Long-term view of the diffusion of durables

A study of the role of price and adoption influence processes via tests of nested models

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This paper extends past research on new product diffusion by taking a long-term view of the diffusion process for several consumer durables.

Specifically, we investigate the role of price and adoption influence processes within the product diffusion framework by assessing the relative superiority of competing model specifications belonging to a nested family. Results indicate that price affects the diffusion process only for relatively high-priced goods; further, our analysis suggests that this is achieved through impact on the probability of adoption.

It is also shown that the traditional diffusion model specification (incorporating both external and internal influence) is not always the most adequate representation of the product adoption process.

1. Introduction

Despite the growing volume of research on the diffusion of new products, several problem issues still remain unresolved. This paper identifies and systematically addresses three such issues: (a) the need for a long-term view of the diffusion process, (b) investigation (across several products) on the role of price in the diffusion process, and (c) examination of the relative importance of internal and external influence processes in product diffusion.

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In marketing a new product or innovation, rapid diffusion of the new product (i.e., quick and complete market penetration) is a reasonable and important goal. A critical appraisal of the entire market penetration histories of related products can provide insights into how important variables (e.g., price) affect the diffusion process, and may be particularly helpful in achieving this goal.

To gain such insights, it is especially appropriate to employ diffusion models estimated on ‘long-term’ data that span the entire market penetration process. This is important since most products achieve complete market penetration only over a long time period. Most prior diffusion studies, however, analyze data spanning a very short term (i.e., the early part of the diffusion process), and thus are not particularly suitable for understanding the entire market penetration process.

Estimating diffusion models with long-term data may help avoid some of the problems faced in earlier diffusion studies; these studies restrict analysis to the first few years of the product’s life (even if sales data were available for a ‘long’ period) in order that the evaluation of the diffusion process is not contaminated by replacement purchases (Bass (1969)). This is necessary because only adoption sales (first-time purchases) are affected by the diffusion process (through word-of-mouth, external influence such as advertising, etcetera), while replacement sales largely depend on the physical decay of the currently owned product and the personal product experience of the buyer.

However, it is well known that the diffusion parameters become unstable when only a few observations are used for model estimation (Bass (1969); Heeler and Hustad (1980)); this instability often causes problems and uncertainty in interpreting the parameter values, thereby preventing clear insights into the diffusion process.

We argue that recent attempts at decomposing total sales data into adoption sales and replacement sales (Olson and Choi (1985); Kamakura and Balasubramanian (1987)) have solved the ‘contamination problem’ referred above: it is now possible to estimate adoption sales accurately for a long period. Since such long-term data greatly increase the degrees of freedom available for estimation, a ‘long-term’ view of the diffusion process can provide stable and interpretable parameter values.

Although there are several diffusion applications reported in the literature, some researchers do not consider these applications as unequivocally successful. For instance, Bernhardt and Mackenzie (1972: 187) suggest that the more successful applications may have stemmed from ‘a judicious choice of situation, population, innovation and time frame for analyzing the data’.

An effective way of countering this criticism is to avoid the ‘time frame and innovation selection bias’ by estimating the diffusion model on long-term data for several durables.

The above reasons provide the motivation for this study, which possesses the following features: (a) studies the entire product life, (b) of several durables with long sales histories, (c) using only adoption sales data. The combination of these features is a unique characteristic of this study, since no study in the product diffusion literature appears to possess all these features.

Of the three features mentioned above, feature (c) is probably the most important, since a long-term view of the diffusion process is only possible if adoption sales could be esti-
mated over an extended time period. We perform this estimation with the help of data on product penetration levels (defined in terms of the number of households who own at least one unit of the product) for successive years, details of which are given below.

Let \( S_t \) represent the total sales of a product in year \( t \) which includes adoption purchases \( y_t \) and repurchases \( r_t \). Given \( S_t \), a meaningful long-term analysis of diffusion effects will be possible only if we could estimate either \( y_t \) or \( r_t \) for each year. Recent research (Olson and Choi (1985); Kamakura and Balasubramanian (1987)) suggests some approaches to estimating \( y_t \); we employ the simplest of these here, which requires data on the cumulative number of owners of the product each year. Based on industry sources (Merchandising, March 1960/1970/1980), we obtained yearly information on the number of U.S. homes owning one or more units of each of several household appliances. If \( \text{OWN}(t) \) is the population of households owning the product at year \( t \), then the number of adoptions \( y_t \) can be estimated by the equation:

\[
y_t = \text{OWN}(t) - \text{OWN}(t-1).
\]

Given this estimate of our dependent variable, our analysis (a) acknowledges that initial adoptions and repurchases are distinct processes, affected by different behavioral considerations, and (b) enables us to study the product’s diffusion process over a long period.

3. Role of price in product diffusion

There is a widespread consensus among researchers on the need to include marketing mix variables in diffusion models to enhance managerial relevance (see Mahajan and Muller (1979) for an excellent review). In particular, the roles of two marketing variables in the product diffusion context have attracted the most research attention: price (e.g., Robinson and Lakhani (1975); Bass (1980) and Dolan and Jeuland (1981)) and advertising (Dodson and Muller (1978); Horsky and Simon (1983); Tapiero (1983)). However, we limit our focus to the price variable in this paper because of data constraints.

It is useful to consider the general form of the diffusion model (Mahajan and Peterson (1985) call this the ‘mixed influence model’ since it contains both internal and external influences) at this point:

\[
y_t = (p + q Y_t) (m - Y_t),
\]

where

\[
y_t = \text{number of adoptions of the product at time } t,
\]

\[
Y_t = \text{cumulative number of adoptions at time } t,
\]

\[
p = \text{coefficient of external influence},
\]

\[
q = \text{coefficient of internal influence},
\]

\[
m = \text{market potential parameter}.
\]

In eq. (2) and elsewhere in this paper, the coefficient of internal influence \( q \) is not divided by the market potential as in Bass (1969) and other diffusion studies. Therefore these estimates are not directly comparable with prior research.
Despite the voluminous research on incorporating marketing mix variables into diffusion models, there appears to be no consensus in the literature on an important issue: how to specify these variables in eq. (2) above. The absence of agreement among researchers on this issue is particularly evident with respect to the price variable. Some authors (Chow (1967); Mahajan and Peterson (1978)) argue that a lower price would place the product within the budgetary limitations of a greater number of buyers, thus increasing the potential market \( m \) for the product. Price changes would then have a long-term impact, by increasing or decreasing the total pool of potential buyers who would eventually purchase the product. On the other hand, other researchers (Robinson and Lakhani (1975); Bass (1980); Dolan and Jeuland (1981)) assert equally convincingly that a price decrease could engender an increase in the probability of adoption. \(^3\) Hence a price reduction would only motivate potential buyers to make an earlier adoption, with no impact on the total market for the product. This latter view suggests that price reduction could be a useful tool for manufacturers of new products to accelerate cashflows and/or pre-empt the market for a possible new competitor.

To enhance model simplicity, all the studies above assume that price either affects the market potential or adoption probability of the product. That price should impact only in one of these two alternative ways appears somewhat restrictive; a third (and more realistic) modeling alternative may lie in acknowledging that price simultaneously impacts both the probability of adoption and market potential.

3 In a diffusion model for the type \( Y_t = g(t)(m - Y_t) \), Mahajan and Peterson (1985) suggest that \( g(t) \) represents the probability of adoption. Note that \( g(t) \) can consist of \( (p + qY_t) \), \( p \) or \( qY_t \), depending on whether the diffusion process is represented as a mixed influence, external or internal influence model, respectively (this issue is discussed further in section 4).

3.1. Theoretical underpinnings of these price roles

Useful theoretical insights into the three possible roles of price outlined above can be obtained by drawing on relevant sections of the product diffusion and pricing literatures. We have elaborated on these issues below.

Mahajan and Muller (1979) divide the total market for a product into three market segments (untapped market, potential market, and current market — see upper half of fig. 1 for definitions) to describe the elements of the diffusion process. According to this conceptualization, product diffusion essentially consists of the flow of households between (a) the untapped and potential markets and (b) the potential and current markets. Interpretively, flow (a) above captures the expansion of the potential market by drawing on ‘new’ households from the untapped market; similarly, flow (b) is an analog for the product adoption process. Hence, price affects only flow (a) or flow (b) above depending respectively on whether it only affects market potential (role 1 in fig. 1) or only the probability of adoption (role 2). The final role of price in the diffusion process (role 3) arises when it affects both flows (a) and (b) above.

It is also instructive to consider the mechanics of how price influences the diffusion process under each of these three roles. Specifically, the concept of reservation price is germane in explaining the flow of households between the three diffusion segments. For a household, this represent a price limit or threshold with respect to a product category: the product will not be considered for purchase if its price exceeds this reservation price. Thus, from a pricing standpoint, the untapped market consists of households whose reservation prices are lower than the product price, while the potential and current market segments contain households with reservations prices equal to or above the product price (see fig. 1).
Under role 1 (price affects only market potential), a decrease in the price level will increment the potential market segment by adding those households from the untapped market whose reservation price structures accommodate the new price (i.e., households whose reservation prices are lower than the old price level, but either equal to or higher than the decreased price); further increases in market potential following another price reduction are contingent on the existence of other untapped households with reservation prices equal to or higher than the newly decreased price. As such, for price to perform this role, reservation prices across untapped households must lie in the range of the price reduction.

Under role 2 (price affects only the probability of adoption), a price decrease stimulates the flow of households from the potential to the current market. This suggests that as the price drops below the reservation price
of households in the potential market, the probability of adoption increases; translated into aggregate terms, the increased adoption probability will manifest as increased adoption demand (first-purchases) for the product. In other words, under this price role scenario, the adoption demand for the product is price elastic below the reservation price.

As can be seen from fig. 1, price roles 1 and 2 are somewhat restrictive in that: (a) role 1, by definition, precludes role 2 (i.e., adoption demand is price inelastic in the price change range, and (b) role 2 precludes role 1 (i.e., reservation prices for untapped households do not lie in the price change range). However, in integrating both roles 1 and 2, role 3 implies that adoption demand is price elastic below the reservation price, and that the reservation prices of untapped households lie in the price change range.

Given these alternative approaches to modeling the role of price, one of the objectives of this paper is to examine the diffusion process of several durables to determine empirically: (a) the role of price in the diffusion process for each durable, and (b) whether there is any consistent pattern in the role of price across durables. Such a study could enhance our understanding of how price affects the diffusion process and could lead to better diffusion model specifications in future research. Mahajan and Muller (1979) refer to the lack of research consensus on how price should be specified in the diffusion equation and underscore the need for such research.

Since the sales histories of durables used in our study range anywhere between 30 and 60 years, we must explicitly incorporate the population of electrified households (all the products analyzed require electricity for use) in the model to capture the increase in market potential due to this variable. Support for specifying market potential as a function of this predictor is derived from the work of Mahajan and Peterson (1978) who incorporate the effect of population growth (using housing starts as a proxy measure) in the diffusion process for washing machines.

Eq. (3) below is a modification of eq. (2) by incorporating the household population variable; this equation suggests that price has no role in the diffusion process. However, eqs. (4), (5) and (6) represent adaptations of eq. (3) by specifying the product’s price as an exogenous variable in terms of the three price roles discussed before:

\[
y_t = (p + qY_t)(ax_t - Y_t),
\]

\[
y_t = (p + qY_t)(ax_t w_t^p - Y_t),
\]

\[
y_t = (p + qY_t)w_t^p(ax_t - Y_t),
\]

\[
y_t = (p + qY_t)w_t^p(ax_t w_t^p - Y_t),
\]

where

\[a = \text{ultimate penetration level},\]

\[x_t = \text{population of electrified households at time } t,\]

\[w_t = \text{price index at time } t \text{ (deflated with the Consumer Price Index), such that } w_1 = 1,\]

\[b \text{ and } c = \text{impact of price on the probability of adoption and market potential, respectively, and } p, q, y_t \text{ and } Y_t \text{ retain their identities from eq. (2)}.\]

It is worth noting that if the population of households is assumed constant, and if the product price remained unchanged for the duration of the diffusion process, model eqs. (4), (5) and (6) reduce to eq. (2).

\[\text{One can argue that the effect of price on the diffusion process will be moderated by income effects. In the early stages of model development, we estimated versions of eqs. (4), (5) and (6) which included both price and average disposable income as exogenous predictors. Since income was not statistically significant in these equations, this variable was not considered in our subsequent analyses.}\]

\[\text{The advantage of using an index } = 1 \text{ for } t = 1 \text{ lies in avoiding the need for a scaling constant (or parameter) to account for the average effect of the price predictor. It is important to indicate that our price index is based on the average prices of each product across time. Bass (1980) has used similar data for investigating the role of price in the diffusion process. Ideally, these prices should have been adjusted for changes in product mix/quality changes across time; however such data are not available for the entire time span analysed.}\]
4. Relative importance of external versus internal influences

Most of the early research work on diffusion models can be classified as 'either pure innovative or pure imitative' (Lilien and Kotler (1983)). Research by Coleman, Katz and Menzel (1966), Fourn and Woodlock (1960), and Hamblin, Jacobsen and Miller (1973) assume that the diffusion process is primarily innovative in character; on the other hand, several researchers (Griliches (1957); Mansfield (1961); Fisher and Pry (1971); and Gray (1973)) employ models characterizing the diffusion process as predominantly imitative (see Lilien and Kotler (1983) and Mahajan and Peterson (1985) for a detailed discussion).

Several recent applications in the diffusion literature, however, specify the new product diffusion process using the 'two-step communication flow' exemplified in the Bass (1969) model (Nevers (1972); Dodds (1973); Tigert and Farivar (1981)). This involves specifying separate parameters for the innovation and imitation processes which operate during adoption (Bass (1969)). Lekvall and Wahlbin (1973) have proposed a re-interpretation of these two processes as obtaining from external influence (direct influence on the innovative behavior of individuals through marketing communication) and internal influence (influence on individuals from members of the social system to which they belong), respectively. These authors further argue that the relative strength of these influences determine the shape of the diffusion curve and that they are not likely to be the same across all situations.

Conceptually, the above discussion implies three broad categories into which any new product diffusion process could be classified: (a) where external influence dominates internal influence, (b) where internal influence dominates external influence, and (c) where both influences are moderately present. Mahajan and Muller (1979) assert that these three categories are represented by the modified exponential curve (Fourn and Woodlock (1960)), the logistic curve (Mansfield (1961)) and the generalized logistic curve (Bass (1969)), respectively. From the perspective of modeling efficiency, we assert that specifying the generalized logistic curve may not lead to parsimonious representation of the diffusion process for categories (a) and (b) outlined above.

The above discussion is summarized as a second objective of this paper: to focus on the relative importance of external and internal adoption influences in the diffusion process of several durables. An ongoing analysis of this type could offer some managerial insights into the approach most appropriate for promoting adoptions of a product. Clearly, if the external influence represents the dominant aspect of the adoption process, communications/presentations should be addressed directly to each potential household, e.g., advertising, cold-canvass salesperson calls, etcetera. On the other hand, for products where internal influence plays a bigger role in product adoption, marketing efforts should focus on (a) exploiting the potential influence that adopters may have over non-adopters and (b) encouraging interactions among adopters and non-adopters. Certain forms of direct-to-home retailing practices for selling durables (Evans and Berman (1987)) achieve this. Customer-referral based direct-to-home retailing takes advantage of (a) above (e.g., a salesperson requests an adopter to suggest a list of potential adopters and uses the former's recommendation to approach the latter). Direct-to-home retailing which employs the party format provides a social setting in which consumers can interact; the objective here is to stimulate word-of-mouth communication (Assael (1987)). Tupperware parties in the U.S are a good example of the latter: typically, and adopter acts as host and invites friends to a product demonstration by a salesperson in his or her home.
5. Methodology and empirical analysis

The arguments above carry implications for eqs. (3) through (6) above. Given that these equations include both parameters \( p \) and \( q \) respectively, it is possible to identify a parsimonious model by constraining either \( p \) or \( q \) to zero.

Accordingly, we developed the nested family of 12 models shown in Table 1. It may be noted that models 1 through 4 represent diffusion processes where internal influences are dominant, models 5 through 8 represent diffusion processes where external influence constitute the dominant force, while models 9 through 12 are analogous to the ‘mixed influence’ specification which acknowledge the importance of both internal and external influences.

Inasmuch as models 1 through 4 incorporate the \( q \) parameter, and models 5 through 8 incorporate the \( p \) parameter, these two sets of models are nested into corresponding models 9 through 12 as they incorporate both \( p \) and \( q \) parameters. Moreover, model 12 is represented as the ‘unrestricted’ model into which all other models are nested.

<table>
<thead>
<tr>
<th>Model number</th>
<th>Model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Internal influence models</td>
<td></td>
</tr>
<tr>
<td>1. ( y_t = q Y_t (a x - Y_t) )</td>
<td></td>
</tr>
<tr>
<td>2. ( y_t = q Y_t (a x, w^*_t - Y_t) )</td>
<td></td>
</tr>
<tr>
<td>3. ( y_t = q Y_t w^*_t (a x, Y_t) )</td>
<td></td>
</tr>
<tr>
<td>4. ( y_t = q Y_t w^<em>_t (a x, w^</em>_t - Y_t) )</td>
<td></td>
</tr>
<tr>
<td>External influence models</td>
<td></td>
</tr>
<tr>
<td>5. ( y_t = p (a x, Y_t) )</td>
<td></td>
</tr>
<tr>
<td>6. ( y_t = p (a x, w^*_t - Y_t) )</td>
<td></td>
</tr>
<tr>
<td>7. ( y_t = p w^*_t (a x, Y_t) )</td>
<td></td>
</tr>
<tr>
<td>8. ( y_t = p w^<em>_t (a x, w^</em>_t - Y_t) )</td>
<td></td>
</tr>
<tr>
<td>Mixed influence models</td>
<td></td>
</tr>
<tr>
<td>9. ( y_t = (p + q Y_t) (a x, Y_t) )</td>
<td></td>
</tr>
<tr>
<td>10. ( y_t = (p + q Y_t) (a x, w^*_t - Y_t) )</td>
<td></td>
</tr>
<tr>
<td>11. ( y_t = (p + q Y_t) w^*_t (a x, Y_t) )</td>
<td></td>
</tr>
<tr>
<td>12. ( y_t = (p + q Y_t) w^<em>_t (a x, w^</em>_t - Y_t) )</td>
<td></td>
</tr>
</tbody>
</table>

The basic objective in building these nested models was to identify the most adequate model specification within each family, based on likelihood ratio tests described below.

Let \( LL_2 \) be the log-likelihood obtained with model 2 in Table 1, and \( LL_1 \) be the log-likelihood obtained with model 1 (which is a special case of model 2, when \( c = 0 \); in other words, model 1 is nested into model 2). Then, the contribution of the parameter \( c \) (and consequently, of price affecting market potential) can be tested by the statistic \( \chi^2 = 2(LL_2 - LL_1) \), which has a chi-square distribution with one degree of freedom. More generally, any two nested models (i.e., where one of them is a special case of the other, by fixing certain parameters equal to zero) can be compared using the same statistic, which will have a chi-square distribution with degrees of freedom equal to the number of parameters set equal to zero.

Thus, if the product history was strongly moderated by internal influences, the likelihood tests may yield any of the models 1 through 4 as the ‘best’ or parsimonious specification. The exact choice of the most parsimonious model (among models 1 through 4) would in turn depend on the role price plays in the diffusion process. Thus, the ‘best’ model will be:

(a) model 1 if price has no effect at all,
(b) model 2 if it impacts the market potential only,
(c) model 3 if it impacts only the probability of adoption, or
(d) model 4 if it impacts both market potential and the probability of adoption.

The family of nested models listed in Table 1 were estimated for six consumer durables.

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*For all analyses pertaining to refrigerators, toasters and vacuum cleaners, data spanning the product's life history (until 1979) was used. Since this data period included the World War II years (during which there was no significant production/sales) for each of these products, we incorporated a war dummy variable for the war years in the regression equation.*
Table 2
Likelihood-ratio tests to derive the most parsimonious model airconditioners (1949–1979). a

<table>
<thead>
<tr>
<th>Loglikelihood of nested model number</th>
<th>Nested model number</th>
<th>Unrestricted model number</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>2</td>
</tr>
<tr>
<td>−220.22</td>
<td>1</td>
<td>6.39 e</td>
</tr>
<tr>
<td>−217.03</td>
<td>2</td>
<td>−</td>
</tr>
<tr>
<td>−218.11</td>
<td>3</td>
<td>−</td>
</tr>
<tr>
<td>−217.03</td>
<td>4</td>
<td>−</td>
</tr>
<tr>
<td>−237.19</td>
<td>5</td>
<td>−</td>
</tr>
<tr>
<td>−229.68</td>
<td>6</td>
<td>−</td>
</tr>
<tr>
<td>−213.84</td>
<td>7</td>
<td>−</td>
</tr>
<tr>
<td>−213.33</td>
<td>8</td>
<td>−</td>
</tr>
<tr>
<td>−219.50</td>
<td>9</td>
<td>−</td>
</tr>
<tr>
<td>−214.25</td>
<td>10</td>
<td>−</td>
</tr>
<tr>
<td>−212.08</td>
<td>11</td>
<td>−</td>
</tr>
<tr>
<td>−212.08</td>
<td>12</td>
<td>−</td>
</tr>
</tbody>
</table>

a Blank cells represent non-nested pairs of models.
b Nested model is rejected in favor of the unrestricted model at the 0.05 level.
c Nested model is rejected in favor of the unrestricted model at the 0.01 level.

(airconditioners, blenders, mixers, refrigerators, toaster and vacuum cleaners) using a non-linear least squares algorithm (time series processor). The estimation period included the entire sales history of each product (data up to 1979 were used – figures beyond this date are unavailable). The log-likelihoods obtained for each model were then used for the comparison of nested models within each family with the objective of identifying the most adequate formulation of the diffusion model for each product.

An example of such an analysis for room airconditioners is presented in table 2 which shows the log-likelihood ratio tests between each nested pair of models listed in table 1. Each row in table 2 represents a 'restricted' model which is nested into those unrestricted models (columns) for which the log-likelihood ratio tests were performed (the blank cells indicate non-nested pairs of models for which log-likelihood ratio tests have no relevance). The value of this approach is immediately apparent when one realizes that all row models are nested into column model 12. Nested comparison of all other models with model 12 indicates that models 7, 8, and 11 cannot be rejected in favor of the full model 12. If we examine row 7, it is clear that model 7 is the most parsimonious of these three models (the tests do not reject row model 7 when compared with column models 8 and 11 separately).

5.1. Discussion

Table 3 summarizes the results of similar log-likelihood tests across all the durable analyzed by listing the parameter estimates of the most parsimonious diffusion model for each product. Interestingly, the results in table 3 clearly show that the full diffusion mode specification (models 9 through 12) is no always the most adequate representation of the process. Except for refrigerators and vacuum cleaners, the most parsimonious model representation reveals a clear dominance of either the external or the internal influences. Based on the discussion in section 4, this implies that (a) direct advertising is more appropriate for promoting adoptions of toasters and airconditioners, and (b) marketing activities directed at stimulating the word-to-mouth interactions among customers wi
Table 3
Parameter estimates of best model for each product.

<table>
<thead>
<tr>
<th>Product and period</th>
<th>Best model number</th>
<th>Parameter estimates</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>$p$</td>
</tr>
<tr>
<td>Toasters (1922–1979)</td>
<td>5</td>
<td>0.03 $^b$</td>
</tr>
<tr>
<td>Mixers (1948–1979)</td>
<td>1</td>
<td>–</td>
</tr>
<tr>
<td>Blenders (1948–1979)</td>
<td>1</td>
<td>–</td>
</tr>
<tr>
<td>Airconditioners (1949–1979)</td>
<td>7</td>
<td>0.01 $^b$</td>
</tr>
<tr>
<td>Refrigerators (1925–1979)</td>
<td>11</td>
<td>0.02 $^b$</td>
</tr>
<tr>
<td>Vacuum cleaners (1922–1979)</td>
<td>11</td>
<td>0.04 $^b$</td>
</tr>
</tbody>
</table>

$^a$ This dummy variable was included to account for the World War II years, during which there was practically no production/sales.

$^b$ Significant at 0.05 level.

affect the adoption demand for mixers and blenders particularly well.

Further, we note that all the parameter estimates of all the best models in table 3 are significant, and all the ‘$b$’ estimates have negative sign as expected, since price should be inversely related to sales volume.

However, the ‘$a$’ estimate for vacuum cleaners has a value above 1.00 and merits some discussion. Interpretively, this estimate implies that the units in use were 5% more than the number of households in the U.S. This result appears unreasonable at first glance, and we employed a deductive approach to determine the reasons for this discrepancy. Since the data ostensibly reflect yearly estimates on the number of households owning at least one unit of the product, one cannot attribute the discrepancy to either (a) the commercial use of vacuum cleaners, or (b) repeat purchases within the same household. However, extensive discussions with several managers in the appliance industry, the data-source agency, and the U.S Vacuum Cleaner Dealer Association led to a critical re-examination of the data-collection process for vacuum cleaners; this in turn suggested that the unreasonable estimate might have stemmed from errors in the published data for vacuum-cleaners.

While vacuum cleaners have existed as a product class since 1922 in the US, a new product class (called electric broom) also became available in the late 1950s. Although the latter product uses the same principle as vacuum cleaners (dust-removal through suction), it has several important differences as well: it is a much smaller contraption inappropriate for heavy duty cleaning jobs, weighs less, is more suitable for use on floors than carpet surfaces, and typically does not have the disposable dust-bag feature found in all vacuum cleaners. The appliance industry recognises these as different product categories serving different user needs; however, given the greater familiarity with vacuum cleaners and some functional similarities between electric brooms and vacuum cleaners, many consumers habitually substitute the latter term to refer to the former product category. This confusion could have inflated the market penetration estimates for vacuum cleaners obtained from the cross-sectional consumer surveys, which were a main part of the data-collection process. In other words, survey respondents who had adopted an ‘elec-
tric broom' may have reported the adoption of a 'vacuum cleaner' instead. It is important to note that our discussions with managers in the appliance industry suggest that the data-credibility for each of the other products studied remains intact, since none of these products had a 'generic product identity' problem as discussed above.

Further, the results in table 4 reveal an interesting pattern. We note that for toasters, mixers and blenders, price does not appear to have any effect on either diffusion probability or market potential or on both these factors simultaneously. However, whenever price registers an impact on the adoption process (e.g., airconditioners, refrigerators, vacuum cleaners), it consistently affects only the probability of adoption. Based on fig. 1, the latter result suggests that (a) the adoption demand is price elastic and (b) the reservation prices of the unadopted households for these three products do not fall in the price change range (i.e., unless there are households with reservation prices even lower than the lowest average price of these durables in the period analyzed, one can conclude that all households belong to either the potential or current markets).

In sum, it appears that price does not impact at all on the somewhat lower-priced goods, while it appears to affect the adoption probability for the relatively higher-priced durables. However, one can question this conclusion by suggesting other factors (such as inadequate price variation across time) to explain the lack of price impact for toasters, mixers and blenders. This possibility is verified in table 4, which presents the price ranges (in constant dollars) for these durables. The coefficients of variation of price for the six durables do not support this suggestion; in other words, since price variation appears comparable across all the six durables analyzed, the reason for the non-significance of price elasticities in toasters, mixers and blenders is not a methodological artifact (i.e., inability to 'capture' the price-quantity relationship), but a reflection of data characteristics (i.e., no effect of price on diffusion).

6. Summary and conclusions

Applications of diffusion models in the marketing literature consistently reflect a pre-occupation with the very early years of the

<table>
<thead>
<tr>
<th>Condition</th>
<th>Product</th>
<th>Price range</th>
<th>Average price</th>
<th>Standard deviation of price</th>
<th>Coefficient of variation of price</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Min</td>
<td>Max</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Price does not affect market</td>
<td>Toasters</td>
<td>7.07</td>
<td>26.10</td>
<td>16.03</td>
<td>4.94</td>
</tr>
<tr>
<td></td>
<td>Mixers</td>
<td>12.80</td>
<td>54.60</td>
<td>26.04</td>
<td>14.04</td>
</tr>
<tr>
<td></td>
<td>Blenders</td>
<td>9.65</td>
<td>52.70</td>
<td>31.62</td>
<td>14.72</td>
</tr>
<tr>
<td>Price affects market potential</td>
<td>Airconditioners</td>
<td>138.12</td>
<td>495.28</td>
<td>269.37</td>
<td>108.38</td>
</tr>
<tr>
<td></td>
<td>Refrigerators</td>
<td>186.80</td>
<td>701.70</td>
<td>361.32</td>
<td>111.81</td>
</tr>
<tr>
<td></td>
<td>Vacuum</td>
<td>51.87</td>
<td>131.60</td>
<td>95.37</td>
<td>21.83</td>
</tr>
</tbody>
</table>

* All prices are in constant 1967 dollars.
product's life. This represents a tacit acceptance of the limitations imposed by the following circular dilemma facing the diffusion researcher:

If a long-term estimation period is used, the data on total sales will be contaminated by repurchases. However, a diffusion model by definition is concerned with adoptions only and such contamination must be avoided. Hence, the analysis must be restricted to the very early years of the product's life when total sales serve as a proxy for adoptions. On the other hand, using the few data points provided by this limited period is known to yield unstable parameter estimates, and therefore, a long-term estimation period is called for!

This study follows the spirit of recent research efforts (Olson and Choi (1985); Kamakura and Balasubramanian (1987)) to avoid the contamination problem referred above by estimating the adoption sales each year using market-penetration data. Apart from avoiding the dilemma described, this approach allows the study of the diffusion process across the entire life of several durables with long sales histories.

The need for incorporating exogenous predictors in innovation diffusion models has been widely acknowledged. However, the extant literature does not provide a unified theory on how the predictors should be specified in the diffusion equation. Using established nested testing procedures, a contribution of this paper has been to determine the relative merit of alternative diffusion model specifications using population and price as predictors. The results indicate that when price does impact on the diffusion process, it is achieved through an effect on adoption probability. It also appears that price affects the adoption process only for relatively higher priced goods.

Another contribution lies in our analysis of the relative importance of external and internal influences in the adoption process of several durables. Our results show that the full diffusion model specification is not always the parsimonious representation of the adoption process. Our nested testing procedure reveals a clear dominance of either the external or the internal influence for some products. Implications of these results are derived based on the theoretical underpinnings of the models developed.

It is important to point out the limitations of this study. First, price is not the only marketing variable affecting the diffusion process. Prior research has shown that other variables such as advertising (Dodson and Muller (1978); Horsky and Simon (1983); Tapiero (1983)) could play an important role in product diffusion. These variables need to be incorporated into the nested model evaluations in future research.

Second, to simplify the nested testing procedure, our study assumes that the coefficients of internal and external influence remain stable over time. Recent work by Easingwood, Mahajan and Muller (1981, 1983) has partially relaxed this assumption to allow for change in the coefficient of internal influence over time. In defense of our model specification, however, we could argue that our focus was on studying relative long-term importance of external versus internal adoption processes rather than how each of these processes changed over time.

Third, the exploratory character of this study needs to be stressed: we have analyzed only six durables for which data were readily available. It will be useful to investigate whether this pattern holds across the diffusion of services (Nevers (1972)) and for other durables as well.

References


