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Marketing innovations to old-age consumers: A dynamic Bass model for different life stages

Matthias Pannhorst[a,*], Florian Dost[b]

[a] European University Viadrina, Große Scharrnstr. 59, D-15230 Frankfurt (Oder), Germany
[b] Lancaster University, Management School, Lancaster LA1 4YX, United Kingdom

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ABSTRACT

To identify context-dependent opportunities to market innovations to the elderly, this study empirically analyzes the most prevalent pathways through advanced age, demonstrating which circumstances in the old-age life course provide the strongest potential for specific targeting strategies. First, using a latent Markov model and longitudinal survey data spanning 15 years, we produce a dynamic life course model with transitions over time. Second, we link a modified Bass diffusion model — using both static and dynamic parameters — to our model, augmenting it with a second cross-sectional consumer behavior data set. The results show comparatively strong consumption spending, high media interaction, but diminishing social inclusion in old age, though all factors exhibit heterogeneity among old-age clusters. Employing dynamic diffusion models, we find that a static view of the elderly market that ignores life course transitions generally overestimates their spending power. Forecasts of cluster-specific adoption dynamics draw a differentiated picture of individual clusters' attractiveness. Our analysis underscores the influence of life events on individual behavior and shows that a dynamic view of elderly markets yields a more nuanced and accurate assessment of their potential and attractiveness. It also confirms that social status and income strongly affect consumer behavior and spending, though we identify several exceptions.

1. Introduction

Innovators have long preferred developing and marketing products to young, healthy, and active consumers, the "core demographic" aged 19–49 years, over targeting consumers aged 50 years and older. As consumers age, they adopt fewer innovations (Charness and Boot, 2009; Gilly and Zeithaml, 1985; Mathur, 1999). Although these consumers tend to develop particular needs, they react sensitively to information that targets them with tailored stereotypical portrayals of senior adults (Cutler, 2005; Kotter-Grühn and Hess, 2012; Moschis and Mathur, 2006; Tepper, 1994). Therefore, outside the medical care sector, innovators and marketers have struggled to successfully tap the elderly consumer market in modern societies (Thompson and Thompson, 2009).

Currently, the demographic weight and economic power in many developed societies has shifted to the population sector aged 50 years and older (Pak and Kambil, 2006; Powell, 2010). Combining this factor with the aforementioned simplistic perception of the elderly's reluctance to adopt innovations spells bad news for individual innovators and entire societies modeled on continuous economic growth. However, an increasing share of elderly consumers is determined to live their post-retirement years actively and autonomously (Bowling and Dieppe, 2005). This consumer segment's growing economic potential is increasingly accompanied by a willingness to spend and consume (Moschis et al., 1997; Thompson and Thompson, 2009). At the same time, the long-standing notion of old age as a monolithic, leveling, and static final stage in a typical consumer's life course is slowly giving way to the appreciation that aging entails diversified, individual, and dynamic life stages (Baltes and Mayer, 2001). Innovators realize that a thorough understanding of the preferences and consumption habits of aging consumers presents a competitive advantage; employable principles to target and serve these consumers are, however, still in their infancy (Pak and Kambil, 2006). In particular, little empirical work in the academic literature addresses marketing innovative products to the elderly (Kohlbacher and Hang, 2011).

To help innovators and marketers understand and seize these developing opportunities, consumer segmentation analyses would need to (1) zoom in and focus on the different life stages of the consumers aged 50 years and older, (2) provide forecasts accounting for the dynamics of life courses through old age, and (3) examine starting points for tailored

* Corresponding author.
E-mail addresses: pannhorst@europa-uni.de (M. Pannhorst), f.dost@lancaster.ac.uk (F. Dost).

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targeting strategies, such as the role of mass media or social influence at any given life stage along the identified life courses. This article sets out to contribute on all three aspects.

The article builds on a life course view of aging, in which sequential "life stages" and the transitions from one stage to the next form pathways through the individual "life course" (Elder, 1985; Mayer, 2009). This originally sociological view lends itself well to segmentation analyses in consumer life cycle studies (Bauer and Auer-Srnka, 2012; Schaninger and Danko, 1993). From a life course viewpoint, changes in consumer behavior, such as spending patterns (Wilkes, 1995), or in consumer attitudes, such as brand preference (Mathur et al., 2003), are often a consequence of changes in life circumstances after important life events. Changed circumstances lead to transitions into new life stages, with possibly different consumer needs and lifestyles (Moschis, 1996). Although previous research shows that using life stages in segmentation models can add explanatory power to traditional age- or cohort-based approaches that treat age as a continuous control variable (Mathur et al., 2006), extant life stage segmentations to date have not focused in detail on older consumers.

To zoom in on consumers aged 50 years and older, this research leverages multiple large-scale, representative, longitudinal panel data sets. In the past, obtaining rich, representative, and longitudinal data on older consumers in broad full-population surveys has been difficult. Data sets are typically sparse for older respondents, because older people often resist participating voluntarily and have fewer means through which to be contacted. Those who do respond show higher rates of panel attrition, often due to deteriorating health and literal (panel) mortality (Deeg et al., 2002; Mirowsky and Reynolds, 2000). The present study models life stage segments and life course transitions on a representative socioeconomic longitudinal panel data set specifically created for the German population aged 50 years and older (German Aging Survey). Hence, the first and most critical step in identifying older consumer segments and segment dynamics is based on unusually rich data, which allows us to estimate life stage transitions across up to 15 years per respondent. The total sample consists of 4232 interviews. In a second step, we merge other variables of interest from other data sets into the identified life courses.

We empirically identify life stages and transitions with a latent Markov model (Du and Kamakura, 2006). These longitudinal models simultaneously cluster data into segments (life stages) and derive dynamic transition probabilities over time separately for each segment. Thus, we can trace back changes over the life course as well as predict future changes. Comparable applications to life course analyses remain rare in the social sciences, although two studies apply a Markov model from a sociological perspective (Espenshade, 1986; Macmillan and Eliason, 2003), and another analysis takes a marketing standpoint (Du and Kamakura, 2006). However, none of these extant studies details the life course in old age.

The second modeling step augments the identified dynamic life stages with data on goods and media consumption and social connectivity, using another representative German population survey data set as well as unused variables and cases from the first data set. This second step addresses a long-standing criticism of prior segmentation models that they "are useful primarily in identifying older consumers …, but they provide little or no information on the responses to marketing strategies and specific tactics" (Moschis, 1993, p. 50; for a similar criticism, see Szmigin and Carrigan, 2001). Using augmented data allows us to specify an innovation adoption model (Bass, 1969; Mahajan et al., 1990) separately for each life stage, providing, in combination with the Markov transitions, dynamic diffusion forecasts over various common life courses in old age.

The resulting dynamic adoption forecasts assess targeting attractiveness of life stage segments or clusters along the three core parameters of the popular Bass innovation diffusion model: mass media interaction, social inclusion, and market potential. Additional insights emerge from two different perspectives of dynamically following the innovation adoption changes of life stage–based cohorts over time: Whereas the first perspective focusing on life courses is more useful for innovators who specialize in building long-term customer relationships and accompanying their customers over a possibly long period of life through old age, a second life stage–focused perspective is useful for innovators specializing on the needs of a specific life stage segment across time.

2. A life course formed by empirically derived life stages

There is no single model of human aging; it comprises a multitude of biological, psychological, and social aspects that are difficult to synthesize into an integrative model. Extant research typically captures and focuses on select aspects of the aging process, such as cognitive adaptation processes, changes in social activity, or health status with advancing age (Finucane et al., 2005; Williams, 2004). Some of these aspects have been linked to adoption resistance among old-age consumers in various product-specific studies, from cars (Coughlin, 2004) to mobile banking applications (Laukkanen et al., 2007) and grocery shopping (Gilly and Zeithaml, 1985). Other innovation adoption studies tend to simplify aging and investigate how chronological age affects reactions to specific types of advertising (Drolet et al., 2007; Fung and Carstensen, 2003; Williams and Drolet, 2005). Thus far, no study offers an integrative, theoretically grounded perspective to segment age-related differences in innovation adoption.

In the social sciences, the life course perspective offers an appealing option for studying age-related changes within an integrative and inherently dynamic worldview. This paradigm, which provides a tool to analyze social transitions (Elder, 1985), originally grew from sociological theory (Mayer, 2009) and has spilled over to other social sciences (Billari, 2009), such as psychology and consumer research. To relate behavioral or attitudinal differences to earlier life experiences, life course research depicts age as an individual developmental process rather than a chronologically delineable phase in all human lives (Baltes and Mayer, 2001). A sequence of social arrangements, or life stages, and the life events or transitions linked to these stages form a trajectory throughout a person's life span (Elder, 1985). Accordingly, it is possible to combine and link different sets of data (e.g., longitudinal data across life stages along with cross-sectional survey data within life stages) to gain new insights on both inherent life stage aspects and consequences and their synthesis into life courses (Butz and Torrey, 2006; Mayer, 2009).

Early empirical life course studies, especially in consumer research, define life stages and their sequencing arbitrarily, rather than deriving them empirically, which subjects the resulting life courses to a researcher's notion of what a "normal" aging trajectory should look like (Wagner and Hanna, 1983). These notions then changed accordingly when new societal developments arose (Schaninger and Danko, 1993). Other empirical life course studies revolve around a single transition between two adjacent life stages and investigate, for example, the social and psychological adjustment processes around retirement (Moen, 2003; Reitzes and Mutran, 2004), the phase when children leave home (Lowenthal and Chiriboga, 1972; Mitchell and Lovegreen, 2009), or the transition into widowhood (Carr and Utz, 2001; Williams, 2004). With this research, we take a different approach by presenting an empirically derived set of life stages with in-between transitions that condense into a full set of life course pathways describing how people move through old age.

We use a latent Markov model to derive life stages and life course pathways. Previous research argues that the probabilistic nature of Markov and related models is particularly suited to explain variations in the life course, because they reflect the uncertain way in which life unfolds (Macmillan and Eliason, 2003). Yet their applications to life course analyses remain rare; to the best of our knowledge, only two Markov model studies in sociology (Espenshade, 1986; Macmillan and Eliason, 2003) and one other analysis in marketing (Du and Kamakura,

2006) do so. To identify life stages in our study, a few easily observable socioeconomic indicators provide the modeling criteria for the underlying latent life stages. Indicators such as work, partnership status, and social class or income delineate many possible life stages accurately (Alwin, 2012; Elder, 1985). In contrast to other old-age consumer segmentation studies (Barak and Schiffman, 1981; Moschis and Mathur, 1993; Sudbury and Simcock, 2009), we do not use chronological age as a life stage indicator.

3. Life stage–based innovation adoption and targeting with broadcast media and social information

To investigate innovation adoption in old age, we combine the outlined latent Markov approach with the Bass model (Bass, 1969), one of the most popular representations of market diffusion processes. The original Bass model uses three main coefficients to describe marginal product adoption in a population: a market potential M; a parameter p describing external, market, or media influences; and a parameter q describing internal or social influences such as word-of-mouth effects. Relying on three parameters allows us to investigate population, or segment, attractiveness with sparse information. Furthermore, differences in the media and social parameters indicate possible targeting opportunities. Typically, these Bass model coefficients are kept constant throughout the analyzed diffusion process, which in turn imposes several restrictions on the possible model results purely by means of calculus – for example, that the peak adoption rate cannot occur after market saturation has reached 50% (Mahajan et al., 1990). However, a single "classic" adoption model for the entire old-age market would not allow the detailed and diverse insights into old-age life stages that are intended in this article, because it does not reflect changes in consumption (market potential), media use, and social interaction at various advanced age life stages.

Many researchers have tried to modify the Bass model and specifically allow for a dynamic component to the market potential, because "there is no rationale for a static potential adopter population" (Mahajan et al., 1990, p. 11). Market potential can vary with population changes of the underlying social system (Mahajan and Peterson, 1978) or depend on mathematical representations of population growth (Sharif and Ramanathan, 1981). Furthermore, it can be specific to a particular product or service (Mesak and Darrat, 2002; Velickovic et al., 2016). In addition, the secondary effects (e.g., from various word-of-mouth influence assumptions) can differ across settings (Guseo and Guidolin, 2009).

Our setup is different from the extant literature on diffusion modeling in that it builds the analysis of diffusion processes on a separate comprehensive Markov model of social evolution that relies on empirical panel data. The Markov model as an underlying layer allows all key coefficients of the Bass model to vary over time. In doing so, the adoption models for different life stages can rely on the theoretical foundation of the life course paradigm and thus account for the often non-continuous, non-linear, and difficult-to-foresee changes in a population's actual life courses. The two-model approach is flexible to a subsequent specialization for analyzing the market diffusion of virtually any kind of product or service. The current study exemplifies the approach at the generic level using monetary spending on durable goods.

4. Methodology and data

Our setup is two-staged: First, we use a latent Markov approach to model the most prevalent life stages in advanced age and their sequencing over the old-age years. Second, we link those life stages to several consumer-related variables to construct a dynamic model of adoption, and thus consumer attractiveness over time. Fig. 1 details the steps and data used in the approach.

4.1. Step 1: Latent Markov model

A latent Markov model is an extension of the more widely known latent class model, which allows for cluster membership to change over time (Kaplan, 2008). As such, it requires longitudinal data. In our analysis, the resulting clusters, or latent states, reflect the life stages of our dynamic aging model.

The model is given by the probability of a particular response vector y_i to the observed manifest variables for each of $i = 1, \ldots, I$ survey participants:

$$P(y_i) = \sum_{s_0=1}^{S} \cdots \sum_{s_T=1}^{S} P(s_0) \prod_{t=1}^{T} P(s_t \mid s_{t-1}) \prod_{t=1}^{T} \prod_{j=1}^{J} P(y_{itj} \mid s_t) \tag{1}$$

A latent Markov model usually estimates three sets of parameters, with the first two sets estimated equivalently in time-constant latent class models. First, the initial state probabilities $P(s_0)$ describe the probability of entering the sample in a given latent state (cluster) $s = 1, \ldots, S$. Second, the item response probabilities $P(y_{itj}|s_t)$ indicate the probability of participant i responding with y_{itj} on the manifest indicator $j = 1, \ldots, J$ at time t, conditional on the latent state at that time. For each categorical indicator variable j, there are $y_{itj} = 1, \ldots, L_j$ response categories. Put differently, the item response probabilities are descriptions of each cluster by the probability distributions of the manifest indicator values. These probabilities can be interpreted such that qualitative descriptions of the clusters can be made. Third, the transition probabilities $P(s_t|s_{t-1})$ represent how individuals move across latent states over time; any current state only depends on the state previously occupied, which is known as the first-order Markov assumption. Across the entire analysis, we apply sampling weights to approximate a representative sample. To estimate our latent Markov model, we use LatentGOLD 5.0 Advanced (Vermunt and Magidson, 2013).

4.2. Markov model data

We base our model on data from the public release of the German Aging Survey (DEAS), provided by the Research Data Centre of the German Centre of Gerontology (DZA), a longitudinal panel survey representative of the German population over 40 years of age. The panel currently comprises four survey waves, from 1996, 2002, 2008, and 2011, containing more than 22,000 interviews with nearly 15,000 individuals. The unit of analysis in the DEAS data is the individual as opposed to the household, as is used in many other segmentation studies (Du and Kamakura, 2006; Wagner and Hanna, 1983).

We imposed two restrictions on the initial sample: First, we excluded the age range between 40 and 49 years from our analysis, which we do not deem old age. This is a common age limit for old-age studies because it includes what is referred to as third and fourth ages, two usually distinct episodes in the old-age life course (Baltes and Smith, 2003; Kohlbacher and Hang, 2011; Neugarten, 1974). Consequently, we dropped approximately 17% of the interview observations from the data set. Second, we selected only respondents who participated in at least three of the four survey waves, to ensure our model is based on an adequate number of real transitions. This resulted in a loss of another 64% from the original total number of interviews. Although this percentage is substantial, we determined that eliminating this second restriction to also include respondents with participation in two survey waves did not strongly alter the resulting clusters but significantly reduced classification accuracy (so-called classification error). The total sample for our latent Markov model thus includes 4232 interviews with 1299 people. We subsequently revert to the full sample above the age of 49 years when generating parameters for the Bass model in the second step of the analysis.

We selected manifest indicator variables from the DEAS data set that explain a broad range of expected transitions in old age and are

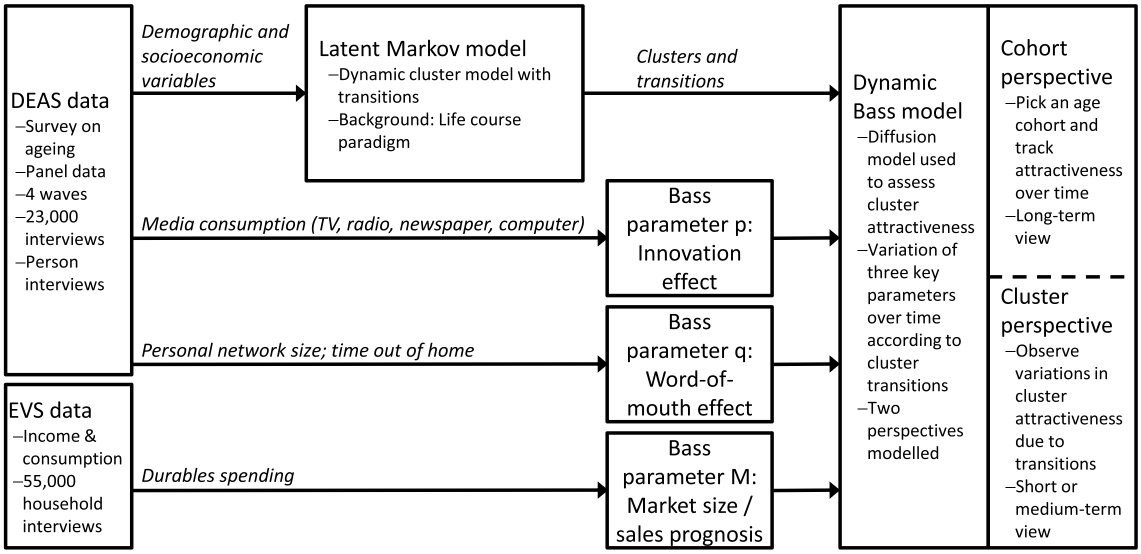


Fig. 1. Approach overview.
The visualization shows the stepwise approach of our setup: Based on two sets of data and a latent Markov model two different perspectives of a dynamic Bass model are constructed.

readily observable in the majority of data sets from the social sciences: marital status, employment status, partner employment status, and household income. Whereas the first three are categorical variables, household income is measured in quintiles. To examine potential effects of very low incomes, we further split the lowest quintile into two 10% quantiles. Taken together, the indicators can capture a substantial number of familial, work-related, social, and economic transitions.

4.3. Step 2: Dynamic Bass model

The Bass diffusion model assesses a market's receptiveness to new goods and services by extrapolating the diffusion process (e.g., cumulative sales) of new products. It operates on the assumption that people adopt new products either through innovation or imitation, which are triggered by different stimuli: Whereas early adopters adopt new products when affected by external stimuli, such as mass media, imitators are influenced internally by their social environment, often through oral communication. Thus, imitation also depends on the number of prior adopters. The Bass model mathematically describes these two diffusion processes, providing estimates for adoption speed and shape of the diffusion curve for the new product in question.

We base our approach on the standard Bass model, in which market size M describes the final market potential that is ultimately realized; the model assumes that a market is always fully penetrated by the end of the diffusion process. The coefficients p and q determine the share of initial adopters through innovation and imitation, respectively. $S(t)$ denotes cumulative sales until time t. Then incremental sales are given by the following differential equation (Mahajan et al., 1990):

$$\frac{dS(t)}{dt} = \left(p + \frac{q \cdot S(t)}{M}\right) \cdot (M - S(t)). \tag{2}$$

First, we estimated diffusion models with separate parameters for each of the clusters from our latent Markov model. Second, the cluster transitions over time—reflecting life events at transition points in the life course—allow for a dynamic version of the Bass model: Now, we can not only assess a cluster's attractiveness (in terms of diffusion speed and rate) at a given time t but also track changes due to consumers migrating through the stages of their life course. As a result, Bass model parameter variations can be followed over time, showing changes in market size as well as in both types of adoption, corresponding to the successive survey waves, which occur every five years on average. For this evolutionary view on old age, we decided to limit the modeled population to a fixed sample as detailed in the next section, meaning that we do not make assumptions for panel entry or exit.

4.4. Estimating Bass model parameters

We employ the Bass model to assess the innovation adoption potential of old-age segments in general, rather than for a specific product. To operationalize the three model parameters, we require data on consumption that are not included in the DEAS set of variables. To attain this data, we connect our latent Markov model results to a second set of data using the scoring approach outlined next. This data set is from the sample survey of income and expenditure 2008 (EVS), provided by the Research Data Centres of the German Federal Statistical Office and the statistical offices of the Länder. The EVS is a representative cross-sectional survey administered every five years. It focuses on household consumption and assets and contains data from more than 55,000 households. Unlike the DEAS, the EVS's primary unit of analysis is the household; however, the survey variables still allow us to deduce all four manifest indicator variables used in our latent Markov model.

To match the new data to the identified life stages, we use the posterior probabilities to classify individual survey observations into the clusters of the latent Markov model. We match each observation to the cluster with the highest posterior probability, which is referred to as modal assignment (Goodman, 2007), so that we can categorize EVS households into our clusters. Again, we apply a minimum cutoff age of 50 years, in this case for the household head. As a result, we classify 23,206 households from the EVS into the clusters. The EVS data provide sampling weights to extrapolate the number of survey responses to the 2008 representative value of approximately 20 million households with a household head aged 50 years and older. In addition, we classify the entire DEAS survey population aged 50 years and older (including all one- and two-wave respondents), which yields 18,619 cases. We use the counts of all (matched) DEAS cases to establish the relative sizes of the life stage clusters, because the DEAS survey is most representative for the elderly population under investigation. The advantage of this scoring procedure is that it can be used to classify any observation from any data set that includes at least the four manifest variables for the latent Markov model, which makes the stepwise procedure a flexible approach.

Using EVS consumption data, we then construct the market size M as a cluster's median annual expenditures on durable goods multiplied by the number of households in that cluster in the EVS reference year 2008. Doing so ensures that we measure the market size in monetary terms, reflecting not only the number of potential adopters, as in classic Bass models, but also their spending power or propensity to adopt and consume. We recommend using durable goods expenditures, because the Bass model is built for modeling (initial) product adoption of infrequently purchased products, rather than the repeated purchases common for non-durable goods and services.

As an internal stimulus, often labeled "word-of-mouth effect", we use a simple composite indicator of an individual's social inclusion, composed of the personal network size and the time spent out of home per day. Both variables are included in the DEAS cases of the matched data. The correlation between both variables is low (r = 0.08), which justifies their use in a formative index. Because the indicators have different units and scales, we standardize them and add the resulting z-values.

For the external stimulus, also referred to as "advertising effect", we employ a person's interaction with mass media by adding the minutes spent daily on the consumption of TV, radio, newspapers, and personal computer use. We include the latter only if the computer has access to the internet, allowing for an interaction with the outside world. We also take these data from the DEAS survey.

With deterministic cluster assignments for observations from both the DEAS and EVS data, we next calculate both the advertising and the word-of-mouth effects per observation and then construct average values per cluster. To arrive at the parameters p and q for the Bass model, we use empirical average values for p and q as developed in various meta-analyses of Bass diffusion models (Mahajan et al., 1995; Sultan et al., 1990). Employing the results of a meta-analysis that examined 213 applications of diffusion models, we find an average $p = 0.03$ and an average $q = 0.38$ (Sultan et al., 1990). We then scale these overall averages using the respective aggregate cluster values for advertising and word-of-mouth effects.

Finally, to put our old-age cluster results into perspective, we construct a reference cluster comprising all individuals (DEAS) or household heads (EVS) aged 40 to 49 years. Because this cluster spans the overall median German age (43 years for 2008), it allows comparing old-age clusters with a population average. Moreover, this age group has particular relevance for marketers as the oldest layer of the core demographic relevant for advertising between the ages of 14 and 49 years.

5. Results

5.1. Life stages in old age

In latent Markov models as well as in the simpler latent class models, the number of latent classes is exogenous; it is commonly empirically determined using the Bayesian information criterion (BIC) or the Akaike information criterion (AIC) (Kaplan, 2008). These measures contrast model fit and parsimony (the BIC penalizes model complexity more heavily than the AIC). In our case, the more restrictive BIC suggests a nine-cluster model as the most favorable fit for the model data, which we confirm qualitatively by examining the interpretability of the nine-class model results. This examination indicated that the clusters of the resulting nine-class model are readily interpretable based on our four input variables; Fig. 2 details these clusters and the major transitions between them, and Table 1 shows the composition of the clusters in terms of chronological age as well as the Bass model parameters relevant for our analysis. We provide detailed tables on BIC and AIC values of different models as well as cluster profiles and transition tables in the supplementary data online.

Fig. 2 depicts the identified latent states as well as the transitions between them over time. Some commonalities are visible already from the cluster sizes: A married couple is the dominant family setup in old age. Single household configurations make up for less than a quarter of our sample. Around 45% live in low income environments, meaning an available per person income of up to 1000 Euros (see supplementary data, Fig. S.2 for details).

Fig. 2 also shows that on average approximately one fourth of the sample population goes through a transition between each of the four survey waves, and the rest stay in their respective clusters. We find that the majority of transitions follow a chronological pattern, that is, from clusters with a lower median age to clusters with a higher one. For couple households, two major age chronologies emerged: First, a couple household in which initially both partners work (cluster 1), which yields a comparatively high income, usually transitions into a high-income retired couple (cluster 6). Second, a working couple with only one partner working full-time and with a low household income (cluster 2) tends to transition to a lower-income retired couple (cluster 7). To some extent, this income difference persists into widowhood (clusters 8 and 9. respectively).

Interestingly, the transitions show that social (upward) mobility does happen but to a very limited extent: We see that around 2.2% of the sample transition from cluster 2 to cluster 6 between two waves denoting a notable increase in available income; some other 0.8% experience an income increase with the onset of widowhood (cluster 7 to 9). Conversely, a direct transition from high to low income clusters is not evidenced by our data.

In addition, other transitions that typically revolve around changing partnerships are evident. As an example, we found that in advanced age, people readily engaged in new partnerships, particularly without marriage: Between any two waves, approximately 1.9% of the sample population formed a new unmarried couple (cluster 4), mostly from previously single household constellations (clusters 3, 5, 8 and 9: divorcées/divorcés, singles, or widows/widowers). From there, transitions into new marriages are rare but existent. Another notable pattern is that marriages rarely result in divorce in the advanced age group. Naturally, at the end of the age spectrum, life stages more typically involve widowhood. Interestingly, high-income widows/widowers have the highest median per-person income to spend of all life stages identified by the model.

5.2. Innovation diffusion in old age

In the second step of our approach, we examine the Bass model parameters for each cluster, as shown in Table 1. The overall market potential of older consumers is impressive: They account for about 20 million German households, or 51% of all households in Germany. Their market potential for durables is approximately €24.6 billion per year, compared with €16.7 billion annually for the 40- to 49-year-old population, which comprises approximately 9.4 million households. This 40- to 49-year-old reference cluster can serve as an average for the working age population. In a household view, we found that older consumers' median spending on durables is on average considerably lower than the younger consumers' reference cluster, though a number of high income clusters stand out with markedly higher spending figures. Although on average the consumers aged 50 years and older spend less on durables, they take in more media communication than the consumers aged 40–49 years: We observed a higher media interaction for the old-age clusters on average when compared with the working age reference cluster. Social inclusion, in contrast, is considerably lower than during the working years. Both coefficients, however, are heterogeneous between the individual old-age clusters, as detailed subsequently.

Upon closer examination of the individual old-age cluster characteristics in Fig. 3, it becomes evident that the household income inequality of the clusters is closely reproduced by similarly unequal levels of household consumption. Working-couple households spend more than three times the amount on durables as the lower-income-couple

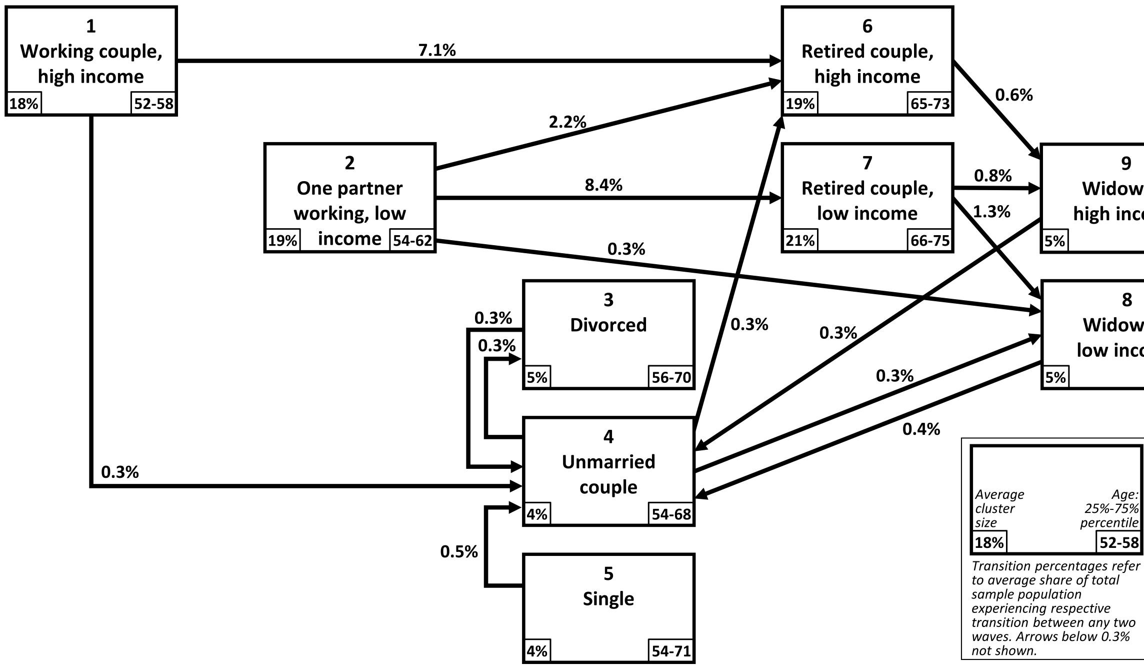


Fig. 2. Old-age segments and transitions.
The cluster transition dynamics as percentages of the overall sample population are shown.

household in which only one partner works. Examining the reference cluster of the working population again, it also becomes clear that a sharp decrease in both income and spending usually accompanies retirement.

With regard to the adoption parameters of the Bass model, media interaction in advanced age is on average higher than for the 40–49 year old reference cluster. It is particularly high in high-income couple clusters (clusters 1, 4, and 6). We observed the lowest media consumption for low-income widows/widowers (cluster 8) as well as low-income couple households with only one partner working (cluster 2).

Social inclusion, on the other hand, is weaker for all of our old-age clusters than for the 40–49 year old reference cluster. This parameter exhibits an age trend as social inclusion further decreases with advancing age. It should be noted that unmarried couples (cluster 4) are socially well integrated considering their median age, as are widows with high income (cluster 9). Widows/widowers with low income (cluster 8) exhibit the lowest social inclusion score.

When integrating both media interaction and social inclusion to estimate Bass diffusion processes for each cluster, we find that on average older consumers adopt durables innovations more slowly compared to the 40–49 year olds: the working age cluster exhibits an earlier sales peak than the old-age population models (after 6.2 vs 6.7 years) meaning the penetration of this market happens more quickly. However, old age consumer clusters show strong heterogeneity in their product adoption: The high-income couple clusters (1, 4, and 6) are fastest in adopting products, with the working couple (cluster 1) and the unmarried couple (cluster 4) even showing earlier sales peaks than the 40–49 year olds.

From a marketer's point of view, the working couple before retirement (cluster 1) and, to a lesser extent, the high-income retired couple (cluster 6) are likely most attractive: Both clusters account for a high fraction of the overall old-age market, they show consumption expenditures well above average, and they are readily accessible through media communication. In addition, the working couple is also exceptionally well integrated into their social environment, allowing for potentially strong word-of-mouth marketing effects directed at this cluster. The unmarried couples (cluster 4) seem an attractive target as well, their share of the sample population, however, is small.

Fig. 4 shows the synthesis of these findings comparing three diffusion models: first, a model for the working age reference cluster, second a static diffusion model of old-age consumers, and third a dynamic diffusion model for old age consumers, where consumers' transitions between clusters over time are taken into account. This model considers that consumers adapt their buying behavior as they experience social transitions, which often entail changes in their spending budget, their media interaction, and their social inclusion.

The perspective of all three models is similar: They all pick a target population at time t_0 and follow the adoption behavior of these consumers through time. The diffusion curves for the three models plot the amount of new money spent on durables for each successive year since market introduction. When considering cluster transitions (the dynamic old age model), we find that the overall market potential is lower than in the static model (red line below green line in Fig. 4). In other words, a static monolithic age model overestimates the spending power of elderly consumers in that it does not take into account that people usually spend less and adopt innovations more slowly with increasing age. Yet, it is worth repeating that such a view on age as a monolithic segment has long been the dominant approach when investigating old-age consumers.

Exploiting the dynamic nature of our model, we can forecast how the number of households per cluster changes after each successive wave (Table 2). We find that the cluster of unmarried couples grows strongly after both one and two waves (5 and 10 years, respectively). Conversely, single and divorcée/divorcé households decrease, albeit not with commensurate strength. This conforms to our earlier finding that people in old age readily form new partnerships. A caveat is that both extreme ends of the examined age spectrum are distorted in that the model does not account for panel entries and exits. In other words, a decrease in working couple households and an increase in widow/widower households strongly reflects the age progression of the population; for such clusters the results of the described short-term cluster-based analysis have to be interpreted more cautiously.

Combining the transition information with cluster behavior and average spending, a forecast of the future potential of today's consumers becomes possible. Specifically, our analysis takes into account

Table 1
Chronological age and Bass model parameters per cluster.

Cluster	1	2	3	4		5	6	7	8	9	Total
Size (after modal assignment)	15%	11%	20%	2%		14%	11%	13%	8%	5%	100%
Age: 25% quantile	52.0	54.0	56.0	54.0		54.0	65.0	66.0	68.0	67.0	56.0
Age: median	55.0	58.0	62.0	60.0		61.0	68.0	70.0	74.0	74.0	63.0
Age: 75% quantile	58.0	62.0	70.0	68.0		71.0	73.0	75.0	80.0	81.0	71.0
Description	Working couple, high income	One partner working, low income	Divorced	Unmarried couple	Single	Retired couple, high income	Retired couple, low income	Widowed, low income	Widowed, high income	All aged 50 years and above	**Reference cluster 40-49 years**
Bass model parameters											
Durables consumption (EUR/year)	3,051	996	599	1,640	561	1,924	912	432	998	1,000	1,784
Absolute size ('000 households)	3,047	2,206	3,946	374	2,795	2,278	2,630	1,669	1,071	20,018	9,387
Market size (M, EUR million)	9,298	2,197	2,362	614	1,568	4,383	2,399	721	1,070	24,612	16,747
Media interaction (p)	0.037	0.029	0.034	0.038	0.032	0.038	0.033	0.029	0.034	0.034	0.030
Social inclusion (q)	0.37	0.30	0.28	0.30	0.26	0.26	0.24	0.22	0.25	0.29	0.38

Note: Differences in magnitude between cluster sizes (DEAS-based) and absolute number of households (EVS-based) are due to the different units of analysis. A household perspective gives greater weight to one person households (divorced, single, widowed) relative to multiple person households.

that people migrate to or from clusters with different profiles along the Bass parameters M, p, and q. Recall the aforementioned two perspectives that our model offers for marketers: to take either a cluster- or a cohort-based view on changes in market size and individual behavior.

5.3. *Cohort-based view on old-age changes for long-term marketers*

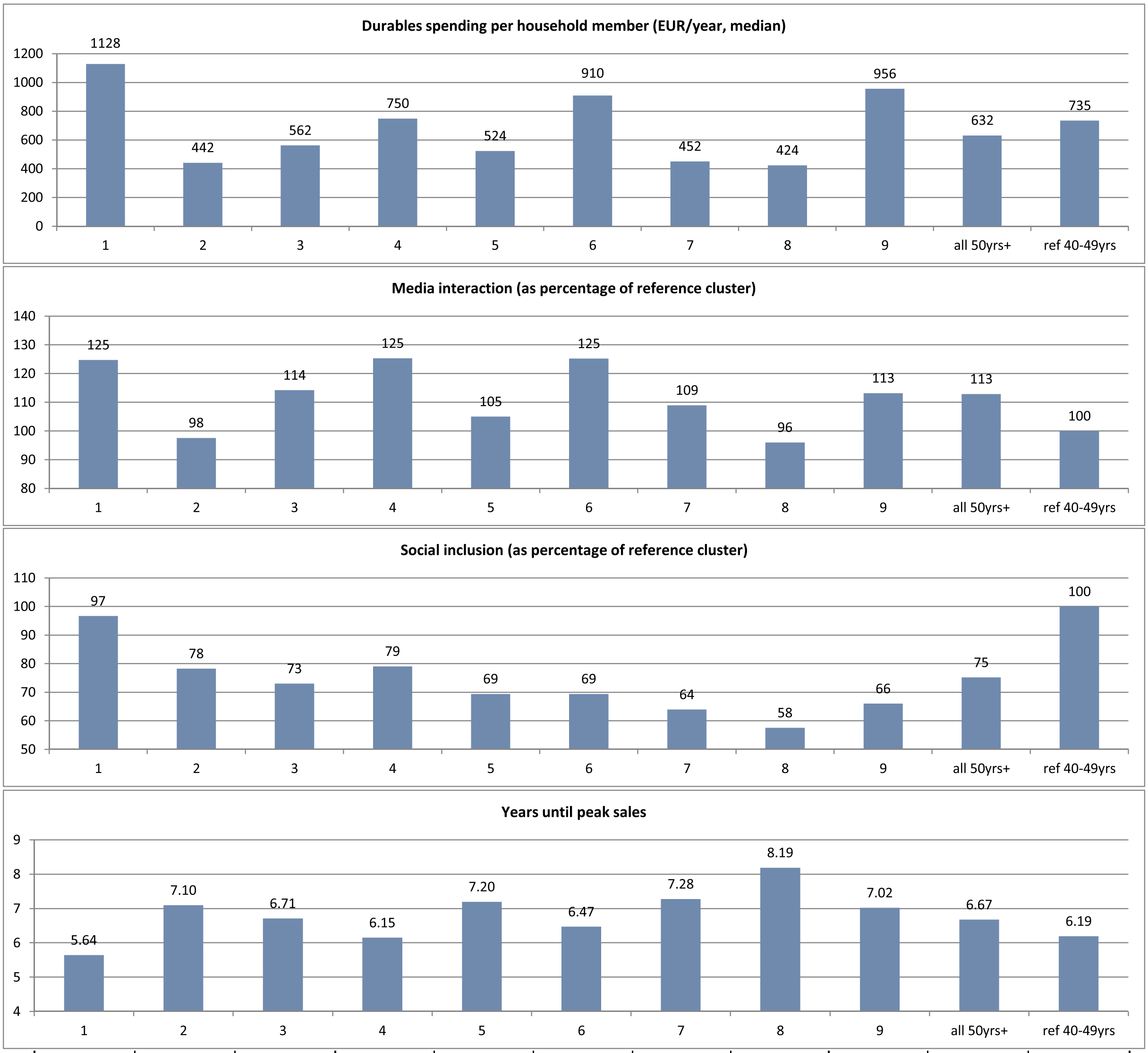
A cohort perspective assumes the position of long-term marketers who pick their target group today and adjust their offerings over time to account for the changing needs of the target population. In this case, we choose a target cluster today (t_0) and dynamically adjust the three Bass model parameters after each successive year. Cluster transitions between the five-year panel waves are interpolated. For the analysis of cohort developments, we limit our analysis to clusters 1 ("working couple, high income") and 2 ("one partner working, low income"), which are both at the beginning of the analyzed age period with a maximum of potential transitions left; in addition, they represent the two ends of the income spectrum of couples before retirement. Clusters at the end of the age progression or that are more transitory are less suited for a cohort view. Fig. 5 depicts the resulting diffusion curves (note different scaling of the two charts).

Naturally, it is more attractive for a marketer to target the high-income working couple and follow them over time. In absolute terms, they are a larger group than couples with only one working partner, and people in that group spend significantly more. The working couple cluster reaches a spending peak after less than six years, about one and a half years earlier than the second cluster, which would allow potential marketers to redirect their investments more efficiently and timely.

When we assume a dynamic perspective, the overall cluster preference stays the same but becomes more nuanced. We find that peak sales for the high-income couple are much lower and occur slightly earlier when we account for cluster transitions (Fig. 5, left panel). The reason is that with retirement, people migrate to clusters with lower spending and slower adoption—in this case, mainly to cluster 6 ("retired couple, high income"). Whereas from the static perspective, sales asymptotically converge toward the x-axis after around 20 years, our dynamic model indicates a full market saturation after only 14 years, because the market size then drops below the installed base as people migrate to less lucrative clusters. In short, a static cohort view significantly overestimates the potential of the working couple cluster in that it suggests a higher cumulative spending over the years with a much later (and only asymptotic) market saturation. For the cluster of households with only one working partner, the difference between both approaches is less pronounced (Fig. 5, right panel). If, however, a marketer is patient, the cluster turns out to be more lucrative than the static view suggests as evidenced by the red line above the blue line after year 10.

Next, we amended our cohort analysis to disentangle monetary and behavioral effects of cluster transitions: The monetary effect refers to the change in average spending after cluster transitions, and the behavioral effect implies that people behave differently in terms of the coefficients p and q as members of new clusters. Fig. 6 shows the dynamic diffusion curves for a cohort view on clusters 1 and 2 – similar to Fig. 5 except that changes in the market size are taken out of the analysis here and shown as a separate line. Hence, differences observed between the static and the dynamic view stem solely from changes in p and q following cluster transitions. Since a monetary effect is no longer included in the behavioral parameters the respective diffusion curve refers to unit sales in this case instead of sales in Euro.

For the working couple cluster (Fig. 6, left panel), the market size or monetary cohort potential continually decreases as people spend less after leaving that cluster. The opposite is true for cluster 2 (right panel), from which people tend to move to clusters with higher spending, though the market size adjustment is less pronounced than in cluster 1. The behavioral parameters for both clusters reveal that from a dynamic perspective, spending occurs later than the static analysis would



1	2	3	4	5	6	7	8	9	all 50yrs+	ref 40-49yrs
Working couple, high income	One partner working, low income	Divorced	Unmarried couple	Single	Retired couple, high income	Retired couple, low income	Widowed, low income	Widowed, high income	All aged 50 years and above	Reference cluster 40-49 years

Fig. 3. Visualization of per-cluster specifications relevant for Bass model.
The chart is a visualization of important input parameters (durables spending, media interaction, social inclusion) as well as preliminary output (years until peak sales) of the static Bass model on a per-cluster basis.

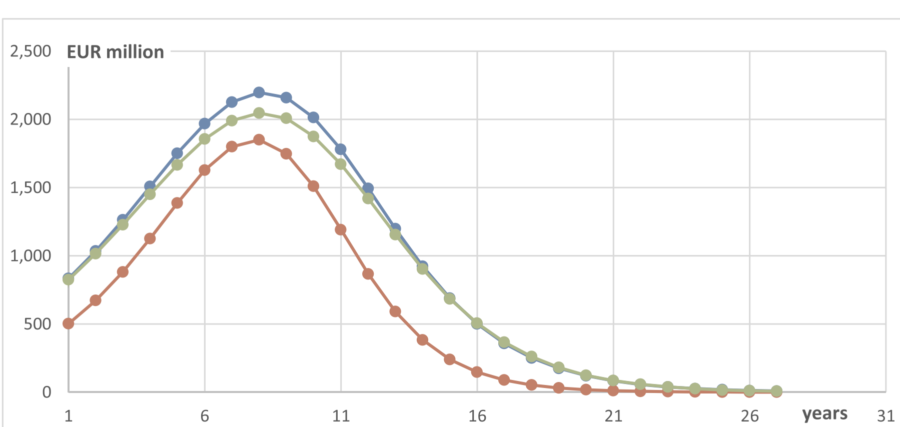


Fig. 4. Adoption dynamics of reference cluster (40–49 yrs, red line) vs. all old-age clusters combined (blue line: static model, green line: dynamic model).
The chart shows diffusion curves for the reference cluster (static) as well as for an average of the old-age clusters (static and dynamic). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Table 2
Transition effects: Household composition forecast after one and two waves (5 and 10 years, respectively).
Based on the modeled transition tables, cluster sizes are extrapolated into the future.

	1	2	3	4	5	6	7	8	9
Cluster	Working couple, high income	One partner working, low income	Divorced	Unmarried couple	Single	Retired couple, high income	Retired couple, low income	Widowed, low income	Widowed, high income
t_0: Number of households ('000)	3047	2206	3946	374	2795	2278	2630	1669	1071
t_1: Number of households ('000)	1962	1152	3737	1136	2356	3430	3176	1749	1321
t_2: Number of households ('000)	1278	603	3586	1627	1994	4135	3279	1897	1617
$t_0 \rightarrow t_1$: percent change	−36%	−48%	−5%	203%	−16%	51%	21%	5%	23%
$t_0 \rightarrow t_2$: percent change	−58%	−73%	−9%	334%	−29%	82%	25%	14%	51%

predict. For cluster 1, purchases are deferred to a point in time with less spending power; for cluster 2, the deferral means more spending power when cluster members migrate to more affluent segments.

5.4. Cluster-based view on old-age changes for short-term marketers

For the second analysis that our setup allows, we adopt the perspective of a marketer with a medium- or short-term orientation who is not willing or able to reflect long-term changes in preferences and behavior of the targeted segment. Rather, the marketer tailors offerings to current needs of the target cluster regardless of potential future changes. Consequently, after introducing a new product, the marketer primarily must adapt to market size changes that the target cluster experiences over time. Our model can account for cluster size change – again with the caveat of no panel entries or exits. However, we observe a second effect: In the Bass model, changes of market size M also directly affect the relative weights of the parameters p and q. In other words, in smaller markets, there is less diffusion by word of mouth and more need for innovation purchases. Fig. 7 shows the Bass diffusion processes for the nine clusters from this cluster-focused point of view. In summary, we find that when compared with our dynamic model, a static approach overestimates the spending volume of four of the nine clusters, while for the remaining five clusters, the potential is underestimated; both effects occur in widely varying degrees.

In absolute terms, the two large clusters for working and retired high income couples have the strongest market potentials at their peaks. As in our first perspective, in some clusters we find conditions for a premature market saturation as cluster populations drop sharply. Cluster 1 of the working couple is the most prominent example in which a static view would strongly overestimate its potential: As people migrate to other clusters, usually starting with retirement, the potential market size drops significantly, and market saturation is reached at about the same time as in cluster 2, which represents the couple segment shortly before retirement.

Conversely, most cluster populations in the middle of the analyzed age spectrum grow more steadily: Here, cluster migration pushes spending peaks to later points in time, while market potential is lifted to levels that a static view could not have anticipated. In many cases, market saturation is not in sight over the 15-year forecast horizon. Additionally, increases are more pronounced if clusters benefit from individual changes as opposed to pure age progression. Cluster 4 is such an example in which significant cluster gains epitomize the trend of newly formed partnerships in advanced age. Along with the two widow/widower clusters, it has the latest sales peak: after 11 years. Clusters 3 and 5 mirror this development with earlier peaks and a conceivable saturation point.

6. Discussion

A mirror of social change in advanced age, our analysis shows the potentially strong influence of life events at the edge of neighboring life stages on behavior and preferences. It confirms that the earlier notion of age as monolithic and static life stage is not justified. Rather, we find substantial differences in the attractiveness of consumer segments pertaining to various life stages in advanced age. As such, our results underscore the diversity of old-age consumers, demonstrating that they are far from constituting a homogeneous consumer group.

Specifically, our study contributes a dynamic longitudinal perspective on elderly consumers that is based on empirical data, a setup researchers have repeatedly called for in the context of social science views on old age, especially in marketing (Fox et al., 1984; Moschis, 2012; Schaninger and Danko, 1993; Szmigin and Carrigan, 2001). As such, it extends extant research on elderly consumers, which to date has mostly focused on cross-sectional segmentation studies. Extending our dynamic approach to market potential and diffusion paths for the elderly population, we show that static views on markets can result in a

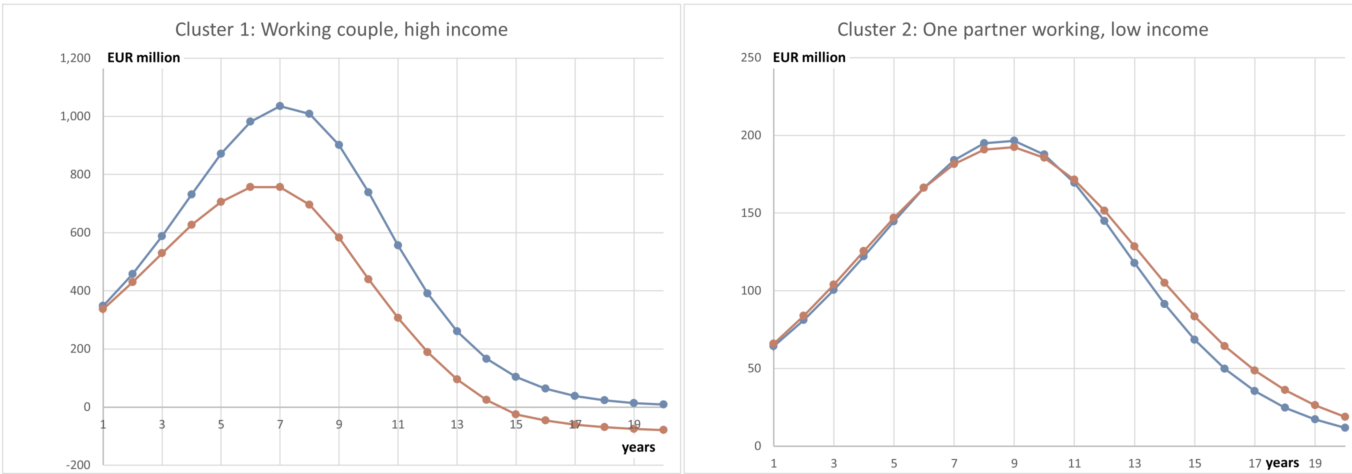


Fig. 5. Bass model in cohort view – static (blue line) vs. dynamic (red line).
Based on a cohort view, the chart underlines that a dynamic view on diffusion processes can yield markedly different results when compared to a static view. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

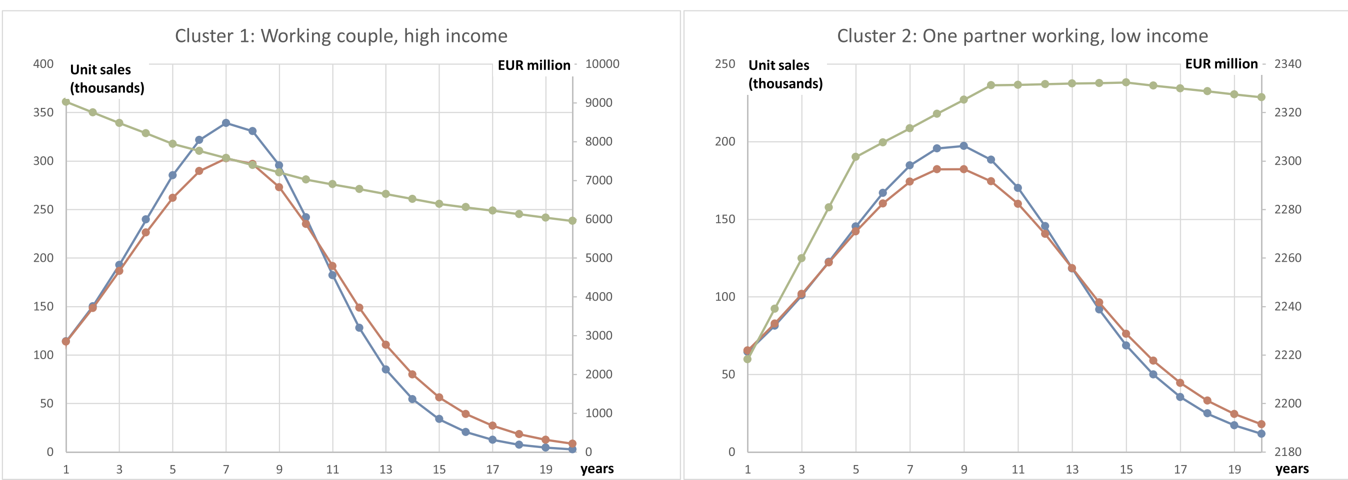


Fig. 6. Dynamic Bass model in cohort view decomposed into monetary (green line, right scale) and behavioral (red line: static model, blue line: dynamic model) effect.
The high-income working couple gradually migrates to clusters with less spending power. For the low-income couple with only one partner working the chart shows the opposite. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

stark misinterpretation of their potential if such analyses do not consider changes in market composition over time.

Our results add a layer of insight that points to new ways for marketers to adapt to changing demographics, in both the long and short run. The overall conclusion is positive: A fragmented and evolving elderly market offers ample potential for specializations and niches. In other words, it is not necessary for all marketers and innovators catering to the elderly to fight for the same overall market in the same way.

Our results cast a new light on the marketing implications that a purely static view of old-age markets would indicate: The long-term attractiveness of a high-income household before retirement (cluster 1) is overrated if successive transitions to other life circumstances are not considered. This is especially true relative the lower-income household (cluster 2), in which we actually observed a minor effect in the opposite direction. Cluster 2 also offers a much stronger relative growth potential to the sales peak, in that people in this cluster are more likely to migrate to clusters with higher spending. For long-term-oriented marketers, cluster 2 could ultimately be a more worthwhile target, especially if ramp-up investments for targeting are low. For planning purposes, our approach can help marketers form strategies in that it gives more accurate view of sales progression and market saturation. Applications in practice could be to determine the timing of specific marketing tactics, to schedule investments and disinvestments, or to define key figures for evaluating the success of overall marketing strategies.

In a short-term cluster-based view, cluster 1 offers more absolute and relative sales potential, even after adjusting for cluster migration. From this perspective, the unmarried couple household is of particular interest in that its sales potential benefits strongly from new partnerships formed out of former one-person households. No other cluster shows a relative growth as strong as this one between two waves.

Our results also underscore that income and social status are the most distinct criteria along which social change happens in advanced age: These factors can help explain many old-age transitions and behavioral patterns. Indeed, the two major paths through old age are strongly defined by social status. In turn, our results also confirm the intense social inequality in advanced age (Dannefer, 2003).

In summary, social status is an obvious starting point for marketers to define their strategy because it strongly influences consumption expenditures. However, its correlation to the other Bass model variables is less straightforward. For example, if we only look at the two main age

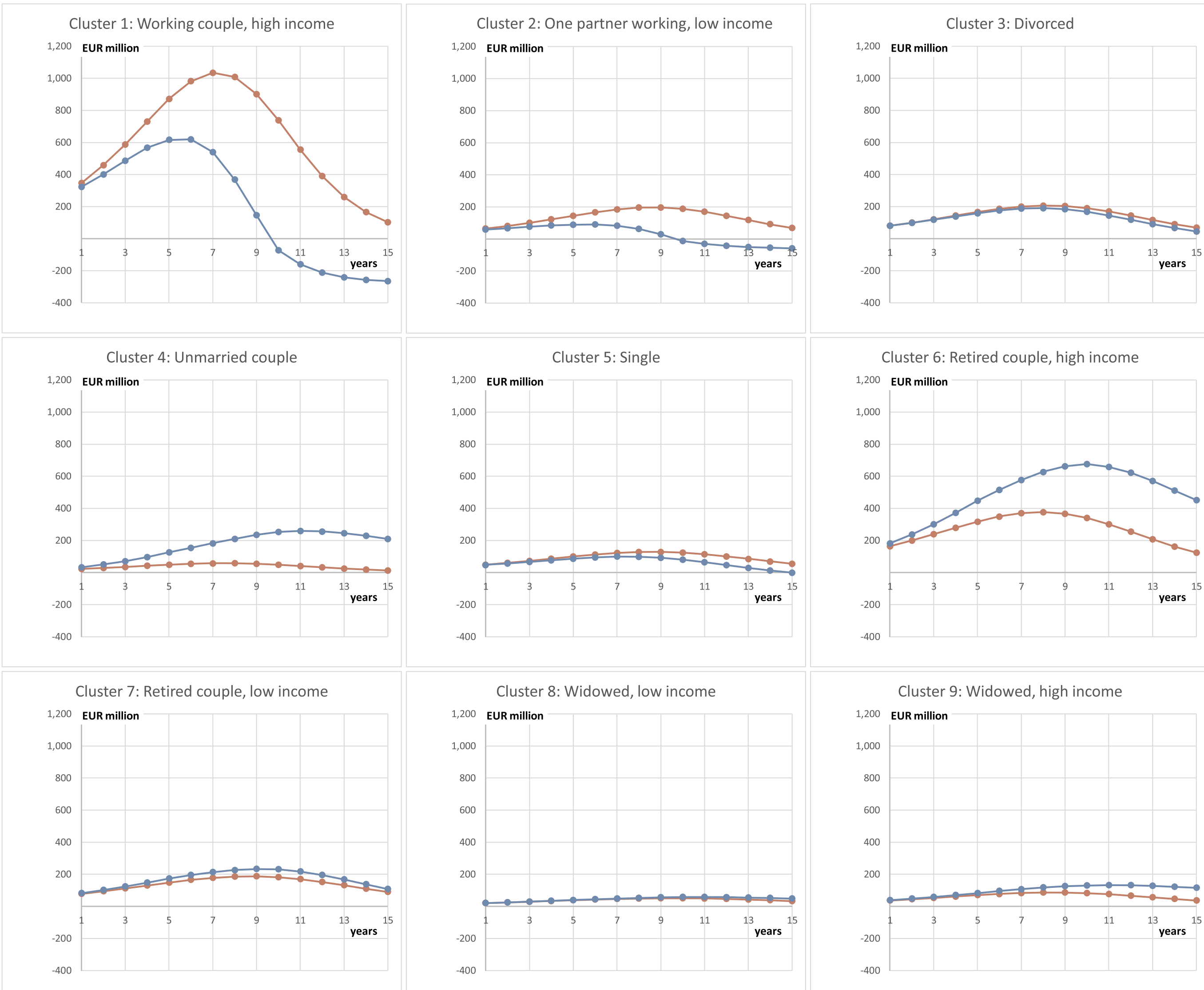


Fig. 7. Bass models in cluster view – static (blue line) vs. dynamic (red line).
The dynamic cluster view shows heterogeneous results: for some clusters it demonstrates a higher spending volume than the static view, for other clusters the volume is comparatively lower. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

chronologies, it is easy to assume that income positively affects social inclusion and that, conversely, low economic status and a reclusive lifestyle often go hand in hand (Savikko et al., 2005; Wenger et al., 1996). Yet we find examples in which this assumption is not true, such as divorcées/divorcés who are socially better integrated than their low income would suggest or the high-income retired couple that ranks slightly below average in terms of social inclusion. These exceptions are especially relevant for marketers focusing on social diffusion such as word of mouth: For example, the high-income retired couple may be an attractive segment for their economic power, but they may not be very accessible for marketing communication relying on social diffusion. Indeed, a rapidly aging society could support or even rejuvenate the beleaguered mass media advertising industry.

From a policy perspective and for society as a whole, however, the overall conclusion is less positive but more nuanced: We find that the openness and capacity to adapt to external changes, particularly to adopt innovations, by and large decreases with advancing age, though there are certain clusters that go against that trend. In a broader view, however, the categorization of a healthy, dynamic, and optimistic third age as distinct from a fourth age in physiological and psychological decline and frailty provides a pragmatic delineation for product diffusion and innovation (Baltes and Smith, 2003).

Although we argue that our dynamic segmentation approach is much closer to the social reality in old age than a static model, we acknowledge room for improvement in our setup. Future research could extend the model to account for panel entries and exits, which could ultimately be non-trivial for two reasons. First, the data, especially on panel exits, are sparse and erratic; researchers have long recognized that panel attrition is a problem in advanced age (Deeg et al., 2002; Mirowsky and Reynolds, 2000; Mollenkopf et al., 2011), which our data also reflect: For the majority of the interviewees, we simply do not know why they left the panel when they did. Second, when including entries and exits from the panel, the distinction between a gerontologic analysis such as ours and demographics becomes blurry: Cohort and period effects potentially overlay age effects (Glenn, 2003) to the extent that it becomes difficult to ascribe social changes to one or the other. To underscore our argument of social change in old age, we decided to exclude panel entries and exits in our analysis. However, the skew this lends to our analysis should not be overestimated: If panel effects dominated the results, the sequence of the clusters in the cluster perspective (Fig. 7) would strongly determine differences between dynamic and static view, which is not the case.

Our examination of life circumstances in advanced age can give rise to hypotheses and questions relative to living together that warrant further investigation. For examples, why are new marriages uncommon in advanced age while people do readily and frequently engage in new unmarried partnerships? Why is divorce less likely for marriages of couples in which only one partner (as opposed to both) is working? Do those couples have a more traditional take on family and marriage? Conversely, our data exhibit some indication that unmarried couples have positive and communicative stance on life and, in contrast to their age trend, are socially well integrated and media oriented. This phenomenon points to other research directions.

Further research could refine such cues to gain a deeper understanding of societal and cultural imprints in advanced age. As an example, our model setup would lend itself to analyze zeitgeist changes: With an adequately long series of panel data, separate Markov models could be estimated for several elderly cohorts to investigate how transitions and old-age paths change with successive generations.

Declarations of interest

None.

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Appendix A. Supplementary data

Supplementary data to this article with details on our Markov model can be found online at https://doi.org/10.1016/j.techfore.2018.12.022. There, we provide BIC and AIC values of different cluster models as well as cluster profiles and transition tables.

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Matthias Pannhorst is a doctoral researcher at the European University Viadrina. His research interests focus on the implications of an aging society on consumer marketing with an emphasis on quantitative analyses and forecasting through empirical models; public policy responses to shifting demographic weights; as well as the macro impact of global aging on institutions like social security and welfare systems.

Florian Dost is a Senior Lecturer for Marketing Analytics at the Lancaster University Management School. His research revolves around forecasting complex systems; macro consequences of aggregate marketing and management phenomena; consumer decisions and willingness to pay under uncertainty; and word-of-mouth marketing and propagation. He is also frequently engaged in market research projects and consulting on collaborative forms of marketing.