PRICE ELASTICITY DYNAMICS OVER THE PRODUCT LIFE CYCLE: A STUDY OF CONSUMER DURABLES

by

P. M. PARKER*
and
R. NEELAMEGHAM**

96/71/MKT

* Associate Professor of Marketing at INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France.

** Assistant Professor of Marketing at INSEAD, Boulevard de Constance, 77305 Fontainebleau Cedex, France.

PRICE ELASTICITY DYNAMICS OVER THE PRODUCT LIFE CYCLE: A STUDY OF CONSUMER DURABLES

Philip M. Parker*

Ramya Neelamegham**

* Associate Professor, INSEAD, Fontainebleau, France.
** Assistant Professor, INSEAD, Fontainebleau, France.

Please address correspondence to: Philip M. Parker, Dept of Marketing, INSEAD, Bd de Constance, 77300 Fontainebleau, France, Tel. 60 72 40 00.

Price Elasticity Dynamics Over the Product Life Cycle: A Study of Consumer Durables

Abstract

Extending the work of Parker (1992) which considers only *first purchases* and Simon (1988) which considers *brand-level sales*, we empirically provide support for the hypothesis that *total category sales* price elasticities, first decease in absolute value, but then ultimately increase if the product in question faces the decline phase of the product life cycle (due to competitive substitutes or changes in tastes, etc.). As an interesting artifact of the methodology, the paper also shows how the Bass model can be easily modified to account for total category sales (first plus repeat purchases) and that, in the limit, the Bass model converges to stochastic repeat purchase models (bridging two radically different modeling traditions). If unadjusted, the Bass model applied to sales data is grossly misspecified when the time series studied exceeds 5 to 10 years for consumer durables.

1. INTRODUCTION

While there is widespread recognition that price elasticities play a critical role in formulating pricing strategies, little empirical research has been conducted to determine if elasticities vary over the product life cycle. Using two different data sets, methodologies and theoretical arguments, Simon (1988) and Parker (1992) conclude that price elasticities, hereafter referred to in absolute value, decline and then ultimately increase for *brand-level sales* and *category-level first purchases*, respectively. Neither consider whether price elasticities for *total category sales* (i.e., blending first and repeat purchases) over the product category life cycle vary. To fill this gap in understanding, in this paper we test the hypothesis that total sales price elasticities also decline and then ultimately increase over the product life cycle (for long lived categories). After motivating this hypothesis, parsimonious discrete-time econometric models which can be used to control for underlying primary demand dynamics are described. These models incorporate both first and repeat purchases. As an artifact of methodology, we show how the Bass model can be easily modified to account for total category sales (incorporating both first and repeat purchases) and that, in the limit, the Bass model converges to stochastic repeat purchase models (Erenberg 1988), thus bridging two radically different modeling traditions. We then report an empirical application of the model which is modified to include price elasticity dynamics. Supporting the need to adjust the Bass model for sales beyond first purchases, we first demonstrate that if unadjusted, the Bass model applied to sales data is grossly misspecified when the time series studied exceeds 5 to 10 years for consumer durables. Next, we co-estimate price elasticities dynamics and diffusion effects using alternative specifications that can yield competing elasticity time paths. We report an empirical analysis which supports the hypothesis using data from thirteen consumer electronic/durable categories. We conclude with certain caveats, managerial implications and areas of future research.

2. THE HYPOTHESIS

The hypothesis we wish to test is applicable to long-lived categories (as opposed to fad products, or those which abort soon after launch):

Ha: as post-launch category sales increase, price elasticities tend to decline,

Hb: if the product life cycle enters into a decline phase, e.g. due to competitive substitutes, elasticities will then increase.

Combined, **Ha** and **Hb** foresee a period of elasticity declines as the product category becomes established within household acquisition priorities, but then increase should the category become threatened by

competitive substitutes. Arguments in favor of Ha include the fact that categories that are long-lived must be supported by repeat/replacement sales (Bayus 1994); the purchases of replacements is a sign of a category becoming more of a necessity to households (Kamakura and Balasubramanian 1987, p. 3). Furthermore, Rogers (1983, pp 166-167, 333) indicates that as adopters confirm their purchases by replacing older or broken versions of the first purchase, they are therefore less sensitive to prices as perceived risks have declined based on learning. This is reinforced by the fact that change agents (firms) are improving product quality to better meet consumer needs. An alternative to this hypothesis is offered by Robertson (1967) who argues that price sensitivities may increase if the innovator-laggard spectrum of adoption is basically determined by the income distribution in the population; later sales will be to populations with lower levels of income, hence elasticities will increase (especially for products which fail to become household necessities – e.g. electric woks). This effect would need to dominate diffusion, or peer pressure, effects that would generally countervail income effects (e.g. the more others purchase the innovation, the lower my price sensitivity; Parker 1992), and fails to consider the existence of replacement sales.

The second part of the hypothesis (Hb) is derived directly from the idea that product life cycles ultimately enter a decline phase, often due to a variety of reasons including shifts in tastes and/or the introduction of a competitive substitutes. The economics of this decline would suggest that elasticities will increase as the number of competitive substitutes increases (Parker 1992). If a product category has yet to enter this phase of the life cycle, then the hypothesis would suggest that one should only observe declines in price elasticities. It should be noted that the hypothesis tested in this paper is related to category-level elasticities; brand-level elasticities within a category will not necessarily vary in the same manner (e.g., they will increase as the number of brands enter the market).

3. THE ECONOMETRIC MODEL

Tellis (1988) and Parker (1992) note that in order to estimate elasticity dynamics, one must control for underlying sales dynamics which may result from diffusion processes. In this spirit, we first describe a category-level sales model which controls for diffusion effects, and then describe how price elasticities are incorporated into that model.

3.1 The Category Sales Model

In order to control for diffusion-based dynamics over the product life cycle we modify the first purchase model proposed in Parker (1992) to incorporate total category sales, s_t, on the left-hand-side of the equation:

$$s_t = \left(a_i + b_i \left(\frac{F_{t-1}}{c_i H_t} \right)^{(1+d_i)} \right) \left(c_i H_t - \frac{F_{t-1}}{Q_{t-1}} \right) \tag{1}$$

Diffusion Effects — Untapped Potential

where a_i, b_i, c_i, and d_i are estimated constants for category i. The parameter c_i ($0 < c_i < 1$) represents the proportion of households that ultimately adopt the category (Jain and Rao 1990; Kamakura and Balasubramanian 1988; Parker 1992), while d_i ($-1 < d_i < \infty$) allows for non-uniform interpersonal influences (Easingwood, Mahajan and Muller 1983). H_t is defined as the number of households wired with electricity (in the case of consumer electronics) in the targeted population. F_t is defined a cumulative first purchases. The traditional Bass model would consider the untapped market potential (the second term on the right-hand-side of equation 1) to be the number of households which have not yet adopted (i.e. $c_iH_t - F_{t-1}$). When households engage in repeat purchasing in the product category, using ($c_iH_t - F_{t-1}$) can systematically overestimate the number of households that have fully adopted (e.g. purchased their life cycle supply). To adjust for repeat purchases, we define Q_t as the average number of units purchased by all households in the population; for most consumer durables, this number infrequently exceeds 3 units over the product's life cycle (e.g., the number of blenders an average household purchases over the life of the average households). For a given household, Q_t has a finite limit because households, themselves, have physical life expectancies (and must eventually die). The ratio $(F_{t-1})/(Q_{t-1})$ deflates first purchases for the current average number of purchases per adopting household and thus allows us to have sales, s_t (as opposed to first purchases, f_t) on the left-hand side of the diffusion equation in (1).[1] If we define R_t as cumulative repeat purchases we can calculate the average level of total life cycle purchases per first purchase, Q_t, as:

$$Q_t = \frac{(F_t + R_t)}{F_t} = \frac{S_t}{F_t} \tag{2}$$

We use Q_t, therefore, in equation (1), to account for a household's long-run purchase behavior.

Alternative adjustments to the Bass (1969) model were considered to allow for total sales, as opposed to first purchases (e.g. multiplying c_iH_t by Q_{t-1}),[2] but these failed to simultaneously provide reasonable asymptotic properties presented by equation (1). For example, one advantage of equation (1) is that a variety or multi-modal and/or asymmetric diffusion patterns can be generated due to the structure of independent variables: dynamic household base (due to population growth), a potentially nondecreasing untapped market (as Q_t may increase), and a flexible diffusion parameter [d_i]. Equation (1) allows for right or

[1] A more complete discussion is available from the authors upon request.

[2] For example, this adjustment leads to long run sales being a function of cumulative repeat purchases, and not the cumulative first purchases, or the numbers of households "in the market".

left skews and/or sales curves having low, high or ever-increasing tails. Market driven product decline or extinction can occur when repeat purchases are extremely low and/or when H_t stagnates or declines. A category can decline out of existence if (1) c_iH_t declines, or (2) Q_t and c_iH_t stagnate simultaneously. A decline in c_iH_t may represent households de-adopting the product permanently (e.g., due to death or dissatisfaction). Conversely, equation (1) can generate life-cycle curves with high right-hand tails (continued growth) provided that R_t and/or H_t grow; the higher Q_t, the higher the tail.

Another desirable asymptotic property of equation (1) not present in alternatives is its ability to reasonably modeling extreme cases. For example, when there are no repurchases of any sort (i.e. R_t=0), equation (1) reduces to the Bass model with a dynamic social system and non-uniform interpersonal influences. If the population stagnates (i.e. H_t is time invariant and Q_t is constant), then the category unit sales will ultimately decline out of existence. When the product category matures in terms of every potential household having implemented the product at least once (i.e., $F_t = c_iH_t$), then category existence completely depends on replacement or multiple purchases. Substituting F_t for c_iH_t, , and equation (2) for Q_{t-1} in equation (1), one finds:

$$s_t = [a_i + b_i]\left[F_{t-1}\left[1 - \frac{1}{1 + \frac{R_{t-1}}{F_{t-1}}}\right]\right] \tag{3}$$

As R_t increases, equation (3) quickly approaches the expression in equation (4):

$$s_t = \alpha F_{t-1} \tag{4}$$

where α represents an asymptotic (long-run) replacement or multiple purchase rate. Equation (4) is analogous to the familiar relationship found in the stochastic modeling literature for repeat purchases of mature, frequently purchased products (Erenberg 1988); sales become a constant function of the number of households "in the market". For sales of consumer durables that mostly consist of repeat purchases, α^{-1}, or $(a_i + b_i)^{-1}$, is an approximation for the average repurchase cycle. If, for example, $\alpha = .15$, then 15 percent of all households repurchase the product each period (year). This implies an average cycle of 6.67 periods (years). One would expect that empirical estimates of α will be less than one and greater than zero for most consumer durables. Empirical estimates of α are not likely to reflect actual average repurchase cycles to the extent that categories have not reached their steady states (where $F_t = c_iH_t$).

3.2 Incorporating Price

Given an underlying diffusion process, we now discuss four ways to incorporate price: (*i*) where price is separable function of the diffusion process, (*ii*) where price affects only a_i, (*iii*) where price affects b_i, or (*iv*) where price affects the long-run penetration level, c_i (for clarity in notation, we omit d_i):

$$s_t = \left(a_i + b_i \frac{F_{t-1}}{c_i H_t}\right)\left(c_i H_t - \frac{F_{t-1}}{Q_{t-1}}\right) P_t^{g(t)} \tag{5}$$

$$s_t = \left(a_i P_t^{g(t)} + b_i \frac{F_{t-1}}{c_i H_t}\right)\left(c_i H_t - \frac{F_{t-1}}{Q_{t-1}}\right) \tag{6}$$

$$s_t = \left(a_i + b_i \frac{F_{t-1}}{c_i H_t} P_t^{g(t)}\right)\left(c_i H_t - \frac{F_{t-1}}{Q_{t-1}}\right) \tag{7}$$

$$s_t = \left(a_i + b_i \frac{F_{t-1}}{c_i P_t^{g(t)} H_t}\right)\left(c_i P_t^{g(t)} H_t - \frac{F_{t-1}}{Q_{t-1}}\right) \tag{8}$$

where P_t is the price in period t, and g(t) is a constant price elasticity function that depends on the age of the innovation. The multiplicative separable formulation in equation (5) is similar to those applied in the literature (see Kalish 1983). The diffusion process shifts the demand function and g(t) allows the demand function to simultaneously pivot (i.e., become more or less elastic). In equation (6), price is assumed to effect external influences or the propensity of households to adopt an innovation independent of internal interpersonal influences. This type of effect can occur when a large portion of opinion leaders (which represent a large portion of potential adopters) adopt as a function of price. In contrast, equation (7) illustrates situations when opinion leaders or innovators do not adopt as a function of price. Price changes enhance information seeking or transmitting behavior and effect the individual's propensity to be influenced by internal factors. A price change, for example, may prompt interactions between adopters and nonadopters. Alternatively, equation (7) would suggest that later adopters are more influenced by price than early adopters in making purchase decisions. Equation (8) hypothesizes that price affects the long-run percent of households that will ultimately purchase at least one product in the category in question. Using static elasticities, this case is considered by Kamakura and Balasubramanian (1988) and Jain and Rao (1990) who find that price generally effects the rate of diffusion (coefficients a_i and b_i) and not the long-run potential, c_i, of consumer durables. Given the lack of theoretical basis for selecting one specification over another

4.2 Estimation and Selection Procedure

Nonlinear least square (NLS) is used to estimate the different specifications discussed in Section 3 above.[6] One advantage of NLS is that standard errors can be estimated for individual coefficients (Srinivasan and Mason 1986).[7] For each category, a "best" diffusion model is selected among those nested in equation (1) by first eliminating all alternatives using χ^2 distributed likelihood ratio tests. Equation (1) consists of four parameters: a_i ,b_i ,c_i ,and d_i. Following Parker (1992), seven models nested within equation (1) can be considered with three, two or one parameters each. Considering all possible combinations, we have 8 alternative models which include/exclude a_i c_i or d_i.[8] The purpose of exploring alternative diffusion models is not to determine the best category sales model for consumer durables, but to reduce risks of multicollinearity common in diffusion models while adequately controlling for the underlying sales process using the appropriate specification for each category individually (Schmittlein and Mahajan 1982; Tellis 1988). If more than one model remains in competition after likelihood ratio tests are performed (e.g., usually two models having the same degrees of freedom), pair-wise Cox tests are performed on remaining non-nested specifications (Pesaran and Deaton 1978). As the Cox test is not symmetric inconclusive results may occur (both models are retained).

Given an appropriate underlying diffusion model, price is incorporated along the lines shown in equations (5) to (8) for either separable or nonseparable cases (or both). Nested likelihood ratio tests are performed to select the appropriate elasticity specification. This stepwise approach eliminates the large number of all possible pair-wise tests (which reaches into the millions). Such a step-wise procedure minimizes possible specification error biases with respect to the estimated price elasticity dynamics. In the final models, both diffusion coefficients and elasticities are co-estimated to allow for pricing to affect the diffusion process (i.e. the estimated diffusion coefficients in the first stage are not used in the final stage).

---

[6] For all estimated models, an additive error term is used; multiplicative error specifications do not generally provide better fits to the data (see also Srinivasan and Mason 1986, p. 170, footnote 3).

[7] The lack of continuous time formulations for each of the alternative models introduces, however, a possible time interval bias (Schmittlein and Mahajan 1982). There is little reason to believe that any bias will systematically vary from one category to another. Further, the goal here is not to forecast the adoption of a particular product, but to compare price elasticities across products. Hence the results reported should be insensitive to such biases. Mahajan, Muller and Bass (1990) note that parameter estimates do not greatly differ across estimation methods which control or do not control for such biases.

[8] All models include b_i; models which do not contain b_i do not yield better fits to the data, and lack plausibility. When c_i is "excluded", it is set to equal 1.0.

5. EMPIRICAL RESULTS

We present below results relating to (i) diffusion model parameter estimates, (ii) nested specifications of the diffusion model (iii) models which incorporate prices. Finally, we present a summary of the results. Table 1 compares parameter estimates and fit statistics for the original Bass model and the Bass model adjusted for multiple/repeat purchases (as in equation 1) for three durables: refrigerators, steam irons, and televisions: black-and-white. These durables ultimately reached 99 percent of first purchase household penetration (F_t/H_t, where H_t is defined as households wired with electricity). Table 1 reports the sum of squared errors (SSE) and simple correlations between actual and fitted observations (r) for the two parameter specifications. The original Bass model has a similar performance to the adjusted model when there are few observations (e.g., less than 10 or 15). As the categories increase in age, the adjusted Bass model represents a substantial improvement over the unadjusted model. This is not surprising as the unadjusted Bass model is specified for first purchases only.

We discuss below the category-level diffusion models retained after likelihood ratio or Cox tests are performed. These tests compared equation (1) with nested alternatives discussed in Section 4.2. The large number of categories studied prevents a complete reporting of all parameter estimates and tests.[9] The model selection procedure yielded a variety of models that best fit the category-level sales data. Similar variations in diffusion model specifications have been found to best fit first purchase data (e.g., Jain and Rao 1990). In general, models with either two or three parameters best represent the diffusion process; only one category is best fit by the four parameter model -- room air conditioners. All parameter values appear plausible. For two categories (clothes dryers and ranges), Cox-tests are unable to eliminate competitive non-nested specifications. Hence multiple models are retained. In cases where both a_i and b_i are retained, both non-separable and separable functional forms are estimated when price is introduced. The fit statistics indicate that the diffusion process is well captured by the retained models. Figure 1 illustrates the ability of the adjusted model to explain highly skewed (asymmetric) and/or multi-modal sales data over very long time horizons (e.g. exceeding 30 years).

Table 2 summarizes the estimates of the retained models with price elasticity dynamics. Of the various ways of incorporating price, the separable function, equation (5) consistently out-performed the alternative specifications (equations 6, 7 and 8). The separable models perform well in explaining the series with correlations between predicted and actual values exceeding 0.9 for all categories. With the exception of clothes dryers, the estimates have face validity in that the elasticities generally have correct signs (some are positive, but very close to zero). The elasticities are of plausible magnitudes and comparable to an estimate

[9] Though voluminous, these are available on request.

of -2.0 for all durable goods reported in Tellis (1988). Table 3 summarizes the price elasticity dynamics revealed by the values of h_i, j_i, and k_i as revealed by the *best* models (statistically) which co-estimate both the elasticity and diffusion parameters.

The hypothesis that price elasticities decline (Ha) and then ultimately increase (Hb), in absolute value, over the category sales life-cycle appears to be supported, with a few exceptions. For two categories (color television and room air conditioning), elasticities are not statistically different from zero over the life-cycle. Clearly, these two categories became necessities so quickly that price elasticities immediately fell to an extremely low level, thus indirectly supporting the hypothesis that as products become necessities their elasticities fall (Ha). For eight categories, elasticities decline throughout, or during the first decades of the product life-cycle, further supporting Ha. In only two cases did elasticities first increase, but ultimately decrease (bed covers and dishwashers). In one case elasticities increase over the product life cycle (disposers). In these three cases where elasticities increase early in the product life cycle, one should note that the variation generally exists within a narrow band where sales are inelastic to price changes (e.g. they are basically necessities which have minimal elasticities throughout the life cycle, though these increase). With respect to Hb, that elasticities increase with competitive substitution, in the case of ironers (a declining category facing extinction), elasticities increase toward the later stages of the life-cycle within an elastic range (-2.9). The same is found for black-and-white televisions and blenders. Though not expected, the same result holds for ranges, though over a limited period of time (perhaps due to the introduction of microwave ovens, or the trend for ranges to be sold with houses, and not purchased individually), and bedcovers (perhaps due to shifts in tastes towards quilts, or concerns for safety). Across all of the categories, price elasticities tend to begin high, then fall to an inelastic range where they show minimal variation (possibly with slight increases) or increase if the category enters the decline phase (lower or non-existent levels of repeat purchases).[10]

6. SUMMARY

In addition to introducing parsimonious diffusion models that incorporate both first and repeat purchases (thus bridging diffusion models with stochastic repeat-purchase models), this research responds to the call for empirical evidence on elasticity dynamics (Simon 1989). In support of the research hypothesis elasticities are generally highest during the earliest phases of the life-cycle, when purchase uncertainties are highest and repeat purchases as a percent of total sales are lowest. Elasticities are lowest (mostly inelastic) as repeat purchases increase. Elasticities then increase for categories facing decline or remain low within a narrow

[10] In unreported analyses, sales were decomposed into two separate series: first purchases and repeat purchases. Estimating elasticity dynamics using methodologies similar to the one reported here, we find that elasticities generally fall for both first and repeat purchases.

range of inelastic values, if the category does not face decline. Overall, category elasticity dynamics appear to vary as a function of the degree to which a category becomes more of a necessity and/or faces competitive substitutes. The dynamics of these forces are claimed to generate elasticity patterns. Our results generate an elasticity time-path similar to that found in Simon (1988) and Parker (1992) who consider brand-level and category-level first-purchase price elasticities, respectively (as opposed to total sales price elasticities).

The consideration of our results can clearly effect efforts to incorporate category elasticities into optimal pricing strategies. In markets that are highly concentrated or monopolized, long-run optimal pricing strategies should not assume constant elasticities when the shares of first and repeat purchases change over the product life-cycle. If declining elasticities are likely to exist for a new category, price initiatives by individual brands to stimulate primary category demand will have their greatest effects during the earlier stages of the product life-cycle. During this period, sales will also be most affected by business cycles and other changes in real prices. Likewise, category sales appear less affected by price changes toward the mature stages of the life-cycle. Only toward the final, or decline, phases do elasticities increase, thus opening the opportunity to use price as a strategic variable (though total sales are low or declining). The future extension of these empirical findings in a normative research framework should prove useful in analyzing the interaction between firm-level strategies and category-level dynamics. Finally, certain data limitations of our study would also suggest expanding empirical research to more categories where a demonstrable decline phase has occurred.

TABLE 1: BASS MODEL: ADJUSTED & UNADJUSTED

	Unadjusted Bass Model (Equation 4)				Adjusted Bass Model (Equation 7)			
Refrigerators								
Obs	a	b	SSE	r	a	b	SSE	r
10	.016 (.00)	.254 (.00)	150,058	.94	.016 (.00)	.239 (.00)	143,326	.94
15	.012 (.13)	.327 (.00)	1,056,738	.91	.017 (.03)	.254 (.00)	1,076,125	.91
20	-.019 (.44)	.505 (.00)	18,828,671	.71	.002 (.86)	.372 (.00)	3,713,309	.95
25	.058 (.34)	.048 (.80)	170,275,593	.00	.012 (.44)	.324 (.00)	12,405,479	.90
Steam Irons								
Obs	a	b	SSE	r	a	b	SSE	r
10	.0009 (.92)	.616 (.00)	2,871,864	.96	.020 (.02)	.381 (.00)	2,221,893	.97
15	.003 (.94)	.605 (.01)	129,792,184	.17	.037 (.03)	.243 (.00)	10,948,266	.91
20	.177 (.02)	-.486 (.00)	407,187,302	.00	.039 (.00)	.249 (.00)	12,010,670	.94
25	.150 (.02)	.048 (.00)	170,275,593	.00	.052 (.00)	.205 (.00)	19,688,475	.93
Televisions: Black-and-White								
Obs	a	b	SSE	r	a	b	SSE	r
10	.037 (.18)	.735 (.00)	27,054,262	.84	.046 (.07)	.541 (.00)	21,966,663	.87
15	.106 (.17)	-.078 (.75)	409,576,649	.00	.067 (.02)	.342 (.00)	51,391,024	.72
20	.128 (.06)	-.335 (.00)	463,157,287	.00	.052 (.00)	.205 (.00)	19,688,475	.93

Note: values of r have been set to ".00" when $r < 0$ and/or when $b > 0$.

TABLE 2: PRICE DYNAMICS

Product	a	b	c	d	h	j	k
Bed Covers	-	0.037 (.88)	2.215 (.85)	-0.944 (.09)	-3.97 (.00)	0.289 (.00)	-0.005 (.00)
Blenders	-	1.003 (.01)	0.375 (.00)	0.853 (.00)	-10.012 (.00)	0.794 (.00)	-0.015 (.00)
Clothes Dryers	-	0.074 (.00)	-	-0.537 (.00)	1.674 (.05)	-0.217 (.00)	0.0047 (.00)
Dishwashers	-	0.183 (.00)	0.428 (.00)	-	2.268 (.01)	-0.28 (.00)	0.0055 (.00)
Disposers	-	0.186 (.00)	0.539 (.00)	-	1.367 (.01)	-0.108 (.02)	0.0016 (.06)
Freezers	0.025 (.00)	4.4E-9 (.83)	-	-	-28.77 (.00)	0.376 (.00)	-
Ironers	-	0.324 (.01)	0.082 (.00)	0.083 (.85)	-2.566 (.40)	0.382 (.27)	-0.017 (.08)
TV: B&W	-	0.243 (.00)	-	-1.107 (.00)	-5.323 (.00)	0.64 (.01)	-0.019 (.01)
Ranges	-	0.012 (.07)	-	-1.585 (.00)	-8.814 (.01)	0.35 (.00)	-0.004 (.00)
Ranges	0.062 (.00)	-0.122 (.00)	-	-	-12.589 (.00)	0.644 (.00)	0.176 (.00)
Refrigerators	-	0.176 (.00)	-	-1.527 (.00)	-6.083 (.00)	0.207 (.00)	-0.002 (.00)
Steam Irons	-	0.153 (.00)	-	-1.458 (.00)	-5.78 (.00)	0.329 (.00)	-0.005 (.00)

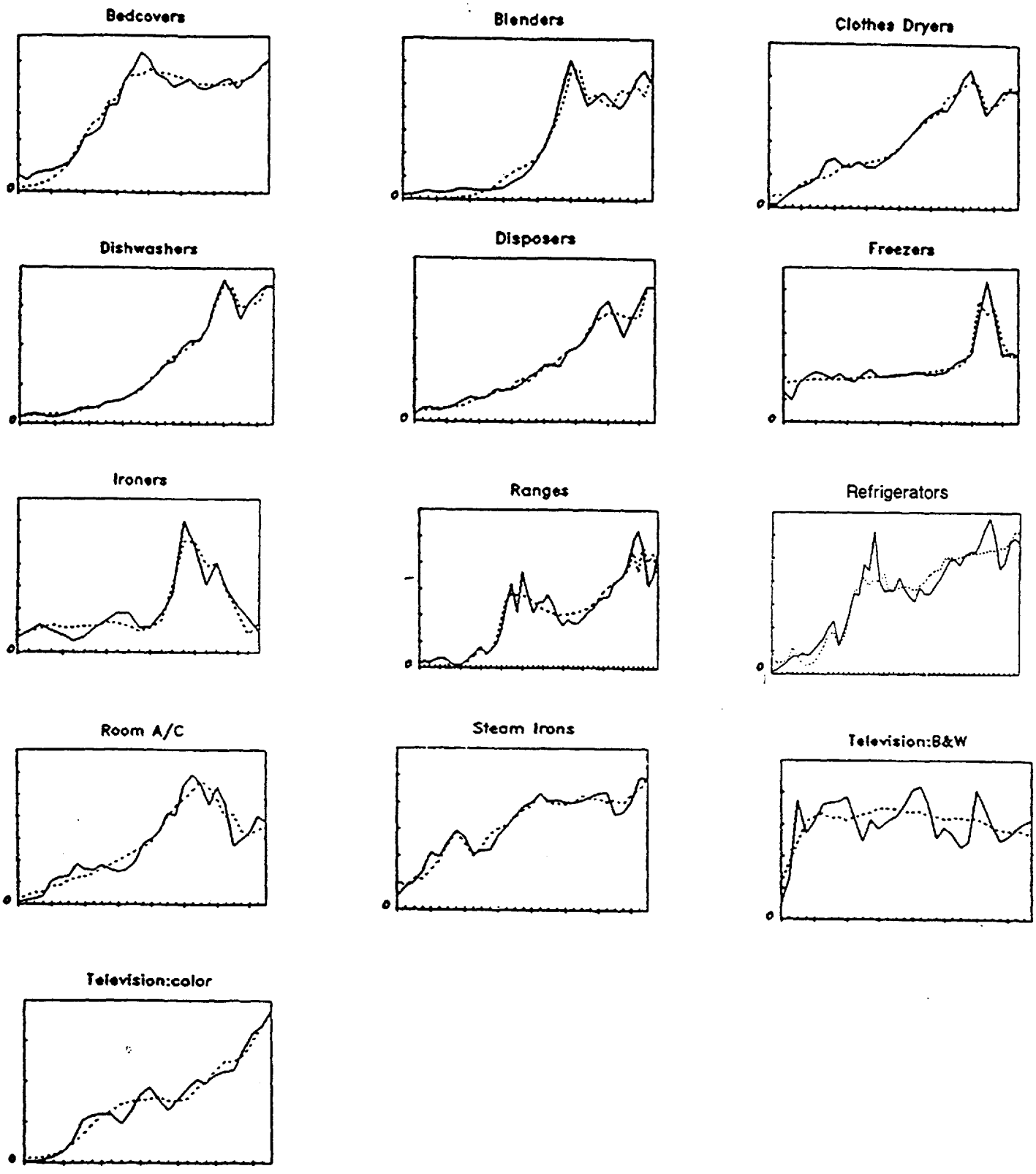
Note: All categories are best fit using the separable form for price elasticities except for freezers which uses the nonseparable internal influence form.

TABLE 3: SUMMARY OF ELASTICITY DYNAMICS OVER THE PRODUCT LIFE-CYCLE

Elasticity Dynamics	Category	Years of Elasticity Decline	Years of Elasticity Increase	Average Elasticity
No Elastic Response	Color Television	-	-	0.0
	Room Air Conditioning	-	-	0.0
Decreasing	Freezers	1-31	-	-22.8
	Ranges	1-48	-	-3.1
	Refrigerator	1-50	-	-2.3
	Steam Irons	1-31	-	-2.2
Decreasing then increasing	Bed Covers	1-28	29-32	-1.0
	Black and White TV	1-16	17-20	-1.4
	Blenders	1-27	28-31	-2.2
	Ironers (b)	1-11	11-23	-1.2
	Ranges (a)	1-40	41-48	-3.2
	Ranges (a)	1-47	48	-1.6
Increasing then decreasing	Bed Covers	23-32	1-23	-0.2
	Dishwashers	26-31	1-25	-0.4
Increasing	Disposers	-	1-31	0.1
			All Categories	-2.7

(a) Ranges yielded three elasticity paths which are not found to be statistically different.
(b) This category faces extinction due to the steam iron and dry cleaners; data were no longer collected after 1954.

Figure 1. Actual Sales Data (s_t) and fitted Sales Data (s_t), versus Category Age



REFERENCES

Bass, Frank M. (1969), "A New Product Growth Model for Consumer Durables," *Management Science,* 15, 215-27.

Bayus, Barry L. (1994), "Are Product Life Cycles Really Getting Shorter?" Journal of Product Innovation Management," 11 (September), 300-308.

Easingwood, Christopher, Vijay Mahajan, and Eitan Muller (1983), "A Nonuniform Influence Innovation Diffusion Model of New Product Acceptance," *Marketing Science,* 2 (Summer), 273-96.

Erenberg, A.S.C. (1988), *Repeat Buying: Theory and Applications*, North Holland: New York.

Jain, Dipak C. and Ram C. Rao (1990), "Effect of Price on the Demand for Durables: Modeling, Estimation and Findings," *Journal of Business and Economic Statistics,* 8-2 (April), 163-170.

Kalish, Shlomo (1983), "Monopolist Pricing With Dynamic Demand and Production Cost," *Marketing Science,* 2, 135-60.

Kamakura, Wagner A. and Siva K. Balasubramanian (1987), "Long-Term Forecasting with Innovation Diffusion Models: The Impact of Replacement Purchases," *Journal of Forecasting,* 6, 1-19.

Kamakura, Wagner A. and Siva K. Balasubramanian (1988), "Long-Term View of the Diffusion of Durables," *International Journal of Research in Marketing,* 5, 1-13.

Parker, Philip M. (1992), "Price Elasticity Dynamics Over the Adoption Life Cycle," *Journal of Marketing Research,* 29 (August), 358-67.

Pesaran, M.H. and A.S. Deaton (1978), "Testing Nonnested Nonlinear Regression Models," *Econometrica,* 46, 677-94.

Robertson, Thomas S (1967), "Determinants of Innovative Behavior," in *Proceedings of the American Marketing Association*, Reed Moyer, ed. Chicago: American Marketing Association, 328-32.

Rogers, Everett M. (1983), *Diffusion of Innovations,* 3rd ed. New York: The Free Press.

Schmittlein, David C. and Vijay Mahajan (1982), Maximum Likelihood Estimation for an Innovation Diffusion Model of New Product Acceptance," *Marketing Science,* 1 (Winter), 57-78.

Simon, Hermann (1989), *Price Management.* Amsterdam: North Holland, Elsevier Science Publishers.

Srinivasan, V. and Charlotte H. Mason (1986), "Nonlinear Least Squares Estimation of New Product Diffusion Models," *Marketing Science,* 5 (Spring), 169-78.

Tellis, Gerard J. (1988), "The Price Elasticity of Selective Demand: A Meta-Analysis of Econometric Models of Sales," *Journal of Marketing Research,* 25 (November, N 4), 331-41.