OBSERVABLE AND UNOBSERVABLE DETERMINANTS OF REPLACEMENT OF HOME APPLIANCES

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Abstract

Despite the dominant role of replacement purchases in many consumer durable categories, the research in this area has not been extensive. Only in the last few years has the economic theory made progress towards to a more rigorous analysis of the dynamic nature involved in replacement decisions. As a consequence of this, applied researchers have switch from conventional discrete choice models to new econometric techniques (e.g., duration analysis) that allow for richer relationships between socioeconomic variables, characteristics of the durable good, and the likelihood of its replacement over time. Our study focuses on two home appliances taken from the "Residential Energy Consumption Survey" (RECS). Based on a duration model that allows for unobserved heterogeneity across households, we conclude that household demographics and product features (both observable and unobservable) in general have statistical power to explain replacement decisions over time.

JEL classification: C41, D12; Keywords: Replacement, Durable Good, Duration Model

I Introduction

Consumer durable goods, such as automobiles and home appliances, have become standard items for a vast majority of households. Electronic innovations have contributed over the years to an increasing inventory of durable goods. Indeed, the high penetration of such goods has led current sales to consist mostly of replacement purchases. For instance, in 1994 about 75 per cent of appliance sales were accounted for by replacements ("U.S. Industrial Outlook 1994," United States Department of Commerce, 1994). As existing units age over time and as new product features are developed, replacement sales are expected to rise even higher.

Despite the dominant role of replacement purchases in many consumer durable categories, the research in this area has not been extensive. There are several factors that make the statistical analysis of the demand for durable goods complex (Raymond, Beard and Gropper, 1993). First, the element of timing involved in the acquisition and replacement of durable goods does not arise in typical demand studies. Second, due to their longevity, consumers generally replace durable goods infrequently, leading to some-data driven difficulties of analyzing durable goods acquisition with conventional statistical tools (e.g., regression analysis). Third, given that the demand for many durable goods is a derived demand, numerous factors that are relevant to explain purchase behavior are unobservable (e.g., tastes for comfort and/or efficiency). Finally, the shortage of suitable data restricts empirical work.[1]

Given that consumers usually buy only one unit at a time of most durable goods, a popular econometric tool to analyze acquisition of durable goods has been discrete or qualitative choice models (e.g., Farrell, 1954; Cragg, 1971; Dubin and McFadden, 1984; Berkovec and Rust, 1985; Train, 1986). However, conventional discrete choice models seem restrictive for analyzing complex dynamic processes, such as those involving replacement decisions. The reason is that the predictive value of these models only accounts for decisions taken in the "next" period of time. Recent studies have shown that using random-parameter logit models may be a solution for this deficiency. Indeed, these models allow for repeated choices by the same economic agents over time (e.g., Revelt and Train, 1998).

In the last few years economists have made progress in modeling the dynamic nature of replacement decisions more rigorously. For example, elements of dynamic programming and stochastic processes have made it possible to develop structural micro replacement models (e.g., Rust 1985, 1986, 1987; Ye 1990; Dixit and Pindyck 1994; Mauer and Ott, 1995; Fernandez, 1999). In addition, applied researchers have turn to new econometric techniques, such as duration analysis, which have proven to be more appropriate than conventional discrete choice models to analyze replacement decisions. For instance, recent empirical studies have shown that duration models allow for richer relationships between socioeconomic variables, characteristics of the durable good, and the likelihood of its replacement over time (e.g., Antonides, 1990; Gilbert, 1992; Raymond, Beard and Gropper, 1993).

Our study focuses on replacement of two home appliances taken from the “Residential Energy Consumption Survey” (RECS). This survey, conducted by the U.S. Department of Energy, provides information on energy consumption within the United States residential sector. Based on a duration model that allows for unobserved heterogeneity across households, we conclude that household demographics and

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[1] The economics literature has by contrast produced a sizeable amount of theory on aggregate demand for durable goods. For instance, there are several studies on the dynamics of investment in the presence of adjustment costs—e.g., search costs, taxes and other transaction costs, and imperfections in the secondary markets.

product features, both observable and unobservable, in general have statistical power to explain replacement decisions over time.

The main contributions of our paper are the following. First, previous work in the area has mostly focused on a single consumer durable good in isolation, and has dealt primarily with samples from a particular geographic region of the United States. Second, the impact of unobservable factors on replacement times has not been explored in the literature so far. Third, our quantification of how socioeconomic factors, energy use characteristics as well as attributes of the durable good determine replacement decisions over time may be relevant for policy making (e.g., assessment of penetration rates of energy efficient appliances),[2] sales forecasting, production planning, and development of new marketing techniques.

This paper is organized as follows. Section II briefly summarizes previous empirical work done in the area of replacement of consumer durable goods. Section III describes the RECS data used in our estimation. Section IV reports our main findings from fitting replacement models to space heating equipment and central air-conditioning systems. We first restrict equipment operation costs to be uncorrelated with unobservable factors, such as product quality. This constraint is later relaxed by modeling unobservable heterogeneity parametrically. We also test the presence of unobservable heterogeneity without modeling it explicitly by using the method of generalized instrumental variables. Finally, Section V summarizes our main conclusions.

II Previous Empirical Research

[2] The National Appliance Energy Conservation Act of 1987 set in the United States efficiency standards for several categories of major household appliances, including refrigerators and freezers, water heaters, dishwashers, clothes washers and dryers, and kitchen ranges and ovens.

From the mid-1980's onwards, progress has been made on determining empirically what factors affect replacement decisions at the consumer level (e.g., Hoffer and Reilly, 1984; Bayus, 1988, 1991; Bayus and Gupta, 1992; Antonides, 1990; Gilbert, 1992; Raymond, Beard, and Gropper, 1993; Cripps and Meyer, 1994; Marrel, Davidsson and Garling, 1995). These studies stress the importance of demographic and lifestyles variables, perceived obsolescence, styling and fashion, prices, environmental awareness, and uncertainty, among other variables, on the likelihood of replacement.

In this section we only refer briefly to three empirical studies that are similar to ours in methodological terms: Antonides (1990), Gilbert (1992), and, Raymond, Beard, and Gropper (1993). These three papers also study replacement decisions using duration models.

Antonides studies replacement of washing machines in the Netherlands. His most important findings are that failure rate of washing machines is increasing with equipment age, household size, and income, and it is decreasing with purchase price.[3] In addition, the author concludes that expected lifetimes corresponding with duration-dependent hazard rates are more plausible that those corresponding with constant hazard rates.

Gilbert analyzes automobile replacement in the United States. She considers three different hazard functions: replacing with a new vehicle (h_n), replacing with a used vehicle (h_u), and disposing without replacement (h_d). Both h_n and h_d are found to be increasing with income, whereas the opposite holds for h_u. While race, household size, life stage of household, education, and car odometer reading seem also relevant to replacement decisions, macroeconomic variables such as interest rate, unemployment rate, new car

[3]The author points out that family size and price can be regarded as proxies for frequency of use and product quality, respectively.

inflation rate, used car inflation rate, auto maintenance rate, and gasoline inflation rate appear as statistically insignificant.

Raymond, Beard, and Gropper study replacement of main heating equipment in the State of Alabama, United States. The authors' results indicate that the probability of equipment replacement depends negatively on the age of the head of the household and the availability of natural gas, and positively on equipment age, and higher than expected household energy usage.[4] Other regressors included in the hazard specification are income, a poor credit rating dummy variable, an urban location dummy, and house square footage. None of these variables, however, turn out to be statistically significant.

In the next two sections we will look at replacement of two appliances from the “Residential Energy Consumption Survey” (RECS), 1990—specifically, space heating equipment, and central air conditioners. Raymond, Beard, and Gropper's work is particularly useful for us because it deals with replacement of one of the appliances we analyze. In selecting the relevant variables to be included in this particular replacement model, therefore, we consider those economic variables used by the authors as well as other economic factors that seemed relevant given the national scope of our data set.

It is important to note that Raymond, Beard, and Gropper’s analysis is focused on a particular geographic region of the United States. Therefore, significant purchase price and fuel price differentials across households are not observed in their sample. Since this is not the case for us, we also control for equipment operation costs. Unfortunately, we do not have information on purchase prices for any of the appliances we analyze. Operation costs, however, may be indirectly correlated with purchase price through

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[4]This variable is measured as $(u-\hat{u})/\hat{u}$, where u is actual consumption of electricity (average kWh/month), and $\hat{u}$ represents the fitted value from a linear regression of u on household's stock of energy using durable goods and exogenous factors such as house square footage and housing unit type.

equipment quality.

In what respects to central air conditioners, their replacement model was expressed in terms of economic variables and equipment characteristics that the economic theory would suggest as relevant. Obviously, such selection was subject to our data constraints.

III The Data

The "Residential Energy Consumption Survey" (RECS) 1990 contains approximately 5,100 households, out of which 3,398 are homeowners. 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 data are gathered by questionnaires mailed to all suppliers for the selected households.

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. The information provided by the RECS about the ages of home appliances refers only to equipment the sampled households currently own. No information is provided about the age at which previous equipment has been replaced. Purchase prices of the sampled appliances—proxy for equipment quality—are not recorded either.

Equipment ages are recorded in intervals. To illustrate, consider the question about the age of air-conditioning equipment depicted in Table 1. The questions about the ages of the other sampled appliances are analogous. As we will see later, such a characteristic of the data will impose some constraints on the functional form of our likelihood function.

[Table 1]

IV Replacement Model

In this section we present replacement models for two appliances from the RECS 1990. Our base model regards operation costs as an exogenous regressor. This assumption is later relaxed to allow for correlation between this variable and unobserved factors, such as equipment quality. Two different approaches are considered to test for unobserved heterogeneity: a modified version of the base model that includes an error term, and instrumental variables in the context of nonlinear models.

4.1 Base Model Specification

In general terms, the focus of duration models is the length of time that passes from the beginning of some event either until its end or until the measurement is taken, which may antecede termination (Greene, 1996). Typically, the observations consist of a cross section of durations or "spells", t_1, t_2,..., t_n. The process under observation has usually begun at different points in calendar time, which means that durations are not spells in "real time" unless they share the same time origin (Kiefer, 1988).

A duration model assumes that the length of time or spell length, T, until an event occurs is a random variable[5] with density f(t) and cumulative distribution F(t). The survivor function, G(t), is defined as the

[5]We work with underlying continuous random variables, although the same concepts can be defined for the discrete case.

probability that the random variable T will equal or exceed the value t. That is, G(t) equals 1-F(t). A particularly useful function for duration analysis is the hazard function, $\lambda(t)$. This can be roughly defined as the rate at which spells will be completed at duration t, given that they have lasted until t.

Under a proportional hazard model specification, the hazard function for household i depends on a vector of explanatory variables, $\mathbf{x}_i$, with an unknown vector of parameters $\mathbf{b}$, and on a nonnegative "baseline" hazard function, $\lambda_0(t,\alpha)$, with α an unknown parameter. That is:

$$\lambda(t|\,\mathbf{x}_i,\alpha,\,\mathbf{b})=\phi(\mathbf{x}_i,\,\mathbf{b})\,\lambda_0(t,\alpha),\quad 0<t<\infty. \tag{1}$$

A popular functional form for $\phi(\mathbf{x}_i,\,\mathbf{b})$ is $\exp(\mathbf{x}_i'\mathbf{b})$. We hypothesize a Weibull baseline hazard model because of both its mathematical convenience and popularity in the literature of duration models (e.g., Lancaster, 1979, 1990). In particular using a Weibull specification enables us to get a closed-form expression for the likelihood function, as explained below. Let $\mathbf{q}=(\alpha,\,\mathbf{b})$. Then

$$\lambda(t|\,\mathbf{x}_i,\,\mathbf{q})=\exp(\mathbf{x}_i'\mathbf{b})\,\lambda_0(t,\alpha), \tag{2}$$

with $\lambda_0(t,\alpha)=\alpha t^{\alpha-1}$.

$$G(t\,|\,\mathbf{x}_i,\,\mathbf{q}) = \exp\left\{-\int_0^t \lambda(s|\,\mathbf{x}_i,\mathbf{q})ds\right\} = \exp(-\exp(\mathbf{x}_i'\mathbf{b})\,t^{\alpha}). \tag{3}$$

Given that the RECS only provides information on (discretized) current equipment ages, we need the p.d.f. of equipment age. An approximation for the p.d.f of U_t, the age of household i's durable good, can be obtained from the renewal theorem (see, for example, Lancaster 1990):

$$f(u|\,\mathbf{x}_i,\mathbf{q})=\frac{\exp(\exp(\mathbf{x}_i'\mathbf{b})\,u^{a})}{\mathbf{n}_i},\quad 0<u<\infty\,, \tag{4}$$

where

$$\nu_i = \int_0^{\infty} \exp\,(\exp(\mathbf{x}_i{}'\mathbf{b})\tau^{\alpha})\,d\tau. \tag{5}$$

By change of variables the integral in (5) becomes:

$$\nu_i = \frac{1}{\alpha \exp(\frac{\mathbf{x}_i{}'\mathbf{b}}{\alpha})} \int_0^{\infty} \exp(\omega)\omega^{\frac{1}{\alpha}-1}\,d\omega, \tag{6}$$

which equals

$$\nu_i = \exp(\frac{\mathbf{x}_i{}'\mathbf{b}}{\alpha})\,\Gamma(1+\frac{1}{\alpha}), \tag{7}$$

where $\Gamma(.)$ denotes the Gamma function. Therefore the probability that the age of household i's appliance is between l and m equals

$$\text{Prob}(l < u < m) = \int_l^m \frac{\exp(\exp(\mathbf{x}_i{}'\mathbf{b})\,u^{\alpha})}{\nu_i}\,du, \tag{8}$$

or equivalently after change of variables[6]

$$\frac{1}{\Gamma(\frac{1}{\alpha})} \int_{\omega_0}^{\omega_1} \exp(\omega)\omega^{\frac{1}{\alpha}-1}\,d\omega, \tag{9}$$

where $\omega_0= \exp(\mathbf{x}_i{}'\mathbf{b})\, l^{\alpha}$, and $\omega_1=\exp(\mathbf{x}_i{}'\mathbf{b})\, m^{\alpha}$.

4.2 Estimation Results of the Base Model

We consider only those sampled households who own their homes, and for whom the home is the

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[6] As we can see from Table 1, the current age of the appliances recorded in the RECS has been discretized. Therefore, an adjustment needs to be made to the data before carrying out the estimation. In particular, if the underlying distribution of elapsed duration is continuous and times are grouped into unit intervals, so that the discrete observed part is Z=[U], with [U] the "integer part of U;" then the probability function of Z can be written as $h(z)=P(Z=z)=P(u<U<u+1)=F(u+1)-F(u)$, with F(.), the c. d. f. of equipment age. For example, the probability that equipment age is between two and four years old is given by $P(2<Z<4)=P(Z=2)+P(Z=3)+P(Z=4)$, which equals $P(2<U<3)+P(3<U<4)+P(4<U<5)=F(5)-F(2)$, and so on.

primary residence. Our focus is electric equipment: electric space heating equipment, and central air-conditioners. In what follows, when not otherwise stated, all the estimation is carried out by the method of maximum likelihood.

Based on the econometric specification presented above, we first fit a replacement model for space heating equipment. The regressors of our model are age of the head of the household, income, house square footage, equipment operation cost, and dummy variables for urban location, natural gas availability, and poor credit rating.[7]

As reported in Table 2, the age of the head of the household as well as the age of the durable are statistically significant indicators of replacement. In particular, the older the head of the household, the less likely that the durable will be replaced. This empirical finding was also reported by Raymond et. al (1993) for heating equipment in the state of Alabama. The authors do not attempt to find an explanation for such finding, but we believe that one possible interpretation is that preferences of older households change more slowly. Or, alternatively, that older households may have higher implicit discount rates (e.g., Train, 1985).

The estimated coefficient on time (i. e, parameter alpha) is greater than one. This implies that, as equipment gets older, it is more likely that replacement takes place. This is due in part to the natural equipment depreciation process. Age of the current unit may be also a good indicator of perceived obsolescence. This may arise from the desire of new technologies and/or features, image or styling preference changes, and changes in price expectations (Bayus and Gupta, 1992). Raymond et al. draw an analogous conclusion with respect to the effect of equipment age on replacement.

[7]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 have been classified as having a poor credit rating.

[Table 2]

As expected, higher income is associated with a higher probability of replacement. Moreover, the probability of replacement of space heating equipment increases with operation costs, once we account for house square footage (our proxy for equipment size.) In turn our estimation shows that increases in house square footage ("equipment size") delay replacement. Intuitively, bigger houses require more expensive equipment, especially designed to heat more extensive areas.

As Raymond et al. conclude, the dummy variable for natural gas availability is statistically significant at the 5 per cent level, and is associated with a lower probability of replacement. This result may arise from differentials in equipment lifetime of gas versus electric powered equipment. In particular, those households without gas service in their neighborhood cannot switch from an electric to a gas powered system and, hence, they are more likely to replace electric equipment, as the authors suggest.

The fit of the model is quite good in overall terms. Except for the first age category of Table 1, the percent prediction error is below 6 per cent. The predicted lifetime for an electric heating system is about 20 years, which is within the age ranges given by the industry in 1992: 10 (low), 20 (high), 16 (average). (Source: "A Portrait of the U.S. Appliance Industry 1992." Appliance, September 1992. Dana Chase Publications).

We also computed marginal effects of changes of economic factors on the probability of heating system replacement. These marginal impacts are calculated as the change in probability of replacement (over a given time interval) per unit change in the explanatory variable, and are computed at the sample means of the regressors. We find, for example, that a 10-year increase in the age of the head of the household reduces the probability of replacement within 20 years by 11 per cent. By contrast, a one-dollar increase in monthly operation costs leads to an increase of 7.3 per cent in the probability of replacement within 20 years. The overall probability of replacement for this time period equals 55 per cent.

Finally, Table 3 reports our results for central air-conditioners. Important factors for replacement are age of the head of the household, cooling capacity, and operating costs. As before, replacement is negatively associated with increases in the age of the head of the household, and positively associated with increases in operating costs. Income and urban location do not seem to play an important role in the replacement decisions of this particular appliance.

We find that a greater cooling capacity leads to later replacement. At a first glance one would conjecture that this might be due to a high and positive correlation between cooling capacity and operation costs. However, cooling capacity is not strongly correlated with operating costs, after controlling for family size, climate and house square footage. Hence, the strong and negative impact of cooling capacity on replacement decisions may come from the fact that more efficient units are probably more technologically advanced, and therefore more expensive to replace. House square footage seems also to be capturing a price effect, given its negative correlation with replacement time.

[Table 3]

The Weibull model fits the data quite well. Except for the second and third age categories, the percent error of the fitted frequencies with respect to the actual ones is below 5 per cent. The fitted lifetime for central air conditioners is approximately 15 years. This seems a reasonable estimate when compared with the industry's average prediction in 1992: 12 years. (Source: "A Portrait of the U.S. Appliance Industry 1992." Appliance, September 1992. Dana Chase Publications.)

Cooling capacity is the variable that has the largest impact on the probability of replacement over time. Indeed, we find that a 1,000 Btu/hr-increase in cooling capacity decreases the probability of replacement by 22 per cent within 20 years.

4.3 Testing for Unobserved Heterogeneity

Operation costs depend on various factors. In the case of heating equipment, for example, they are a function of exogenous variables such as climate, and utility rate structure; choice variables such as housing structure, type and size; and, product features such as quality. These factors usually affect ownership spells but quantifying their marginal impact on replacement may be difficult (or impossible) because they are in general unobservable to researchers. In particular, product quality cannot be exactly measured, so assuming operation costs as exogenous may lead to biased estimates.

To test the validity of the hypothesis of exogenous operation costs, we follow two different approaches: i) a parametric approach that explicitly models unobserved heterogeneity; and, ii) generalized instrumental variable estimation.

4.3.1 Modeling Unobserved Heterogeneity

Suppose that v_i represents unobserved heterogeneity of household i coming from, for example, equipment quality or any other source that is not currently captured by the above model specification.[8] Furthermore, following Lancaster (1979), let us assume for mathematical convenience that v_i lies in the Gamma family. Specifically, assume that this error term is distributed as Gamma with mean 1 and variance σ_i^2 and uncorrelated with regressors and duration, T. Moreover, suppose that σ_i is a linear function of a

[8] As Greene (1996) points out, introducing v_i is a counterpart to the incorporation of a disturbance term in a regression model.

constant term, operation costs, and equipment size. Such a specification in principal enables us to detect some forms of unmeasured household heterogeneity that may be correlated with operation costs, such as equipment quality. Specifically,

$$f(v_i|\mathbf{x}_i) \propto v_i^{\sigma_i^{-2}} \exp(-v_i\sigma_i^{-2}), \tag{10}$$

where $\sigma_i=\delta_1+\delta_2$*operation costs$_i$ + δ_3*equipment size$_i$, δ_j, j=1, 2, 3, are parameters, and $\mathbf{x}_i$ is a vector containing household's operation costs and equipment size.

The distribution function of T conditional on the current value of the regressors can be obtained by integrating over the distribution of v_i:

$$S_i(t|\mathbf{z}_i) = \int_0^\infty v_i^{\sigma_i^{-2}-1} \exp\{v_i(\sigma_i^{-2} + \exp(\mathbf{z}_i'\beta)\}dv_i = \{1+\sigma_i^2 \exp(\mathbf{z}_i'\beta)t^\alpha\}^{-\frac{1}{\sigma_i^2}}, \tag{11}$$

with $\mathbf{z}_i$=($\mathbf{x}_i$, other relevant regressors for household i), and α and $\mathbf{b}$, parameters. In order to obtain (11), we kept our previous assumption of a proportional hazard model with an underlying Weibull distribution. Letting $\sigma_i^2 \rightarrow 0$ yields the Weibull model of the previous section.[9]

By change of variables we get:

$$E(t|\mathbf{z}_i) = \int_0^\infty \{1+\sigma_i^2 \exp(\mathbf{z}_i'\mathbf{b})\, t^\alpha\}^{\frac{-1}{\sigma_i^{-2}}} dt = \frac{1}{\alpha\sigma_i^{\frac{2}{\alpha}}} \exp(\frac{\mathbf{z}_i'\mathbf{b}}{\alpha})\, B(\frac{1}{\sigma_i^2}\frac{1}{\alpha}, \frac{1}{\alpha}), \tag{12}$$

where B(.) represents the Beta function, and $B(\sigma_i^{-2} - \alpha^{-1}, \alpha^{-1}) = \Gamma(\alpha^{-1})\, \Gamma(\sigma_i^{-2} - \alpha^{-1}) / \Gamma(\sigma_i^{-2})$. By (11) and (12) we can obtain an asymptotic approximation of the density of equipment age, U:

[9] As δ_1, δ_2 and δ_3 become statistically insignificant, the model boils down to that of the previous section.

$$g(u|\mathbf{z}_i) = \frac{\{1+\sigma_i^2 \exp(\mathbf{z}_i{}'\mathbf{b})\, u^{\alpha}\}^{\sigma_i^{-2}}}{\frac{1}{\alpha\,\sigma_i^{\frac{2}{\alpha}}}\exp(\frac{(\mathbf{z}_i{}'\mathbf{b})}{\alpha})\ B(\frac{1}{\sigma_i^2}\frac{1}{\alpha},\frac{1}{\alpha})} \quad , u > 0\,. \tag{13}$$

By change of variables, the terms in the likelihood function for the RECS data take the form

$$\text{Prob}(w_a < w < w_b) = \frac{1}{B(\frac{1}{\mathbf{s}_i^2}\frac{1}{\mathbf{a}},\frac{1}{\mathbf{a}})}\int_{w_a}^{w_b} w^{\frac{1}{\mathbf{s}_i^2}-\frac{1}{\mathbf{a}}-1}\ (1-w)^{\frac{1}{\mathbf{a}}-1}\ dw\,, \quad 0 < w < 1\,, \tag{14}$$

with $w_a = (1+\sigma_i^2 \exp(z_i{}'\mathbf{b})u_a{}^{\alpha})^{-1}$, $w_b = (1+\sigma_i^2 \exp(z_i{}'\mathbf{b})u_b{}^{\alpha})^{-1}$.

Table 4 reports our estimation results for space heating equipment. Given that the RECS does not record equipment size, we used house square footage as a proxy. Hence, the standard deviation of v_i is given by $\sigma_i=\delta_1+\delta_2$*monthly operation $\text{costs}_i+\delta_3$*house square footage_i. Our estimates suggest some evidence of unobserved heterogeneity across the sampled households: both δ_1 =0.784 (constant term) and δ_2 =-0.144 (estimated coefficient on monthly operation cost) are significant at the 5 per cent level.

[Table 4]

The statistical significance of the beta estimate on operation costs, β_7 =0.195, is slightly reduced by allowing for unobserved heterogeneity. This means that operation costs affect replacement timing mostly through unobserved factors such as product efficiency. However, the β 's are in general quite robust to the inclusion of σ_i. Indeed, their magnitude and statistical significance are not noticeably changed when compared with those of the base model. In addition, our estimate of expected lifetime of electric heaters, 19.6 years, is only a 4.1 per cent smaller than that obtained in the previous section. The marginal effects of changes in household characteristics and product features on the probability of system replacement are also robust to our parametric specification of unobserved heterogeneity (Table 5).

[Table 5]

Table 6 presents our results for central air conditioners. In this case the standard deviation of v_i takes the form $\sigma_i=\delta_1+\delta_2$*monthly operation $\text{costs}_i+\delta_3$*cooling capacity_i. Our estimation suggests that unobserved heterogeneity may be partially associated with operation costs and cooling capacity. As we pointed out in the previous section, the latter variable may be correlated with the cost of replacing an existing unit. If price is a proxy for equipment quality, then the statistically significance of operation costs and cooling capacity would give some support to our hypothesis of unobservable heterogeneity being partially associated with product quality.

[Table 6]

The bottom of Table 6 shows that accounting for unobserved heterogeneity also reduces the estimate of expected lifetime in this case. This is now 14.3 years, that is, about 6 per cent smaller than in the base model.

Table 7 shows the effect of marginal changes in the explanatory variables on the probability of replacement. In particular, marginal changes of operation costs and cooling capacity now have a larger impact on the timing of replacement than in the base model. The reason is that these two variables affect the survival probabilities not only through the proportional hazard function but also through σ_i^2.

[Table 7]

As we see, there is some evidence of unobserved household heterogeneity associated with equipment operation costs for both appliances. The existence of correlation between v_i and operation costs suggests, therefore, that the latter may be indeed affected by product quality.

However, this evidence is not overwhelming, as the estimated probabilities of replacement and the marginal impact of changes in demographics and product features on replacement do not vary much. Probably the strongest effect of unobserved heterogeneity shows in the reduction of the expected lifetime estimate. Such finding may be indicative that low product quality accelerates replacement because it possibly translates into higher operation costs.

4.3.2 Instrumental Variables Approach

The above conclusions certainly hinge upon the parametric functional form chosen to model unobserved heterogeneity. So this section turns to an alternative approach that does not rely upon any specific parameterization of unobserved heterogeneity: Hansen-Singleton (1982)'s method of generalized instrumental variables (GIV). Our strategy is to test for possible endogeneity of operation costs by comparing the GIV estimates with those of the base model found by maximum likelihood (section 4.1). Under the Weibull specification of the base model, duration, T, has expectation and variance given by equations (15) and (16), respectively:

$$E(t|\ \mathbf{x}_i) = \exp(\frac{\mathbf{x}_i\text{'}\mathbf{b}}{\alpha})\,\mathbf{G}(1+\frac{1}{\alpha})\,, \tag{15}$$

$$Var(t|\mathbf{x}_i) = \exp(\frac{2\,\mathbf{x}_i\text{'}\mathbf{b}}{\alpha})\,\{\mathbf{G}(1+\frac{2}{\alpha})\,\mathbf{G}^2\,(1+\frac{1}{\alpha})\}\,. \tag{16}$$

As before the vector $\mathbf{x}_i$ contains household characteristics and product features. Based on Lancaster (1990), we find expressions for the expectation and variance of equipment age, U:

$$E(u|\mathbf{x}_i) = \exp(\frac{\mathbf{x}_i\text{'}\mathbf{b}}{\alpha})\frac{\mathbf{G}(\frac{2}{\alpha})}{\mathbf{G}(\frac{1}{\alpha})}\,, \tag{17}$$

$$\mathrm{Var}(u|\,\mathbf{x}_i) = \exp(\frac{2\,\mathbf{x}_i'\mathbf{b}}{\alpha})\frac{\Gamma(\frac{3}{\alpha})}{\Gamma(\frac{1}{\alpha})}\{\exp(\frac{\mathbf{x}_i'\mathbf{b}}{\alpha})\frac{\Gamma(\frac{2}{\alpha})}{\Gamma(\frac{1}{\alpha})}\}^2. \tag{18}$$

Provided that we have at least as many orthogonality conditions of the form (19) and (20) as parameters there are in the model, (17) and (18) will suffice for parameter identification.

$$E\{\mathbf{Y}_i\,(U_i\text{-}E(U_i|\mathbf{Y}_i))\}=0, \tag{19}$$

$$E\{\mathbf{Y}_i\,[(U_i\text{-}E(U_i|\mathbf{Y}_i))^2\text{-}\mathrm{Var}(U_i|\mathbf{Y}_i)]\}=0, \tag{20}$$

where $\mathbf{Y}_i$ is a vector of instrumental variables for household i.

In order to compute the GIV estimates, we need to find exogenous variables that are correlated with operation costs but that are uncorrelated with unobservable factors, such as equipment quality. In choosing our instruments, we looked at those exogenous variables that mostly explain the total variation in operation costs in the context of a linear regression.

For the heating equipment data, we selected as instruments family size, house square footage, dummy variables for urban location and natural gas availability, age of the house, number of heating degree-days,[10] average electricity rate, and income. Our estimates are shown in Table 8.

[Table 8]

Under the null hypothesis that the likelihood function in (9) is correctly specified and operation costs are indeed exogenous, both the ML estimates of the base model and the GIV estimates are consistent but the ML estimates are more efficient. The Wald statistic, q, in (21) is asymptotically distributed as chi-square

[10] Heating degree-days (HDD) is the number of degrees the average daily temperature is below 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, HDD = base temperature (65 Fahrenheit degrees) – ADT.

with p degrees of freedom (see Hausman, 1978):

$$q = N[\hat{\theta}_{GIV} - \hat{\theta}_{ML}]'[\mathrm{Var}\,\hat{\theta}_{GIV} - \mathrm{Var}\,\hat{\theta}_{ML}]^{-1}[\hat{\theta}_{GIV} - \hat{\theta}_{ML}] \rightarrow \chi^2(p), \tag{21}$$

with $\mathbf{q} = (\alpha\ \mathbf{b})$, N, the sample size, and p, the number of parameters.

From the set of estimates in Tables 2 and 8, we obtain q=19.4. The critical values for $\chi^2(9)$ at the 5 and 1 per cent level are 16.9 and 21.67, respectively. So we reject the null hypothesis at the 5 per cent level but not at the 1 per cent level. Consequently, the evidence of unobserved heterogeneity being partially captured by operation costs is not conclusive under this approach.

[Table 9]

In Table 9 we present the results of our GIV estimation for central air conditioners. The selected instruments are house square footage, cooling degree-days,[11] average electricity rate, age of the house, humidity,[12] family size, and cooling capacity. In this case the Wald statistic, q, equals 27.9, which leads us to reject the null hypothesis at the 1 per cent level. Therefore, in this case there is more evidence of unobserved heterogeneity than for electric heaters.

In summary, both the parametric approach of section 4.3.1 and the GIV estimation method of this section show some evidence of unobserved heterogeneity partially associated with equipment quality. However, this evidence is not conclusive for electric heaters, and it is not overwhelming for central air-conditioners either. Therefore, our base model is a reasonable approximation to describe replacement decisions of these two particular home appliances from the RECS 1990. Obviously, such a conclusion may

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[11] Cooling degree-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).

[12] Average humidity June-August 1990.

change depending upon the appliances and sample utilized. Therefore, it is advisable to test for the existence of unobserved heterogeneity by some method(s), such as those described in this paper. Failure to do so may lead to inconsistent estimates.

V Conclusions

Despite the dominant role of replacement purchases in many consumer durable categories, the research in this area has not been extensive. Only in the last few years has the economic theory made progress towards to a more rigorous analysis of the dynamic nature involved in replacement decisions. As a consequence of this, applied researchers have switch from conventional discrete choice models to new econometric techniques (e.g., duration analysis) that allow for richer relationships between socioeconomic variables, characteristics of the durable good, and the likelihood of its replacement over time.

Our study focuses on two home appliances taken from the Residential Energy Consumption Survey (RECS). Based on a duration model that allows for unobserved heterogeneity across households, we conclude that household demographics and product features (both observable and unobservable) in general have statistical power to explain replacement decisions over time. For example, we have found that while older equipment is more likely to be replaced, older heads of households are less likely to acquire new systems. In addition, there is evidence from our estimation that higher operations costs (possibly correlated with unobserved quality) lead to earlier replacement.

For home heating systems, natural gas availability also affects replacement decisions. In particular, due possibly to lifetime equipment differentials, electric equipment is replaced earlier than natural gas powered equipment. In addition, economic variables that are correlated with replacement cost also affect the probability of equipment survival over time. For example, house square footage is negatively correlated with the likelihood of replacing a heating system while the same relationship holds for cooling capacity and central air conditioners. Other variables such as income, family size and urban location do not in general seem to play an important role in replacement decisions.

The main contributions of our work are the following. First, previous work in the area has mostly focused on a single consumer durable good in isolation, and has dealt primarily with samples from a particular geographic region of the United States. Second, the impact of unobservable factors on replacement times has not been explored in the literature so far. Third, our approach may be particularly useful to general planning of appliances production for two reasons: (a) it makes it possible to quantify the marginal impact of percent changes in demographics and product characteristics on replacement; (b) it predicts equipment lifetimes that are within the age ranges given by the industry. Fourth, our analysis may be valuable to policy making. Indeed, operation costs seem to play an important role in replacement of electric heaters and central-air conditioners. This implies that the development of more efficient technologies may indeed affect the replacement rates of these and other home appliances.

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Tables

Table 1. About How Old is Your Central Air-Conditioner Equipment?

	Age Category
1	Less than two years old
2	2-4 years old
3	5-9 years old
4	10-19 years
5	20 years old or older
96	Does not know
99	Not applicable

Table 2. Weibull Replacement Model for Electric Space Heaters

Variable	Parameter estimate	Standard error	T-statistic
Constant term	-7.193	0.933	-7.707*
Age head of household (per 10 years)	-0.144	0.047	-3.084*
Monthly income (per $10,000)	0.739	0.449	1.650**
Urban area dummy (=1 if yes)	0.180	0.172	1.050
Natural gas availability (=1 if yes)	-0.473	0.158	-2.992*
House square footage (per 1,000)	-0.105	0.077	-1.372***
Monthly operation cost ($)	0.092	0.046	2.005*
Poor credit rating dummy (=1 if yes)	-0.183	0.311	-0.591
Alpha	2.414	0.255	9.477*

Log of likelihood function at convergence =-737.65
Number of observations = 505
Estimated expected lifetime evaluated at sample means =20.4 years

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* : Statistically significant at 5 per cent level for H_o: $\beta=0$ against H_1: $\beta\neq0$
** : Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1: $\beta\neq0$
*** : Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1: $\beta<0$

Table 3 Weibull Replacement for Central Air Conditioners

Regressor	Parameter estimate	Standard error	T-statistic
Constant term	-3.598	0.398	-9.028*
Age head of household (per 10 years)	-0.127	0.028	-4.533*
Monthly income (per $10,000)	-0.036	0.229	-0.158
Urban area dummy (=1 if yes)	-0.121	0.093	-1.309
House square footage (per 1,000)	-0.061	0.041	-1.489***
Cooling capacity (per 1,000 Btu/hour)	-0.156	0.017	-9.429*
Monthly operation cost ($)	0.052	0.024	2.146*
Poor credit rating dummy (=1 if yes)	0.192	0.233	0.823
Alpha	1.925	0.124	15.538*

Log of likelihood function at convergence =-1,859
Number of observations = 1,245
Estimated expected lifetime evaluated at sample means =15.2 years

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* : Statistically significant at 5 per cent level for H_o: $\beta=0$ against H_1: $\beta\neq0$
** : Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1:$\beta<0$
*** : Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1:$\beta<0$

Table 4 Weibull Replacement Model with Unobserved Heterogeneity for Electric Space Heaters

	Parameter estimate	Standard error	T-statistic
Regressors associated to d_i			
Constant term	0.784	0.187	4.196*
Monthly operation cost ($)	-0.144	0.017	-8.489*
House square footage (per 1,000)	-0.046	0.066	-0.711
Regressors associated to b_i			
Constant term	-8.328	1.417	-5.875*
Age head of household (per 10 years)	-0.167	0.052	-3.184*
Monthly income ($1,000)	0.883	0.498	1.771**
Urban area dummy (=1 if yes)	0.152	0.184	0.824
Natural gas availability (=1 if yes)	-0.477	0.171	-2.777*
House square footage (1,000)	-0.094	0.102	-0.921
Monthly operation cost ($)	0.195	0.102	1.910**
Poor credit rating dummy (=1 if yes)	-0.129	0.335	-0.386
Alpha	2.614	0.319	8.174*

Log of likelihood function at convergence =-735.69
Number of observations = 505
Estimated expected lifetime evaluated at sample means = 19.6 years

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* : Statistically significant at 5 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$
**: Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$

Table 5 Marginal Impacts on the Probability of Replacing Electric Space Heaters under Unobserved Heterogeneity

	Time period (years)			
Regressor	1-3	4-6	7-9	1-20
Age of head of household (per 10 years)	-0.009	-0.004	-0.008	-0.129
Monthly income (per $10,000)	0.005	0.020	0.043	0.630
House square footage (per 1,000)	-7.9e-4	-0.003	-0.006	-0.083
Monthly operation cost ($)	6.9e-4	0.002	0.005	0.077
Overall probability of replacement	0.005	0.022	0.045	0.548

Note: Marginal impacts are evaluated at sample means.

Table 6 Weibull Replacement Model with Unobserved Heterogeneity for Central Air Conditioners

	Parameter	Standard error	T-statistic
Regressors associated to d_i			
Constant term	1.169	0.349	3.349*
Monthly operation cost ($)	-0.046	0.026	-1.760*
Cooling capacity (per 1,000 Btu/hr)	-0.093	0.028	-3.380**
Regressors associated to b_i			
Constant term	-2.990	0.640	-4.670*
Age head of household (per 10 years)	-0.142	0.031	-4.504*
Monthly income (per $10,000)	-0.062	0.254	-0.241
Urban area dummy (=1 if yes)	-0.107	0.102	-1.043
House square footage (per 1,000)	-0.057	0.045	-1.242
Cooling capacity (per 1,000 Btu/hr)	-0.264	0.051	-5.212*
Monthly operation cost ($)	0.053	0.450	1.178
Poor credit rating dummy (=1 if yes)	0.216	0.296	0.731
Alpha	2.085	0.199	10.436*

Log of likelihood function at convergence = -1,855.0
Number of observations = 1,245
Estimated expected lifetime evaluated at sample means = 14.3 years

* : Statistically significant at 5 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$
** : Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$

Table 7 Marginal Impacts on the Probability of Replacing a Central Air Conditioner under Unobserved Heterogeneity

	Time period (years)			
Regressor	1-3	4-6	7-9	1-20
Age of head of household (per 10 years)	-0.004	-0.010	-0.017	-0.199
Monthly income (per $10,000)	-0.002	-0.004	-0.007	-0.087
House square footage (per 1,000)	-0.002	-0.004	-0.007	-0.080
Cooling capacity (per 1,000 Btu/hr)	-0.007	-0.002	-0.019	-0.331
Monthly operation cost ($)	0.001	0.004	0.007	0.092
Overall probability of replacement	0.027	0.066	0.094	0.770

Note: Marginal impacts are evaluated at sample means.

Table 8 Generalized Instrumental Variables Estimation for Electric Space Heaters

	Parameter estimate	Standard error	T-statistic
Constant term	-8.767	1.411	-6.213*
Age head of household (per 10 years)	-0.302	0.127	-2.381*
Monthly income (per $10,000)	1.176	1.080	1.088
Urban area dummy (=1 if yes)	0.374	0.266	1.408
Natural gas availability (=1 if yes)	-0.332	0.178	-1.863**
House square footage (per 1,000)	-0.249	0.364	-0.683
Monthly operation cost ($)	0.379	0.082	4.616*
Poor credit rating dummy (=1 if yes)	3.936	5.099	0.772
Alpha	2.593	0.380	6.824*

Chi-square test of over-identifying restrictions=7.64, p-value=0.18
Number of observations = 505

* : Statistically significant at 5 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$
**: Statistically significant at 10 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$

Table 9 Generalized Instrumental Variables Estimation for Central Air Conditioners

	Parameter estimate	Standard error	T-statistic
Constant term	-2.613	0.940	-2.779*
Age head of household (per 10 years)	-0.236	0.083	-2.862*
Monthly income (per $1,000)	1.385	1.095	1.269
Urban area dummy (=1 if yes)	-0.419	0.459	-0.913
Cooling capacity (per 1,000 Btu/hr)	-0.166	0.032	-5.219*
House square footage (per 1,000)	-0.158	0.062	-2.535*
Monthly operation cost ($)	0.006	0.034	0.189
Poor credit rating dummy (=1 if yes)	-1.322	1.187	-1.113
Alpha	1.901	0.208	9.157*

Chi-square test of over-identifying restrictions=7.03, p-value=0.30
Number of observations = 1,245

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*: Statistically significant at 5 per cent level for H_o: $\beta=0$ against H_1:$\beta\neq0$