FORESCATING HOME APPLIANCES SALES: INCORPORATING ADOPTION AND REPLACEMENT[1]

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Abstract

Empirical research on diffusion of consumer durable goods have mostly focused on adoption disregarding the importance of replacement sales. This article develops a demand model that incorporates both elements. Unlike previous studies, we allow adoption to depend on several economic variables (e.g., product price, disposable income, energy prices, and new private housing starts), and compute replacement sales from micro data rather than from an arbitrary survival function. We fit our model to U.S. data of electric heaters for 1946-1995, and show that sales forecasting can be improved by allowing adoption to depend on various economic factors.

JEL Classification: D12, C53; Keywords: Adoption, Replacement, Consumer Durables

1 Introduction

Consumer durable goods— products that are not immediately consumed but provide a stream of services over a long period of time—have become standard items for a vast majority of households.[1] Electronic innovations have contributed over the years to an increasing inventory of durable goods. Indeed, virtually every household in the United States owns or has access to a refrigerator and a color television set. And, the penetration of items such as

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microwave ovens, compact disc players, and video cassette recorders has increased dramatically since the late 1980's (Table 1).

[Table 1]

In spite of the rich theoretical body of knowledge existing in the economic literature to analyze durable goods purchases (e.g., models dealing with adjustment/transaction costs, habits, technological change, markets imperfection, volatility and discreteness of purchases), only in the past few years have researchers succeeded in getting a better grasp of the key economic forces behind both adoption and replacement of consumer durable goods.

Recent empirical studies on adoption have dealt with diffusion of automatic teller machines as a function of bank and market characteristics (e.g., Hannan and McDowell, 1984; Sinha and Chandrashekaran,1992), cointegration analysis applied to new car sales (e.g., Franses,1994), the effect of firm size and educational level of its employees on adoption of computers (e.g., McWilliams and Zilberman,1996), and the impact of culture on adoption of home-office and high-end consumer electronics innovations (e.g., Parker and Sarvary,1996).

Recent work on replacement has looked at replacement decisions of home appliances (Antonides, 1990; Bayus and Gupta, 1992; Raymond, Beard, and Gropper, 1993) and automobiles (e.g., Gilbert, 1992) by incorporating demographics and product features as determinants of replacement timing. In addition, some research has been conducted on the impact of advertising, new features, and styling on replacement purchases (e.g., Bayus, 1988). Important work in the area of replacement has been also done by Rust (1986, 1987).

A great deal of studies on adoption of consumer durable goods found in the literature—particularly in the marketing field—have dealt with aggregate data. One of the earliest attempts was Bass model (1969)—a generalization of Mansfield model (1961). In its original version this model concentrated on sales growth neglecting the effect of economic variables on adoption. Specifically, Bass postulated that the timing of a consumer's initial purchase is related to the number of previous buyers.

In recent years, however, empirical work has shown that economic factors may play a role in adoption of new products. In particular, some authors have found that price seems to affect the product market potential (e.g., Bass, 1980; Kamakura and Balasubramanian, 1987; Jain and Rao, 1990). Nevertheless, other factors that economic theory would suggest as relevant to adoption (e.g., disposable income, energy prices, and new private housing starts) have been systematically neglected in most empirical studies (e.g., forecasting models of durable goods sales. For a critical review, see Parker, 1994).

This article presents an improved methodology to model aggregate demand for consumer durable goods—particularly home appliances— that takes account of those economic factors that may be relevant to the adoption and replacement processes. Given that micro data on adoption and replacement of durable goods are rarely available,[2] a well-specified aggregate model can provide some insight about the economic forces driving diffusion of consumer durable goods. In addition, if one is concerned with forecasting, such models may be also a useful tool. Indeed, we show that sales forecasting can be improved by allowing adoption to depend on various economic factors.

The contribution of our study is twofold. First, unlike previous studies (e.g., Bass, 1969, 1980; Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986; Karshenas and Stoneman, 1992), we allow adoption to depend on several economic variables (e.g., product price, disposable income, energy prices, real interest rates, and new private housing starts). Second, when incorporated, aggregate replacement sales have been merely constructed from either actuarial tables or arbitrary functional forms (e.g., Olson and Choi, 1985, and Kamakura and Balasubramanian, 1987). We move a step forward and calculate the aggregate replacement demand from a household replacement model.

We believe that a better understanding of the economic factors governing adoption of consumer durable goods may be useful to policy makers. For example, measuring the sensitivity of adoption timing to the evolution of fuel prices can help to assess the potential diffusion of more energy-efficient appliances. In addition, a good understanding of the adoption and replacement processes may help firms to do accurate forecasting of market demand of new and existing products, a critical element to production, distribution, and marketing planning.

This article is organized as follows. In section 2 we present the methodology used to derive an aggregate model for home appliances sales, and explain how to construct series for adoption and replacement from aggregate data. In section 3 we present an application of our methodology for U.S. data of electric heaters for the time period 1946-1995. We consider the case where the eventual probability of adoption depends on economic variables such as product and fuel prices, real per capita income, and new housing starts. Finally, in section 4 we present some further remarks and overall conclusions.

2 Modeling the Demand for Home Appliances: Replacement and Adoption

Let us start by determining how many pieces of equipment need to be replaced per year.[3] In equation (1) X(t) represents the expected total number of units at use at the beginning of year t, assuming that all "dead" units are immediately replaced. The variable y(t) represents sales of the product at year t. Notice that X(t) represents the expected cumulative number of people who at t-1 have already bought the product at least once. S(i) is the percentage of units that are expected to "survive" until i-years after purchase.

$$X(t) = \sum_{i=1}^{t} S(i)\, y(t-i)\,. \tag{1}$$

The label "dead" does not indicate that a piece of equipment is replaced only when it breaks down. Demographic and technological factors—particularly product efficiency—may lead households to replace a unit before technical failure occurs. The term "survive" is interpreted in a similar fashion.

In order to determine the survival function, S(.), we first fit a replacement model to household data. For the particular application shown below, we take data from the U.S. Department of Energy’s “Residential Energy Consumption Survey (RECS)” 1990, and model replacement as a function of households characteristics.

In equation (2) R(t) represents the expected number of units that have "died" or need replacement at year t. The expression [S(i-1)-S(i)] in turn represents the percentage of units produced i years ago that have "died" at year t.

$$R(t) = \sum_{i=1}^{t} [S(i-1) - S(i)]\, y(t-i)\,. \tag{2}$$

The functional form of the survival function, S(.), above is obtained from a structural duration model based on the theory of stochastic processes. Specifically, if we postulate that operation costs, x(t), of a consumer durable evolve according to a Wiener process with drift and variance parameters b and σ^2, respectively, the dynamics of x(t) can be described by:

$$dx = b\,dt + \sigma\,dW, \tag{3}$$

where dW represents the increment of a standard Wiener process (see, for example, Ye, 1990).

If replacement takes place when operation costs reach an upper barrier α, it can be shown that the probability density function of the time elapsed until replacement is given by the inverse Gaussian distribution (see Cox and Miller, 1965, or Lancaster, 1990):

$$g(t|b, \sigma, \alpha) = \frac{\alpha}{\sigma\sqrt{2\pi t^3}} \exp\left(\frac{-(\alpha - bt)^2}{2\sigma^2 t}\right), \qquad t \geq 0, \tag{4}$$

with survivor function

$$S(t|b, \sigma, \alpha) = \Phi\left(\frac{\alpha - bt}{\sigma\sqrt{t}}\right) - \exp\left(\frac{2\alpha b}{\sigma^2}\right)\Phi\left(\frac{-\alpha - bt}{\sigma\sqrt{t}}\right). \tag{5}$$

In order to incorporate household characteristics into our analysis, we assume that for household ‘i’ the ratio α_i/σ_i takes the form:

$$\frac{\alpha_i}{\sigma_i} = \exp(\beta' \mathbf{z}_i), \tag{6}$$

where $\mathbf{z}_i$ is a vector of household characteristics. This functional form ensures that α_i/σ_i is non-negative (see Fernandez, 1997, for further details).

Olson and Choi (1985), and Kamakura and Balasubramanian (1987) also incorporate replacement into their demand models. However, the survival probabilities used in their estimation do not arise from any household replacement model. Instead, they are arbitrary functional forms that neglect the potential impact of economic factors. Therefore, it is likely that the estimates of their adoption models are biased because they might be overestimating the impact of economic variables on adoption.

In order to determine the expected number of adopters in a particular year, we estimate the effective market potential as the difference between the number of electrified homes at t and X(t), the expected product stock at the beginning of year t:

$$A(t)=[Pop(t)-X(t)]P_a^c(t), \qquad (7)$$

where A(t) denotes expected adoption at time t, Pop(t) is the population of electrified homes at t, and $P_a^c(t)$ represents the conditional probability that a randomly chosen individual from the population adopts the product in the time interval (t, t-1). $P_a^c(t)$ can be written as:

$$P_a^c(t) = \frac{c[F(t)-F(t-1)]}{[1-cF(t-1)]}, \qquad (8)$$

where c denotes the eventual probability of adoption, and F(.) represents the cumulative distribution function (c.d.f.) of time elapsed until adoption — if this ever takes place. In other words, expression (8) can be interpreted as the conditional probability of an individual adopting in the time interval (t, t-1), given that she or he has not adopted the product by time t-1 (Jain and Rao, 1990).

If c equals one for all t, it implies that, from the moment the product becomes available in the marketplace onwards, the whole population adopts it according to the probability distribution F(t). This is the case originally considered by Bass. More realistically, one can make c depend on economic variables so that it varies over time. For instance, one functional form for c considered by Jain and Rao incorporates product price. As discussed in the next section, we also take other economic variables into account.

Instead of taking the total number of electrified homes in each year, most studies have assumed some fixed population of households (e.g., Bass 1969, 1980; Schmittlein and Mahajan, 1982; Srinivasan and Mason, 1986; Jain and Rao, 1990). In some cases, this is assumed known while in others it is estimated from the model. In our view, such an approach is rather ad-hoc so we allow the population of homes to change over time.

From (2) and (7), total sales at time t can be written as:

$$y(t)=A(t)+R(t)+e(t), \tag{9}$$

where e(t) represents a disturbance term.

It is important to make clear that y(t) represents shipments for domestic sale whether home or foreign made. Consequently, exports are excluded from (9).

In order to model the timing of adoption, we state that this follows a lognormal process. This distribution ensures that the likelihood of adoption time is non-monotonic—that is, increasing in the initial years, then declining as product maturation sets in (Sinha and Chandrashekaran, 1992). In this particular case the c.d.f. of adoption time, F, is given by:

$$F(t) = \Phi\{\frac{\ln(t)-\mu}{\sigma}\}\ , \tag{10}$$

where $\Phi(.)$ represents the c.d.f. of a standard normal random variable, and μ and σ are parameters.

Following Jain and Rao (1990), and Sinha and Chandrashekaran (1992), we choose a logistic functional form for c:

$$\log[\frac{c(\mathbf{x}(t))}{1-c(\mathbf{x}(t))}] = \alpha + \beta' \log(\mathbf{x}(t))\ , \tag{11}$$

where $\mathbf{x}(t)$ denotes a vector of exogenous variables. Equation (11) yields the following expression for c:

$$c(\mathbf{x}(t)) = \frac{1}{1 + \exp(\alpha + \beta' \log(\mathbf{x}(t))} \quad . \tag{12}$$

where β can be interpreted as a vector of elasticities.

3 An Application: Aggregate Demand for Electric Heater in the U.S.

In this section we estimate an aggregate demand model for electric heaters for the time period 1946-1995. We have chosen this appliance for two reasons. First, its saturation level is still relatively low in the United States so adoption is not negligible when compared to total annual shipments. Second, it appears not to have been analyzed in the existing literature. Indeed, previous studies have primarily concentrated on room air conditioners, clothes dryers, color televisions, and refrigerators, among others.

In order to determine the survival function of electric heaters in the United States—and, therefore its replacement demand, we first fitted a replacement model to household data from the "Residential Energy Consumption Survey (RECS)" 1990. The RECS is a national sample survey for the United States that has been conducted triennially by the U.S. Department of Energy since 1984.

The universe of the RECS comprises all housing units occupied as a primary residence in the 50 states and District of Columbia. The two major parts by which the RECS is conducted are the Household Survey and the Energy Suppliers Survey. The Household Survey gathers information regarding the housing unit through personal interviews with the selected households. The Energy Suppliers Survey collects data regarding actual energy consumption from household billing records maintained by the fuel suppliers.

The Household Survey covers questions on type of the housing unit, year the housing unit was constructed, space-heating fuels and equipment, water-heating fuels and equipment, air-conditioning fuels and equipment, cooking fuels and equipment, number, type, age, and size of refrigerators, inventory of appliances, and demographic characteristics of the occupants of the housing unit.

Table 2 shows the results for our replacement model for electric heaters with the RECS 1990 data. We modeled α_i/σ_i as an exponential function of a constant term, age of the head of the household (per ten years), nominal monthly income (per $10,000), home square footage (per thousand square feet), dummy variables for urban location (=1 if urban), natural gas availability (=1 if available), and poor credit rating (=1 if poor credit rating)—proxy for liquidity constraints,[4] price of electricity (cents per kWh) and heating degree days (per thousands, base = 65 Fahrenheit degrees). Except for the price of electricity and heating degree days, these are the economic variables considered by Raymond, Beard, and Gropper (1993) in their replacement model for electric heaters in the state of Alabama. Given the national scope of the RECS, we deem the two latter variables relevant as well. Our estimates are obtained by the method of maximum likelihood. (For mathematical convenience, we assume that $b_i/\sigma_i \equiv b/\sigma$—the standardized parameter of physical deterioration).

[Table 2]

As we see from Table 2, natural gas availability and age of the head of the household are negatively correlated with replacement times—the function α_i/σ_i is increasing in these two variables. This implies that the older the head of the household the less likely is that he/she will replace his/her electric heating system, and that when natural gas is available in the household's neighborhood replacement is also less likely to occur. The same conclusions were reached by Raymond et al. Regarding age of the head of the household, the authors do not attempt to find the reason-why for such relationship. We think that two plausible explanations are the following. It is possible that preferences of older heads of households change more slowly. Alternatively, older heads of households may have higher implicit discount rates.

Regarding natural gas availability, Raymond et al. think that the negative association of this variable and replacement time may be due to differentials in the lifetimes of electric versus natural gas powered systems. More likely, we think that such relationship holds because of differentials in the operation costs of gas versus electric powered equipment. Indeed, electricity is much more expensive than natural gas. According to the RECS, in 1990 the average price of natural gas was 0.57 cents/thousand BTU versus 2.19 cents/ thousand BTU for the average price of electricity. Those households without gas service in their neighborhood cannot switch from an electric to a gas powered system so they are more likely to replace electric equipment, as Raymond et al. suggest.

Table 2 also shows that the variable heating degree days is negatively correlated with replacement time. It is likely that this covariate is capturing some equipment characteristics such as quality. In particular, electric equipment for colder regions may be more expensive to replace.[5] Unfortunately the RECS does not provide any information on heating equipment characteristics other than fuel type. As expected, higher income is associated with a higher probability of replacement. However, this covariate is not statistically relevant at the standard levels of significance. This is also the case for the urban location dummy and the price of electricity.

Figure 1 shows the survival function obtained for electric heaters from the RECS data. In the early years after purchase, electric heaters are replaced with an almost negligible probability. The expected lifetime we estimated for this appliance is about 20 years, which is within the range given by the U.S. industry in 1992 for warm-air electric furnace—10 years (low)-20 years (high), with an average of 16 years (“Appliance,” Dana Chase Publications. September, 1992). The study of replacement of electric heaters conducted by Raymond, Beard, and Gropper yielded an estimate of an overall time to replacement a bit higher than ours (25 years).

Figure 2 shows annual changes in the U.S. stock of home electric heaters for 1947-1995 derived from the series constructed with equation 1. These data seem highly volatile, which might be partially explained by fluctuations in economic variables such as new private housing starts, interest rates, and energy prices. Figure 3 shows the proportion of replacement sales to total annual shipments. Despite some fluctuations over time, this series presents a rather upward trend. The reason is that, as maturation of the product sets in, adoption becomes a less important component of total demand over time.

[Figures 1, 2 and 3]

Data on annual shipments were obtained from the "Statistical Abstract of the United States," 1946-1996, and from the 43rd annual report of "Appliance," Dana Chase Publications, 1996. Annual series of existing stock and replacement of electric heaters[6] have been constructed from equations (1) and (2) using information on annual shipments and the survival probabilities estimated with the RECS data. We were careful of obtaining a good estimate of appliance stocks and units to be replaced at the beginning of 1946. Electric heaters became first available in the marketplace approximately in the late 1930's. Information from the "Statistical Abstract of the United States" on unit shipments for 1940 as well as on the number of homes owing these appliances by the early 1950's made it possible to get an approximation of unit shipments for the late 1930's until mid-1940's.

In order to estimate the adoption demand, we specify the vector **x**(t) in (12) as consisting of product price, energy prices, new housing starts, real disposable income, real interest rates, and unemployment rate. Our choice is justified as follows. First, as mentioned in the introduction, in recent years researchers have found evidence that product price may affect the speed of adoption of consumer durable goods (e.g., Bass, 1980; Jain and Rao, 1990; Karshenas and Stoneman, 1992). Second, since energy prices affect operating costs, they may affect adoption through a substitution effect. In the special case of heaters, the evolution of relative energy prices may determine which fuel is adopted by the household.[7]

Third, new private housing starts may also play an important role in adoption because, as new households are formed, appliances such as heaters become essential items. Given that secondary markets for these durable goods either do not exist or are not highly developed, equipment installed in new homes should mostly correspond with current unit shipments.[8]

Fourth, adoption of consumer durable goods may be also affected by the evolution of real interest rates (see Parks, 1974, Deaton and Muelbauer, 1980). In particular, given that durable goods provide a stream of services over time, they resemble capital goods. Their accumulation, hence, is affected by fluctuations of real interest rates. In particular, higher real interest rates decrease investment on consumer durable goods[9]. Finally, increases (drops) in real income have a positive impact (negative) on adoption of durable goods—assuming they are normal goods (see Deaton et al.), and increases in the unemployment rate may reduce adoption because they may reflect an aggregate economic slowdown.

We use the household appliances price index deflated by the implicit deflator for consumer durable goods as a proxy for price (sources: "Statistical Abstract of the United States," 1979-1996, "Business Statistics", U.S. Department of Commerce, 1975-1992, and "Monthly Labor Review," 1994, 1995, and 1996). The reason is that an individual price index for electric heaters is not available for the entire period 1946-1995. Indeed, nominal average prices can be obtained from the "Statistical Abstract of the United States" only from 1946 until approximately the mid-1980's.

Real consumer price indices for electricity, piped gas, and fuel oil were constructed with the implicit deflator for personal consumption expenditures (sources: "Historical Statistics of the United States: Colonial Times to 1970," "Statistical Abstract of the United States," 1979-1996, and the "Economic Report of the President," U.S. Government Printing Office, 1990-1995). Data on new private housing starts were taken from the "Historical Statistics of the United States: Colonial Times to 1970," the "Business Statistics," U.S. Department of Commerce, 1992, and from the "Economic Indicators," U.S. Government Printing Office, December 1996.

The nominal series of interest rates was obtained from the "Economic Report of the President," 1987-1996, and was adjusted by the annual percent variation in the consumer price index collected from the "Statistical Abstract of the United States," 1996. Data on real disposable per capita income were taken from the "Economic Report of the President," 1995-1996; and, data on unemployment were obtained from the "Datapedia of the United States:

1790-2000," and the "Economic Report of the President," 1996.

Before describing our results, we should point out that, when modeling aggregate demand, the assumption of exogeneity of the price of heaters is no longer appropriate.[10] Indeed, changes in the aggregate demand of a given appliance will lead to changes in its price. This in turn implies that a more complete model specification should also take account of the supply side.

In our estimation, however, such an endogeneity issue is highly reduced because we utilize an average appliance price index[11] rather than an individual price series. Indeed, significant changes in the appliance price index will not be in general accounted for by changes in the price of an individual appliance in isolation. This in turn implies that the evolution of the appliance price index may be regarded as exogenous when estimating each individual appliance demand. Consequently, we do not attempt to model demand and supply jointly in this study but instead we take this issue as an interesting topic for future research.

We use the econometric technique of nonlinear least squares to estimate the vector of parameters β in (12). Alternative computational methods such as maximum likelihood can be also utilized provided that one makes an assumption about the probability distribution function of the error term, e(t), in equation (9) (e.g., Schmittlein and Mahajan, 1982; Olson and Choi, 1985).

The inclusion of economic variables in the lognormal model estimated below proved that correction for serial correlation of the disturbance e(t) was unnecessary. The macroeconomic indicators have been expressed in natural logarithms except for the real interest rate, which takes on negative values in some years. The number of new private units and the real per capita income are all expressed in thousands.

Table 3 shows the estimation results for electric heaters under a lognormal specification when the eventual probability of adoption takes the functional form in (12). A higher price of electricity at constant dollars leads to a lower probability of adoption. In particular, a 1 percent increase in the price of electricity leads to a 7.7 percent decrease in the probability of adopting an electric heater, given that adoption has not yet occurred. This relatively high impact can be explained by the fact that electricity is a much more expensive input than other fuel types (e.g., gas). Our proxy of real price of heaters is also negatively correlated with the probability of adoption. For example, a 1 percent increase in price leads a 4 per cent drop in the conditional probability of adoption.

[Table 3]

Due to a substitution effect, an increase in the real price of fuel oil makes more likely that households turn to electric heating equipment. From our calculations we see that a 1 percent increase in the price of fuel oil leads to a 2.2 per cent increase in the conditional probability of adopting an electric heater. Although the price of piped gas at constant dollars also has the expected sign, it does not appear as statistically relevant.

Both the real interest rate and the unemployment rate are negatively correlated with adoption of an electric heater. Higher real per capita income and new housing starts in contrast make adoption more likely. However, none of these variables are statistically significant at the 10 per cent level. Both the overall fit of the model, 96 per cent, and its forecasting performance (MAPE), 10.4 per cent, are quite good.[12]

Figure 4 shows actual and fitted unit shipments of electric heaters. Despite some fluctuations, annual shipments present an increasing trend over 1946-1995. Figure 5 shows our estimate of adoption of electric heaters as a share of total unit shipments. The series labeled as "actual" is that constructed from both the unit shipments data and our estimate of annual equipment replacement. It is noticeable that adoption becomes a smaller share of annual sales over time.

In short, our analysis suggests that increases in the price of heaters and electricity delay adoption. The eventual probability of adoption seems to be also affected by alternative fuel technologies. These findings are both plausible and have economic content. We next estimate the lognormal model excluding the last five years of observations in order to examine its forecasting performance more closely.

[Figures 4 and 5]

Table 4 shows actual and predicted shipments of electric heaters for 1991-1995. The average forecasting error for the five-year period is relatively small, 4.92 percent. This leads us to conclude that, despite its limitations, the aggregate model we have presented performs quite well for this particular appliance.

[Table 4]

In order to test the robustness of our conclusions, we instead imposed that the probability that an individual has adopted the product by time t takes the well-known Bass functional form (1969):

$$F(t) = \frac{1 - e^{-(p+q)t}}{1 + \frac{q}{p} e^{-(p+q)t}}, \tag{13}$$

where p and q are termed the coefficients of innovation and imitation, respectively (for further details, see Bass, 1969; or Jain and Rao, 1990). We find that both statistical significance and direction in which the economic variables considered may affect adoption are generally unchanged under either the Bass or lognormal models. In addition, both fit and forecasting accuracy only slightly change as we move from one functional form to the other (see Table 4).

4 Further Remarks and Final Conclusions

In this article we have modeled demand for home appliances as a function of its two key components: adoption and replacement. Specifically, we have incorporated into the aggregate replacement demand information on survival probabilities obtained from a household replacement model. Although there exist some examples in the literature where replacement has been considered, the survival probabilities of those studies have not been derived from micro data. Neglecting the impact of economic factors on replacement decisions may lead to a serious bias of the coefficients on the variables considered in the adoption demand.

As shown in Table 1, appliances such as refrigerators, television sets, and washers have reached high saturation levels in the United States. This implies that an important component of annual shipments of such goods is replacement sales. The household replacement model we have presented can be potentially useful to production and marketing planning because it makes it possible to assess the importance of demographics and equipment features on the timing of replacement purchases. Table 5 illustrates this point for the appliance analyzed in this study. For example, within twenty years a 10-year increase in the age of the head of the household reduces the probability of replacement by 18 per cent, whereas a $10,000 increase in monthly income increases the probability of replacement by 58 per cent. In terms of overall probability of replacement, the chance that a replacement takes place is 53 per cent within 20 years.

[Table 5]

Except for price, economic factors potentially relevant to adoption have been neglected in aggregate models. In this article we propose a more complete model specification that incorporates variables such as real disposable income, real interest rates, fuel prices, and new housing starts. In general, we find that the evolution of these economic indicators may help to explain adoption over time. Our approach may be particularly useful to general planning of new market products because it illustrates how to quantify, in aggregate terms, the impact of percent changes in economic indicators on the diffusion of new products. Our analysis may also be valuable to policy making. Indeed, energy prices seem to play an important role in adoption of electric heaters because of their impact on total operation costs. This implies that the development of more efficient technologies may indeed affect the adoption rates of certain appliances.

We have also illustrated the goodness of our model as a forecasting tool. One interesting exercise is to see how much forecasting power is gained by incorporating economic variables into the adoption demand. In order to answer that question, we neglect economic variables altogether and set $c=1$ for the whole sample period. Although this assumption may not be realistic for the early years of a product's life, it may be a good approximation in the long-run. In this case the conditional probability of adoption depends only on the p.d.f. of adoption time.

Analysis of the fitted residuals of equation (9) for electric heaters led us to conclude that the error term, e(t), followed a first-order autoregressive process. Consequently, we respecified the model as follows:

$$y(t) = A(t)+R(t)+e(t), \qquad (14)$$

where

$$e(t) = \rho\, e(t-1)+\xi(t), \qquad (15)$$

$|\rho| <1$ and ξ (t) is white noise. Our results are shown in Table 6.

Table 7 presents the result of estimating the model in (14) excluding the five last observations, and forecasting electric heaters unit shipments for 1991-1995. It is interesting to see that, except for 1995, allowing c to depend on economic variables yields a more accurate forecasting of annual shipments.

[Tables 6 and 7]

Finally, it is important to point out that the approach we have presented in this paper is by no means limited exclusively to electric heaters. Indeed, it can be used to model aggregate sales of any durable good with a relatively low saturation level. That is, any durable good for which neither adoption nor replacement is negligible when compared to total shipments. For those goods for which either adoption or replacement is dominant, each demand component can be modeled separately by the methodology proposed in this paper.

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Table 1. Home Appliance Saturation Levels[1]

Category	1978	1987	1992	1993	1994
Major Appliances					
Dishwasher	41.9%	47.7%	50.0%	51.0%	52.2%
Dryer, Electric	45.1%	42.4%	50.8%	52.4%	53.7%
Microwave oven	7.2%	65.7%	84.5%	85.5%	88.8%

Refrigerator, Standard	99.9%	99.9%	99.0%	99.3%	99.5%
Washer	68.9%	69.8%	73.9%	73.9%	74.9%
Water heater, Electric	47.8%	46.9%	41.3%	43.9%	44.5%
Comfort Conditioning Appliances					
Air-Conditioner, Room	28.0%	26.8%	29.5%	30.5%	33.3%
Air-Conditioner, Unitary	24.0%	38.5%	42.8%	44.5%	44.7%
Furnace, Electric	n.a	8.5%	11.0%	10.9%	11.0%
Heat pump	n.a	14.5%	18.6%	19.8%	20.5%
Consumer Electronics					
Compact Disc Player	n.a	5.0%	42.3%	43.0%	45.0%
Television, Color	85.2%	96.0%	98.0%	97.0%	97.0%
Video Cassette Recorder/Player	2.0%	52.0%	80.0%	81.0%	80.0%

1: Percentage of U.S households with a particular class of appliance; n.a: not available.

Source: "A Portrait of the U.S. Appliance Industry 1995". Appliance, a Dana Chase Publications Inc. September 1995.

Table 2. Replacement Model for Electric Heaters

Covariate	Parameter Estimate	Standard Error	Asymptotic t-statistic
Constant term	2.362	0.309	7.644*
Age head of household (10 years)	0.076	0.022	3.454*
Monthly income ($10,000)	-0.217	0.206	-1.053
Urban area dummy	-0.092	0.080	-1.150
Natural gas availability	0.213	0.069	3.087*
Home area (1,000 square feet)	0.038	0.036	1.056
Heating degree days (1,000)	0.065	0.018	3.611*
Price of electricity (cents/kWh)	-0.233e-2	0.193e-2	-1.207
Poor credit rating dummy	0.056	0.132	0.424
Standardized parameter of physical deterioration, b/σ	0.832	0.150	5.547*

Log of likelihood function at convergence = -726.6
Number of observations = 505

*: Statistically significant at the 5 per cent level.

Notes (1) Cooling degrees days (CDD) is the number of degrees the average daily temperature is above the base temperature from January 1990 to December 1990. The average daily temperature (ADT) is calculated as the arithmetic average of the highest and lowest temperatures recorded on a given day. That is, CDD = ADT-base temperature (65 Fahrenheit degrees). (2) Heating degrees days (HDD) is the number of degrees the average daily temperature is below the base temperature from January 1990 to December 1990. That is, HDD = base temperature (65 Fahrenheit degrees) –ADT.

Table 3. Lognormal Model Fitted to Electric Heaters Data

Variable	Estimate	Standard error	Asymptotic t-statistic
Constant	4.455	12.039	0.370
Real product price (proxy)	-4.008	1.172	-3.418*
Real interest rate	-0.032	0.032	-0.983
Real income per capita	2.329	1.865	1.249
Real electricity price	-7.695	2.017	-3.815*
Real fuel oil price	2.213	0.736	3.008*
Real gas price	1.263	1.209	1.045
New housing starts	0.470	0.467	1.007
Unemployment rate	-0.035	0.310	-0.114
μ	1.043	0.245	4.250*
σ	0.791	0.066	11.906*

Number of observations = 49
R^2 =0.969
Adjusted R^2 =0.961
MAPE =10.402 per cent

*: Statistically significant at the 5 per cent level.

Table 4. Forecasted Electric Heaters Shipments

Year	Actual (thousands)	Forecast Bass	% Error	Forecast lognormal	% Error
1991	5385.26	5273.68	2.115	5326.24	1.108
1992	5563.00	5386.59	3.275	5445.72	2.154
1993	6209.00	5507.56	12.763	5568.06	11.511
1994	6071.29	6144.91	6.986	5667.31	7.129
1995	5868.75	6132.99	3.464	5714.99	2.691

Note: The forecasting percent error is calculated as 100*(actual value -forecasted value)/forecasted value.

Table 5. Marginal Impacts on the Probability of Replacing Electric Heating Equipment

	Time period (years)			
Covariate	1-3	4-6	7-9	1-20
Age of head of household (per 10 years)	-3.05e-5	-1.26e-4	-0.004	-0.176
Monthly income (per $10,000)	3.50e-4	0.003	0.027	0.583
House square footage (per 1,000)	-1.1e-5	-1.04e-4	-0.003	-0.144
Overall probability of replacement	9.00e-4	0.001	0.033	0.525

Note: Marginal impacts are evaluated at sample means.

Table 6. Lognormal Model without Economic Variables Fitted to Electric Heaters Data for 1946-1995

Parameter	Estimate	Standard error	t-statistic
μ	3.353	0.085	39.387*
σ	0.417	0.045	9.238*
ρ	0.764	0.076	10.002*

Number of observations	= 48
R^2	=0.965
Adjusted R^2	=0.964
MAPE	=9.467 per cent

*: Statistically significant at the 5 per cent level.

Table 7. Electric Heaters Forecasting Sales for 1991-1995 Using a Lognormal Model without Economic Variables

Year	Actual (thousands)	Forecasted (thousands)	Percent forecasting error (%)
1991	5385.26	5265.43	2.276
1992	5563.00	5375.31	3.492
1993	6209.00	5511.76	12.650
1994	6071.29	5647.33	7.507
1995	5868.75	5743.68	2.177

Note: The forecasting percent error is calculated as 100*(actual value -forecasted value)/forecasted value.

Figure 1 Survival Function of Electric Heaters

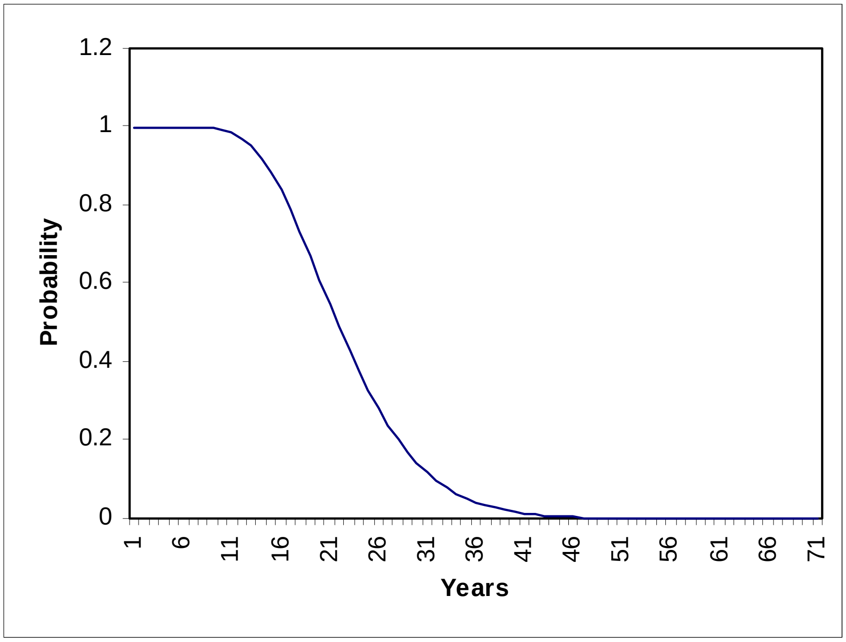


Figure 2 Annual Variation in the Stock of Electric Heaters, 1947-1995

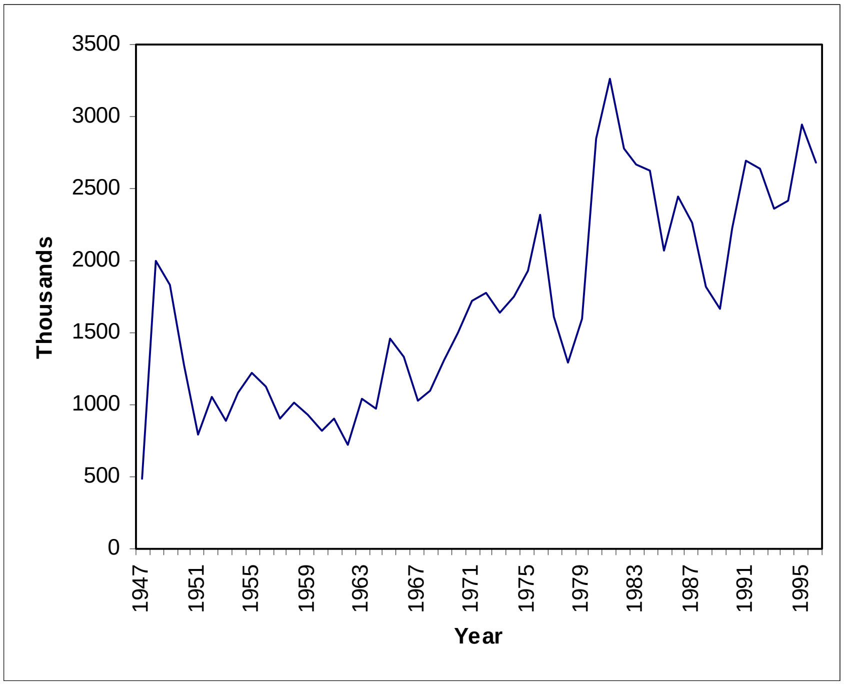


Figure 3. Annual Replacement to Shipments of Electric Heaters, 1946-1995

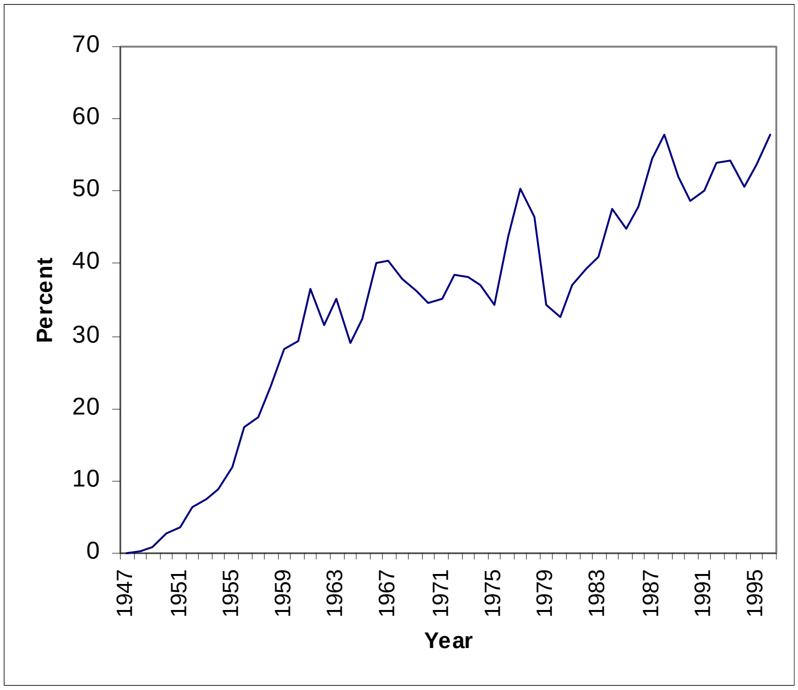


Figure 4. Annual Shipments of Electric Heaters, 1946-1995

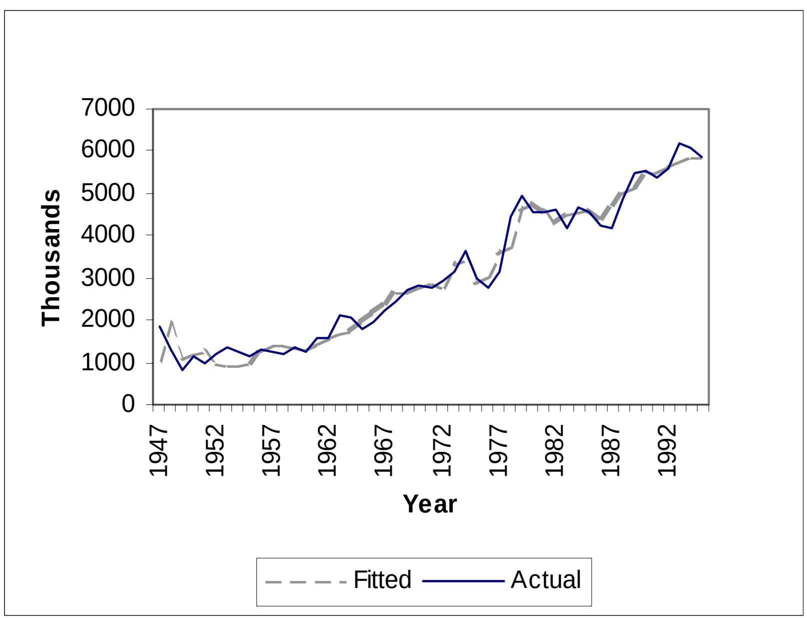
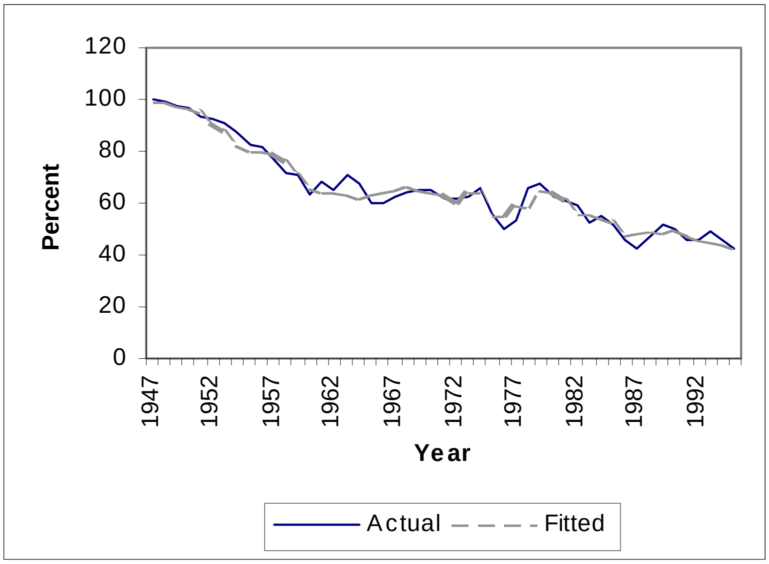


Figure 5 Annual Adoption of Electric Heaters, 1946-1995



Endnotes

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[1] The United States Department of Commerce defines durable goods as items with an average life expectancy of three years of more ("U.S. Industrial Outlook 1994").

[2] The most comprehensive survey on residential energy usage in the United States, the "Residential Energy Consumption Survey" (RECS) conducted by the U.S. Department of Energy, does not provide enough information to infer equipment adoption dates. However, it does record equipment ages, which can be used to model replacement decisions as shown in this study.

[3] This methodology was introduced by Olson and Choi (1985), and utilized later by Kamakura and Balasubramanian (1987).

[4] Those people who received aid in terms of food stamps, unemployment benefits or income from AFDC (Aid to Families with Dependent Children) during the 12 months prior to the conduction of the survey were classified as having a poor credit rating.

[5] We do not have information on equipment purchase prices, which would allow us to control for quality heterogeneity.

[6] Portable and non-portable electric heaters have been considered.

[7] Once a particular type of unit has been adopted, relative energy prices may also affect the probability of switching to another fuel.

[8] This is not necessarily true for portable appliances. For example, a household moving into a new house will not necessarily replace equipment purchased in the past.

[9] An increase in the real interest rate leads to a higher spot rental or service price for a unit of the durable good (Parks, 1974).

[10] Previous studies such as Jain and Rao's (1990), and Kamakura and Balasubramanian's (1987) do not raise this issue.

[11] Indeed, this appliance price index includes television, video and sound equipment, and household appliances such as refrigerators, home freezers, laundry equipment, stoves, dishwashers, heaters, and air conditioners (see "CPI Detailed Report", U.S. Bureau of Labour Statistics).

[12] MAPE= $\dfrac{\sum_{t=1}^{n} \dfrac{|\hat{\zeta}(t)|}{y(t)}}{n}$, where $\hat{\zeta}(t) = y(t) - \hat{y}(t)$ represents the forecast error or fitted residual defined as the difference between the actual value, y(t), and the fitted value, $\hat{y}(t)$, and n is the sample size. Notice that here we are referring to the within-sample forecast. The forecast error will be small when the model is doing a good job in forecasting the actual data (see Gaynor and Kirkpatrick, 1994).