March 1997 No. 409

Factors Affecting the Timing of Purchases of Butter, Margarine and Blends: A Competing Goods Analysis

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The dynamics of the purchase process for a subset of food fats and oils are investigated using a competing risk version of event history analysis. A panel of U.S. households are observed over a 170 week period. A variety of household and purchase characteristics are identified as impacting the probability of a household switching between these commodities across purchase occasions. As expected we find that price, previous purchases amounts, seasonality, household size and composition impact the probability of product switching.

Keywords: Event History Analysis, Fats and Oils, Hazard Rates, Panel Data

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The relationship between dietary fat intake and increased risk of chronic diseases has been the subject of considerable debate since the early 1960's. The nutrition education programs that have arisen from this debate have increased awareness of such linkages. For example, 8% of U.S. adults were estimated to be aware of the link between dietary fat intake and heart disease in 1970. This percentage increased to 55% by 1988 (Putler and Frazao, 1991). One result of this increased awareness has been a decrease in relative consumption of food fats and oils high in saturated fats. Previous analyses of changing food fats and oils consumption based on time series data have focused on the role of advertising, demographic characteristics and health knowledge on demand for a variety of food fats and oils (Goddard, 1992; Gould, Cox and Perali, 1991). Also within a time series framework, Chern, Loehman and Yen (1995) examine the impact of increased information about the relationship between cholesterol intake and heart disease on food fats and oils demand. The authors estimate that compared to 1988 consumption levels, this information resulted in a 13% and 43% **reduction** in butter and lard consumption and a 15% and 19% **increase** in corn and soybean oil consumption, respectively (p. 563).

These analyses have two shortcomings that the present analysis will address. First, they have not investigated the dynamics of fats and oils purchase process. What is the role of past purchases on current purchase behavior. Our use of household level panel data enables us to adopt a methodology where the fats and oils purchase dynamics are explicitly modelled. Second, these time-series based models being based on disappearance data have not been able to differentiate the form of product used. For example they have not been able to examine the demand structure of butter/margarine blends which have been used by many consumers to reduce their saturated fat intake while maintaining butter's flavor characteristics. Evidence from household level data indicates that the use of butter/margarine blends is becoming an important mechanism by which household reduce saturated fat intake. Using a weekly household panel data we found that 17% of the butter, margarine and blend purchase occasions (i.e., purchase trips where one of these commodities were purchased) was associated with butter/margarine blend purchases and accounted for 15% of quantity purchased.

Butter and margarine have the characteristics that: (i) both commodities are composed of approximately 80% fat; (ii) more than 60% of the fat in butter is saturated fat compared to less than 20% in corn based margarine; and (iii) both have similar functional (e.g., cooking and baking) characteristics. The question remains as to how sensitive household purchases of these commodities are to price changes, promotional programs and changes in attitudes towards health. Are the influences of these factors similar across commodity? If there is a price reduction in butter, is the impact on the probability of a nonconsuming household switching to butter the same as would be observed for a household currently not consuming margarine, switching to margarine when there is a decrease in its price? With increased concerns about the intake of saturated fat, is the impact on the probability of switching from butter to margarine the same as the probability of switching to butter/margarine blends of increased nutrition knowledge? What is the impact of such concern on switching behavior away from blends?

Given our focus is on the occurrence of a series of discrete event over a given time period (e.g. switching between purchases of butter, margarine or blends), an event- history model analysis is used to identify important determinants of the occurrence of these events. Under this model, the dependent variable of an event history analysis is the length of time between consecutive changes of state defined by some qualitative variable (Blossfeld, Hamerle, and Mayer, 1989, p.27). A characterization of the dependent variable is obtained from an analysis of the density and related functions of the duration of time between event occurrence. In order to undertake any event history analysis, the minimum data required is a longitudinal record of when events happened to a sample of individuals. If additional information with respect to time and individual purchase and demographic characteristics are added to this information than compared to cross-sectional analyses and similar to other regression-based longitudinal analyses, there are increased data requirements for implementing this methodology. Fortunately, with increased availability of scanner based purchase histories, it is now possible to use longitudinal methods for the analysis of household food purchases (Capps).

Similar to traditional panel data models, event-history analysis allows for an investigation of the dynamics of the purchase process. The entire "history" of purchases of each household is considered in the likelihood function.[1] Analogous to the use of logit and probit analyses to examine the probability of an event occurring within a static framework, event-history analysis extends traditional regression based longitudinal analyses. With the use of the duration of time between events as our dependent variable, the output from an event-history analysis are a series of conditional and unconditional probabilities of a household experiencing a particular event as time elapsed since the previous event occurrence.

The present analysis examines the determinants of factors affecting the purchases of butter, margarine, and butter/margarine blends on a purchase occasion basis. We choose these three commodities as they are often viewed as competing goods (Goddard, 1992). To examine the dynamics of the purchase process, we adopt a "competing risks" version of traditional event history analysis which is described in the next section. In this analysis we include variables representing household and purchase characteristics as determinants of the length of time between purchases. We use a model that contains commodity specific parameters thus allowing for unique responses in purchasing behavior to changes in these exogenous variables. The purchase behavior we are interested in here is the switching (or repeat purchases) between the three commodities included in this analysis.

Econometric Model Specification

Event history analysis refers to the broad category of models concerned with examining the determinants of the occurrence of various life events such as births, deaths, labor force participation, etc. By examining the distribution characteristics of the timing between these events, the role of household and other exogenous factors on the probability of an event occurring can be studied. Gupta (1991, 1988) and Gould (1997a) provide examples of applications of event history analysis where the event of concern is the purchase of a non-durable commodity. In these analyses, single commodities were the subject of investigation. Gonul and Srinivasan (1993) extend these analyses to a brand analysis where the event of concern was brand switching within a single commodity type. The type of model used in their analysis is referred to as a "competing risk" model and can be used to examine factors affecting the transition to multiple end states (Blossfeld, Hamerle and Mayer, 1989).

Under the competing risk specification, there are multiple, mutually exclusive events that the decision maker can experience during a particular risk period.[2] The occurrence of one of these events implies the termination of the risk period. Under the competing risk model developed here, the "competing events" are the decision to switch from one type of commodity to another over consecutive purchase occasions.[3] Unlike the analysis of Gonul and Srinivasan(1993) which focused on the timing of purchases of different brands of the same commodity (e.g., disposable diapers), we focus on the timing of purchases of three commodities that are close substitutes. Given the previous purchase decision and a choice between these three commodities, it is assumed that a household may repeat-purchase or switch to one of the other commodities during a particular purchase occasion.

In this analysis a household experiences an "event" by *switching* from one commodity to another over consecutive purchase occasions. The probability of experiencing such an event is captured via use of a "hazard function" defined as the conditional probability density function of product switching on a particular purchase occasion **given that no switch has taken place** since the last event. Lets define V to be a random variable for *duration* of nonoccurrence of an event (i.e., the number of weeks between consecutive events), T the time period (e.g. week) at which an event occurs and t a point in time *since the occurrence* of the last event (i.e., the number of weeks since the last switch).

Figure 1 shows a hypothetical "history" of these three commodities for a particular household. In this example we see that there are four events, occurring at T1, T2, T3, and T4 with associated durations of V1, V2, V3, and V4. Event 1 represents a switch from margarine to butter, event 2, butter to blends, event 3, blends to margarine and event 4, margarine to butter. In this example there is right censoring, (e.g., the end of the panel occurs before the next event. In this example there are repeat purchases occurring at times t1, t2, t3, t4, t5 and t6 since the previous event.[4]

For our specific application we represent the three commodities included in this analysis by B (butter), M (margarine) and L (blends). We represent the hazard rate (function), $\mathbf{H_{ij}(t)}$, for switching between commodity i and j at time T as:

$$(1)\quad H_{ij}(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P\left(t \leq T \leq t + \Delta t, \sigma_{ij} = 1 \mid T \geq t; i,j = B, M, L; i \neq j\right)$$

where σ_{ij} is equal to 1 if there is a switch from commodity i to j on a particular purchase occasion and $P(\cdot)$ represents the probability that the event occurs druing the time $(t, t+\Delta t)$ given that the event did not occur prior to time t. The total hazard rate is defined as the sum of all commodity specific hazard rates:

$$(2)\quad H_i(t) = \sum_{j,\, i\neq j} H_{ij}(t) \quad (i,j = B,M,L)$$

which is the conditional probability that in the time interval, $(t, t+\Delta t)$ a switch will occur under given that up to time since last purchase, t, no switch has occurred (Yamaguchi 1991, p.58).

In addition to the hazard rate, an additional probability function used in event history analysis is the "survivor function", $\mathbf{S_i(t)}$, which under the present application can be interpreted as the probability of purchasing the same commodity over consecutive purchase occasions (e.g. repeat purchases of commodity i) and is hypothesized to be a function of the time since last occurrence. The survivor function can be represented as:

$$(3)\quad S_i(t) = 1 - P(T < t) = 1 - F_i(t) = e^{\left(-\int_0^t \left(\sum_{j,i\neq j} H_{ij}(s)\right) ds\right)} = e^{\left(-\int_0^t H_i(s)ds\right)}$$

where F_i is the cumulative density function of switching time from commodity i (Blossfeld, Hamerle and Mayer, 1989, p.31-32). Using the definition of the switching hazard function in (1) and as Yamaguchi (1991) notes, the hazard function is equal to the ratio of the *unconditional* probability density function of an event occurring, (e.g. switching from commodity i to commodity j) $\mathbf{f_{ij}(t)}$, and the survivor function (p. 10):

$$(1')\quad H_{ij} = \frac{f_{ij}(t)}{S_i(t)}$$

That is, the hazard function is a conditional probability density function, where the weight is the inverse of the probability of not having an event happen at time t since the last event. The formulation in (1') emphasizes that the hazard rate is not equal to the unconditional probability density function of the time since the last event. Rewriting (1'), switch specific probability density functions can be represented as:

$$(4)\quad f_{ij}(t) = H_{ij}(t)\, S_i(t) = \lim_{\Delta t \to 0} \frac{1}{\Delta t} P\left(t \le T \le t + \Delta t, \sigma_{ij} = 1\right) = H_{ij}\, e^{\left(-\int_0^t H_i(s)ds\right)}$$

Using (3) and (4), the likelihood function for the n^{th} household's consists of the probability density function of the time since the last event (i.e., interswitch time) for those purchase occasions when switches occur (f_{ij}) or survivor functions when there is a repeat purchase or a right censored observation, S_i (i.e., panel ends without an event):

$$(5)\quad L_n = \prod_{k=1}^{K_n} \left(\prod_{i=1}^{3} \left(\left(\prod_{j=1, j \ne i}^{3} f_{ij}\left(t_k^n\right) \right)^{\sigma_{ijk}^n} S_i\left(t_k^n\right)^{\left(1 - d_k^n\right)} \right) \right)$$

$$= \prod_{k=1}^{K_n} \left(\prod_{i=1}^{3} \left(\left(\prod_{j=1, j \ne i}^{3} H_{ij}\, e^{\left(-\int_0^t H_i(s)ds\right)} \right)^{\sigma_{ijk}^n} e^{\left(-\int_0^t H_i(s)ds\right)^{\left(1 - d_k^n\right)}} \right) \right)$$

$$\text{where } d_k^n = \sum_{1=1}^{3} \sum_{j=1, j \ne i}^{3} \sigma_{ijk}^n$$

d_k is a 0/1 variable equal to 1 if there is a switch on a particular purchase occasion, σ_{ijk}^n corresponds to the σ_{ij} presented in (1), and K_n the number of purchase occasions for the n^{th} household. From (5), the log-likelihood for the n^{th} household (LL_n) can be represented as:

$$(6)\quad LL_n = \sum_{k=1}^{K_n} \left(\sum_{i=1}^{3} \left(\sum_{j \ne i, j=1}^{3} \sigma_{ijk}^n H_{ij}^k\left(t_k^n\right) \right) - \int_0^{t_k^n} H_i(s)\, ds \right)$$

(Gonul and Srinivason, 1993, p.1221).

In order to apply this model to purchase data, we need to make some assumptions concerning hazard rate functional form. Gonul and Srinivason (1993) use Cox's proportional hazards specification where exogenous purchase and household characteristics are assumed to impact hazard rates. Given their application was one of examining switching behavior across brands of the same commodity, the authors assume that the slope coefficients do not vary across switching regimes. That is, they implicitly assumed that the marginal impact of a change in product A's price on the hazard rate of switching from product B to A is the same as the impact of a change in the price of product C on the probability of switching from product B to C.

Instead of using Cox's proportional hazards model we adopt the Erlang-2 form of the gamma distribution which has been used in previous analyses of non-durable purchase duration times (Herniter, 1971; Chatfield and Goodhardt, 1973; Zufryden, 1978; Jeuland, Bass and Wright, 1980; Gupta, 1988; 1991; Gould, 1997a).[5] When interswitch times are distributed according to Erlang-2, the density function, survivor function, and hazard rates are:

$$
\begin{aligned}
& f_{ij}\left(t_k^n\right) = \lambda_{ij}^2\, t_k^n\, e^{\left(-\lambda_{ij}\, t_k^n\right)} \\
(7) \qquad & S_i\left(t_k^n\right) = \sum_{j,i\neq j} \left(1 + \lambda_{ij}\, t_k^n\right) e^{\left(-\lambda_{ij}\, t_k^n\right)} \qquad i,j = B, M, L;\ i \neq j \\
& H_{ij}\left(t_k^n\right) = \frac{f_{ij}\left(t_k^n\right)}{S_i\left(t_k^n\right)} = \frac{\lambda_{ij}^2\, t_k^n}{\sum_{j,i\neq j} \left(1 + \lambda_{ij}\, t_k^n\right)}
\end{aligned}
$$

where λ is the distribution location paramater and $\lambda > 0$ (Gupta, 1991). A reason for using the Erlang-2 assumption instead of other distrubutions such as the expenential is that hazard rates, H_{ij}, are dependent on the time since the last switch, $\partial H_{ij}/\partial t > 0$ and $\partial S_i/\partial t < 0$.

With the use of the Erlang-2 form of the gamma distribution, the expected interswitch time (V_{ij}) from commodity i to j ($i \neq j$) can be shown to equal $2/\lambda_{ij}$ (Gupta, 1991). From (7), $\partial H_{ij}/\partial\lambda_{ij} > 0$, $\partial f_{ij}/\partial\lambda_{ij} > 0$, $\partial S_i/\partial\lambda_{ij} < 0$ and $\partial V_{ij}/\partial\lambda_{ij} < 0$ implying that an increase in λ_{ij} results in an increase in the density of switching from i to j, decreases the probability of repeat purchases, and decreases expected time between commodity switching.

Combining (6) and (7) the log-liklihood function incorporating the Erlang-2 form of the gamma distribution can be represented as:

$$(6') \quad LL_n = \sum_{k=1}^{K_n} \left(\sum_{i=1}^{3} \left(\sum_{j \neq i, j=1}^{3} \sigma_{ijk}^{n} \frac{\lambda_{ij}^{2} t_k^{\,n}}{\left(1 + \lambda_{ij} t_k^{\,n}\right)} \right) - \int_{0}^{t_k^{\,n}} \left(\sum_{j, i \neq j} \left(\frac{\lambda_{ij}^{2} s}{\left(1 + \lambda_{ij} s\right)} \right) \right) ds \right)$$

The above specification assumes that all consumers have the same hazard functions given constant λ_{ij} distribution parameters. Previous analyses have found non-durable commodity purchase rates differing across consumers due to unique household and local market characteristics (Gupta, 1988; Helsen and Schmittlein, 1992, 1993; Ward and Davis, 1978; Neslin, Hendersen and Quelch, 1985). Similar to Gupta(1991) we modify (7) and allow market and household characteristics to switching behavior via the following:

$$(8) \quad \lambda_{ij}(t) = \lambda_{0,ij}\, e^{\left(X_{jt} \beta_{ij}\right)}$$

where X are time dependent explanatory variables and β and λ_0 estimated paramaters and $\lambda_{0,ij} > 0$. The present analysis, being concerned with switching across commodities and in contrast to Gonul and Srinivasan (1993), allows the slope coefficients to vary across switching regime, e.g. β_{ij}'s are allowed to vary across regime. As shown later, we can test whether the marginal effects on the hazard rates are the same across commodities.

We can interpret $\lambda_{0,ij}$ in (8) as the base gamma distribtuion paramater in the absence of covariates (i.e., $\lambda_{ij}(t) = \lambda_{0,ij}$). By substituting (8) into the likelihood function the impacts of a change in an exogenous variable on the probability of switching, the probability of repeat purchases and mean switch times. With the restriction on $\lambda_{0,ij}$, the sign of β_{ij} gives the direction of the impacts of a change in X_j on H_{ij} and f_{ij} and opposite of the directional effects of a change in X_j on S_i and V_{ij}.

Description of the Household Consumer Panel

We apply the competing risk model and associated likelihood function presented in (6') to an analysis of U.S. household purchases of butter, margarine and butter/margarine blends. The purchase history data are obtained from a March, 1991-June, 1994 U.S. weekly consumer panel maintained by Nielsen Marketing Research (NMR). Only fats and oil commodities purchased for at-home consumption are included in this data. On each purchase occasion a panel member records: date, UPC code, expenditures and quantity purchased. This recording process is conducted at home via the use of hand held UPC scanners. Households notify NMR if no purchases had occurred during the previous week because of not purchasing during a given week or the result of being away from home due to vacation, business trip, etc. For this analysis we include households that reported continuously over 170 weeks. This does not imply that households in the panel purchased each week but during weeks where fats and oils were not purchased for at-home consumption, NMR was given this information. Given the size of the household panel we randomly selected households from the continuous panel. In order to avoid extremely long interpurchase times, we include households that have more than 3 purchase occasions. Purchase opportunities and occasions are defined on a weekly basis. Given that the original panel consisted of more than 5,000 households we use a 33% random sample of 1,318 households with 61,373 purchase occasions in this analysis.[6]

Table 1 provides an overview of purchase characteristics. The commodity least purchased are butter/margarine blends where 21% of the households in our sample did not purchase any blends over the 170 week study period. More than 60% of household purchase occasions are associated with margarine compared to less than 20% for blends.

As noted above, we define an "event" as the switching from the purchasing of one commodity to another on consecutive purchase occasions. Less than 20% of margarine purchase occasions are the result of a switch from either butter or blends from the previous purchase occasion. This compares to 44% of purchases for blends originating from a commodity switch. This result may be reflecting the small role blends play in overall household food fats and oils budget. The relative use of coupons is similar across switch versus non-switch purchase occasions. Slightly more than 20% of margarine purchases occurred with the use of a coupon regardless of whether a switch occurred compared to approximately 40% for blends and 12% for butter. Table 2 shows the distribution of the 61,373 purchase occasions encompassed in this analysis across commodity and event status. Values along the diagonal represent repeat purchase occasions and off-diagonal values represent purchase occasions where a switching event occurred.

From (8) we need to identify a set of exogenous variables. Both household and purchase characteristics are used. Table 3 provides an overview of these exogenous variables.[7] Gonul and Srinivasan (1993) in their analysis of switching behavior across brands of disposable diapers used a dummy variable to indicate whether a coupon was used in the switch from one brand to another. We also hypothesize that coupon based promotions provide an incentive to switch to a commodity, increase switching probabilities and reduce expected interswitch times. Previous applications of event history analysis to a single commodity have found that a price drop result in consumers purchasing earlier (e.g., increased hazard rate) than otherwise (Gupta; 1988,1991). Similarly, Gonul and Srinivasan (1993) found a negative relationship between price and hazard rate in their competing goods analysis. Here, we examine the impact of net price (e.g., shelf price - coupon value) on switching behavior timing. Unlike previous analyses that have examined the timing of purchases of competing brands, we do not use the net prices directly in the model given that we are examining the switching between commodities that have similar characteristics except for fat composition. Instead, we standardize each net price relative to the household's commodity specific anticipated (reference) purchase price for each commodity.

Following Rajendran and Tellis(1994) the consumer's reference price is defined as the standard price against which consumers evaluate the actual prices of the products they are considering (Rosch, 1975). The use of this reference price implies that consumers do not respond to prices absolutely but relative to the reference price (Thaler, 1985, Rajendran and Tellis, 1994, p.22). Rajendran and Tellis (1994) suggest that a reference price has a temporal component determined by the prices faced by the consumer on past purchase occasions. We define reference price (Ref_price) as:

$$\text{(9)} \quad \text{Ref\_price}_{c,i} \equiv 0.571 * \text{Price}_{c-1,i} + 0.286 * \text{Price}_{c-2,i} + 0.143 * \text{Price}_{c-3,i} \quad i = B, M, L$$

where c refers to the c^{th} purchase occasion and Price_i is the i^{th} commodities shelf price. The use of the above declining weights approximates a geometric function with a common ratio of .5 (Rajendran and Tellis, 1994, p.27).[8] Using (9), the ratio of the current net price and reference price (PRRATIO) are used to capture the response of switching behavior to price changes.

In his analysis of the timing of cheese purchases, Gould (1997a) found limited evidence of the effect of seasonality on switching hazard rates. We include the dummy variables SUMMER and HOLIDAY to account for differential hazard rates during the summer months, June, July and August, and over the Thanksgiving and Christmas holiday period, respectively. It is unclear as to the impact of these time periods on switching behavior.

The panel data set used here encompasses a 170 week period. Similar to a model developed by Chern, Loehman and Yen (1995), we use the time trend variable, WEEK, which identifies the week during which a particular event occurs, with a range of values of 1 to 170 to represent the state of health awareness of the main meal planner. Previous research has indicated that health knowledge has a direct impact on food choice and nutrient intake (Gould and Lin, 1992; Variyam, Blaylock and Smallwood, 1996; Gould, 1997b). If health knowledge increases with time, we hypothesize that there is an increased probability of switching to margarine and blends from butter the greater the value of the time trend.[9]

Household characteristics such as household size, composition, ethnicity and income are hypothesized to be important determinants of fat commodity demand. The variable HHSIZE represents the number of resident household members. One would expect that the greater the household size, the more quickly household inventories will be depleted, ceteris paribus, implying increased hazard rates and smaller expecter interswitch times. Thus we would expect positive β_{ij} coefficients for this variable (Jain and Vilcassim, 1991). We control for household composition by including the variables SENIOR and ADULT which represent the percent of household members over 65 and between 64 and 19 years of age, respectively. Since our data includes birth month and year for each household member, we update these variables on a monthly basis. It is unclear as to the impact of having young children in the household on the timing of purchases. Very young people eat less compared to adults implying that a given inventory is depleted over a longer time. Alternatively, many adults face dietary restrictions on the amount of fat and cholesterol that can be consumed.

We do not have an estimate of either initial household inventories or consumption of the commodities included in this analysis. Jain and Vilcassim(1991) outline several problems with estimating household inventory from a data set that does not explicitly collect such information. In order to avoid potential biases in making assumption concerning initial inventories and household consumption rates, we follow Jain and Vilcassim(1991) by including lagged volume purchases, LAGQUANT, as an explanatory variable (Helsen and Schmittlein 1992, 1993). We hypothesize that expected interswitch time would increase (and hazard rate would decrease), the greater the amount purchased on the last occasion. Thus we expect a negative impact on switching hazard rates.

We hypothesize that there may be some cultural differences in purchase behavior. The characterization of the race of each household is based on characteristics of the main meal planner which was assumed to be the female head, if present, otherwise the race of the male head. We include the household characteristic variable, BLACK, which is a dummy variable equal to 1 if the meal planner is black, to test this hypothesis of cultural differences.

Household pre-tax income in the data set is reported in 16 categories ranging from less than \$5,000 to more than \$100,000. To convert these categorical data to a continuous form, we assumed the midpoint of each category to be household income. For households with income above \$100,000 an income of \$150,000 was assumed. To control for household size, composition *and* income, the variable POVRATIO is the ratio of household pre-tax income to poverty threshold income as defined by the Bureau of Census (Department of Commerce, 1995). Poverty threshold income is used by the Bureau of Census to estimate the number of individuals and families in poverty and are determined by the number and age distribution of household members. We are unsure of the effect of this variable on purchase behavior. For low income households, the ability to purchase large amounts per purchase occasion may be limited, thus implying relatively shorter times between purchases and greater likelihood of switching, ceteris paribus. Alternatively, given limited income, they may purchase smaller total amounts, thus implying longer times between purchases and less likely to switch.

Econometric Results

Incorporating (7) and (8), the likelihood function in (6') is used to estimate the parameters of the six switching hazard functions.[10] A "switch independent" version of our model can be obtained using the structure adopted by Gonul and Srinivasan(1993) where the exogenous variable slope coefficients are assumed the same regardless of switching regime (e.g., for the r^{th} exogenous variable, $\beta_{ij,r} = \beta_{ji,r} = \beta_r$). The more flexible "full model" specification presented in (6) - (8) allow exogenous variable parameters to vary across regime. Under the full model, for example, the impact of a change in relative net butter price on hazard rate H_{MB} may be different than the marginal impact on hazard rate H_{LB}. An intermediate formulation that allows some difference in hazard rate response but less than that represented by full model would specify commodity specific marginal responses. Under this "intermediate model" for example, the marginal impacts of a change in butter price on the hazard rate of switching to butter is the same for current margarine and blend purchasers but different than the marginal impact of switching to margarine $(\text{e.g., } \beta_{MB,PRRATIO} = \beta_{LB,PRRATIO})$.

Under the full model we allow the impact of interswitch time to have a differential impact on the switching regimes. That is, λ_{ij} is assumed to differ across switching regime and household characteristics. We can test the null hypothesis of no difference in duration dependence across switching regime and household by imposing the constraints that $\beta_{ij} = 0$ and $\lambda_{0,ij} = \lambda_0, \forall i,j,\ i \neq j$.

The three alternatives to the full model are evaluated using likelihood ratio tests (Table 4). The first test result in Table 4, is a test of switch independent specification, indicating a rejection of the switch independent specification. When compared to the full model, the second row of Table 4 indicates a rejection of the intermediate model. The null hypothesis of no difference in duration dependance is also rejected as shown by the χ^2 statistic in row 3 of Table 4.

A final alternative to the full model and similar to the intermediate model is the "symmetric" specification where there is symmetry in hazard rates, e.g. $\lambda_{ij} = \lambda_{ji}$. In the fourth row of Table 3, this null hypothesis is clearly rejected. Given the above test results, we use the full model with regime specific purchase and household (β_{ij}) coefficients in the following analysis. The resulting full model paramater estimates are shown in Table 5.

Significance of Purchase Characteristics

There are 4 variables describing a household's current purchase occasion which were hypothesized to impact butter, margarine and blends switching behavior. Of the associated 24 parameter estimates, 20 were found to be statistically significant. From Table 5, we see that, as hypothesized, relative price has a negative impact on hazard rates for the six switching regimes. The null hypothesis that price has no impact on hazard rates is clearly rejected as shown in the fifth row of Table 4. We use WEEK to represent a time trend as well as the level of health knowledge. As such we hypothesized a negative impact on H_{MB} since butter is high in saturated fat and a positive impact on H_{BM} given that margarine is low in saturated fat, ceteris paribus. There does not appear to much support for this hypothesis given the negative and significant H_{BM} and H_{BL} coefficients and insignificant H_{MB} coefficient.

There appears to be some seasonality in the timing of purchases. All significant coefficients associated with the variable identifying purchases occurring during June, July and August were negative, implying an increase in interswitch time during summer months. These results may be reflecting changes in diet during that time as well as reduced at-home consumption due to vacations, active schedules, etc. Of the four statistically significant coefficients associated with HOLIDAY, three are positive. The positive coefficients indicate an increased probability of switching during the holiday periods and associated reduced interswitch times. Surprisingly, we find that $\beta_{MB,HOLIDAY}$ and $\beta_{BM,HOLIDAY}$ were both positive. The null hypothesis of no seasonality in purchase timing is clearing rejected given the results reported in Table 4.

Significance of Household Characteristics

There were 6 household characteristics that were hypothesized to impact switching hazard rates. Of the 36 estimated coefficients, 20 were found to be statistically significant. The last five rows of Table 4 present the results of alternative hypothesis tests as to the statistical significance of these household characteristics. The null hypothesis that these characteristics have no impact on hazard rates is rejected. As hypothesized, the variable LAGQUANT generated negative coefficients for four of the regimes. These negative coefficients imply that with greater additions to the household inventory of food fats, there is a decrease in hazard rates and conversely greater expected interswitch time. The resulting χ^2-

statistic shows a rejection of the null hypothesis of lagged purchases not impacting purchase timing.

In his analysis of the timing of cheese purchases, Gould(1997a) found that larger households had shorter interpurchase times and larger hazard rates, ceteris paribus. This result was explained by larger households drawing down a given household inventory faster than smaller sized households and thus requiring greater market participation. Our results find a similar result as shown by the positive HHSIZE coefficients. The larger the number of household members the larger the hazard rates and smaller expected interswitch times, ceteris paribus. Besides household size, household composition was hypothesized to impact purchase timing and thus switching behavior. Surprisingly, we find that H_{BM} and H_{MB} by current consumers are positively related to the percent of adult household members between the age of 18 and 65. The presence of senior citizens in the household has a positive impact on the hazard rate of switching from margarine to blends.

Three of the coefficients associated with the POVRATIO variable were statistically significant, $H_{BM, POVRATIO}$, $H_{MB, POVRATIO}$ and $H_{LM,POVRATIO}$, with the butter/margarine versus margarine/butter coefficients of opposite signs. Current butter and blend consuming households are less likely to switch to margarine the higher the level of household income. Our likelihood ratio tests indicate significant POVRATIO impacts on switching behavior.

Five of the six coefficients associated with the BLACK dummy variable are negative and statistically significant indicating greater expected interswitch times and lower switching probabilities when comparing BLACK to non-BLACK households.

Simulation of Hazard and Survival Rate Profiles

Using the parameters of the full model presented in Table 5 we simulate hazard and survival rate profiles for the six switching regimes. We evaluated commodity specific profiles using the mean values of the exogenous variables (except interswitch time) for those occasions where a particular commodity was consumed. With the Erlang-2 form of the gamma distribution being time dependent we simulate hazard and survival rate profiles at the time since the last event increases from 0 to 20 weeks. From (7), three survival rate profiles can be generated depending on the initial state (commodity consumed) of the consumer.

Survival rate profiles are shown in Figure 2. From these profiles we see that butter and blend consumers behave similarly in that they are more likely to switch (e.g., have lower survival probabilities) than current margarine consumers. After 4 weeks in which there has not been a switch, the "average" margarine consumer has an 85% probability of repeat purchasing compared to 64% probability of repeat purchasing for the average blend purchasing household. After 8 weeks these probabilities decreased to 60% and 26%.

Similarly, Figure 3 shows three of the six estimated hazard function profiles, again evaluated at the mean values of the exogenous household and purchase characteristics. We see that there are substantial differences in the hazard rate for current butter consumers with respect to switching to margarine versus blends (given that there are no previous switches). After 2 weeks since purchasing butter, there is an 9.1% probability of a switch to margarine compared to a 1.6% probability of switching to blends. After 4 weeks these values increase to 13.6% and 2.8%, respectively. From Figure 3 we also see that there are substantial differences in the hazard function profiles for switching from butter to margarine compared to the profile for switching from margarine to butter. This supports the above results of the testing of the null hypothesis of symmetric hazard functions presented in Table 4.

As noted above, the model developed here is similar to that applied to brand switching behavior. Typically these models have been used to examine how some type of promotional activity impacts the probability of switching from one brand to another (Gonul and Srinivasan, 1993, p.1225). Similarly, we can use this model to answer the question as to the impacts of continued promotion campaign on purchase timing. For example, what is the impact of a prolonged promotion of butter through a 50% off coupon? As an example, Figure 4 shows hazard rate profiles for current margarine consumers with and without the use of the coupon.[11] The response to coupon utilization on switching from margarine to blends is much greater than from margarine to butter. The base H_{ML} profile is consistently below that of the base H_{MB} profile. With the 50% off coupon program there is a dramatic increase in the simulated H_{ML}. Under the base pricing scenario, after 2 weeks since the last switching event there is a 1.4% probability in a current margarine consuming household purchasing a butter/margarine blend. This probability increases to 2.4% after 4 weeks and 3.8 percent after 8 weeks. With the presence of the coupon promotion, after 2 weeks there is a 7.3%

probability of an event, 11.0% after 4 weeks and 14.9% after 8 weeks. Given the physical composition of blends, it is not surprising that the hazard rate for blends is increased to a greater degree than that for butter.

Besides the impacts of purchase characteristics, we can examine how purchase patterns vary across households with differing characteristics. As an example, Figure 5 shows the impact of household composition on the probabilities of repeat purchases of margarine over consecutive purchase occasions. Single person households with this person being over 65 years of age appear to be the least likely to switch with a 92.4% probability of not switching after 4 weeks since the last switch. This decreases to 76.3% after 8 weeks. A household with four persons with 2 being children and 2 adults under the age of 65, have a greater tendency to switch among commodities. Childless, two person households have survival rates that fall between the above two household types.

Conclusions

The increasing availability of scanner data has made it possible to study the dynamics of the food purchase process at the household/individual level. The ability to match these purchase histories with individual and household characteristics makes such panel data especially useful for economic and public policy analysis. The event history model presented here is an extension of previous market research analyses that have focused on the phenomenon of brand switching. The present analysis is an extension in that it examines the dynamics of the purchasing of three substitute commodities: butter, margarine and butter/margarine blends.

Although concerned with commodity definitions that are fairly broad, the methodology used here can be used by a variety of analysts such as those involved in evaluating the effectiveness of brand specific as well as generic advertising/promotion programs. In our example we simulated the impacts of a long term coupon based promotion program on purchase behavior. Although not available in the data used in this analysis, similar analysis can be used to examine the impacts of increased media exposure (e.g., print, radio, TV, etc. advertisements) on purchase dynamics. Given our focus is on food purchased for home consumption, this analysis could also be used to differentiate the purchase dynamics of households that spend a significant share of their food budget for consumption away from home compared to households that tend not to purchase food away from home.

We find that both purchase and household characteristics impact the profile of commodity purchases. We also find that the relative impact of these characteristics on switching behavior varies across switching regime. Such information is important to market analysts wanting to determine which households are the least likely to switch from one commodity to another regardless of promotion effort/price cut.

The one shortcoming the current analysis is the lack of good information with respect to the level of health knowledge/awareness and its impact on switching behavior. One method that could be used to overcome the shortcomings of having to use a time trend variable as a proxy for health knowledge is to supplement the panel data with another data set such as USDA's Diet and Health Knowledge Survey. This additional data could be used to generate predicted health knowledge variables which could then be used as an explanatory variable in a competing risk model (Gould, 1997b).

This research effort is an initial first step in the development of dynamic models of household purchase behavior. The next step will be to incorporate the quantity purchased and to develop a dynamic variant of the traditional Heckman sample selection model. With such a model, we will be able to address such questions as to whether the primary effect of commodity promotion is a reduction in interpurchase time with little overall impact on commodity demand, e.g., a stockpiling effect.

Table 1. Characteristics of Butter, Margarine and Blends Purchases

	Consuming Households (#)	Quantity Purchased Per Purchase Occasion (lbs)	Purchase Occasions	Total Quantity Purchased (%)[a]	Purchase Occasions that are Switches (%)
Butter	1061	1.3	12676	19.4	40.7
Margarine	1299	1.9	9834	66.2	19.0
Blends	931	1.3	38870	14.4	43.7
	Percent of Switches with Coupon Use (%)[b]	Percent of No Switch with Coupon Use (%)[c]	Coupon Value/ Total Gross Expenditure (%)	Coupon Value/ Total Gross Expenditure When Coupon Used (%)	Net Purchase Price (%/lb)
Butter	12.1	13.5	0.041	0.409	1.50
Margarine	22.7	23.6	0.094	0.421	0.79
Blends	39.1	42.0	0.169	0.437	1.14

Note: [a]These percentages are calculated as the mean of household averages over 1,318 households.

[b]These are calculated as the mean percent of switches that occurred with the use of coupons by households that had some switches for this commodity.

[c]These are calculated as the mean percent of nonswitches that have occurred with the use of coupons by household that had some non-switches for this commodity.

Table 2. Distribution of Purchase Occasions Across Event Status

Previous Purchase	Current Purchase			
	Butter	Margarine	Blends	Total
Butter	7515	4102	938	12555
Margarine	4194	31489	3358	39041
Blends	967	3276	5534	9777
Total	12676	9834	38870	61373

Table 3. Definition of Hazard Function Exogenous Variables

Variable Description	Mean
Purchase Characteristics	
Ratio of Net Purchase Price to Reference Price: PRRATIO	
Butter	0.974
Margarine	0.957
Blends	0.831
Time Trend (Range is 1 to 170) : WEEK (#)	84.9
Dummy Variable Equal to 1 if purchased during June, July or August: SUMMER (%)	25.2
Dummy Variable Equal to 1 if purchased during November or December HOLIDAY (%)	17.4
Household Characteristics	
Dummy Variable Identifying a Black Household: BLACK (%)	4.6
Per Cent of Household Members $\geq$ 19 and $\leq$ 65 Years Old: ADULT (%)	60.4
Per Cent of Household Members > 65 Years Old: SENIOR (%)	24.9
Ratio of Household Income to Poverty Level Income: POVRATIO	3.52
Household Size: HHSIZE (#)	2.73
Amount of Butter, Margarine or Blends Purchases on Last Purchase Occasion: LAGQUANT (lbs.)	1.89

Table 4. Results of Alternative Hypothesis Tests

Null Hypothesis	Degrees of Freedom	χ^2 Statistic
Model Structure		
Switch Independent Model Specification: $\beta_{LB} = \beta_{MB} = \beta_{BM} = \beta_{LM} = \beta_{BL} = \beta_{ML}$, $\lambda_{0,LB} = \lambda_{0,LM} = \lambda_{0,BM} = \lambda_{0,BL} = \lambda_{0,MB} = \lambda_{0,ML}$	55	9,308.0[a]
Intermediate Model Specification: $\beta_{LB} = \beta_{MB}, \beta_{BM} = \beta_{LM}, \beta_{BL} = \beta_{ML}$, $\lambda_{0,LB} = \lambda_{0,MB}, \lambda_{0,BM} = \lambda_{0,LM}, \lambda_{0,BL} = \lambda_{0,ML}$	33	274.9[a]
No Difference in Duration Depdendance: $\beta_{ij} = 0, \lambda_{ij} = \lambda_0$	65	14,853.6[a]
Symmetric Variable Impacts: $\beta_{ij} = \beta_{ji}, \lambda_{ij} = \lambda_{ji} \ \forall\ i, j\ i \neq j$	33	7,229.8[a]
Variable Significance		
No Price Impacts: $\beta_{ij,NETPR} = 0 \ \forall\ i, j\ i \neq j$	6	3,063.0[a]
No Seasonality Impacts: $\beta_{ij,SUMMER} = \beta_{ij,HOLIDAY} = 0 \ \forall\ i, j\ i \neq j$	12	402.5[a]
No Household Characteristics Impacts: $\beta_{ij,HOUSEHOLD\ CHARACTERISTICS} = 0 \ \forall\ i, j\ i \neq j$	36	2,374.2[a]
Lagged Quantity does not Impact Hazard Rates: $\beta_{ij,LAGQUANT} = 0 \ \forall\ i, j\ i \neq j$	6	870.4[a]
Household Compostion does not Impact Hazard Rates: $\beta_{ij,ADULT} = \beta_{ij,SENIOR} = 0 \ \forall\ i, j\ i \neq j$	12	499.8[a]
Household Income does not Impact Hazard Rates: $\beta_{ij,POVRATIO} = 0 \ \forall\ i, j\ i \neq j$	6	799.5[a]
No Difference in Hazard Rates Across Ethnic Groups: $\beta_{ij,BLACK} = 0 \ \forall\ i, j\ i \neq j$	6	274.7[a]

Note: [a] indicates significance at the .001 level.

Table 5. Hazard Function Paramater Estimates For "Full" Model Specification

Variable	Estimated Coefficient	Std. Error	Estimated Coefficient	Std. Error	Estimated Coefficient	Std. Error	Estimated Coefficient	Std. Error	Estimated Coefficient	Std. Error	Estimated Coefficient	Std. Error
	Butter/Margarine		**Butter/Blends**		**Margarine/Butter**		**Margarine/Blends**		**Blends/Butter**		**Blends/Margarine**	
λ_0	0.196[a]	0.039	0.432[a]	0.126	0.060[a]	0.014	0.545[a]	0.171	0.125[a]	0.447	0.278[a]	0.094
	Purchase Characteristics											
PRRATIO	-0.436[a]	0.078	-1.706[a]	0.237	-0.526[a]	0.094	-1.861[a]	0.133	-0.602[a]	0.184	-0.446[a]	0.076
WEEK	-0.217[a]	0.030	-0.160[b]	0.055	-0.047	0.0246	-0.150[a]	0.029	-0.025	0.057	-0.111[a]	0.033
SUMMER	-0.151[a]	0.030	-0.118[c]	0.052	-0.115[a]	0.023	-0.116[a]	0.027	-0.099	0.057	-0.194[a]	0.036
HOLIDAY	0.142[a]	0.037	-0.035	0.070	0.261[a]	0.027	-0.116[a]	0.033	0.317[a]	0.060	0.008	0.034
	Household Characteristics											
HHSIZE	0.225[a]	0.029	0.122[b]	0.042	0.214[a]	0.027	0.063	0.036	0.191[a]	0.048	0.198[a]	0.043
POVRATIO	-0.472[a]	0.146	-0.042	0.218	0.243[c]	0.123	0.154	0.139	0.065	0.202	-0.791[a]	0.149
LAGQNT	-0.070[a]	0.016	-0.071[b]	0.026	-0.006	0.009	-0.066[a]	0.021	0.006	0.015	-0.036[b]	0.016
ADULT	0.704[a]	0.165	0.163	0.310	0.716[a]	0.179	0.107	0.241	0.079	0.305	0.443	0.255
SENIOR	0.139	0.084	0.204	0.138	0.138	0.072	0.273[a]	0.081	0.147	0.136	0.147	0.087
BLACK	-0.395[b]	0.157	-0.521[a]	0.190	-0.326[b]	0.132	-0.241	0.163	-0.502[a]	0.169	-0.527[b]	0.182
Log-Likelihood Function Value: -66805.9												

Note:[a] indicates significance at the .001 level, [b] significance at the .01 level and [c] significance at the .05 level.

Figure 1. Example of Purchase History

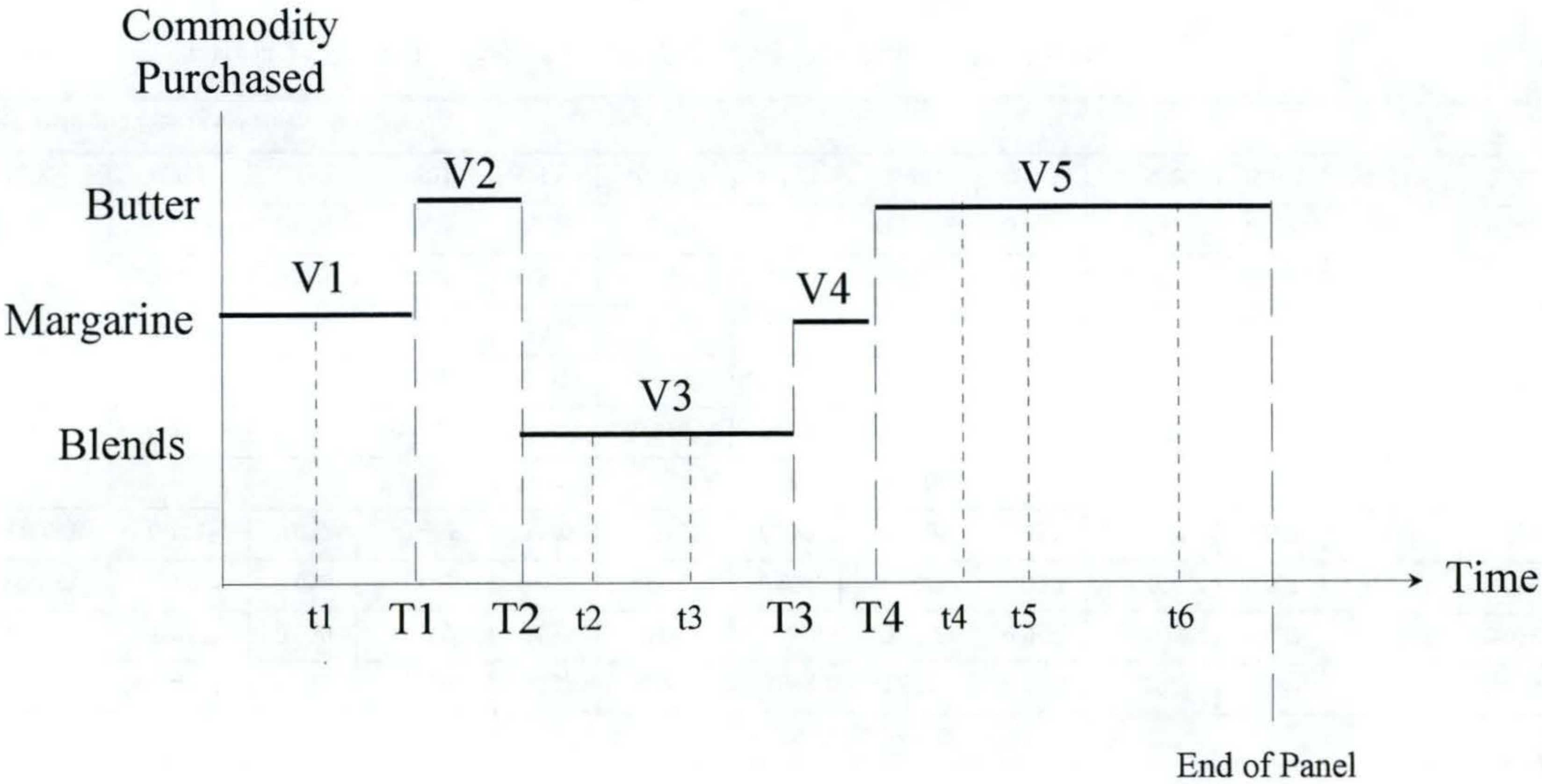


Figure 2. Butter, Margarine and Blends Survival Rate Profiles

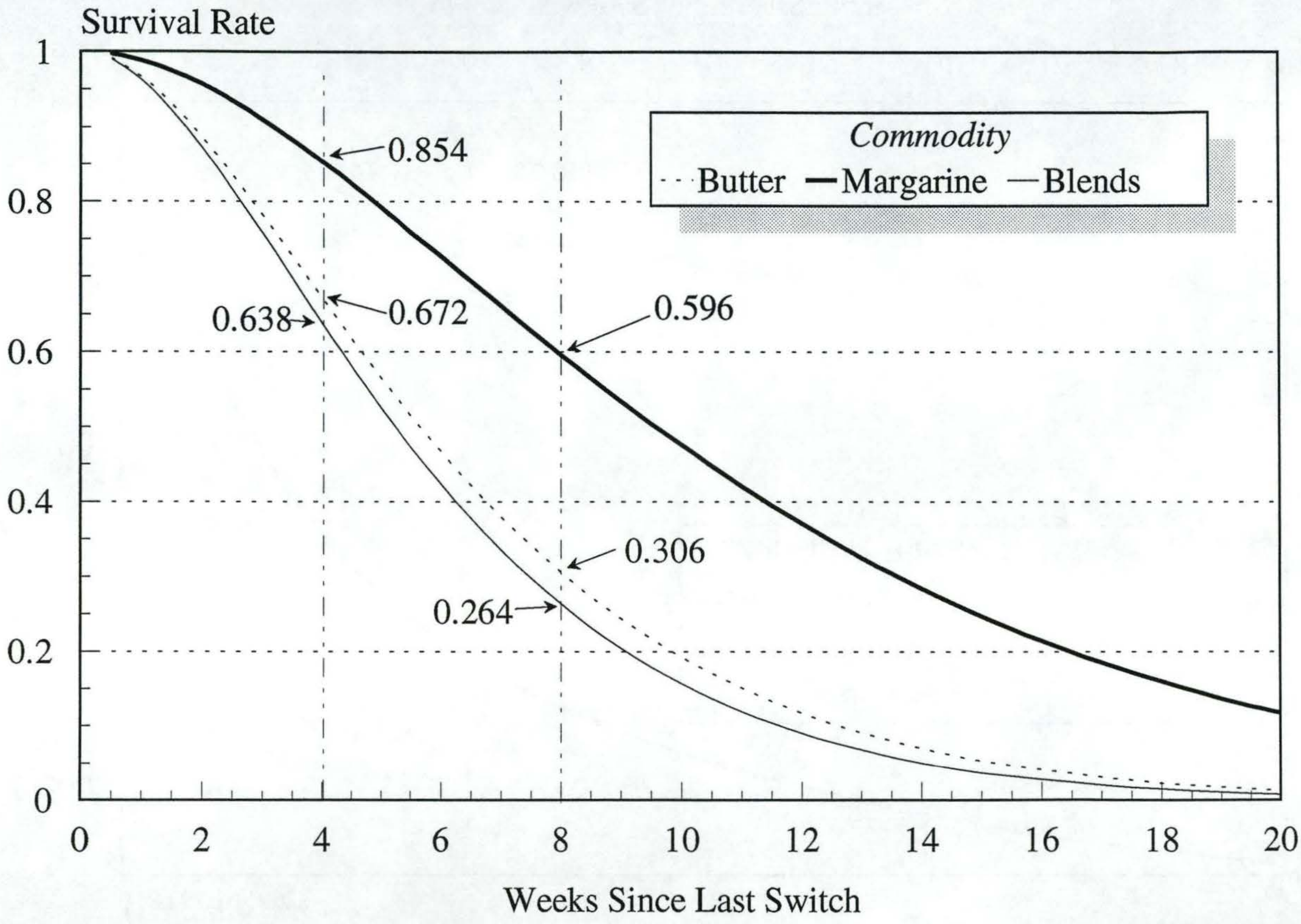


Figure 3. Selected Hazard Function Profiles

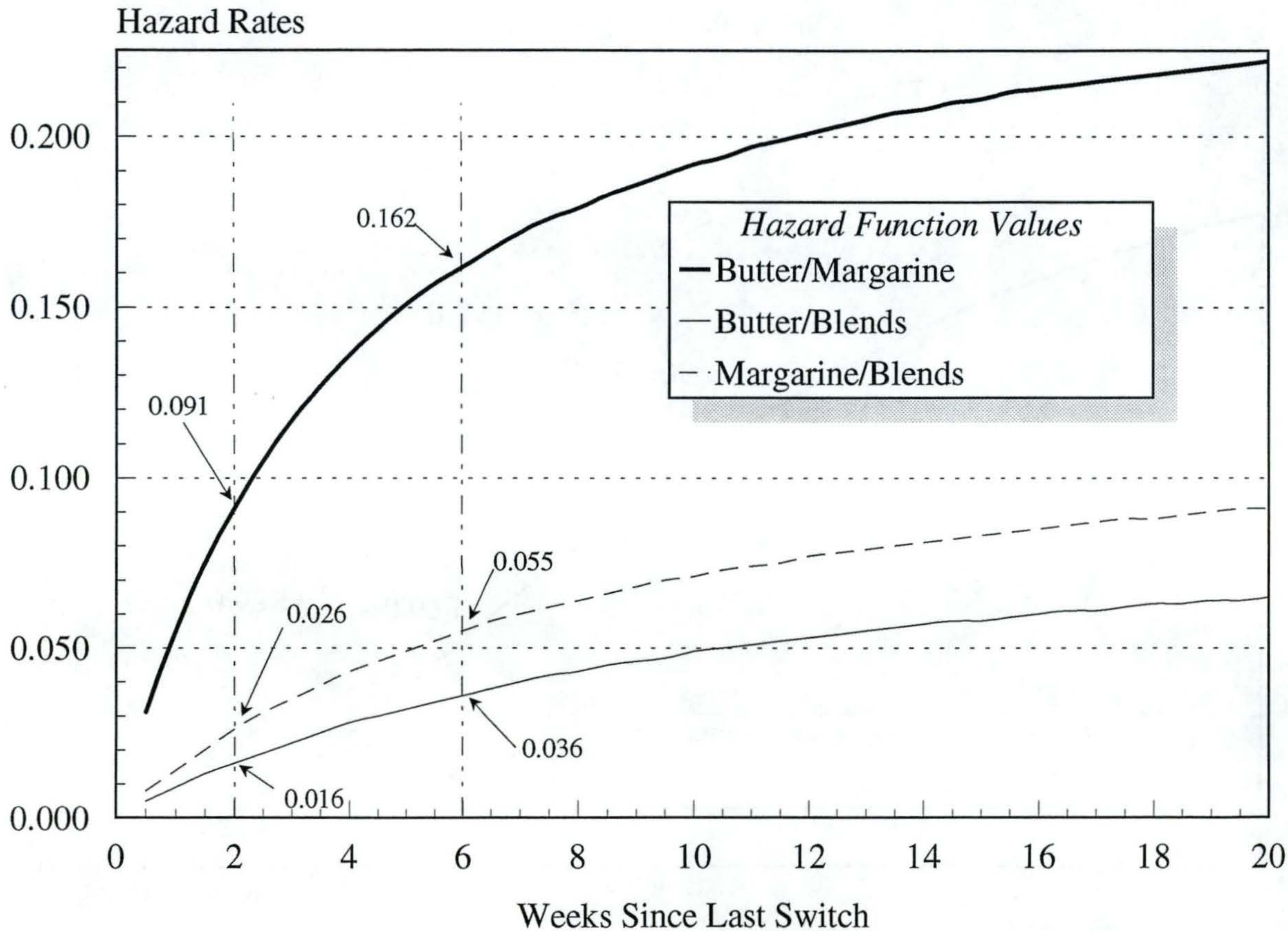
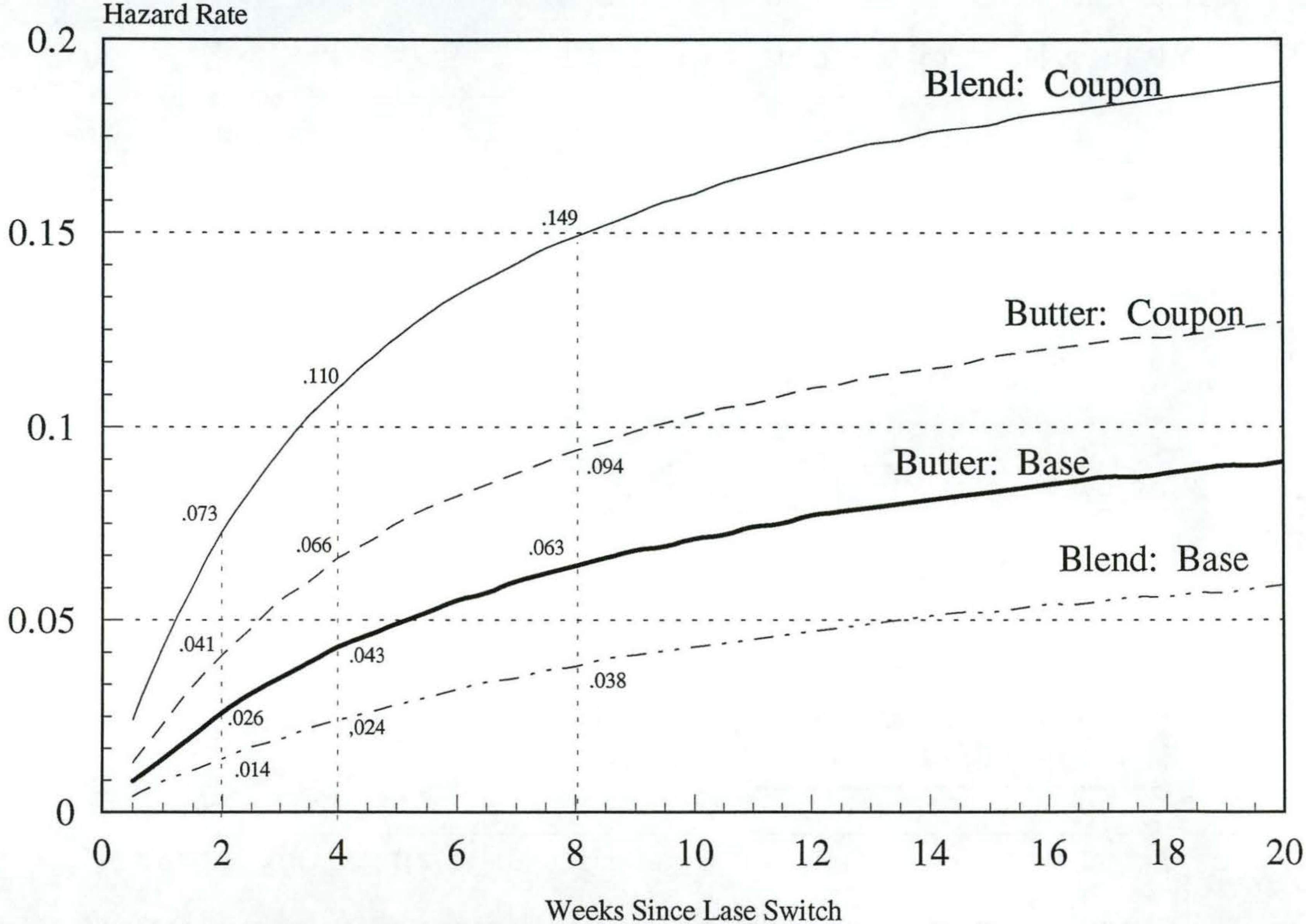
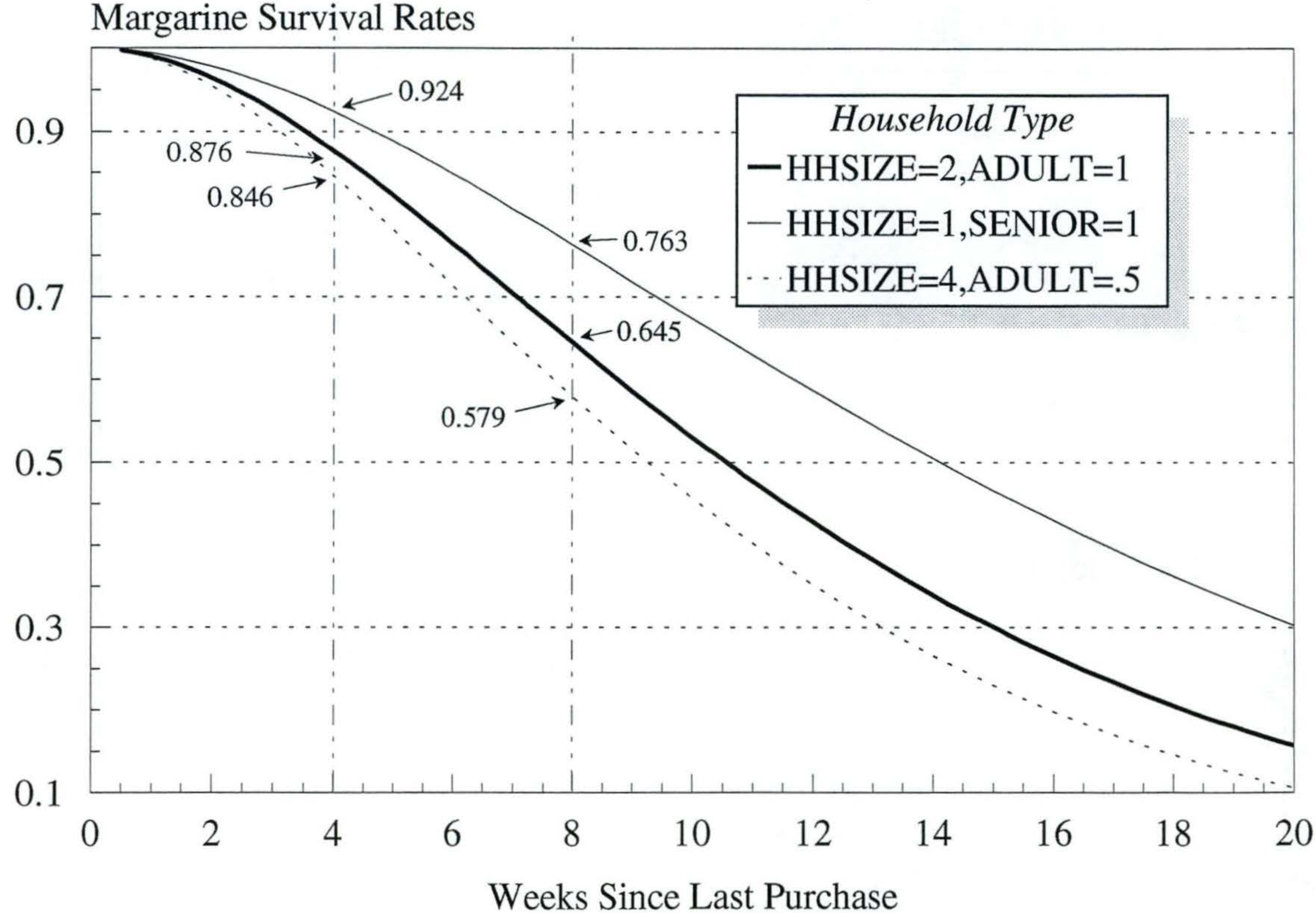


Figure 4. Effect of Coupon-Based Price Reduction on Margarine Hazard Rates



Note: Each line represents a unique margarine hazard rate. For example: **Blend: Coupon** represents the hazard rate profile for switching from margarine to blends given the use of a 50% off blends coupon.

Figure 5: Effect of Household Composition on Margarine Survival Rate Profiles



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Footnotes

1. For an example of the use of panel data to investigate the consumption dynamics refer to Naik and Moore(1996). Unlike the present analysis, their dependant variable is current annual food expenditures.

2. The risk period is defined as a time period when an individual could possible experience an event. For example, if one was examining the event of unemployment, then the risk period is defined during those times when an individual is employed.

3. To implement the competing risk model used here we make a simplifying assumption that on any one purchase occasion only one of the three commodities are purchased. In the consumer panel used in this analysis, 7 percent of the purchase occasions implied multiple commodity type purchases.

4. For more detail, refer to Yamaguchi (1991), p,1-9 and Blossfeld, Hamerle and Mayer (1989), p.28-30.

5. We can represent the gamma distribution (f_G) as:

$$f_G(t) = \frac{\lambda^r t^{r-1} e^{-\lambda t}}{r-1}$$

When the distribution parameter **r** takes only integer values this distribution is referred to as an Erlangian distribution. When **r** is set equal to 2, this is referred to as an Erlang-2 distribution (Cox and Lewis, 1966).

6. As shown in Figure 1, there is a difference between purchase occasions and the occurrence of an event. That is, there can be a purchase occasion without an event occurring, i.e., purchase the same commodity over consecutive purchase occasions. As shown in equation (6'), for each household the number of observations a household contributes to the likelihood function is the number of purchase occasions.

7. Earlier versions of the model had included 9 regional dummy variables as well as a dummy variable identifying whether a household was located in a rural versus urban area. Little evidence in mean interswitch time was found across region or the degree

of urbanization. Given the size of the model, these variables were dropped from the final analysis.

8. As noted by a reviewer, there is an implicit assumption that the weights used to define the reference prices does not vary with the amount of time between purchase occasions.

9. As noted by a reviewer, the panel encompasses a relatively short time period in spite of having many observations per household. Instead of the time trend variable to represent the state of knowledge we could have used education level of household head given that previous studies have shown education as an important determinant of nutrition knowledge (Gould and Lin, 1994; Gould, 1997). We did not include this given that very few respondents changed their education level over the study period and we wanted to include as many time dependant exogenous variables as possible in the model.

10. The six regimes are identified as switching from: (i) butter to margarine, (ii) butter to blends, (iii) blends to butter, (iv) blends to margarine, (v) margarine to butter and (vi) margarine to blends. Estimation was undertaken using the MAXLIK routines within the GAUSS software system. The GAUSS code can be obtained from the author upon request. A heteroskedastic-consistent parameter covariance matrix was computing using the following: $V = A^{-1}BA^{-1}$ where A^{-1} is the inverse of the Hessian and B the cross product of first derivatives.

11. We simulated a 50% off butter coupon promotion by setting the PRRATIO for butter equal to .50 and PRRATIO for blends and margarine equal to 1. The base scenario assumed that PRRATIO for the 3 commodities were set equal to 1. The remainder of the exogenous variables were set at their mean values.