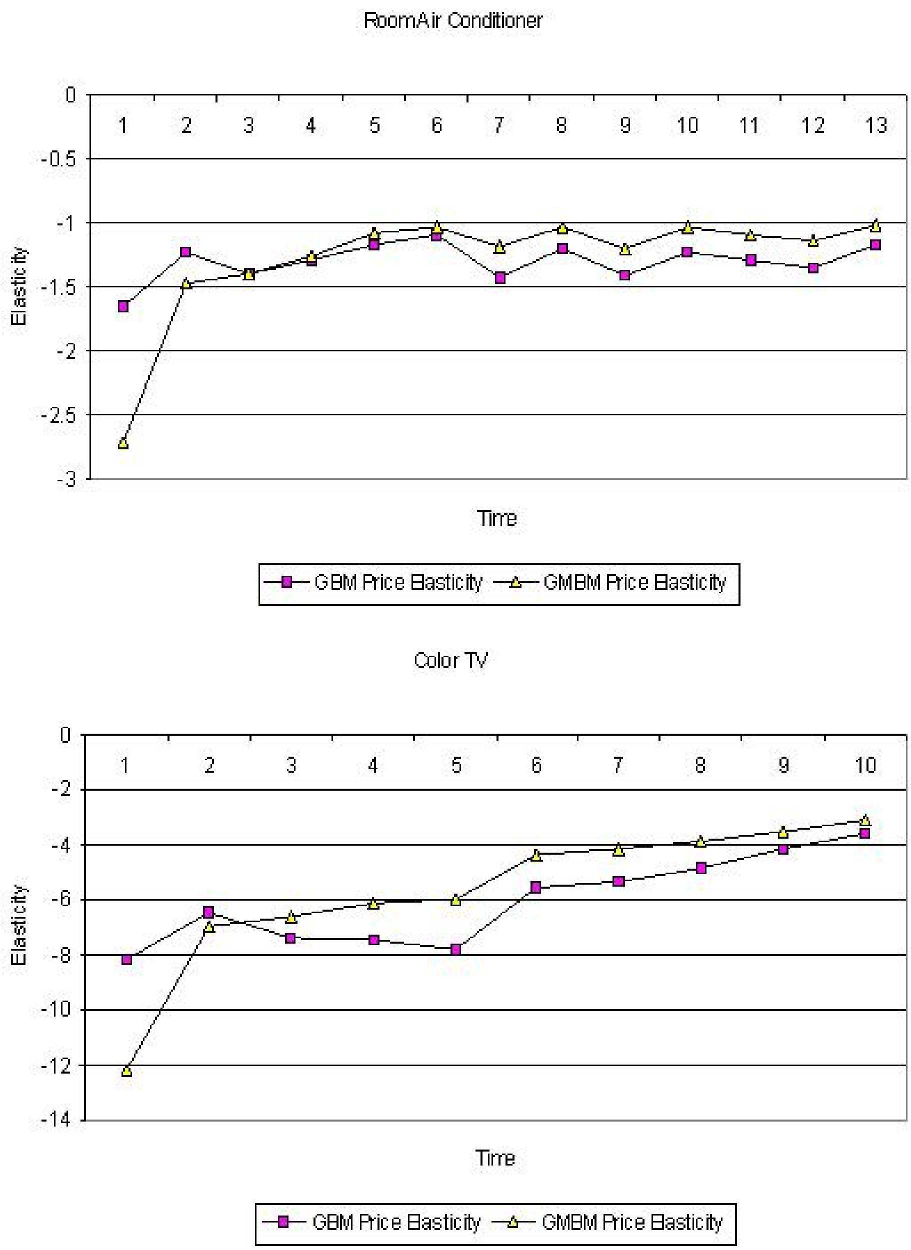

Figure 5: Estimated Price Elasticities

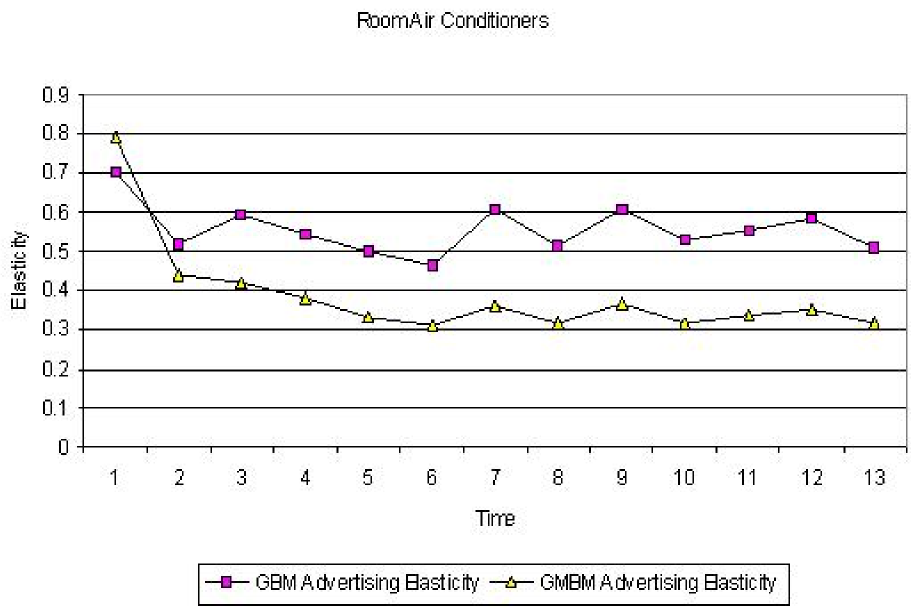

Figure 6: Estimated Advertising Elasticities

Product	p	q	m	β_P	β_A
Room AC	0.0037 (0.0011)	0.3324 (0.0299)	19502.4 (1128.5)	-1.3698 (0.6468)	0.6188 (0.2583)
Color TV	0.0022 (0.0006)	0.5995 (0.0410)	39753.3 (1090.7)	-4.7859 (2.091)	-0.0072 (0.1316)
Clothes Dryer	0.0067 (0.0015)	0.3074 (0.0301)	16980.4 (1069.5)	0.4197 (0.9033)	0.6492 (0.2878)

Table 8: *Parameter Estimates for the GBM (standard errors within parentheses).*

the Non-Uniform Influence (NUI) Model of Easingwood, Mahajan and Muller (1983) – that also overlays an additional parameter over the BM, and find that our proposed MBM outperforms the NUI model for 46 out of 48 products in the data.

We also compare an extended version of the MBM, called the GMBM, which incorporates the effects of marketing mix variables (i.e., price and advertising) on new product adoption patterns, versus the GBM proposed by Bass, Krishnan and Jain (1994). We find that our proposed GMBM better fits the observed data than the GBM. We find that the estimated value of p is larger (smaller), while the estimated value of q is smaller (larger), under the GMBM compared to the GBM, provided the estimated value of α is smaller (larger) than 1. We interpret these systematic distortions in light of the fact that the GMBM estimates the Bass Diffusion pattern at the awareness (usage) stage of adoption, while the GBM estimates the Bass Diffusion pattern at the purchase stage of adoption. We also find that the market potential m is systematically under-estimated or over-estimated by the GBM, depending on whether the skew parameter α is smaller or larger than 1 respectively. We also find that marketing mix elasticities are significantly mis-estimated during the early periods of new product adoption under the GBM when compared to the GMBM.

Just as Krishnan, Bass and Jain (1999) investigate the normative implications of the GBM, it will be interesting to investigate the normative implications of our proposed GMBM for optimal pricing and advertising policies for new products. We leave this as an avenue for future research.

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