The Value of Household Life Cycle Variables in Consumer Expenditure Research: An Empirical Examination

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Abstract
We examine why studies reach contradictory conclusions concerning the value of the household life cycle model as a predictive tool in consumer expenditure research. Using a database of roughly 14,000 Canadian households, we find that household life cycle variables do not generally enhance prediction over a more parsimonious model containing a basic set of socioeconomic and demographic variables, even when comparing less aggregated to more aggregated expenditure categories. However, they do enhance prediction for categories that are defined such that the typical users of the category fall into a fairly narrow age range. The theoretical and applied significance of our findings are discussed and directions for future research are offered. Copyright © 2007 ASAC. Published by John Wiley & Sons, Ltd.

JEL Classifications: C53, D12, D13, D91, M31

Keywords: administrative science, consumer research, household life cycle, marketing research.

Résumé
Nous cherchons à savoir pourquoi les études aboutissent à des conclusions contradictoires sur la valeur du modèle de cycle de vie des biens ménagers comme outil de prévision en recherche sur les dépenses de consommation. En nous appuyant sur une base de données d’environ 14,000 foyers canadiens, nous avons trouvé que les variables relatives au cycle de vie des biens ménagers n’amélioraient généralement pas les prévisions par rapport à un modèle moins élaboré, construit sur un ensemble élémentaire de variables socioéconomiques et démographiques, même lorsqu’on effectue une comparaison entre des catégories de dépenses peu regroupées et des catégories plus regroupées. Elles améliorèrent cependant les prévisions dans le cas de catégories définies de telle sorte que les usagers représentatifs (d’une catégorie) se situent dans une tranche d’âge assez étroite. Nous examinons les retombées théoriques et pratiques de nos découvertes et proposons des pistes pour les recherches à venir. Copyright © 2007 ASAC. Published by John Wiley & Sons, Ltd.

Mots clés : science administrative, étude de consommation, cycle de vie des biens ménagers, recherche en marketing.

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The household (or family) life cycle construct has had a prominent place in consumer expenditure and behaviour research for nearly 50 years (Danko & Schaninger, 1990; Derrick & Lehfeld, 1980; Fritzscbe, 1981; Gilly & Enis, 1982; Lansing & Morgan, 1955; Murphy & Staples, 1979; Schaninger & Danke, 1993; Soberon-Ferrer & Dardis, 1991; Wagner & Hanna, 1983; Wells & Guber, 1966; Wilkes, 1995). It refers to the notion that most households pass through an orderly progression of stages, each with its own characteristics, financial situations, and purchase patterns (Wells & Gubor) and is frequently discussed and utilized in consumer research, education, and marketing practice. We surveyed 48 recently published textbooks in marketing management and consumer behaviour and found that 90% present household life cycle as valuable for predicting consumer purchases and consumption. In practice, the use of household life cycle in predictive models has become more commonplace in recent years due to the increasing availability of household level data and the popularity of geodemographic segmentation products. Popular commercial packages that are at least partially based on the household life cycle construct include MapInfo’s Pysyte System and Environics Analytics’s PrizmCE System for Canada as well as Claritas’s Prizm System and ESRI’s Tapestry System for the US.

However, despite such popularity of the household life cycle construct, only limited empirical research has been conducted to evaluate its ability to predict consumer expenditure behaviour relative to other, more parsimonious, models. Remarkably, the findings among the few existing studies are contradictory. Whereas Wilkes found that “the household life cycle is a significant tool in the analysis of consumers and not simply a conceptual model” (1995, p. 42), Wagner and Hanna found that “while family life cycle variables offer a convenient conceptual framework, socioeconomic and demographic variables may be better choices for expenditure research” (1983, pp. 289–290).

Both Wagner and Hanna’s (1983) and Wilkes’s (1995) assessments are based on the ability of household life cycle variables to improve within sample prediction of spending levels on an expenditure category compared to more parsimonious models. The two studies differ in the definition and number of expenditure categories examined and in the measure of predictive fit for the assessments. Specifically, Wagner and Hanna examine total clothing spending, while Wilkes examines 21 different categories, including women’s, men’s, girls’, boys’, and infant wear, each as separate categories. Wilkes suggests, without further exploring the issue, that Wagner and Hanna did not find substantial predictive benefits from household life cycle variables because of the highly aggregated nature of the total clothing expenditure category.

Studies have also not discussed the issue of statistical measures used to assess the predictive ability of the household life cycle construct. $R^2$ never decreases as additional explanatory variables are added (Judge, Griffiths, Hill, & Lee, 1980, p. 601). By using $R^2$ alone, Wilkes’s study could have been biased in favour of the addition of household life cycle variables. Since all three previous studies (Derrick & Lehfeld, 1980; Wagner & Hanna, 1983; Wilkes, 1995) focus on the ability of household life cycle variables to improve the prediction of household expenditure behaviour beyond more parsimonious models, measures of model fit based on predictions for a sample of households that is different from the estimation sample, rather than $R^2$ or adjusted $R^2$ based on the estimation sample as used in existing studies, are more appropriate for this assessment.

Derrick and Lehfeld (1980) compare three models to assess the usefulness of the household life cycle construct. One model includes a base set of socioeconomic and demographic variables (i.e., the base model). Another model includes these base variables plus a full set of household life cycle stages (i.e., the full household life cycle stage model). A third model contains these socioeconomic and demographic variables plus the variables that are used to construct the life cycle stages. By examining the ability of the models in explaining total food spending, a highly aggregated expenditure category, Derrick and Lehfeld found that the third model is preferable to the full household life cycle stage model, which in turn, is preferred to the base model.

A common hypothesis of household life cycle models is that the life cycle stage of a household influences household behaviour. The driving force behind the household life cycle stage is the interactions between the underlying household composition variables (e.g., the number of household heads, and whether any children are present in the household), which by themselves reflect the main effect of the household life cycle construct. Fritzscbe (1981) is one of several authors to explicitly underline the potential benefits of these interactions and suggests that “absolute energy requirements may be more a function of the location of the family in its life cycle than of any individual set of demographic characteristics” (p. 228). If these interactions do not help to predict expenditure behaviour, then the value of the household life cycle construct as a predictive tool comes into question.

As such, further examination is needed to determine whether the household life cycle construct can predict consumer expenditure behaviour. We examine whether the level of category aggregation (i.e., whether a category
is defined at a more aggregate level such as all apparel, or at a less aggregate level such as boy’s apparel) influences the predictive ability of the construct. Moreover, we examine a large number of expenditure categories to determine whether a main effects approach to the use of the household life cycle construct (i.e., merely using the household composition variables that are used to construct the life cycle stages) can yield a superior prediction than the traditional interaction effects approach of using the full set of household life cycle stages.

We make two further improvements on the existing literature. First, the estimation equations are derived from an explicit microeconomic model of household expenditure behaviour. While providing a sound theoretical framework, this approach allows the effect of household life cycle variables to vary with changes in a household’s total consumption expenditures. Second, we use a heteroscedasticity corrected tobit maximum likelihood model for estimation. We discuss this econometric issue in detail in the method section of the paper.

Method

Data and Expenditure Categories

We used the 2000 Survey of Household Spending (Statistics Canada 2002), which is based on a probability sample of households across Canada. The expenditure amount on all family expenditure items was collected for 14,731 households using in-home interview surveys that were conducted between January and March of 2001. Given that a primary objective of this study is to examine how the level of category aggregation influences the usefulness of household life cycle variables as a predictive tool, a major criterion we used to select and define expenditure categories was how finely detailed a category definition could be made. Because of the conflicting findings of Wagner and Hanna (1983) and Wilkes (1995) regarding household spending on clothing, we were particularly interested in examining the effect of the level of category aggregation on clothing expenditures. In our analysis we first examined the higher level (more aggregated) category, what we call a “major” category, and then examined its underlying component categories as a way of assessing the influence of category aggregation on the usefulness of household life cycle variables as predictors. Table 1 describes the expenditure categories used.

Household Life Cycle Definition and Socioeconomic and Demographic Variables

We used a slightly modified version of the household life cycle model of Gilly and Enis (1982). Previous studies have found that this model results in a small number of unclassified households and outperforms other household life cycle models in predicting both expenditure behaviour and the attitudes of head of household (e.g., Schaninger & Danko, 1993). This model was also used by Wilkes (1995) and can be viewed as a straightforward extension of the model of Wells and Gubar (1966), which was examined by Derrick and Lehfeld (1980) and Wagner and Hanna (1983). Moreover, the Gilly and Enis framework allowed us to cleanly assess the relative merits of the main effects versus the full interaction effects of the household life cycle construct.

Three variables were used to define household life cycle stages by Gilly and Enis (1982): (a) number of “household heads” (one or two); (b) whether children are present and whether the youngest child is below the age of 6, or between the ages of 6 and 17; and (c) whether the female household head (or male head if no female head is present) is under 35 years old, between the ages of 35 and 64, or age 65 or older. The cross-classification of these three variables leads to 18 (= 2 × 3 × 3) life cycle stages. Following Gilly and Enis, we further omitted households with children present where the head is 65 years or older (a total of four cases), obtaining 14 life cycle stages in total. The final data set contains 13,236 households, and the estimation and holdout samples were created (each containing 6,618 households) through random assignment. Table 2 describes the life cycle stages and the distribution of households in our sample.

The three previous studies all used additional variables beyond those intended to capture the household life cycle construct. There are two reasons for this. First, there may have been determinants of expenditure behaviour that were not captured by the household life cycle construct. We controlled for three such factors as indicated by past consumer expenditure research. They were (a) whether both household heads in a two household head family work outside the home; (b) the level of urbanization of the area in which the household resides; and (c) the geographic location of the household’s residence. Briefly, the working status of both household heads not only influences income, it also relates to in-home production of goods (e.g., preparing food) that otherwise need to be purchased (Becker, 1965); the level of urbanization (this matters as it influences the availability of some goods and services to the household); and the geographic area where a household resides (may have a distinctive climatic and cultural influence on spending).1

Second, we need to cope with possible within life cycle stage heterogeneity. This refers to the possibility that important predictive information is lost during the construction of household life cycle stages. For example,
one argument often advanced to justify household life cycle models is that the life cycle stages capture different income levels across households reasonably well. While it is true that, on average, a household comprised of a married couple between the ages of 35 and 64 and a child that is older than age 6 will have a greater annual income than a household comprised of a single, unmarried individual below the age of 35, this is unlikely to be the case for all households of these two types. Moreover, there is likely to be a great deal of heterogeneity in income levels within each of these two household types. We included three factors frequently used in existing studies to account for within stage heterogeneity: the age of the household head, the number of household members, and the level of total household expenditures. Together these two groups of factors constitute a base set of socioeconomic and demographic variables.

Model Specification and Measures of Predictive Capability

The functional form we used to estimate the expenditure equations is based on a microeconomic model in which consumers maximize utility subject to a level of total expenditures and prices. On a conceptual level, we modeled a household’s life cycle stage and other socio-

Table 1
Expenditure Categories and Category Summary Statistics

<table>
<thead>
<tr>
<th>Expenditure category</th>
<th>Mean spending ($)</th>
<th>Percent of households with non-zero spending</th>
<th>Conditional mean spending ($)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total clothing</td>
<td>2094.75</td>
<td>98.8</td>
<td>2119.25</td>
</tr>
<tr>
<td>Women’s and girls’ wear</td>
<td>1058.56</td>
<td>89.9</td>
<td>1177.50</td>
</tr>
<tr>
<td>Men’s and boys’ wear</td>
<td>797.22</td>
<td>87.1</td>
<td>915.73</td>
</tr>
<tr>
<td>Infant and toddler wear</td>
<td>95.80</td>
<td>39.1</td>
<td>242.11</td>
</tr>
<tr>
<td>Clothing material and notions</td>
<td>30.59</td>
<td>25.4</td>
<td>120.44</td>
</tr>
<tr>
<td>Laundry and dry cleaning</td>
<td>112.58</td>
<td>60.5</td>
<td>186.22</td>
</tr>
<tr>
<td>Other clothing services (e.g., tailoring, rentals)</td>
<td>23.49</td>
<td>28.4</td>
<td>82.81</td>
</tr>
<tr>
<td>Total home entertainment</td>
<td>833.77</td>
<td>93.6</td>
<td>890.42</td>
</tr>
<tr>
<td>Audio equipment (e.g., radios, CD players)</td>
<td>85.02</td>
<td>22.1</td>
<td>385.27</td>
</tr>
<tr>
<td>Prerecorded entertainment (CDs, DVDs) and blank audio</td>
<td>116.78</td>
<td>62.8</td>
<td>186.07</td>
</tr>
<tr>
<td>and video tape</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TVs and other video equipment</td>
<td>142.61</td>
<td>23.6</td>
<td>604.24</td>
</tr>
<tr>
<td>Video tape and DVD rentals</td>
<td>91.72</td>
<td>59.0</td>
<td>155.58</td>
</tr>
<tr>
<td>Miscellaneous home entertainment (e.g., cable subscriptions and equipment rentals)</td>
<td>397.64</td>
<td>79.3</td>
<td>501.31</td>
</tr>
<tr>
<td>Total entertainment</td>
<td>191.29</td>
<td>71.1</td>
<td>269.21</td>
</tr>
<tr>
<td>Movie theater admissions</td>
<td>74.46</td>
<td>55.5</td>
<td>134.21</td>
</tr>
<tr>
<td>Live sports events (as a spectator)</td>
<td>32.44</td>
<td>19.7</td>
<td>164.85</td>
</tr>
<tr>
<td>Live performing arts</td>
<td>54.93</td>
<td>33.8</td>
<td>162.63</td>
</tr>
<tr>
<td>Admissions to museums and other activities</td>
<td>29.46</td>
<td>33.8</td>
<td>87.13</td>
</tr>
<tr>
<td>Total sports and recreation</td>
<td>852.63</td>
<td>65.1</td>
<td>1308.75</td>
</tr>
<tr>
<td>Sports and recreation equipment</td>
<td>137.48</td>
<td>35.7</td>
<td>385.27</td>
</tr>
<tr>
<td>Bicycles, parts, and accessories</td>
<td>33.94</td>
<td>12.7</td>
<td>268.16</td>
</tr>
<tr>
<td>Bicycle maintenance and repair</td>
<td>4.23</td>
<td>5.9</td>
<td>71.19</td>
</tr>
<tr>
<td>Recreational vehicles (e.g., boats, snowmobiles)</td>
<td>472.77</td>
<td>23.7</td>
<td>1994.14</td>
</tr>
<tr>
<td>Sports and recreation facilities membership and use fees</td>
<td>187.52</td>
<td>40.1</td>
<td>468.23</td>
</tr>
<tr>
<td>Other recreational services (e.g., fishing licenses, sports facility rental)</td>
<td>16.69</td>
<td>22.3</td>
<td>74.71</td>
</tr>
<tr>
<td>Total reading material and printed matter</td>
<td>248.92</td>
<td>86.5</td>
<td>287.92</td>
</tr>
<tr>
<td>Newspapers</td>
<td>96.00</td>
<td>66.0</td>
<td>145.55</td>
</tr>
<tr>
<td>Magazines and periodicals</td>
<td>56.61</td>
<td>56.0</td>
<td>101.13</td>
</tr>
<tr>
<td>Books and pamphlets (excluding school books)</td>
<td>81.13</td>
<td>47.2</td>
<td>171.92</td>
</tr>
<tr>
<td>Other printed matter (e.g., maps, sheet music)</td>
<td>15.18</td>
<td>26.1</td>
<td>58.07</td>
</tr>
</tbody>
</table>
We have specified a household’s total expenditure function as
\[
\log c(p, u, d_h) = \sum_i \alpha_i(d_i) \log p_i + u \prod_j p_j^{\beta_j(d_h)},
\]
(1)

where \(d_h\) is household \(h\)’s vector of life cycle construct and other socioeconomic and demographic variables (but excludes total expenditures), and \(j\) indexes expenditure categories. The first term on the right side of (1) can be interpreted as the cost of subsistence and the second term the cost of utility above and beyond the subsistence level. This form of the total expenditure function was also the basis of Deaton and Muellbauer’s Almost Ideal Demand System, which has been extensively used in applied demand analysis in economics.

Differentiating (1) with respect to \(\log p_i\), substituting for \(u\), and relabeling minimum total expenditures for household \(h\) as \(y_h\), \(c(p, u, d_h) = y_h\), lead to the expenditure share equation for good \(i\),
\[
w_i(p, y_h, d_h) = \alpha_i(d_i) + \beta(d_i) \left[ \log y_h - \sum_j \alpha_j(d_j) \log p_j \right].
\]
(2)
The physical units in which the quantity of products is measured are arbitrary. Because we are dealing with data from a single cross-section and there are no published geographically based price indices that report differences in consumer prices between different regions, we need to further assume that all households face the same prices. For a base period, the physical units of each good can be set such that one dollar purchases a single physical unit of that product in that period. Using this normalization of the physical units allowed us to rewrite (2) as
\[
w_i(y_h, d_h) = \alpha_i(d_i) + \beta(d_i) \log y_h.
\]
(3)

Equation (3) represents the basic functional specification we applied to the data. This structure is much more flexible than the functional specifications used in the previous studies. It allowed for fairly flexible Engel curves whose curvature varies across different household types depending on the life cycle stage the household falls in and the other socioeconomic and demographic factors.

Next we parameterized \(\alpha_i(d_i)\) and \(\beta(d_i)\) based on the discussion in previous sections. It is through the inclusion, or lack of inclusion, of variables related to the household life cycle construct in \(d_i\) that the predicative capability of the construct was examined. For the base specification,
\[
\alpha_i(d_i) = \alpha_{i0} + \alpha_{i1} \ln (HHAGE_h) + \alpha_{i2} \ln (HHSZ_h)
+ \alpha_{i3} BTWRK_h + \alpha_{i4} REGION_h + \alpha_{i5} URBAN_h,
\]
(4a)
\[ \beta(d_i) = \beta_0 + \beta_1 \ln(HHAGE_i) + \beta_2 \ln(HHSZ_i) + \beta_3 BTWRK_i + \beta_4 REGION_i + \beta_5 URBAN_i, \]

where \( HHAGE_i \) is the age of the female head (male head if there is no female head), \( HHSZ_i \) is the number of household members, \( BTWRK_i \) indicates whether both household heads work, \( REGION_i \) is a set of four dummy variables for the geographic regions of Canada, and \( URBAN_i \) is whether the household resides in an area with a population of at least 100,000 persons.

The specification that captures the main effects of the household life cycle construct was obtained by appending onto (4a) and (4b) the five variables that were used to define household life cycle stages: \( AGEMID_i \) (whether the household head is between 35 and 64 years of age), \( AGEOld_i \) (whether the household head is 65 years of age or older), \( YNGCHLD_i \) (whether the youngest child present in the household is under six years of age), \( OLDCHLd_i \) (whether the youngest child present in the household is between the ages of 6 and 17 years old), and \( TWHOED_i \) (whether there are two household heads present). Finally, the specification that captures the full household life cycle construct (the full cross-classification) was obtained by appending onto (4a) and (4b) 13 zero-one dummy variables for 13 of the 14 household life cycles stages constructed on the basis of Gilly and Enis’ (1982) model.

We completed the specification by attaching a normal random error term to (3). As Table 1 indicates, all the expenditure categories have at least some, and often many, households that have zero spending. As a result, least squares estimation becomes biased and a tobit model should be used (Amemiya, 1985, pp. 361–367; Tobin, 1958). Furthermore, using tobit estimation allows us to examine (a) the influence of household life cycle and other variables on the probability that a household spends on a category; (b) the expected expenditure level conditional on a positive level of spending; (c) the unconditional expected expenditure level; and (d) the variance in spending levels for a category across households with the same observable characteristics. These elements, as we show later, affect the results regarding the value of household life cycle construct in explaining household expenditure behaviour. However, unlike least-squares, tobit models are not robust to heteroscedastic errors. To avoid this problem we used a multiplicative heteroscedasticity correction, where both \( d_i \) (which varies across the different models estimated for a category) and \( y_i \) were used to correct for the non-constant error variance. A multiplicative structure is used here since it is numerically more stable than an additive structure as the probability of estimating a (undefined) negative variance for a household is much lower. If \( \varepsilon_{ih} \) is household \( h \)'s error for category \( i \), then in the base specification, \( \varepsilon_{ih} \) is specified as

\[
\varepsilon_{ih} = \eta_i \gamma_i HHAGE_i^\gamma_i HHSIZE_i^\gamma_i \exp(\gamma_i BTWRK_i) \exp(\gamma_i REGION_i) \exp(\gamma_i URBAN_i),
\]

where \( \eta_i \) is a normally distributed error term with zero mean and unit variance. As a result, \( \varepsilon_{ih} \) is normally distributed with mean zero and

\[
\sigma_i = \gamma_i HHAGE_i^\gamma_i HHSIZE_i^\gamma_i \exp(\gamma_i BTWRK_i) \exp(\gamma_i REGION_i) \exp(\gamma_i URBAN_i).
\]

As with the specification of \( \alpha(d_i) \) and \( \beta(d_i) \), we appended on the appropriate household life cycle construct variables for both the main effects and the full household life cycle specifications.

The models were estimated using maximum likelihood. The specifics of this model and the estimation process can be found in most references on tobit models (e.g., Amemiya, 1985). The measure of model fit for tobit models that is closest to traditional \( R^2 \) is the squared correlation coefficient between the actual and the unconditional expected value of expenditures across households. In least-squares regression \( R^2 \) and the squared correlation coefficient between the actual and unconditional expected values are identical. We calculated this measure for each expenditure category for the three model specifications.

**Results**

To examine whether household life cycle effects are statistically significant (as opposed to being important for prediction) we conducted nested likelihood ratio tests for each expenditure category. For all the expenditure categories we rejected the base model in favour of the full household life cycle model at the \( p < 0.01 \) level. When the main effects of the household life cycle construct were tested against the base specification, there was only a single expenditure category (total reading material and other printed matter) for which we failed to reject the base specification at the \( p < 0.01 \) level. Finally, for only two categories (total home entertainment and newspapers) did we fail to reject (at the \( p < 0.01 \) level) the main effects model in favour of the full household life cycle model. Taken together, these results suggest that household life cycle stages have a statistically significant influence on household expenditure behaviour. However, given the large sample size used in this study, even fairly minor effects will be statistically significant as likelihood ratio tests tend to favour models with more independent
variables and tend to overstate differences between the models when the sample size is large. Furthermore, results based on likelihood ratio tests can be inconclusive when choosing from many competing models (Amemiya, 1985, p. 146).5

Household Life Cycle as a Predictive Tool

We are primarily interested in whether the use of household life cycle construct based variables noticeably enhances the ability to predict consumer expenditure behaviour. Table 3 provides the out-of-sample results. It reveals that, with the exception of a few expenditure categories, there tends to be very small or no difference in the squared correlation coefficients across the three models. That is, household life cycle variables provide little or no improvement in prediction relative to a parsimonious model using a base set of socioeconomic and demographic variables. The most noticeable exception is the infant and toddler wear category (which mirrors Wilkes’s 1995 findings), where the squared correlation coefficient is nearly three times as large for the full life cycle model than it is for the base model. There is a noticeable, but much smaller, improvement attributable to the use of household life cycle variables for movie theater admissions. In addition, there are very small improvements for women’s and girls’ wear; men’s and boys’ wear; total entertainment; and bicycles parts and accessories.

Finding 1. For most expenditure categories we examined, the use of household life cycle construct-based variables provide little or no improvement in prediction relative to a parsimonious model using a base set of socioeconomic and demographic variables. The most noticeable exception is the infant and toddler wear category (which mirrors Wilkes’s 1995 findings), where the squared correlation coefficient is nearly three times as large for the full life cycle model than it is for the base model. There is a noticeable, but much smaller, improvement attributable to the use of household life cycle variables for movie theater admissions. In addition, there are very small improvements for women’s and girls’ wear; men’s and boys’ wear; total entertainment; and bicycles parts and accessories.
diction relative to a much more parsimonious model that contains a base set of socioeconomic and demographic variables.

To further confirm this finding, we estimated two additional models that included only the household life cycle construct variables but not the basic set of socioeconomic and demographic variables. Specifically, we estimated a “main effects only” model that included the household composition variables used to construct the life cycle stages and a “household life cycle stages only” model that included the full set of household life cycle stages. The results are presented in the last two columns of Table 3. Consistent with the previous findings, the base model outperforms these two new models in almost all product categories. The only exception, not surprisingly, is infant and toddler wear.

Combined with Wilkes’s results, we believed that the effect of using household life cycle variables would be much larger for the clothing category if women’s and girls’ wear had been further disaggregated into separate categories, with the same being true for the men’s and boys’ wear. As Table 3 shows, greater aggregation of the clothing category does appear to mask the influence of household life cycle variables. This is consistent with Wilkes’s (1995) conjecture on why his results differ from those of Wagner and Hanna (1983). However, there is little evidence of category aggregation masking the effects of household life cycle variables for the remaining four major categories. Actually, the improvement in the squared correlation coefficient from the use of the household life cycle construct-based variables is greater for total entertainment than it is for three of its component categories, while in the remaining three major categories household life cycle variables have little effect on either the aggregated major categories or the underlying component categories.

Finding 2. For most expenditure categories we examined, category aggregation does not mask the effect of household life cycle construct based variables.

Table 3 also shows the relative importance of the main effects underlying the household life cycle construct vis-à-vis the full set of household life cycle stage variables (e.g., the main effects model versus the full cross-classification model). For the categories in which household life cycle variables result in a noticeable improvement in model fit, it appears that nearly all of the improvement is due to the main effects. Although there is some marginal improvement gained by using the full household life cycle model in infant and toddler wear and men’s and boys’ wear, there is actually a slight decrement in fit compared to the main effects model for clothing material and notions and total entertainment.

Finding 3. In the few categories where the household life cycle construct helps to predict household expenditure behaviour, it is the main effects of the construct that provide the majority of this improvement rather than the interactions implied by the full set of household life cycle stages.

We next examined whether there is a significant difference if one uses within-sample rather than out-of-sample results, and if one uses a less flexible, simple linear functional form (such as the one used in the existing study). We find that a much larger number of categories (16 versus 8) show predictive improvement from the use of household life cycle variables according to within-sample squared correlation coefficients. Therefore, using within sample measures appears to overstate the actual predictive capabilities of the household life cycle construct. The use of a linear functional form skews the results towards finding improved prediction for models incorporating household life cycle variables compared to the more flexible functional form based on our theoretical model.

Categories in which Household Life Cycle Variables are Predictive

To gain further insight on why the household life cycle variables improve prediction for a few (but not the majority) of categories, we examined two component categories (infant and toddler apparel and movie theatre admissions) where these variables provide the greatest improvement in predictive capability. Figures 1 and 2 contain the fitted unconditional expected expenditure, the fitted conditional expected expenditure, and the fitted probability of non-zero spending for nine traditional life cycle groups.

In Figure 1, the probability of non-zero spending, the conditional expected expenditures, and the unconditional expected expenditures for infant and toddler wear all follow a similar pattern that has, predictably, the pronounced peak for the life cycle stages in which at least one child under age six is present (i.e., Full Nest 1 and Delayed Full Nest). This peak is higher for households with a younger household head, perhaps due to a hand-me-down effect. Somewhat more surprising is that the Empty Nest 1 households (households with two heads where the female head is between 35 and 64 years of age and there are no children present) have the third highest unconditional expected spending levels. This high unconditional expected spending is primarily due to this group’s conditional expected expenditure levels, as its probability of non-zero expenditures is comparable to that of a number of life cycle groups that do not contain a child under age six. This pattern is consistent with a “grandpar-
<table>
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<th>Household Life Cycle Variables</th>
<th>Unconditional Expenditures</th>
<th>Conditional Expenditures</th>
<th>Probability of Non-Zero Expenditures</th>
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</table>

Figure 1. Expenditures on infants and toddler wear
Figure 2.
Expenditures on movie theatre admissions

**Unconditional Expenditures**

- Yng Single
- Yng Couple
- Full Nest1
- Full Nest2
- Full Nest3
- Delayed Nest
- Empty Nest1
- Empty Nest2
- Old Single

**Conditional Expenditures**

- Yng Single
- Yng Couple
- Full Nest1
- Full Nest2
- Full Nest3
- Delayed Nest
- Empty Nest1
- Empty Nest2
- Old Single

**Probability of Non-Zero Expenditures**

- Yng Single
- Yng Couple
- Full Nest1
- Full Nest2
- Full Nest3
- Delayed Nest
- Empty Nest1
- Empty Nest2
- Old Single
ent effect” in which only a fairly small percentage of Empty Nest 1 households have an infant or toddler grandchild. However, those in this small percentage spend a relatively large amount on infant and toddler wear. The combination of concentrated spending among households with one or more children under age six and the grandparent effect appears to be responsible for the strong household life cycle effect for this category.

Figure 2 provides a detailed examination of spending on movie theatre admissions. For this category, the probability of non-zero spending is fairly stable (at around 60%) over a wide range of household life cycle stages. However, there are considerable differences in conditional expected spending levels. Specifically, households with children over age six present, young couples, and (on a per person basis) young singles have relatively high conditional expected spending. This pattern suggests that spending on this category is highest among young, childless adults and among households with older children and teenagers present, which appears to be responsible for the comparatively strong effect of household life cycle variables for this category. The large difference between the probability of non-zero spending and the conditional expected spending levels is due to significant differences across household life cycle stages in the standard deviation in category expenditures within each life cycle stage group. The data shows that the variance in spending is greatest for Young Couples, Full Nest 2 and Full Nest 3, and, on a per person basis, Young Singles.

The above analysis suggests that, for infant and toddler wear, the inclusion of household life cycle variables improves the ability to predict both whether a household will have positive expenditures on the category, and the household’s conditional expenditure level on the category. In contrast, these variables appear to improve mainly the ability to predict conditional expenditures for movie theatre admissions.

Examining the squared correlation between the fitted and actual values for both the predicted probability of positive expenditures and the expected conditional expenditures reveals that the inclusion of household life cycle variables improves the ability to predict both components.9 For infant and toddler wear category in greater detail using a set of histograms. Figure 3 presents an analysis of the predicted probability of positive expenditures. The left panels of the figure are for those households that had zero expenditure for the category, while the right panels are for those that did have positive expenditures. As a result, a model that fits perfectly would have a left panel with a single bar at zero, while the right panel would have a single bar at one. An examination of this figure reveals that the inclusion of household life cycle variables makes the predicted probabilities much sharper.9 While the predictions of the base model provide an appropriate “skew,” the predictions tend to be concentrated around 0.5. In contrast, when household life cycle variables are included, the density of predictions around 0.5 becomes much smaller. In the case of households with zero expenditure, the density becomes concentrated from a predicted probability of roughly 0.1 to 0.45, while the density becomes bimodal for households with positive expenditures. The right panel mode is as expected while the left panel mode is somewhat surprising. However, it is consistent with the notion of a “grandparent effect” (described earlier) or any gift giving on the part of households with no young children present (housesholds one would expect to have a low probability of purchasing in the category for explicit use in the household). The figure indicates that the predicted probability distributions exhibit the same basic pattern for both the main effects and the full household life cycle stage models.

Figure 4 further presents a histogram of the errors in the predicted conditional expected expenditures for all three models in the case of the infant and toddler wear category. Consistent with the squared correlation results presented earlier, this figure shows that the distribution of errors becomes more concentrated around zero for the main effects and full household life cycle stage models compared to the base model. Also, as expected, the pattern for the main effects and full household life cycle stage models are nearly identical.
Figure 3.
Predicted expenditure probability for infant and toddler wear
In summary, when the household life cycle construct improves prediction, it tends to do so by improving both the ability to predict whether a household will have positive expenditures for a category and the amount of those expenditures. In addition, our analysis reveals that nearly all of the improvement in prediction for both components is associated with the inclusion of the main effects of the household life cycle construct, with the use of the full household life cycle model providing little or no improvement over the main effects.

**Household Life Cycle as a Predictive Tool**

Our results indicate that, in general, even for very disaggregated categories, the use of variables based on the household life cycle construct does little to improve the ability to predict household spending behaviour beyond a base set of socioeconomic and demographic variables. Only in a minority of component expenditure categories may these variables be predictive. For example, both our results and those of Wilkes (1995) indicate they
are useful for component clothing categories, but not the aggregated total clothing category.

What makes the clothing category (where the category aggregation effect is strong) special is that the component categories are mostly defined by the age and gender of the intended wearer of the clothing. In contrast, the component categories within, for example, the reading material and printed matter category (where there is no evidence that household life cycle variables improve prediction) are based on the physical form of the products.

Our conjecture is that if the component categories within the reading material and printed matter category were also structured based on the characteristics of the likely readers (e.g., a “young readers” category including expenditure on magazines targeted towards 6 to 10 year olds, such as children’s books and Sport Illustrated for Kids), then we would find that household life cycle variables improve prediction at the component category level and that these improvements would be masked by aggregation. Similarly, if the component categories for clothing were defined by product form (e.g., pants and trousers, shirts and blouses, footwear, etc.), then household life cycle variables would provide little help in predicting component category spending levels and there would be little evidence of aggregation masking the effects of these variables at the major category level.

The data do not allow us to examine whether user age-based category definitions increase the predictive power of the household life cycle model as opposed to alternative category definitions. However, we were able to analyze three additional component categories where expenditures were closely associated with the presence of individuals within a particular age range in the household. These include child care (where the likely user of the service are young children and the parents of young children); toys, games, and art/hobby materials (where the most likely users of the products purchased from the category are children); and educational tuition fees (where the most likely users of this service are in their late teens and early twenties). The functional forms estimated, the estimation methods used, and the procedures followed are identical to those used earlier.

Although the toys, games, and art/hobby materials category and the educational tuition fees category are not as precisely defined as we would like, because the former includes art and hobby materials and the latter includes all tuition for education, not just college and university tuition fees, the results of predictive capability of the three specifications are consistent with our conjecture. That is, the use of household life cycle variables improves prediction over the parsimonious base model for these three categories (Table 4).

**Conclusion**

**Summary**

We find that household life cycle variables do not in general enhance prediction over a more parsimonious model containing a basic set of socioeconomic and demographic variables, even when comparing less aggregated to more aggregated expenditure categories. However, they do enhance prediction for categories that are defined such that the typical users of the category fall into a fairly narrow age range.

**Contribution to Scholarship**

Extending the previous research (e.g., Derrick & Lehfeld, 1980; Wagner & Hanna, 1983; Wilkes, 1995), this paper shows that the level of aggregation does not reduce the predictive ability of household life cycle construct for many expenditure categories. We also highlight the result that the main effect of the household life cycle construct can be more useful than the interaction effects the life cycle stages capture. This is an important issue that existing consumer research has not yet addressed, particularly in light of authors (e.g., Fritzsche, 1995).
A key finding that emerges from our analyses is that the household’s life cycle stage appears to have a greater effect on spending behaviour within a category (e.g., the shift from adult apparel to toddler and infant apparel as a married couple moves from the “Young Couple” stage to the “Full Nest 1” stage due to the birth of a child) than it does on spending across different categories (e.g., the lack of a shift in spending on newspapers versus books). Given this, focusing on spending patterns within categories seems to be the most promising avenue for future theoretical refinement of the household life cycle model.

Our analyses are based upon improved econometric method (i.e., tobit estimation) and a predictive measure (i.e., out-of-sample squared correlation). Together with the use of a comprehensive dataset that contains large numbers of households and product categories, these improved econometric aspects help enhance the internal and external validities of the findings. The reason is that past work has relied on a limited number of product categories (typically a single category), reducing the ability of generalizing the authors’ findings. Moreover, all the previous studies have only examined the merits of the household life cycle model on the ability of this model to improve within-sample prediction, but have not examined the ability to help predict out of sample, thereby reducing the external validity of these studies. Finally, past studies have not explicitly accounted for the censored nature of household spending behaviour (e.g., zero spending levels). This results in statistical bias that reduces the internal validity of the analysis.

Contributions to Practice

For marketing practice, this paper suggests that managers and researchers should be aware that the definition of a product category directly influences the effectiveness of the use of household life cycle variables in predicting household expenditures for that category. If the definition does not segment potential users into clear age groups, one can simply use basic socioeconomic and demographic variables instead of being concerned with capturing the household life cycle construct. For those products or markets where household life cycle constructs can be useful, rather than relying on the full set of household life cycle variables, managers and researchers can rely on the life cycle composition variables that capture the main effects of the household life cycle construct.

Limitations and Future Research Directions

There are two limitations to the study. First, the analyses were conducted using a single Canadian database. While the main findings are not based upon any particular features of the Canadian context, one may wish to replicate this study using data from other countries or regions to examine the robustness of the findings. Nevertheless, we hope that using a Canadian database and incorporating several Canadian-specific variables into the model sheds light on Canadian household expenditure behaviour. Second, this paper, and most existing studies, focuses on the predictive value of the household life cycle construct for household expenditure behaviour. As a traditional conceptual and segmentation tool, the household life cycle construct may have other uses that have not been considered here. While the limited predictive value found here does not invalidate the use of the construct for other purposes, it is the task of both academic research and marketing practice to determine when and where this construct is useful in other purposes.

Finally, there has been both debate and research regarding the construction of household life cycle stage models. Researchers should develop a set of household life cycle stages customized for Canadian households, perhaps by using methods along the lines of those employed by Du & Kamakura (2006).

Notes

1 The Household Expenditure Survey data does not include a number of demographic variables (such as race) that are often included in expenditure survey data.

2 Both Wagner and Hanna (1983) and Wilkes (1995) use total household expenditures instead of household income as a proxy for income. We use it to maintain consistency with these previous studies, and also because total expenditures provide the basis for the theoretical model used to specify our estimating equations. The inclusion of household head age also helps maintain consistency with the study by Wilkes (1995), which finds that the household life cycle construct has significant explanatory power despite the inclusion of this variable in his model.

3 In contrast, the linear specification used by Wilkes (1995) assumes that spending on an expenditure category as total expenditures increase can be captured by a straight line that is identical for all household types. The double-log specification that was used by both Derrick and Lehfeld (1980) and Wagner and Hanna (1983), where a logarithmic transformation is applied to both the dependent and all continuous explanatory variables, allows a nonlinear relationship between total household expenditures and spending on a particular category. However, it assumes that the nature of the nonlinear relationship is identical across households of different types.

4 For all expenditure categories, the null hypothesis of no heteroscedasticity can be rejected at the $p < 0.001$ level.
Another measure that can be used for model selection is the Bayesian Information Criterion (BIC), which balances the likelihood value with the number of parameters and sample size. We calculated the BIC for all the expenditure categories and all model specifications. The results are consistent with what we find based on the predictive measure of the squared correlation coefficient between the estimated unconditional expenditures and actual expenditures reported in the next subsection. Specifically, the use of household life cycle construct variables does not improve the prediction of household expenditure for most categories examined. The base model performed better than or equally well as the models with household life cycle constructs on 18 out of 30 product categories. We provide a detailed discussion later in the paper as to why the predictive performance of household life cycle construct variables may differ across categories.

The details of these results are available from the authors upon request.

We examine these nine groups only to ease the exposition, but our conclusions based on this reduced set are consistent with that based on all 14 life cycle stages. Note that the fitted unconditional expected expenditure is a product of the fitted conditional expected expenditure and the fitted probability of non-zero spending.

The squared correlation for the predicted probability of positive expenditures is obtained by correlating a 0–1 variable for positive expenditures (with 0 indicating no expenditure and 1 indicating positive expenditures) with the predicted probability of positive expenditures. The squared correlation between actual expenditures and predicted expected conditional expenditures is calculated only for households with positive expenditures.

We originally looked at “hit rates” as a measure of model improvement. Under the hit rate criteria, a “success” is recorded when the predicted probability is greater than or equal to 0.5 and the household has positive expenditures or when the predicted probability is less than 0.5 and the household has zero expenditures for the category. For all three models the hit rates are nearly identical. However, the models that include household life cycle variables provide much sharper probability predictions (i.e., further from 0.5) than does the base model. Consequently, we are of the opinion that hit rates are a less than satisfactory measure of model performance as a result of the information lost in creating this measure.

References


