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Country and consumer segmentation: Multi-level latent class analysis of financial product ownership

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Abstract

The financial services sector has internationalized over the last few decades. Important differences and similarities in financial behavior can be anticipated between both consumers within a particular country and those living in different countries. For companies in this market, the appropriate choice between strategic options and the resulting international performance may critically depend on the cross-national market structure of the various financial products. Insight into country segments and international consumer segments based on domain-specific behavioral variables will therefore be of key strategic importance. We present a multi-level latent class framework for obtaining simultaneously such country and consumer segments. In an empirical study, we apply this methodology and several alternative modeling approaches to data on ownership of eight financial products. Information is available for 15 European countries, with a sample size of about 1000 consumers per country. We find that both country segments and consumer segments are highly interpretable. Also, consumer segmentation is related to demographic variables such as age and income. Our conclusions feature implications, both academic and managerial, and directions for future research.

Keywords: International segmentation; Financial products; Multi-level latent class analysis

1. Introduction

The market for financial products has become more international—even global—over the past few decades. Contemporary financial institutions often sell products to consumers outside their national market (Chryssochoidis & Wong, 2000) or are involved in international mergers, acquisitions, or alliances (Berger, Dai, Ongena, & Smith, 2003; Focarelli & Pozzolo, 2001; Glaister & Thwaites, 1994; Marois, 1997). Positioning one's products and targeting consumers across multiple nations raises new challenges and requires specific competences (see, for example, Jain, 1993, Chapter 11 and Kotabe &

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Helsen, 2001, Chapter 7). When formulating an international marketing strategy, a firm must have a thorough understanding of the various foreign markets and the ability to act upon these insights.

Ownership of financial products is a fundamental element of this market. It has been shown that product ownership represents highly relevant information to support decisions regarding product development, product introduction, cross-selling, and segmentation (Dickenson & Kirzner, 1986; Kamakura, Ramaswami, & Srivastava, 1991; Kamakura & Wedel, 2003; Kamakura, Wedel, de Rosa, & Mazzon, 2003; Paas, 1998, 2001; Ramaswami, Srivastava, & McInish, 1992; Ramaswamy, Chatterjee, & Chen, 1996; Soutar & Cornish-Ward, 1997). The portfolio of financial products, owned by a consumer, has consequently received considerable attention in both marketing and economic literature (for a recent overview of the economic literature, see Guiso, Haliassos, & Jappelli, 2002). Additionally, marketing research on financial markets, including on ownership patterns, has increased considerably throughout Europe (Bartram, 1998). In internationalized markets specifically, insights in cross-national similarities and differences in ownership patterns of financial and other products may reveal fruitful directions for international marketing strategy formulation (Ganesh, 1998; Helsen, Jedidi, & DeSarbo, 1993; Kumar, Ganesh, & Echambadi, 1998; Paas, 2001).

Segmentation will play an essential role in the formulation of international marketing strategies, because of cross-border dissimilarities and similarities in consumer needs, preferences, and behavior. Acting upon these dissimilarities and similarities calls for the grouping and subsequent targeting of countries and consumers within countries. Furthermore, assessment and implementation of international segmentation requires specific procedures and methodologies that take account of the international setting of the issue under study. For many years, however, international market segmentation has been largely ignored in the academic literature (Douglas & Craig, 1992), although interest has increased since the early 1990s (Steenkamp & ter Hofstede, 2002).

Structuring heterogeneity of international markets may refer to the act of segmenting countries or consumers. Companies use country segmentation to select entire foreign markets, and consumer segmentation to target specific groups of consumers within and across countries. Studies on international segmentation typically assess either country segments or consumer segments (for an overview, see Steenkamp & ter Hofstede, 2002). Recently, Kotabe and Helsen (2001) and Steenkamp and Ter Hofstede (2002) proposed a two-stage framework to combine such country and consumer segmentations, which should result in a more comprehensive understanding of the demand structure of international markets.

The contribution of this paper is twofold. First, we propose a methodological framework for international segmentation in which we build on the notion of combining segmentations of countries and consumers, as proposed by Kotabe and Helsen (2001) and Steenkamp and Ter Hofstede (2002). In their approach, a two-stage segmentation is suggested, where in the first stage country screening and grouping is typically based on macro-characteristics, such as demographic and economic indicators. New in our approach is the framework for simultaneously deriving country segments and cross-national consumer segments on the basis of disaggregate data on consumer behavior. In particular, country segmentation will be determined based on the relative sizes of cross-national consumer segments. The simultaneous approach ensures that both country-specific and cross-national consumer segments can be accommodated. Due to the direct connection between the country and consumer segmentations, the resulting country segments will be highly relevant for international marketing management. The methodology underlying our model is based on multi-level latent class analysis, as recently proposed by Vermunt (2003).

Next to the methodological objective, we aim at a substantive contribution, namely enhancing understanding of ownership patterns of financial products. Most previous research concentrated on such patterns in a single country (e.g. Dickenson & Kirzner, 1986; Kamakura et al., 1991). To the best of our knowledge, Paas (2001) is the only international study on differences between consumers living in different countries. However, Paas did not study differences between consumers within specific countries, which are expected to be substantial in most cases. Below we assess similarities and differences across a large set of European countries. In particular, we study the extent to which there are cross-national versus country-specific consumer segments defined by ownership patterns and whether groups of countries exist that are homogenous in their consumer segment structure.

To realize these two contributions, we first discuss the concept of international segmentation and the framework of simultaneous country and consumer segmentation. We present the methodological framework of multi-level latent class modeling to perform the segmentation analysis. Next, we discuss the market of financial products. In an empirical study, we apply the proposed methodology to obtain country and consumer segments for the financial products market. The segmentation utilizes information on ownership of eight financial products. Data are available for 15 EU countries, with a sample size of about 1000 consumers per country. We conclude with academic and managerial implications, and directions for future research.

2. International segmentation

International segmentation aims to structure heterogeneity that exists among countries and consumers by identifying relatively homogenous segments of countries and/or consumers. The revealed structure helps companies to develop and implement international marketing strategies.

International studies have traditionally focused on countries as basic units of analysis (Douglas & Craig, 1992; Steenkamp & ter Hofstede, 2002). That is, international segmentation typically consists of a preliminary screening of countries to identify which are potentially the most interesting (Kotabe & Helsen, 2001, p. 220). Through a strategic analysis of opportunities and risks within this primary set of countries, management decides upon its country portfolio (Harrell & Kiefer, 1993; Perlitz, 1985). Next, international segmentation is used for grouping the selected countries (Helsen, Jedidi, & Desarbo, 1993). Classification of countries is usually based on aggregate data (at the national level) reflecting demographic, socio-economic, political, and cultural factors (Jain, 1993, pp. 425–437; Nachum, 1994), instead of consumer-level and domain-specific variables. However, variables specific for a certain domain, e.g. product ownership or benefits, are often more effective segmentation bases than general variables (Van Raaij & Verhallen, 1994; Wedel & Kamakura, 2000). Recently, penetration rates of products and international diffusion patterns have been suggested as a means for comparing, selecting and segmenting countries (e.g. Dekimpe, Parker, & Sarvary, 2000; Ganesh, 1998; Helsen et al., 1993; Kumar et al., 1998). In research exploring international segmentation, attention could be directed also towards within-country differences and to behavioral variables measured at the consumer level.

Few studies have addressed the international segmentation issue by deriving cross-national segments of consumers (e.g. Luqmani, Yavas, & Quraeshi, 1994; Ter Hofstede, Steenkamp, & Wedel, 1999; Ter Hofstede, Steenkamp, & Wedel, 2002). This could be due to the relative high cost and low availability of international databases at the consumer level. International consumer segmentation research is partly analogous to segmentation within a single country. To a large extent, the same consumer variables could be applied as segmentation bases, and the same criteria for effective segmentation hold (see, for example, Chapters 1 and 2 of Wedel & Kamakura, 2000). However, the international nature of the problem at hand introduces additional conceptual and methodological challenges (for a recent overview, see Steenkamp & ter Hofstede, 2002).

A particularly promising approach, namely a two-stage approach to international segmentation, has been proposed by Kotabe and Helsen (2001, p. 225) and Steenkamp and Ter Hofstede (2002). Countries are screened, selected and grouped, in the first step. This step is similar to international country segmentation as previously discussed. In the second step, consumer segments are derived with either a cross-national analysis or a country-by-country analysis. In case of the latter, similarities between country-specific consumer segments could be assessed across the countries.

Here, we build on the work by Kotabe and Helsen (2001) and Steenkamp and Ter Hofstede (2002). However, we propose to study country segmentation and consumer segmentation in a single step, instead of sequentially. Segmentation at both levels is thereby based on disaggregate, domain-specific behavioral variables, such as product usage or ownership. Consumers are grouped on the basis of individual behavioral characteristics. Parallel to consumer segmentation, the formation of country segments is based on the relative size of consumer segments. Two countries will belong to the same country segment if they have highly similar within-country structures of consumer segmentation. This direct connection between the country and consumer segmentations ensures that the resulting country segments are highly relevant and actionable for international marketing management. Furthermore, as will be illustrated in the empirical study, a particular consumer segment obtained with our approach can be cross-national, because it can be present in multiple country segments or in a single country segment containing multiple countries. The other extreme is also facilitated, a consumer segment can potentially be country-specific, namely if it is present only in a single country segment which consists of just one country. Hence, the procedure proposed here is flexible in the characteristics of the segmentation and yields complete information on the segment structure of the international market.

3. Multi-level latent class analysis

3.1. Model formulation

Latent class analysis or mixture modeling has been suggested as a model-based tool for regular market segmentation (Wedel & Kamakura, 2000) and international segmentation (Steenkamp & ter Hofstede, 2002). Here, we present multi-level latent class analysis to attain simultaneously country segmentation and cross-national consumer segmentation.

Suppose data are available on an international sample of consumers, denoted i=1,..., I, originating from a set of countries, denoted j=1,..., J. For each individual i, it is recorded whether this person owns each product from a set of products, denoted k=1,..., K, where Y_{ijk}=1, if consumer i from country j owns product k, and Y_{ijk}=0 otherwise. The ownership data of an individual i are represented in vector Y_{ij}, and Y_j denotes the observed ownership data of all consumers of country j. We assume a limited number of *consumer segments*, denoted s=1,..., S. The countries under study are assumed to belong to a limited number of *country segments*, denoted t=1,..., T. Discrete latent variables X_{ij} and Z_j represent consumer segment and country segment membership, respectively.

A multi-level latent class model (Vermunt, 2003) consists of a mixture model equation for the consumer level and one for the country level. At the consumer level, we specify probabilities of product ownership Y_{ij} for a consumer i from country j, conditional on membership of country j to country segment t, as follows:

$$P(Y_{ij}|Z_j = t) = \sum_{s=1}^{S} P(X_{ij} = s|Z_j = t) \times \prod_{k=1}^{K} P(Y_{ijk}|X_{ij} = s). \qquad (1)$$

Basically, Eq. (1) is a regular mixture model, with the novelty that the relative sizes of latent classes (consumer segments) depend on country segment membership. Note that within a consumer segment, ownership of different financial products is assumed to be independent. Empirical relationships between ownership of two or more products, either positive or negative, will be captured by the mixture structure, i.e. the country and consumer segments.

At the country-level, a similar mixture model equation is specified, namely:

$$P(Y_j) = \sum_{t=1}^{T} P(Z_j = t) \prod_{t=1}^{N_j} P(Y_{ij}|Z_j = t), \qquad (2)$$

where N_j denotes the sample size in country j. Combining Eqs. (1) and (2) yields:

$$P(Y_j) = \sum_{t=1}^{T} \left[P(Z_j = t) \prod_{i=1}^{N_j} \left[\sum_{s=1}^{S} P(X_{ij} = s|Z_j = t) \times \prod_{k=1}^{K} P(Y_{ijk}|X_{ij} = s) \right] \right]. \qquad (3)$$

The right-hand side of Eq. (3) consists of three components, respectively: (a) the probability that country j belongs to a particular country segment, (b) the probability that consumer i belongs to a particular consumer segment, given country segment membership, and (c) the probability that consumer i owns a particular product k, given the consumer segment membership of i. Hence, the probability of the observed ownership data occurring is a weighted average probability, where the weights are the country segment and consumer segment probabilities.

Component (c) of Eq. (3) captures the key differences between consumer segments, namely the conditional probability that a consumer owns a particular product k, given the segment membership probabilities this consumer has. This is modeled as a logit equation:

$$P\left(Y_{ijk}=1|X_{ij}=s\right)=\frac{\exp(\beta_{ks})}{1+\exp(\beta_{ks})}. \quad (4)$$

Component (b) of Eq. (3) captures the key differences between the country segments, namely the relative size of each consumer segment. This is also modeled through a logit equation:

$$P\left(X_{ij}=s'\ |Z_j=t\right)=\frac{\exp(\gamma_{s'\,t})}{\sum_{s=1}^{S}\exp(\gamma_{st})}. \quad (5)$$

We also anticipate effects of consumer characteristics, e.g. demographic variables, on product ownership and consumer segment membership. Such consumer heterogeneity effects can be included in various ways (for a review and discussion, see Andrews & Currim, 2003a). Of these approaches, the concomitant variable approach performs best in terms of recovering the choice model coefficients (Andrews & Currim, 2003a; Table 1). As the focus here is on recovering the international segmentation structure that underlies product ownership patterns, we introduce demographic effects into Eq. (5) by means of one or more concomitant variables, denoted by W_{lij} (Dayton & MacReady, 1988; Gupta & Chintagunta, 1994; Wedel, 2002), leading to:

$$P\left(X_{ij}=s'\ |W_{lij},Z_j=t\right)=\frac{\exp\left(\gamma_{0s'\,t}+\sum_{l=1}^{L}\gamma_{ls'}\,W_{lij}\right)}{\sum_{s=1}^{S}\exp\left(\gamma_{0st}+\sum_{l=1}^{L}\gamma_{ls}W_{lij}\right)}. \quad (6)$$

3.2. Model estimation

The parameters of the multi-level latent class model can be estimated by Maximum Likelihood. Maximization of the likelihood function can be achieved by an adapted version of the EM algorithm. For details on estimation of model parameters and obtaining standard errors, see Appendix A or Vermunt (2003, 2004). The multi-level latent class methodology will be available

Table 1
Descriptive statistics for the international sample

Country	Sample size	Average weight	Ownership of financial product (sample proportion)							
			Current account	Savings account	Credit card	Other bank card	Cheque book	Overdraft facility	Mortgage	Loan
Austria	1093	0.34	71.5	82.3	33.7	61.0	21.6	41.4	17.7	21.8
Belgium	1031	0.43	85.2	85.9	39.2	74.0	34.2	33.3	25.9	21.1
Denmark	1001	0.22	78.5	63.2	48.2	60.8	33.9	55.2	51.8	36.3
Finland	1023	0.21	87.5	50.2	31.5	84.7	0.7	16.0	22.0	26.5
France	1002	2.42	87.8	69.8	57.7	31.0	87.9	50.6	18.6	26.6
Germany East	1024	0.67	91.8	76.1	22.5	81.2	41.5	35.7	13.0	23.0
Germany West	1023	2.87	89.5	84.2	29.9	78.0	40.9	39.8	16.8	16.5
Great Britain	1041	2.37	75.2	77.1	52.3	58.7	76.4	29.3	37.1	20.1
Greece	1001	0.45	11.0	79.7	18.7	25.9	6.3	3.4	14.6	11.6
Ireland	1002	0.15	51.4	71.7	32.3	40.3	45.1	16.2	25.7	26.6
Italy	998	2.52	65.6	19.4	36.3	51.3	62.7	10.0	12.3	12.8
Luxembourg	609	0.03	84.7	81.8	65.0	69.6	49.6	50.9	29.7	30.0
Netherlands	1047	0.65	89.5	82.5	37.2	94.3	26.6	63.6	33.6	14.9
Northern Ireland	305	0.22	62.3	59.7	42.3	41.3	62.3	21.3	35.7	14.1
Portugal	1000	0.42	70.0	44.2	33.0	33.0	60.8	2.5	13.0	8.0
Spain	1000	1.70	61.6	67.2	52.1	33.2	17.4	8.2	19.4	17.2
Sweden	1000	0.37	76.1	77.5	57.0	59.4	19.7	19.0	34.7	25.8

in the computer program LatentGOLD 4.0 (see: www.statisticalinnovations.com).

International research using consumer-level data is typically based on national samples that are not proportional to actual population sizes. If one requires conclusions on the entire international population, re-weighting would be necessary to ensure the pooled sample represents the population (Steenkamp & ter Hofstede, 2002). To achieve valid inferences in the multi-level latent class analysis, we weight each observation by sample size relative to population size per country. To account for discrepancies between sample size and population size across countries, we obtain estimates of model parameters by means of the pseudo maximum likelihood method (Patterson, Dayton, & Graubard, 2002; Wedel, ter Hofstede, & Steenkamp, 1998). Estimates are obtained for fixed numbers of country segments (T) and consumer segments (S). Appropriate values for these numbers can be determined by estimating the multi-level latent class model for different values of T and S, and examining the relative fit of alternative model specifications, e.g. by using the minimum CAIC rule (Andrews & Currim, 2003b; Bozdogan, 1987; Vermunt, 2003; Wedel & Kamakura, 2000).

To assess how well each consumer can be assigned to a single international consumer segment and how well each country can be assigned to a single country segment, we apply entropy measures (see Wedel & Kamakura (2000, p. 92)). At the consumer-level, we use the country-specific entropy $E_{s|j}$, proposed by Ter Hofstede et al. (1999). At the country-level, we use the entropy measure E_T, defined as $E_T = 1 + \sum_{j=1}^{J} \sum_{t=1}^{T} \left(\alpha_{jt} \ln \alpha_{jt}\right) / (J \ln T)$, where α_{jt} is the posterior probability of country j belonging to country segment t.

4. Empirical study: the market for financial products

4.1. Internationalization of the market for financial products

Most contemporary banks, insurance companies, and other financial service providers operate in multiple countries. The internationalization of the financial products market has been stimulated by deregulation of the sector and developments in information technology. Additionally, the foundation of a single market within the European Union and the introduction of the Euro have accelerated internationalization within the region (Hartmann, Maddaloni, & Manganelli, 2003). However, internationalization of the financial services industry lags behind many other industries and is often not quite successful (Berger et al., 2003).

Managers in this internationalized market face strategic issues, such as whether or not the same strategy can be used in several countries. Firms offering financial products employ different strategies for surviving in an increasingly international environment (Marois, 1997). The strategic options are: independently entering a foreign market (Chryssochoidis & Wong, 2000) or cross-national mergers, acquisitions, or alliances (Berger et al., 2003; Focarelli & Pozolo, 2001; Glaister & Thwaites, 1994). Most academic and management attention has been directed to the supply side of the market. The little attention for the consumer side has usually been directed towards the general market structure, whereas insight into micro-level aspects, such as the behavior of individual consumers, would also be highly relevant.

Important differences and similarities in financial behavior could be anticipated both between consumers within a particular country as well as between consumers living in different countries (Guiso et al., 2002; Paas, 2001). For example, consumers in countries with less developed economic systems typically have different financial needs than consumers in more industrialized countries, and within Europe substantial differences can indeed be observed (Bartram, 1998). Such differences often lead to different consumer segments being present in various countries. Now, the appropriate choice between strategic options and the resulting (lack of) international success may critically depend on the cross-national demand structure for various financial products. In particular, success in an international market depends strongly on the appropriateness of the international segmentation, just as success in a national market depends on an effective segmentation (Wedel & Kamakura, 2000). Therefore, insight into country and international consumer segments based on domain-specific behavioral variables will be of key strategic importance in the financial products market.

4.2. Database on product ownership

We apply the model proposed in this paper to a recently collected data set: Eurobarometer 56.0 (Christensen, 2001). The data were collected between August 22nd and September 27th 2001 by a consortium of market research agencies at request of the European Commission, Directorate-General Press and Communication, Opinion Polls. The Eurobarometer survey covers the population (aged 15 years and over) of the 15 EU member states in 2001. There are 17 sampling areas: Germany is divided into East and West, United Kingdom into Great Britain and Northern Ireland, and one sampling area is designated for each of the other countries. Below the terminology "country" will refer to a sampling area. Sample sizes were targeted to be 1000 per country, with the exception of Luxembourg (600) and Northern Ireland (300). The total sample size is 16,200. From the Eurobarometer database, we obtained a weighting variable that ensures each national sample is representative with respect to basic demographic variables and, additionally, corrects for cross-national differences in sample versus population size (see Table 1). All interviews were conducted face-to-face at the respondent's home and in the appropriate national language.

From questions 25 to 28 of the Eurobarometer 56.0 survey (Christensen, 2001), information has been extracted on ownership of eight financial products: current account, savings account, credit card, other bank card, cheque book, overdraft facility on a current account[1], mortgage, and other loan. A limitation of the database concerns the lack of information on cross-national equivalence. In general, the basis used for the segmentation should be equivalent across countries (Steenkamp and Ter Hofstede, 2002), whereas the products in our study may have slightly different functions and conceptual bases in different countries. Fortunately, definitions of the various products were provided in the questionnaire, which increases cross-national equivalence of the ownership variables. Furthermore, country-specific examples are given when further explanation is considered necessary, e.g. for other bank cards. Ownership information refers to an individual consumer, not an entire household. The set of products corresponds to the set of core products in previous studies such as Kamakura, Ramaswami, and Srivasta (1991). Preliminary inspection of product penetration levels shows large differences across the countries, but also some striking similarities (Table 1). In addition, the following four demographic variables, which probably are relevant for the topic at hand, are available: age (15 to 29, 30 to 59, 60 and older), marital status (living with partner, single), income (below median, above median, not available), and type of community (rural area or village, small city to large city).

5. Results

5.1. Country and consumer segments

To study the similarities and differences in ownership patterns of the eight financial products across 16,200 respondents and 17 countries, we applied the multi-level latent class analysis model described previously. We incorporated effects of four demographic variables (age, marital status, income, and type of community) by means of concomitant variables, as shown in Eq. (6). While obtaining parameter estimates, we weighted the observations to correct for sampling discrepancies both within and between countries, as recommended by Steenkamp and ter Hofstede (2002). Model estimates were obtained for alternative numbers of consumer segments (S=1,…, 15) and country segments (T=1,…, 8). To account for sub-optimal solutions, we estimated the model 10 times for each combination of S and T with different random starting values. We retained the best solution for each combination.

Table 2 reports model fit (in particular, the CAIC value) for each combination of S and T. The optimal

[1] There is a deterministic relationship between the overdraft facility and the current account as one cannot have an overdraft without owning a current account. Specifying the products as current accounts with and without overdraft facility is not possible, because if someone has an overdraft facility (and hence a current account with an overdraft) it can not be determined whether or not this person also owns a current account without overdraft facility. Therefore, this relationship is not taken into account while modeling the data.

Table 2
Model fit (CAIC) for alternative numbers of country and consumer segments[a]

Number of consumer segments (S)	Number of country segments (T)							
	1	2	3	4	5	6	7	8
1[b]	*156943*	–	–	–	–	–	–	–
2	141777	140541	140144	140163	*139954*	139974	139996	140017
3	137585	135774	134505	134451	133918	133873	133814	*133619*
4	136777	133629	131286	131075	130694	130129	129956	*129931*
5	136276	131236	129223	128462	128119	128097	*127885*	127907
6	135706	130956	128089	126340	125834	125716	125644	*125534*
7	135392	130461	127202	125629	124979	124808	124806	*124771*
8	135126	130170	126799	124484	123819	123754	123710	*123709*
9	134912	129622	126198	123951	123202	122777	122744	*122715*
10	134687	128919	125851	123651	122680	122543	*122440*	122543
11	134545	128629	125643	123408	122686	122402	*122245*	122275
12	134492	128506	125445	123107	122263	122199	121926	*121891*
13	**134440**	128468	125404	122989	121904	**121669**	121619	*121515*
14	134443	**128160**	125227	122898	122068	121765	***121314***	**121458**
15	134485	128201	**125184**	**122876**	**121590**	121684	*121495*	121655

[a] Lowest CAIC within each row is printed italic, and within each column in boldface; lowest CAIC overall is underlined.
[b] If S=1, the number of country segments (T) is also restricted to 1 by definition.

number of consumer segments, applying the minimum CAIC rule[2], varies between 13 and 15; fairly independently from the number of country segments. From the opposite perspective: when the number of consumer segments is larger than two, the optimal number of country segments varies between seven and eight. The overall minimum CAIC is attained at 14 consumer segments and 7 country segments, which we identify as the most appropriate solution. These results are presented in Tables 3 and 4.

Posterior classification of countries to segments is almost deterministic: the country-level entropy measure E_T is extremely high: 0.985. This reflects that all posterior probabilities of country-segment membership are virtually indistinguishable from 0 or 1 (Table 3). The only exception is Luxembourg, which has fairly high membership probabilities for two country segments instead of one. The relatively high country-level entropy measure and posterior probabilities can be explained partly by the fact that each individual respondent provides classification information for a country, and the number of observations per country is much higher than the usual number of measures per subject.

The classification of countries into segments is strongly related to the European geography, with several noteworthy peculiarities. Country segments have been ordered in size to support interpretation.

Table 3
Model results: country segments

Country segment	Relative size	Posterior probabilities of country-segment membership $\{P(Z_j=t\|Y_j)\}$[a]	
		Country	Probability
1	0.256	Belgium, Germany (East), Germany (West), The Netherlands	1.000
		Luxembourg	0.811
2	0.260	Austria, Denmark, Finland, Sweden	1.000
		Luxembourg	0.189
3	0.175	Great Britain, Ireland, Northern Ireland	1.000
4	0.119	Italy, Portugal	1.000
5	0.064	Spain	1.000
6	0.064	Greece	1.000
7	0.064	France	1.000

[a] All unlisted posterior probabilities <0.001.

[2] Given the large sample size of our study, the minimum CAIC rule imposes a much larger penalty than AIC2 or AIC3. This will lead to smaller numbers of segments being indicated as most appropriate. In general, CAIC may lead to underfitting, but this tendency reduces with sample size, whereas the tendency towards overfitting of AIC2 and AIC3 increases with sample size (Andrews & Currim, 2003b; Bozdogan, 1987). In our study, AIC2 and AIC3 did not yet reach a minimum value within the range of models estimated. Based on the very large sample size and the number of segments derived, we do not expect applying CAIC has led to underestimating the number of segments.

Table 4
Model results: consumer segments

	Consumer segments													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Financial products:	Product ownership probabilities $\{P(Y_{ijk}=1 \mid X_{ij}=s)\}$													
Current account	0.049	0.051	0.325	1.000	0.999	0.920	0.981	0.999	1.000	0.881	1.000	0.989	0.984	1.000
Savings account	0.387	0.850	0.606	0.135	0.653	0.605	0.908	0.905	0.150	0.705	0.780	0.728	0.925	0.857
Credit card	0.000	0.087	0.000	0.291	0.836	0.232	0.159	0.620	0.760	0.806	0.957	0.494	0.506	0.833
Other bank card	0.002	0.192	0.002	0.615	0.323	0.795	0.849	0.525	0.895	0.685	0.000	0.994	0.946	0.871
Cheque book	0.085	0.005	0.859	0.787	0.131	0.018	0.292	0.997	0.947	0.303	0.975	0.999	0.504	1.000
Overdraft	0.000	0.034	0.308	0.016	0.038	0.423	0.191	0.111	0.221	0.293	0.654	0.678	0.679	0.603
Mortgage	0.008	0.107	0.249	0.013	0.142	0.060	0.001	0.033	0.285	0.601	0.221	0.055	0.546	0.893
Loan	0.022	0.081	0.211	0.013	0.143	0.313	0.000	0.024	0.265	0.468	0.334	0.329	0.294	0.392
Country segments	Relative sizes of consumer segments													
1	0.065	0.030	0.013	0.000	0.004	0.167	0.388	0.027	0.000	0.004	0.003	0.078	0.217	0.005
2	0.050	0.166	0.040	0.004	0.057	0.263	0.106	0.009	0.000	0.184	0.000	0.007	0.105	0.009
3	0.149	0.105	0.091	0.026	0.006	0.002	0.035	0.256	0.000	0.022	0.004	0.072	0.000	0.231
4	0.367	0.000	0.059	0.285	0.018	0.001	0.000	0.005	0.264	0.000	0.001	0.000	0.000	0.000
5	0.162	0.267	0.005	0.005	0.341	0.000	0.024	0.031	0.005	0.145	0.008	0.000	0.000	0.009
6	0.133	0.786	0.005	0.000	0.000	0.001	0.006	0.018	0.000	0.044	0.000	0.004	0.000	0.001
7	0.063	0.000	0.112	0.065	0.000	0.015	0.021	0.135	0.000	0.000	0.408	0.139	0.000	0.041

The largest segment contains the low-countries (Belgium and The Netherlands), Germany, and Luxembourg (for 81%). The second segment is nearly as large and contains the Scandinavian countries, Austria, and Luxembourg (for 19%). Great Britain, Northern Ireland, and Ireland are combined to form segment 3. Contrary to other parts of Europe, Southern Europe consists of multiple small segments: Italy and Portugal together form country segment 4, and Spain, Greece, and France remain three single-country segments. Apparently, ownership patterns of financial products are relatively diverse across the countries in Southern Europe.

At the consumer-level, classification is also satisfactory. The country-specific entropy $E_{s|j}$ for the consumer segmentation is on average 0.765, and varies between 0.659 for Austria and 0.875 for Italy, which is comparable to the entropy statistics presented by Ter Hofstede et al. (1999). Hence, within each country, most consumers can be classified with fairly high certainty to 1 of the 14 segments.

Product ownership within each international consumer segment is presented in the upper part of Table 4. To aid interpretation, we ordered the consumer segments in ascending order of product-penetration levels aggregated across the financial products. The most pronounced feature of the first three segments is the very low penetration of basic payment product (current account) and more advanced payment products (credit card or other banking card). Segment 1 actually has low probabilities for all products, whereas segment 2 has a fairly high penetration rate for the savings account only, and segment 3 for the savings account and the cheque book only. Consumer segments 4 to 9 have penetration rates close to one for the current account and some other payment-facilitating products. Which payment product is owned is the key factor differentiating between these segments. For example, credit card ownership is very high in segment 5, while cheque book ownership is common in segments 8 and 9. Furthermore, segments 10 to 14 have relatively high ownership probabilities for at least one credit product (overdraft, mortgage, and other loans). Segments 13 and 14 contain heavy users: penetration rates for all eight financial products are relatively high; most notably the rate pertaining to mortgage in segment 14.

Model results linking country and consumer segments are presented in the lower part of Table 4.[3]

[3] Note that segment probabilities represent relative sizes within a country segment. A consumer segment of 0.05 in a large country segment may concern more people than a consumer segment of 0.20 in a small country segment.

Fourteen consumer segments may seem to be a large number of segments. However, many consumer segments have relative sizes below 1% or even 0.1% for most country segments. This effectively results in much smaller numbers of consumer segments existing within each particular country segment. Almost all consumer segments, in particular those with high product penetrations (3 to 14), are sizeable (e.g. larger than 10%) in only one or two country segments. On the other hand, consumer segments 1 and 2, with low overall product penetrations are more cross-national (or even pan-European). Their relative size is fairly large in four country segments.

The country segments typically contain several relatively large consumer segments, often some with low penetration rates (consumer segments 1 to 3), some with medium to high rates for payment products but low rates for credit products (consumer segments 4 to 9), and some with high rates for most products (segments 10 to 14). For instance, country segment 2 (Austria, Scandinavian countries, and Luxembourg) primarily contains consumer segments 2, 6, 7, 10 and 13, all of which have very low penetration levels for the cheque book. Consumer segments shaping country segment 3 (Ireland, Northern Ireland, Great Britain) are highly diverse: ranging from extremely low rates on all products (consumer segment 1) to extremely high rates for all products (consumer segment 14). Consumer segment 2, with low penetration rates for all products, with exception of the savings account, is extremely dominant in Greece. France (single-country segment 7) mainly consists of consumer segments 2, 8, 11, and 12, which have very high ownership rates for cheque book.

5.2. Effects of demographic variables

Ownership of financial products, and thereby membership of consumer segments, is often related to demographic variables such as age and income (Browning & Lusardi, 1996; Guiso et al., 2002; Javalgi & Dion, 1999; Ramaswamy et al., 1996; Tin, 2000). We assessed effects of four demographic variables: age, marital status, income, and type of community. The probability a consumer belongs to a particular segment is modeled to depend on his/her demographics and on country segment membership. The relationship between the consumer-segment classification and demographics supports interpretation of segments and subsequently increases targeting possibilities for a company.

Next to estimating the full model including all four concomitant variables, we estimate four sub-models each omitting one of the variables. To assess significance of the demographic effects, we employ the well-known likelihood ratio test for nested models. All four demographic variables significantly effect consumer segment membership: age (χ^2=913.61; df=26; p<0.001), income (χ^2=506.75; df=26; p <0.001), marital status (χ^2=253.76; df=13; p<0.001), and type of community (χ^2=66.13; df=13; p<0.001).

The findings on the effects of demographic variables are presented in Table 5. To facilitate interpretation, we do not present logit parameters, but instead segment membership probability per category of each demographic variable, averaged across all categories of the other variables.

Age has a large influence on the consumer segment probabilities. The low penetration segments 1 and 2 are over-represented in the age groups 15 to 29 and 60 and older, whereas the high penetration segments 10 to 14 are highly over-represented in the intermediate age group (30 to 59 years). Segments with generally moderate penetration rates are mixed in that sense: some are over-represented in the younger group (segment 6), whereas other segments are strongly present in the middle group (segment 9) or in the older group (segments 3, 7, and 8). The effect of income resembles that of age, where the high-income group corresponds to the age group of 30 to 59 years. Consumers living together with a partner have a relatively high probability to be member of segments 10, 13, or 14, which all have high penetration rates for many financial products. These three segments originate from the Northern and Western parts of Europe (country segments 1 to 3). Of the demographics included in this study, type of community has the smallest impact, as shown by the chi-square test values and the differences between the segment membership probabilities. Consumers living in rural areas or villages are over-represented in segments 2, 3 and 14, whereas consumers living in a city are over-represented in segment 6. The other consumer segments have similar probabilities for both types of communities.

Table 5
Model results: effects of demographic variables

Consumer segments:	Relative sizes of consumer segments													
	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Age														
15–29	0.186	0.200	0.018	0.054	0.065	0.115	0.082	0.015	0.028	0.041	0.070	0.057	0.032	0.037
30–59	0.096	0.164	0.049	0.036	0.070	0.071	0.036	0.030	0.067	0.107	0.072	0.050	0.074	0.078
60+	0.143	0.217	0.072	0.074	0.048	0.007	0.130	0.161	0.020	0.022	0.039	0.022	0.033	0.012
Income														
Below median	0.161	0.228	0.058	0.057	0.065	0.094	0.087	0.064	0.016	0.035	0.051	0.044	0.029	0.012
Above median	0.085	0.170	0.041	0.045	0.044	0.045	0.072	0.076	0.059	0.095	0.080	0.046	0.067	0.073
Unknown	0.177	0.182	0.041	0.062	0.073	0.054	0.090	0.066	0.040	0.041	0.051	0.039	0.042	0.042
Marital status														
Living with partner	0.094	0.195	0.051	0.050	0.059	0.060	0.066	0.073	0.044	0.078	0.063	0.040	0.066	0.062
Single	0.188	0.192	0.042	0.060	0.063	0.068	0.100	0.065	0.033	0.037	0.058	0.046	0.027	0.022
Type of community														
Rural area or village	0.140	0.209	0.054	0.050	0.055	0.054	0.083	0.069	0.033	0.062	0.061	0.032	0.050	0.049
Small to large city	0.142	0.178	0.038	0.060	0.067	0.075	0.083	0.069	0.044	0.052	0.060	0.054	0.042	0.036

5.3. Alternative model specifications: accounting for country effects

In an international segmentation study, the similarities and differences between countries can be accommodated through other approaches than the multi-level latent class model discussed above. In particular, we propose two benchmark models: the relative sizes of consumer segments are considered to hold for all countries in the sample or estimated specifically for each country, respectively. The multi-level latent class model is in between these two extremes: countries having a similar structure are grouped together. We compare the multi-level latent class model to these two benchmark models, on model fit and empirical findings.

One could apply a traditional single-level latent class model to the entire cross-national sample of consumers, and cluster countries in a second step based on the relative consumer segment sizes. In fact, the single-level latent class model without the country effect is the same as the multi-level latent class model assuming a single country segment. Assuming that a single consumer segment structure holds for all countries does not accurately describe the data. Compared to the model assuming multiple country segments, the minimum CAIC level is considerably higher (134440 versus 121314; see Table 2). Furthermore, the average country-level entropy value is considerable lower (0.699 versus 0.765), indicating that classification of consumers to segments is less precise. A second stage cluster analysis (Ward's method) of the countries based on consumer segment sizes yields results that are radically different from the results of the multi-level latent class model, where the latter model has much higher face validity. For example, in the seven-cluster solution, Spain is combined with Ireland and Northern Ireland, whereas Great Britain, France, Denmark and Luxembourg also form a country cluster. We conclude that accounting for across country heterogeneity in the consumer segment structure, in one way or another, is called for.

The second benchmark proposed here estimates a single-level latent class model including country as a consumer-level covariate in Eq. (6), as has been applied previously by Ter Hofstede et al. (1999). This model captures the country effect by allowing the consumer segment sizes to be specific for each country separately. We estimated the single-level latent class model with country as one of the concomitant variables for 1 to 25 cross-national consumer segments. Minimum CAIC was achieved at 19 consumer segments and is 121315. This is nearly identical to the minimum CAIC for the multi-level latent class model. It turns out that the improvement of the log likelihood due to large model flexibility counterbalances the dramatic increase in number of parameters (566 versus 287 parameters). The similarity in model fit is in line with findings by Ter Hofstede et al. (2002), who reported comparable fit levels for models with segments related to geography and with segments based on spatial independence. Overall, the consumer segment structure is highly similar between this benchmark and the proposed model. However, the model with country as covariate identifies a somewhat larger number of consumer segments, because it is more sensitive to revealing consumer segments that are unique for a single country. The models yield similar country-specific entropy measures, on average 0.787 for the concomitant variables specification versus 0.765 for the multi-level latent class specification. For most countries, both models yield approximately the same entropy value. However, for Finland the entropy is substantially better for the concomitant variable model specification (0.882 versus 0.715). This is caused by the fact that this model recovers a country-specific consumer segment that is relatively large (0.550 of the population) in Finland, but small (below 0.160 of the population) in all other countries. Contrarily, the multi-level latent class model is much more parsimonious and yields a country segmentation in addition to the consumer segmentation. Another advantage of the multilevel latent class model is that the country segmentation provides general substantive insights in the international market structure. In addition, the segmentation of countries can act as a filter to screen out groups of countries that are unattractive for financial firms, as in the first stage of the approach by Kotabe and Helsen (2001) and Steenkamp and Ter Hofstede (2002).

Summarized, for this empirical study, model fit does not clearly discriminate between the two model specifications accommodating country differences. However, the two alternative models lead to different substantive interpretations of the data and, therefore, have distinct merits. Their relative usefulness will depend on the characteristics of the application at hand.

5.4. Alternative model specifications: hierarchical ordering of financial products

Next, we examined another type of model specification within the framework of multi-level latent class models. Results of several studies (Dickenson & Kirzner, 1986; Kamakura et al., 1991; Paas, 1998, 2001; Soutar & Cornish-Ward, 1997) suggest consumers acquire financial products in a certain order. In particular, products with high penetration levels offer benefits for which consumers have a relatively high priority. Therefore, these products are generally acquired relatively early in the consumer lifecycle. If the prioritization of products is similar for most consumers then it is to be expected that products are acquired in a more or less common order, more commonly products with higher priorities before products with lower penetrations (lower priority). Latent trait models (see, for example Embretson & Reise (2000) or Van der Linden & Hambleton (1997)) can be applied to ownership data to investigate such an acquisition pattern. If the proposed acquisition order indeed holds in empirical data than product ownership patterns should fulfill the assumptions of Rasch's one-parameter logistic model (Soutar & Cornish-Ward, 1997) or those of Birnbaum's two-parameter logistic model (Kamakura et al., 1991). Vermunt (2001) showed the Rasch and Birnbaum models can be specified in latent class measurement models, by imposing certain constraints.

We altered the multi-level latent-class model to accommodate hierarchical ordering of the financial products and consumer segments. Component (c) of Eq. (3), the measurement model, is no longer modeled through a logit specification, as in Eq. (4), but through a parametric latent trait model (Vermunt, 2001). In particular, we specified it as Rasch's one-parameter logistic model and as Birnbaum's two-parameter logistic model. We kept S=14 and T=7, and estimated each model 10 times with different random starting values to account for sub-optimal solutions. The Rasch model yielded the following ordering of financial products, based on the complexity parameter of the products: current account, savings account, other bank card, cheque book, credit card, overdraft facility, mortgage, and loan. The Birnbaum model yielded a highly similar ordering, with only loan and mortgage in the reversed order. These orderings are largely consistent with findings of previous studies (Dickenson & Kirzner, 1986; Kamakura et al., 1991; Paas, 1998, 2001; Soutar & Cornish-Ward, 1997).

Compared to the original model, the CAIC is substantially higher for the Rasch model with 184 parameters: CAIC=140943, and for the Birnbaum model with 191 parameters: CAIC=136923; indicating that these models are outperformed by the original multi-level latent class model, which does not assume a hierarchical ordering. Furthermore, results of the original, unrestricted model (Table 4) clearly indicate the hierarchical ordering assumption is invalid. For example, consumer segment 11 has an ownership probability smaller than 0.001 for other bank card and 0.975 for cheque book, whereas for consumer segment 6 these probabilities are opposite 0.795 and 0.018, respectively. This finding and many similar patterns are inconsistent with a hierarchical ordering of products and consumer segments. Therefore, we conclude that the empirically observed ownership data poorly fit with a hierarchical ordering, and a more flexible specification, like in Eq. (4), is preferred.

5.5. Segmentation effectiveness

The following criteria have been put forward as determinants of the effectiveness of market segmentation (Kotabe & Helsen, 2001, p. 219; Steenkamp & ter Hofstede, 2002; Wedel & Kamakura, 2000, p. 4): substantiality, stability, identifiability, accessibility, responsiveness, and actionability. The number of consumer segments as derived by the multi-level latent class model may appear relatively large. However, all segments are large in size, because consumer segments are cross-national or else represent a large fraction of a single country (substantiality). Furthermore, financial product ownership does not change frequently at the consumer level (Browning & Lusardi, 1996; Wärneryd, 1999), which ensures the segments do not change dramatically over time (stability). However, the segmentation will not be excessively fixated, and trends could be monitored regarding demographics and ownership levels of certain financial products. Also, the country segmentation should be monitored over time, among other reasons because of potential convergence within the EU. The high entropy measures indicate that recognizing distinct groups (identifiability) will be relatively easy to accomplish in the proposed segmentation. Although financial companies automatically register ownership of financial products, from the perspective of a single company, some information will be missing, which poses an additional challenge (Kamakura & Wedel, 2003; Kamakura, Wedel, de Rosa, & Mazzon 2003).

The relation with demographic variables further facilitates identification of the segments. This relationship also enhances the extent to which a company can reach particular targeted segments (accessibility). Whether or not the segmentation proposed will perform well on responsiveness and actionability is a priori somewhat unclear. Fortunately, relationships between product ownership and marketing mix instruments have been demonstrated, for example, to suggest cross-selling opportunities (Kamakura et al., 1991, 2003). The substantial differences between and within countries in product ownership, as observed in this study, clearly suggest actions regarding cross-selling, product introductions, and targeting of particular country and/or consumer segments. Hence, considering the criteria for effective segmentation, the solution obtained here qualifies as excellent.

6. Discussion

6.1. Conclusion

International segmentation is essential for increasing understanding of international markets and thereby supports companies to formulate strategies to deal effectively with consumer heterogeneity across borders. However, to fulfill this potential, a number of issues have to be dealt with. Steenkamp and Ter Hofstede (2002, Fig. 2) mentioned: (1) combining country segmentation and cross-national consumer segmentation, (2) model-based segmentation, (3) correction for response styles, and (4) sample reweighting.

In this paper, we presented a framework using multi-level latent class analysis, which simultaneously derives country segments and consumer segments. The model implies a direct connection between the country segmentation and consumer segmentation, ensuring the resulting segments at both levels are relevant and actionable for international marketing management. In addition, the consumer segmentation is flexible in the sense that obtained segments can be cross-national or country-specific. Moreover, the procedure proposed meets the guidelines for effective international market segmentation as mentioned previously. The two levels are modeled as interdependent: countries are grouped on the basis of similarities between their within-country structures of consumer segments. Segments at both levels are obtained using consumer-level data on ownership of financial products. Given the type of data, objective measures rather than attitude ratings, biases due to response styles are reduced. Furthermore, marketing and economic theory on ownership of financial products and statistical model formulation allow a model-based approach. Finally, by using pseudo maximum likelihood, which re-weights observations to correct for relative sample size differences between countries, we construct an internationally representative sample and obtain generalizable findings. Hence, the presented procedure promises to be a fruitful direction for international market segmentation.

6.2. Substantive insights

Besides the methodological contribution, the empirical study of ownership patterns of financial products yields several interesting substantive insights. Although convergence could be anticipated within the EU (Berger et al., 2003; Ganesh, 1998; Hartmann et al., 2003) because of the Euro and regulatory standardization, for the moment Europe consists of a partly heterogeneous group of countries considering the ownership of financial products. The consumer segment structure is highly similar within certain small groups of European countries, whereas it differs considerably between alternative groups of countries. The country grouping is related to the European geographical map, which is somewhat consistent with findings by Ter Hofstede et al. (2002), who performed an international consumer segmentation based on importance of store image. For example, as in our study, Ter Hofstede et al. found very similar segment structures for Belgium, Germany and The Netherlands. Interestingly, there are also differences, Ter Hofstede et al. reported similar consumer segmentation structures across various Southern European countries, such as France, Italy, Spain, and Portugal, whereas our study suggests little similarity in segmentation structures across Southern European countries.

The consumer segmentation is strongly related to demographic variables such as age, income, and marital status. Segments with high penetration rates for many financial products are typically over-represented in the intermediate age group, the high-income group, and in the group of consumers living with a partner. This finding is consistent with previous research on the family life-cycle effects within the financial products market (Javalgi & Dion, 1999; Soutar & Cornish-Ward, 1997; Tin, 2000) and to the life-cycle theory (Browning & Lusardi, 1996; Wärneryd, 1999). Potentially these findings could also support the idea of preset acquisition patterns (Dickenson & Kirzner, 1986; Kamakura et al., 1991; Paas, 1998, 2001; Soutar & Cornish-Ward, 1997), which model the order in which consumers acquire financial products. However, in our empirical study, ordering the financial products in ascending penetration levels does not yield an ordered structure for the consumer segments.

6.3. Managerial implications

Our findings are highly relevant for contemporary international marketing, as studying financial markets is a growing practice and now takes a prominent place in marketing research worldwide (Bartram, 1998). Important managerial insights can be obtained on behavior of consumers within such markets. In particular, our empirical study reveals a clear international segmentation structure. All country and consumer segments have high face validity and are easy to label. Furthermore, the relation with demographic variables supports targeting of cross-national segments.

Our results show that it is essential not to treat Europe as a single market (yet). Although integration trends have been observed (Berger et al., 2003; Hartmann et al., 2003), major differences (still) exist between countries, which need to be accounted for when formulating a marketing strategy. Our model clearly shows that, based on the within-country structure of consumer segments, a firm offering financial products may treat for example Belgium, Luxembourg, the Netherlands and Germany as a single market. On the other hand, a country specific approach should be developed for most of the Southern European countries. Although geographical factors play a role, they do not offer a complete explanation for the country segmentation that we reported. For example, Portugal and Spain do not classify to the same country segment, while Portugal and Italy do. This illustrates that a model approach as suggested here is called for.

The results of our model provide suggestions for international marketing of products. Typically only a small number of consumer segments exist within each country segment. For some country segments, these consumer segments can be ordered on overall penetration rates and there seems to be a strong relationship with stages in the family life-cycle. For example, in country segment 1 (Belgium, Luxembourg, The Netherlands, and Germany), consumer segments 6, 7 and 13 are ordered in increasing overall penetration rate and reflect family life-cycle in the segment order of 6, 13, and 7. Such a sequential structure within a country segment clearly suggests opportunities for customer-relationship management, product introductions, and cross-selling.

The results of the multi-level latent class model (Table 4) can also be utilized from the perspective of a single product. A company offering credit cards, for example, can use the insights obtained to select one or more country segments and next target within each country segment the appropriate consumer segment. Suppose this company introduces a new credit card hoping to attract consumers who currently own a credit card of a competing company. In that case, they could target consumer segment 5 in country segment 5 (Spain), consumer segment 11 in country segment 7 (France), and consumer segment 14 in country segment 3 (Great Britain, Northern Ireland, and Ireland). In these consumer segments, credit card ownership is relatively high and the consumer segments are strongly represented in these country segments.

6.4. Limitations and future research

The multi-level latent class results describe the current market segmentation structure based on ownership patterns, without making inferences on what may have caused these patterns. In general, the products owned by consumers will not only depend on consumer needs, but will partly be driven by what banks offer in a country. It remains unclear to what extent demand or supply factors have generated the product ownership patterns observed. For a conclusion on this topic, further research could investigate the influence of the product offerings and other marketing efforts by banks on consumer product-portfolios in different countries.

The multi-level latent class model proved to be an effective tool for international market segmentation of the European market of financial products. In future international segmentation research, the framework can be applied to other product categories, other countries, and other segmentation variables. The relatively small set of European countries forms a limitation of the empirical study presented in this paper. Future research using a larger and broader set of countries could highlight the value of simultaneously grouping countries and consumers. It can be expected that performance of the multi-level latent class model will depend on the number of countries or the number of consumers per country. However, minimum data requirements for applying the multi-level latent class model are not available. Future research could assess model recovery, stability, and robustness while varying the data input systematically, in line with Andrews and Currim (2003a, 2003b) and other simulation studies. In addition, the performance of the multi-level latent class model should be assessed in comparison with alternative methods for incorporating country effects, such as the method by Ter Hofstede et al. (1999). Finally, the method could be extended to incorporate country-level covariates, such as economic and cultural factors (Jain, 1993, pp. 425–437; Nachum, 1994; Steenkamp & Ter Hofstede 2002).

To the methodological and substantive contributions, we would like to add a final point regarding the general applicability of the multi-level latent class model (Vermunt, 2003). The method could be applied in other marketing settings also. Of key importance is the nested classification structure that is not directly observed but has to be inferred from the data. A multi-level classification might be sought, for example, for customers nested within outlets of a retail chain. A similar structure can be found for business-to-business customers of multiple offices of a particular financial service provider. In both cases, the model would yield segments of customers and simultaneously a grouping of the store outlets or offices. Hence, the multi-level latent class procedure presented in this paper warrants further application in international segmentation studies and in studies that search for nested classification structures that are statistically similar.

Appendix A. Model estimation

A.1. Upward–downward algorithm

The parameters of the multilevel latent class model were estimated by means of maximum likelihood (ML). For that purpose, we used a variant of the EM algorithm that makes use of the conditional independence assumptions implied by the model. As is well known, in the E step of EM, one computes expectation of the complete data log-likelihood and, in the M step, one maximizes or improves this log-likelihood function using standard complete data methods.

As explained by Vermunt (2003, 2004), in order to make EM practical for the multilevel latent class model, it requires a special implementation of the E step. Here, we describe the basic idea of this so-called upward–downward algorithm. For more information, see Vermunt.

In the multilevel latent class model, the expected value of the complete data log-likelihood has the form:

$$\ln L_j = \sum_{t=1}^{T} P\left(Z_j = t|Y_j\right) \ln P\left(Z_j = t\right) + \sum_{t=1}^{T}\sum_{s=1}^{S}\sum_{i=1}^{N_j} \times P\left(Z_j = t, X_{ij} = s|Y_j\right) \ln P\left(X_{ij} = s|Z_j = t\right) + \sum_{s=1}^{S}\sum_{i=1}^{N_j}\sum_{k=1}^{K} P\left(X_{ij} = s|Y_j\right) \ln P\left(Y_{ijk}|X_{ij} = s\right). \tag{A1}$$

In other words, in the E step, we have to compute the posterior probabilities $P(Z_j{=}t{,}X_{ij}{=}s|Y_j)$. Note that $P(Z_j{=}t|Y_j)$ and $P(X_{ij}{=}s|Y_j)$ can be obtained by collapsing $P(Z_j{=}t{,}X_{ij}{=}s|Y_j)$. The key for obtaining $P(Z_j{=}t{,}X_{ij}{=}s|Y_j)$ in an efficient manner is using the fact that

$$\begin{aligned} P\left(Z_j = t, X_{ij} = s|Y_j\right) &= P\left(Z_j = t|Y_j\right) P\left(X_{ij} = s|Y_j, Z_j = t\right) \\ &= P\left(Z_j = t|Y_j\right) P\left(X_{ij} = s|Y_{ij}, Z_j = t\right), \end{aligned} \tag{A2}$$

that is, that given Z_j, X_{ij} is independent of the other observations within a country. The most-right terms $P(Z_j{=}t|Y_j)$ and $P(X_{ij}{=}s|Y_{ij}{,}Z_j{=}t)$ can be obtained as follows:

$$P\left(X_{ij} = s|Y_{ij}, Z_j = t\right) = \frac{P\left(X_{ij} = s, Y_{ij}|Z_j = t\right)}{P\left(Y_{ij}|Z_j = t\right)}, \tag{A3}$$

and

$$P\left(Z_j = t|Y_j\right) = \frac{P\left(Z_j = t, Y_j\right)}{P\left(Y_j\right)}, \tag{A4}$$

where the numerators are defined as $P\left(X_{ij} = s, Y_{ij}|Z_j = t\right) = P\left(X_{ij} = s|Z_j = t\right)\prod_{k=1}^{K} P\left(Y_{ijk}|X_{ij} = s\right)$ and $P\left(Z_j = t, Y_j\right) = P\left(Z_j = t\right)\prod_{i=1}^{N_j} P\left(Y_{ij}|Z_j = t\right)$. After obtaining $P(X_{ij}{=}s{,}Y_{ij}|Z_j{=}t)$ for each case and collapsing over X_{ij} to get $P(Y_{ij}|Z_j{=}t)$, we can compute $P(Z_j{=}t{,}Y_j)$. This is the upward part of the algorithm. The downward part involves filling in Eq. (A2).

A.2. Weighting, standard errors, and identification

In the analyses presented in this paper, we used individual level weights to correct for stratified sampling. To obtain the so-called pseudo ML estimates, the last two terms in the complete data likelihood were multiplied by a sampling weight w_{ij}. In other words, dealing with sampling weights involves maximizing a weighted complete data log-likelihood in the M step of the EM algorithm. In addition, to avoid potential problems of parameters estimates at the boundaries of the parameter space, we used a Bayesian prior of a single observation with equal probability for each latent class.

Standard errors can be obtained by computing the second-order derivatives of the incomplete data log-likelihood function. Contrary to standard mixture models, it is not straightforward to obtain standard errors that take into account weighting at consumer level. This means that standard errors will be somewhat downwards biased when case weights are used. Note that it is no problem to correct standard errors for higher-level weights.

As was shown by Vermunt (2003), the multilevel latent class model is a graphical model similar to a second-order factor model. Item responses serve as indicators for lower-level latent variables and all the lower-level latent variables within a group serve as indicators for the higher-level latent variable. This gives the required information for determining whether a model is identified. The lower-level part of the model is identified if there are enough observed variables for each case given the number of consumer classes in the model, and the higher-level latent variable is identified if there are enough cases within a group. In the current application, we have information on ownership of eight products, which means that many consumer segments can be identified. The number of cases with a country is huge, thus also identification of models with a large number of country segments is not a problem.

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