Acquisition patterns of financial products

Paas, L.J.; Bijmolt, T.H.A.; Vermunt, J.K.

Published in:
Journal of Economic Psychology

Publication date:
2007

Document Version
Publisher's PDF, also known as Version of record

Citation for published version (APA):
Paas, L. J., Bijmolt, T. H. A., & Vermunt, J. K. (2007). Acquisition patterns of financial products: A longitudinal investigation. *Journal of Economic Psychology*, *28*(2), 229-241.

Available online at www.sciencedirect.com
ScienceDirect
ELSEVIER
Journal of Economic Psychology 28 (2007) 229–241
JOURNAL OF Economic Psychology
www.elsevier.com/locate/joep

Acquisition patterns of financial products: A longitudinal investigation

Leonard J. Paas [a,*], Tammo H.A. Bijmolt [b], Jeroen K. Vermunt [c]

[a] *Department of Marketing, Faculty of Economics and Business Administration, VU University Amsterdam, De Boelelaan 1105, 1081HV, Amsterdam, The Netherlands*
[b] *Department of Marketing, Faculty of Economics, University of Groningen, PO Box 800, 9700 AV Groningen, The Netherlands*
[c] *Department of Methodology and Statistics, Faculty of Social and Behavioral Sciences, Tilburg University, PO Box 90153, 5000 LE Tilburg, The Netherlands*

Received 18 November 2005; received in revised form 6 June 2006; accepted 19 June 2006
Available online 10 August 2006

Abstract

Acquisition pattern analysis investigates orders in which households acquire products. Extant empirical studies employ cross-sectional data, providing limited insight into acquisition orders and no insight into timing of product acquisitions. We use an extensive longitudinal database for studying acquisition patterns in the financial product market, in particular financial assets. We find support for a common order of acquisition, reflecting risk levels of the financial products, and provide insight into the timing for acquiring products. We show developments of product portfolios are strongly related to the lifecycle stage of the household, income and household assets.

JEL classification: C49

PsycINFO classification: 2240; 3900

Keywords: Consumer psychology; Saving behavior

* Corresponding author. Tel.: +31 20 5986003.
E-mail address: lpaas@feweb.vu.nl (L.J. Paas).

0167-4870/$ - see front matter
doi:10.1016/j.joep.2006.06.006

1. Introduction

In various markets household units acquire products in common orders. For instance, households generally acquire cookers before vacuum cleaners and last washing machines. Another example, households often acquire savings accounts before investment trusts and last shares (Paas, 1998). Behavioral scientists use such acquisition patterns to evaluate the priorities that households have for products (Kamakura, Ramaswami, & Srivastava, 1991) and marketing managers for purposes such as segmentation (Bijmolt, Paas, & Vermunt, 2004) and estimating the potential of an innovation by predicting its position in existing acquisition patterns (Gatignon & Robertson, 1985). Recently, acquisition patterns have been applied to predict which product a household is most likely to acquire next: lead generation (Li, Sun, & Wilcox, 2005; Paas & Molenaar, 2005; Prinzie & Van den Poel, 2006). Below we analyze household acquisition patterns in the financial product market. Households are studied, instead of individuals, because in this market the household is the principal decision making unit (Guiso, Haliossos, & Jappelli, 2002).

Acquisition pattern analysis has a strong theoretical foundation in the financial product market. Stafford, Kasulis, and Lusch (1982) suggested that the investments involved imply households cannot acquire all financial products that they desire at one point in time. Instead, products are acquired over longer periods in a manner that satisfies the utility function: Financial products relevant for more basic objectives generally being acquired before products satisfying higher order objectives.

Stafford et al. (1982) suggested that the order for acquiring financial products is highly similar across households. Situational factors such as culturally mandated lifestyles or the wish to confirm to group-norms dictate the priorities that consumers have for products (Olshavsky & Granbois, 1979). In this regard, the saving motives hierarchy and the household lifecycle are particularly relevant. Concerning the first, four hierarchically ordered saving motives have been studied extensively in the field of economic psychology (e.g., Canova, Rattazzi, & Webley, 2005; Gunnarson & Wahlund, 1997; Lindqvist, 1981; Wärneryd, 1989, 1999). The most basic motive is cash management, involving short-term financial issues, such as direct payment for transactions. At the second level, the precautionary motive, households develop a financial reserve for unexpected expenditures. This is followed by the down-payment motive at the third level, i.e., accumulation of financial deposits for buying a house, a car or durables. Fourth and last is wealth management, incorporating enterprise and investing assets. The second construct, the lifecycle hypothesis (Modigliani & Brumberg, 1954) and the related permanent income hypothesis (Friedman, 1957), assumes acquisitions result from household circumstances, such as household lifecycle phase and income. Young households require financial products for borrowing or investing small amounts of assets. Later in life, when income and assets increase, households require more sophisticated products for purposes such as speculation and asset accumulation. Kamakura et al. (1991) argued that the two discussed constructs are interrelated and lead to a common order of acquisition within populations, reflecting amounts of assets that are invested and the risk levels of the different products. Households in early lifecycle stages have higher priority for products related to basic motives in the saving motive hierarchy, involving fewer assets and relatively low risk levels. Young households have lower priorities for products meeting higher order motives, involving more assets and more risk. Such products are acquired later in the lifecycle, when households possess more assets and financial knowledge.

Despite the strong theoretical support, extant empirical studies on acquisition patterns are rather limited. These studies typically employ cross-sectional data (e.g. Kamakura et al., 1991; Paas, Kuijlen, & Poiesz, 2005; Soutar & Cornish-Ward, 1997). However, cross-sectional ownership patterns contradicting or supporting a specific order of acquisition may result from changes in the order of acquisition over time and/or from different segments of households acquiring different sets of products over the lifecycle. For example, if we find households owning an investment trust also tend to own savings accounts and households having shares also own both a savings account and an investment trust, acquisition pattern analysis predicts the following order of acquisition: (1) savings account, (2) investment trust and (3) shares. However, cross-sectional ownership patterns can also results from the presence of different segments acquiring different sets of products: (1) a segment of households acquiring only savings accounts during the entire lifecycle, (2) a segment of households acquiring savings accounts and investment trusts and (3) a segment acquiring all three products. Thus, household- and time-specificity are confounded in cross-sectional data. Another limitation is very obvious: Cross-sectional studies fail to provide insight into the timing of acquisitions. Besides this, the results of extant cross-sectional studies are inconsistent. Some questioned whether households acquire financial products in the same order (Bijmolt et al., 2004; Paas et al., 2005), while others find a single common order (Dickenson & Kirzner, 1986; Kamakura et al., 1991; Soutar & Cornish-Ward, 1997; Stafford et al., 1982). The few extant longitudinal studies fail to provide additional insight. These studies concern three very general product categories (Li et al., 2005) or acquisitions at a single firm (Prinzie & Van den Poel, 2006), while households often acquire products from multiple banks and insurance firms.

The study reported here is the first to employ suitable longitudinal data for acquisition pattern analysis. We analyze disaggregate data, collected in four bi-yearly panel-waves. General ownership, at multiple firms, of six specific financial assets is analyzed, using the latent class Markov model (Vermunt, Langeheine, & Böckenholt, 1999; Wedel & Kamakura, 2000). Our contribution to theory is that time-specific and household-specific effects are disentangled, providing better insight into acquisition patterns of financial products. Also, insight is provided into the timing of product acquisitions. Empirically, we provide a suitable longitudinal approach for acquisition pattern analysis, which can be utilized in future studies. Below we first report the conducted empirical analysis, followed by the results and last a discussion on the implications of the study.

2. Method

2.1. Data

The Dutch division of the international market research firm, GfK, provided the database consisting of a representative sample of 7676 Dutch households. Information was retrieved from the respondents on demographics and household ownership of six financial assets in 1996, 1998, 2000, and 2002. Interviews were face-to-face and respondents showed their financial administration to verify answers. Panel attrition occurs and some households signed up after 1996. Between the 1996 and 1998 waves 29.6% of the households dropped out of the panel, between 1998 and 2000 this was 39.5% and between 2000 and 2002 it was 34.7%. These rates are of a common magnitude for market research (Winer, 1983). The attrition is unlikely to bias our analysis, as the replacement of households is conducted in such a manner that the sample remains representative for the population with regard to various important demographic variables, such as age, income, and marital status. Moreover, the latent class Markov model, which we employ, ensures all panel members are considered equally in the analyses, also those that dropped out before 2002 or joined the panel after the 1996 wave (Vermunt, 1997).

Table 1 presents penetration levels of the analyzed products at the four measurement occasions. The products are ordered according to decreasing risk levels. Shares are the most risky assets, depending on highly volatile exchange values on the stock market. Investment trusts concern a mix of different shares and corporate/government bonds. The latter are subjected to smaller value fluctuations. Next are the pure corporate/government bonds. Life insurances and pension funds are less risky again. Like investment trusts these products concern a mix of shares and bonds, but investments are over longer periods, in which values of bonds and shares usually increase. Also, life insurance policies and pension funds have a guaranteed minimum pay-off. The risk level of these two products is the same. The main difference is that the pension fund has a monthly pay-off, while assets accumulated in the life insurance are paid in a lump sum. Least risky is the savings account.

The dataset also provides relevant household demographics: A modified version of the Murphy and Staples (1979) family lifecycle model, household income and household assets. These demographics were previously shown to be strongly related to household portfolios (Gunnarson & Wahlund, 1997; Soutar & Cornish-Ward, 1997).

2.2. The latent class Markov model

The data are analyzed using the latent class Markov model with concomitant variables (Vermunt et al., 1999; Wedel & Kamakura, 2000). The model has three components. First, a measurement component is employed for segmenting households at each measurement occasion. Each segment is defined by a prototypical product portfolio, which is expected to represent a household's phase of development in an acquisition pattern. Second, a regression structure represents covariate effects of the available demographics on segment membership at the first measurement occasion, i.e., 1996 in our analysis. Third, as households can switch from one segment to another, between consecutive measurement occasions, another regression structure models transitions and covariate effects on transitions.

Table 1
Penetration levels of the analyzed assets per panel wave

Product	1996	1998	2000	2002
Investments				
(1) Shares	0.08	0.10	0.11	0.11
(2) Investment trusts	0.11	0.20	0.23	0.21
(3) Corporation/government bonds	0.04	0.04	0.03	0.03
Long-term contractual saving				
(4) Life insurance	0.59	0.60	0.59	0.55
(5) Pension fund	0.62	0.67	0.64	0.59
Regular saving				
(6) Savings account	0.93	0.95	0.96	0.96

For a formal description of the latent class Markov model consider:

- $i = 1 \ldots I$: index of the I households;
- $j = 1 \ldots J$: index of the J products;
- $k = 1 \ldots K$: index of K covariates;
- $s = 1 \ldots S$: index of S segments;
- $t = 1 \ldots T$: index of T measurement occasions.
- $X_{it} = s$ implies that household i is member of segment s at measurement occasion t;
- Y_{ijt} denotes the ownership indication for product j of household i at measurement occasion t, $Y_{ijt} = 1$ if household i owns j at t otherwise $Y_{ijt} = 0$;
- $\mathbf{Y}_{it}$ denotes the $(1 \times J)$ vector of J product ownership indications for household i at t;
- $\mathbf{Z}_{it}$ denotes the $(1 \times K)$ vector for the K covariates at measurement occasion t;
- $P(\mathbf{Y}_i|\mathbf{Z}_i)$ denotes the probability that household i has ownership pattern $\mathbf{Y}_i$ across all measurement occasions, given that the covariate vector of this person takes on the values $\mathbf{Z}_i$.

Based on this, the three main components of the model are defined as:

- The measurement component: $\prod_{t=1}^{T}\prod_{j=1}^{J}P(Y_{ijt}|X_{it} = s_t)$.
- The regression structure for studying covariate effects on initial state membership: $P(X_{i,t=1} = s_1|\mathbf{Z}_{i,t=1})$.
- The regression structure modeling transitions and covariate effects on the transitions: $\prod_{t=2}^{T}P(X_{it} = s_t|X_{i,t-1} = s_{t-1},\ \mathbf{Z}_{it})$.

These three components together constitute the latent class Markov model as follows:

$$P(\mathbf{Y}_i|\mathbf{Z}_i) = \sum_{s_1=1}^{S}\sum_{s_2=1}^{S}\cdots\sum_{s_T=1}^{S}\left[P(X_{i,t=1} = s_1|\mathbf{Z}_{i,t=1}) \times \prod_{t=2}^{T}P(X_{it} = s_t|X_{i,t-1} = s_{t-1}, \mathbf{Z}_{it})\prod_{t=1}^{T}\prod_{j=1}^{J}P(Y_{ijt}|X_{it} = s_t)\right].$$

The equation specifies the probabilities for the occurrence of household i's manifest data pattern, $P(\mathbf{Y}_i|\mathbf{Z}_i)$. The model has four basic assumptions. First, ownership indicators, Y_{ijt}, are mutually independent, given segment membership of household i at $t-1$ the local stochastic independence assumption (Vermunt, 2001). Second, the latent transition structure, $\prod_{t=2}^{T}P(X_{it} = s_t|X_{i,t-1} = s_{t-1}, \mathbf{Z}_{it})$, has the form of a first-order Markov chain, meaning that besides the values on the covariates at t, i.e., $\mathbf{Z}_t$, X_{it} depends only on $X_{i,t-1}$ and not on segment membership at earlier occasions. Third, covariates do not directly affect product ownership, but only indirectly through an effect on segment membership. Fourth, at each measurement occasion, a household belongs to only one segment. This segment cannot be established with certainty, thus, assignment to segments is probabilistic.

Model parameters are estimated using the EM algorithm (Dempster, Laird, & Rubin, 1977), leading to the maximum likelihood for occurrence of the manifest patterns. Relative fit of alternative model specifications is compared using the well-known BIC statistic (Wedel & Kamakura, 2000). The model is applied using an experimental version of the Latent GOLD computer program (Vermunt & Magidson, 2000).

3. Results

3.1. Model selection

Alternative latent class Markov models can be formulated by incorporating various types of change (Brangule-Vlagsma, Pieters, & Wedel, 2002). Our initial analyses concern models with the same measurement component for 1996, 1998, 2000 and 2002. Moreover, time-constant transition probabilities are assumed. That is, the probability to switch from segment s to segment s' between t and $t+1$ is the same as the probability to switch from s to s' between $t+1$ and $t+2$, for all s and t. We estimated models with 1 to 10 latent classes. The model with an eight-segment measurement component, called the final model, is most suitable (BIC = 56092). Models with fewer or more segments have higher BIC values.

To assess the assumptions of the final model, we evaluated relative fit of various benchmark models. The first only differs from the final model in that it assumes time-varying switching probabilities; the probability to switch from segment s to segment s' between t and $t+1$ may differ from the probability to switch from s to s' between $t+1$ and $t+2$. We specified a second benchmark model with a time-varying measurement model that embraces time-constant transition probabilities. In this model product ownership probabilities may differ between the segment s at occasion t and the same segment s at $t+1$ or other measurement occasions. Third, we considered a no-change model. This model has a time constant measurement model and assumes respondents stay in the same segment over time, which is achieved by fixing all the transition probabilities to 0. The benchmark models were run with 1–10 latent classes. For all benchmark models the BIC statistic is considerably higher than for the final model. Thus, the assumptions of the final model are feasible for our data. Note that the assumption of time-independence is unlikely to apply over longer periods, when more extensive changes of product penetrations occur and new financial products are introduced to the market. However, we have fitted the most suitable model for our data, collected over a six-year period, which is sufficient for disentangling household and time-specificity of acquisition patterns and for investigating the timing of product acquisitions, which this paper aims to realize.

3.2. Product portfolios and their dynamics

The measurement component of the final model, reported as Table 2, defines the product portfolios of households at the different measurement occasions. The segments reflect the phases of the acquisition pattern. To illustrate the interpretation, consider for instance the first column, which represents segment 1. The first row in the first column shows that 2% of the households in segment 1 owns shares. The eight segments, in Table 2, are ranked according to increasing overall product penetrations; segment 1 members own fewest products on average (0.68) and segment 8 members the most (4.27). Products are ranked according to decreasing risk levels. Table 2 shows that in segments where households have a high probability of owning risky assets, the penetration levels of the less risky assets are also high. Only segment 5 contradicts this tendency. Besides this, bonds have a low penetration in all segments, with a slightly higher penetration level in segments 5 and 8 in which the two other risky assets have high penetrations.

Table 2
Measurement component: Segment-specific ownership levels

Product	Segment							
	1	2	3	4	5	6	7	8
(1) Shares	0.02	0.00	0.01	0.02	0.36	0.02	0.09	0.81
(2) Investment trust	0.00	0.02	0.02	0.12	0.74	0.01	0.74	0.58
(3) Bonds	0.01	0.01	0.01	0.01	0.15	0.01	0.03	0.18
(4) Life insurance	0.32	0.01	0.03	0.98	0.02	0.98	0.93	0.98
(5) Pension fund	0.32	0.07	0.93	0.15	0.38	0.95	0.95	0.77
(6) Savings account	0.01	0.99	1.00	0.94	0.97	0.99	1.00	0.97
# Products owned	0.68	1.10	2.00	2.22	2.46	2.96	3.74	4.27

Table 3
Segment-size across measurement occasions and switching probabilities

Segment in 1996	Transition matrix Segment in 2002							
	1	2	3	4	5	6	7	8
1	0.59	0.14	0.18	0.00	0.00	0.09	0.00	0.00
2	0.05	0.53	0.30	0.12	0.00	0.00	0.00	0.00
3	0.00	0.27	0.34	0.04	0.04	0.29	0.04	0.00
4	0.00	0.10	0.10	0.57	0.00	0.15	0.00	0.08
5	0.00	0.00	0.00	0.03	0.94	0.00	0.00	0.03
6	0.00	0.00	0.08	0.03	0.00	0.57	0.32	0.00
7	0.00	0.00	0.00	0.04	0.05	0.27	0.59	0.05
8	0.00	0.00	0.00	0.00	0.11	0.00	0.14	0.75
				Segment size				
1996	0.06	0.14	0.10	0.08	0.05	0.46	0.06	0.05
1998	0.05	0.13	0.12	0.08	0.05	0.41	0.11	0.05
2000	0.04	0.13	0.12	0.09	0.05	0.37	0.15	0.05
2002	0.04	0.13	0.12	0.09	0.05	0.34	0.18	0.05

The dynamic output of the latent class Markov model is presented in Table 3. The lower part of the table shows segment sizes at different measurement occasions. For example, at all four occasions 5% of the households were in segment 8. Changes in relative size occur for six of the eight segments. Besides overall changes in segment size, there are also individual changes. The upper part of Table 3, presents probabilities for household units in each segment, to remain in that segment or to switch to another segment between 1996 and 2002. For example, 14% of the households that were in segment 1 switched into segment 2. This switch corresponds with acquiring a savings account. Only 1% of the households in segment 1 owns this product, while in segment 2 its penetration level is 99% (see Table 2).

Fig. 1 summarizes the product portfolios in the final model. For example, in segment 4 the savings account and the life insurance have high penetrations, while the other four products have much lower penetrations. In Fig. 1 bonds are included in brackets, to indicate in which segments this uncommonly owned product has relatively high penetrations. Penetration levels of each product are also specified, e.g., in segment 6 the pension fund has a 95% penetration. Beside this, Fig. 1 presents the switches with at least a 5% probability to occur in the 1996–2002 period and specifies the precise switching probabilities, e.g., 32% of the households that are in segment 6 in 1996 switch to segment 7 in the 1996–2002 period.

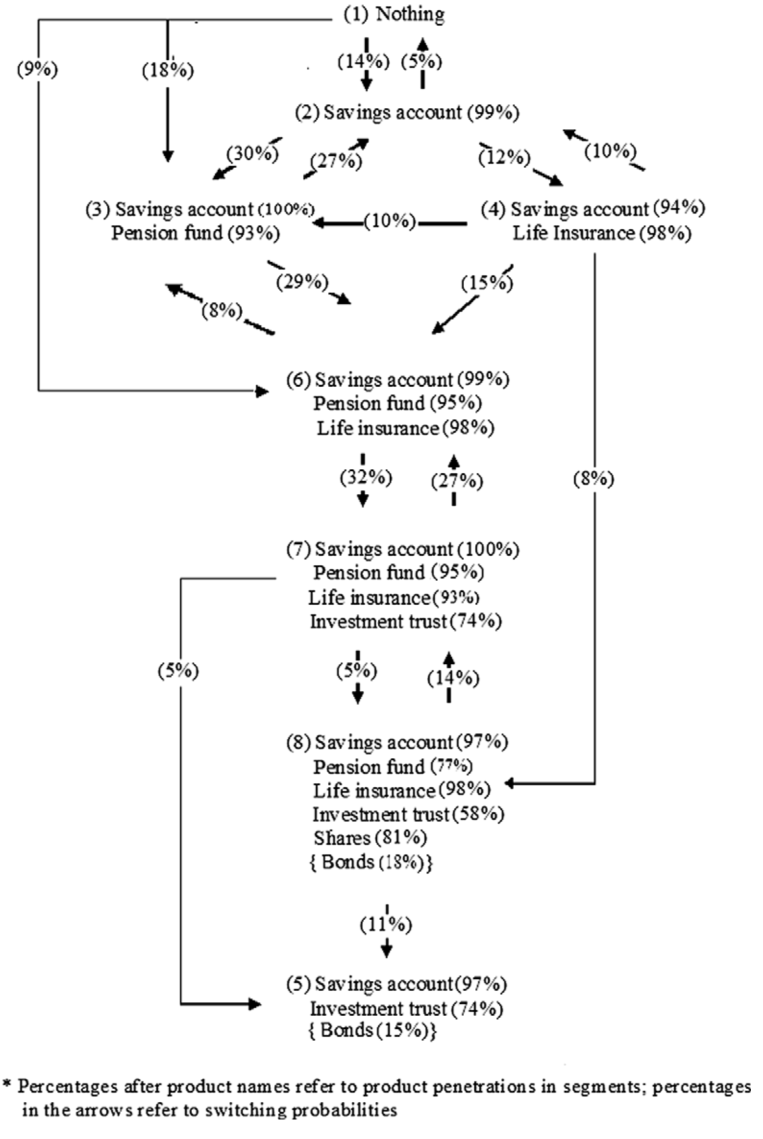

Fig. 1. Main acquisition patterns *.

We find households generally first acquire the least risky asset, the savings account. After this they either acquire a pension fund or a life insurance. These two products are likely to have received the same position in the acquisition pattern, because they involve similar risk levels. After acquiring the pension fund and the life insurance, households acquire the more risky assets, that means investment trusts, shares and sometimes bonds. Segment 5 seems inconsistent with the regular patterns, as it contains households that only own the least risky product, savings account, in combination with the more risky investment trust. Switching from segment 7 or 8 to segment 5, implies the reduction of product portfolios can involve discarding life insurances and pension funds, while more risky assets are maintained in the portfolio. Such reduction of product portfolios has not been discussed in extant papers based on cross-sectional data. Note that such data cannot be used for distinguishing acquisition from reduction.

Interestingly, Fig. 1 captures the product portfolios of most households and most developments therein. As mentioned above, only switches that are not represented in Fig. 1 are those with a very low probability of occurrence (below 5%). Besides this, products are only represented in segments if their penetration level in the segment is high. Notable exceptions are the 32% penetration levels of the pension fund and the life insurance in segment 1, see Table 2, suggesting some households acquire these two products before the savings account. However, segment 1 only consists of 4% to 5% of the households at each measurement occasion. Another exception concerns the relatively high probability to own pension funds (38%) and shares (36%) in segment 5. This is, however, consistent with the acquisition order described above. It suggests that at the end of the order some households also keep the pension fund and shares, besides the savings account and the investment trust. Also, the pension fund has a 7% penetration level in segment 2, 12% of segment 4 own the investment trust and shares are owned by 9% of the households in segment 7. These percentages are low and all other segment specific penetration levels presented in Table 2, but not in Fig. 1, are below 5%. In sum, most households follow the acquisition orders represented in Fig. 1.

Concerning the timing of product acquisitions, Fig. 1 shows developments of financial product portfolios are gradual, generally involving the acquisition or discarding of a single product in the 1996 to 2002 period. Exceptions involve the switches from segment 1 to 6, from 4 to 8, from 7 to 5 and from segment 8 to 5. A different interesting observation is that one of the most commonly occurring switches, from 6 to 7, involves the acquisition of a product with an increasing penetration level in the 1996 to 2002 period, namely the investment trust (see Table 1). Previously it was found that changes in product penetrations acquisitions patterns could not be modeled using cross-sectional data (Paas & Molenaar, 2005). The latent class Markov model incorporates such a change as a commonly occurring switch between segments. That is, 46% of the sample is in segment 6 in 1996, in which only 1% owns an investment trust. The switching probability from segment 6 to 7, in which 74% of the population owns the investment trust, is 32%. Thus, 15% (0.32∗0.46∗100%) of the sample is involved in this switch. A similar calculation shows only 2% of the sample switches from segment 7 to 6, which would generally involve discarding the investment trust.

3.3. Covariate effects

Our model incorporates demographics as covariates to explain segment membership of household units and changes therein. Each covariate significantly affects initial segment membership (1996): for income d.f. = 21, $\chi^2 = 271.30$, $p < 0.001$; for household assets d.f. = 14, $\chi^2 = 314.02$, $p < 0.001$, and for household lifecycle d.f. = 63, $\chi^2 = 730.81$, $p < 0.001$. The effects in Table 4 are interpreted as effect-coded beta-coefficients in logistic regression (Vermunt, 1997). We find that households with high incomes and assets are over-represented in segments with high product penetrations. This finding is consistent with extant theory on financial product portfolios (Guiso et al., 2002; Kamakura et al., 1991). Also, households in the intermediate lifecycle stages are over-represented in the segments with high product penetration levels, which is consistent with the lifecycle

Table 4
Covariate-effects on initial segment membership at t (1996)

Segment	1	2	3	4	5	6	7	8
Lifecycle								
Single, nk, <35	0.32	1.67	1.43	1.00	2.40	0.16	−3.22	−3.77
Couple, nk, <35	0.67	−0.51	0.76	−0.37	−3.77	1.12	1.68	0.43
Single, k, <35	1.22	1.38	−1.36	0.23	2.30	0.92	−1.70	1.61
Couple, k, <35	−0.42	−0.81	−0.39	0.16	−0.61	1.98	1.29	−0.31
Single, nk, 35–64	−0.49	−0.70	0.25	−1.14	0.74	−0.43	0.80	0.97
Couple, nk, 35–64	0.27	−1.91	0.36	−0.69	0.30	0.33	0.85	0.48
Single, k, 35–64	1.12	−0.52	0.27	0.74	0.19	−0.03	0.45	0.03
Couple, k, 35–64	−1.72	−0.95	−0.09	0.24	−0.42	0.95	1.32	0.68
All 65+	1.43	2.38	−1.37	0.26	2.63	−3.67	−1.14	−0.51
Not allocated	−0.17	−0.02	0.13	−0.41	0.84	−0.43	−0.33	0.39
Income								
<2500	1.27	1.15	0.27	0.28	0.05	−0.55	−0.84	−1.64
2500–3499	−0.07	0.05	0.25	−0.37	0.07	−0.05	0.04	−0.02
3500–4999	−0.82	−0.43	0.27	−0.27	−0.29	−0.46	0.46	0.62
⩾5000	−0.39	−0.78	−0.79	0.37	0.17	0.05	0.34	1.03
Household assets								
<10000	2.36	0.93	0.45	0.74	−1.88	0.27	−1.22	−1.65
10000–50000	−0.87	−0.07	0.22	−0.30	0.34	0.32	0.14	0.23
>50000	−1.48	−0.85	−0.66	−0.44	1.53	−0.59	1.08	1.42

hypothesis (Modigliani & Brumberg, 1954; Wärneryd, 1999). Interestingly, the covariate effects also explain the occurrence of segment 5, in which households tend to own risky assets in combination with only a savings account. Households late in the lifecycle (65+) are strongly overrepresented in segment 5. These households are reducing their product portfolios by discarding products for long-term saving, the pension fund and the life insurance, which they do not require at their age. More surprising is the strong representation of singles without kids in segment 5. Perhaps young people without children interpret financial risks differently than others, implying a relatively early extension of the product portfolio with risky assets.

Each covariate also has a significant effect on switching probabilities. These covariates effects are highly parallel to the effects on initial class memberships and therefore not reported in detail. For example, Table 4 shows that members of segment 8 relatively often have an income over 5000 Euro per month, while households switching into segment 8 also tend to have this high income level. In addition we analyzed the effects of demographics on the participation of households in individual assets, using logistic regression analysis. We find households with high incomes and assets and in the intermediate phases of the lifecycle have higher probabilities of owning each of the six assets. Because of the high consistency with the covariate effects in the latent class Markov model, the outcomes of logistic regression analysis are not reported in detail.

4. Discussion

Acquisition pattern analysis provides behavioural scientists with insight into the priorities that households have for products and potentially have various marketing applications, such as lead generation. In the financial product market this analysis has a highly plausible theoretical foundation. However, extant empirical studies are based on cross-sectional data, which provide incomplete understanding, as discussed in the introduction to this paper. We analyzed a highly suitable longitudinal data set, by applying the latent class Markov model for acquisition pattern analysis. The reported empirical results led to a rather simple figure (Fig. 1), in which most household product portfolios and switches are reported. The represented acquisition pattern reflects the risk levels of the products, less risky products generally being acquired before products with higher risk levels. Contrary to extant studies that are based on cross-sectional data, we provide explicit insight into the occurrence of divergence from the common order of acquisition, which is insubstantial in our dataset for products with different risk levels. However, products with the same risk level, the pension fund and the life insurance in our data set, could not be ordered with regard to each other. Some households acquire the life insurance before the pension fund, while others acquire the pension fund first.

Also new in this study is that we found the reported acquisition pattern is not only relevant when households develop their financial product portfolios by acquiring an additional asset, but also when discarding assets. Households generally discard the more risky assets before those involving lower risk levels. The only major exception herein is that a household may continue to own the more risky investment trust and sometimes shares after they discard pension funds and life insurance policies.

Our study also provides insight into timing of product acquisitions. We find substantial change occurs in financial product portfolios, of individual households, over the six-year period in which our data were collected. Another important implication is based on the surprising occurrence of multiple acquisitions, by individual households, in a relatively short period. We suggest major changes in the household circumstances lead to such behavior. This finding may be particularly relevant for event marketing. Predicting the occurrence of major changes in household circumstances that influence changes in product portfolios may support marketers in defining target groups for financial products.

The reported study incorporated covariate effects explaining the occurrence of product portfolios and changes therein. We found that households with higher incomes and assets and in the intermediate phases of the household lifecycle, tended to own more financial assets. Also, such households are more likely to extend their financial product portfolios by acquiring additional financial assets. These findings are consistent for the latent class Markov model and logistic regression, and with extant theory (Guiso et al., 2002; Modigliani & Brumberg, 1954; Wärneryd, 1999). This consistency supports the validity of the acquisition pattern represented by the latent class Markov model reported in this paper.

Our results suggest common orders for acquiring financial products are highly relevant for development of household financial product portfolios. Extant theories on behavioral finance, such as the lifecycle hypothesis and the saving motive hierarchy, should take such aggregate behavior more explicitly into consideration. Nevertheless, additional longitudinal studies should be conducted in various countries to assess the generalizability of the results reported in this paper. More generally, we suggest future research into choice behavior should also consider aggregate behavior within populations outside the financial product market. Obviously, aggregate behavior should be further evaluated in the durable product market using longitudinal data, where acquisition pattern analysis has been applied using cross-sectional data (Paas, 1998; Soutar & Cornish-Ward, 1997). For such future studies an important empirical contribution of our study is that the latent class Markov model is shown to be suitable for conducting acquisition pattern analysis.

Acknowledgements

We would like to express our gratitude towards GfK in the Netherlands for making the dataset available. We also thank Harald van Heerde for useful suggestions on a previous draft of the paper. Also, useful suggestions were given during presentations of the paper at the Marketing Department of Tilburg University and the Graduate School of Management at the University of Western Australia. Furthermore, we are grateful to the editor for this paper, David Leiser, and two anonymous reviewers for their constructive suggestions.

References

Bijmolt, T. H. A., Paas, L. J., & Vermunt, J. K. (2004). Country and consumer segmentation: Multi-level latent class analysis of financial product ownership. *International Journal of Research in Marketing, 21*(4), 323–340.

Brangule-Vlagsma, K., Pieters, R. G. M., & Wedel, M. (2002). The dynamics of value segments: Modeling framework and empirical illustration. *International Journal of Research in Marketing, 19*(3), 267–285.

Canova, L., Rattazzi, A. M. M., & Webley, P. (2005). The hierarchical structure of saving motives. *Journal of Economic Psychology, 26*(1), 21–34.

Dempster, A. P., Laird, N. M., & Rubin, D. B. (1977). Maximum likelihood estimation from incomplete data via the EM algorithm (with discussion). *Journal of the Royal Statistical Society, Series B, 39*(1), 1–38.

Dickenson, J. R., & Kirzner, E. (1986). Priority patterns of acquisition of financial assets. *Journal of the Academy of Marketing Science, 14*(2), 43–49.

Friedman, M. (1957). A theory of the consumption function. Princeton: Princeton University Press.

Gatignon, H., & Robertson, T. S. (1985). A propositional inventory for new diffusion research. *Journal of Consumer Research, 11*(1), 849–867.

Guiso, L., Haliossos, M., & Jappelli, T. (2002). Household portfolios. Cambridge: MIT Press.

Gunnarson, J., & Wahlund, R. (1997). Household financial strategies in Sweden: An exploratory study. *Journal of Economic Psychology, 18*(2–3), 211–233.

Kamakura, W. A., Ramaswami, S. N., & Srivastava, R. K. (1991). Applying latent trait analysis in the evaluation of prospects for cross-selling of financial services. *International Journal of Research in Marketing, 8*(4), 329–349.

Lindqvist, A. (1981). A note on the determinants of household saving behavior. *Journal of Economic Psychology, 1*(1), 39–57.

Li, S., Sun, B., & Wilcox, R. T. (2005). Cross-selling sequentially ordered products: An application to consumer banking services. *Journal of Marketing Research, 42*(2), 233–239.

Modigliani, F., & Brumberg, R. (1954). Utility analysis and the consumption function: An interpretation of the cross section data. In K. Kurihari (Ed.), *Post-Keynesian Economics* (pp. 388–436). New Brunswick: Rutgers University Press.

Murphy, P. E., & Staples, W. A. (1979). A modernized family lifecycle. *Journal of Consumer Research, 6*(2), 12–22.

Olshavsky, R. W., & Granbois, D. (1979). Consumer decision making – fact or fiction. *Journal of Consumer Research, 6*(3), 93–100.

Paas, L. J. (1998). Mokken scaling characteristic sets and acquisition patterns of durable- and financial products. *Journal of Economic Psychology, 19*(3), 353–376.

Paas, L. J., Kuijlen, A. A. A., & Poiesz, Th. B. C. (2005). Acquisition pattern analysis for relationship marketing: A conceptual and methodological redefinition. *The Service Industries Journal, 25*(5), 661–673.

Paas, L. J., & Molenaar, I. W. (2005). Analysis of acquisition patterns: A theoretical and empirical evaluation of alternative methods. *International Journal of Research in Marketing, 22*(1), 87–100.

Prinzie, A., & Van den Poel, D. (2006). Investigating purchasing patterns for financial services using Markov, MTD and MTDg models. *European Journal of Operational Research, 170*(3), 710–734.

Soutar, G. N., & Cornish-Ward, S. (1997). Ownership patterns for durable goods and financial assets: A Rasch analysis. *Applied Economics, 29*(11), 903–911.

Stafford, E. F., Kasulis, J. J., & Lusch, R. L. (1982). Consumer behaviour in accumulating household financial assets. *Journal of Business Research, 10*(4), 397–417.

Vermunt, J. K. (1997). *Log-linear models for event histories*. *Series QASS* (Vol. 8). Beverly Hills: Sage.

Vermunt, J. K. (2001). The use of restricted latent class models for defining and testing nonparametric and parametric item response theory models. *Applied Psychological Measurement, 25*(3), 283–294.

Vermunt, J. K., Langeheine, R., & Böckenholt, U. (1999). Latent class Markov models with time-constraints and time-varying covariates. *Journal of Educational and Behavioral Statistics, 24*(2), 178–205.

Vermunt, J. K., & Magidson, J. (2000). *Latent GOLD 2.0 User's Guide*. Belmont: Statistical Innovations Inc.

Wärneryd, K.-E. (1989). On the psychology of saving: An essay on economic behaviour. *Journal of Economic Psychology, 10*(4), 515–541.

Wärneryd, K.-E. (1999). *The psychology of saving: A study of economic psychology*. Northampton, UK: Edward Elgar Publishing.

Wedel, M., & Kamakura, W. A. (2000). *Market segmentation: Conceptual and methodological foundations* (2nd ed.). Amsterdam, The Netherlands: Kluwer.

Winer, R. S. (1983). Attrition bias in econometric models estimates with panel data. *Journal of Marketing Research, 20*(2), 177–186.