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Abstract

Prior international segmentation studies are static, i.e., they identify segments that are stable over time. This paper shows that country segments in new product growth are intrinsically dynamic. We propose a semiparametric hidden Markov model to dynamically segment countries based on the observed penetration pattern of new product categories. The methodology allows countries to switch between segments over the new product's life cycle, with time-varying transition probabilities. Our approach is based on penalized splines and can thus be flexibly applied to any non-stationary phenomenon, beyond the new product growth context.

For the penetration of six new product categories in 79 countries, we recover each country's dynamic membership to segments over the life cycle. Our findings reveal substantial dynamics in international market segmentation, in particular at the beginning of the product life. Finally, we exploit the dynamic segments to predict the national penetration patterns of a new product before its launch and show that our forecasts outperform forecasts derived from alternate parametric and/or static methods. Our results encourage multinational corporations to adopt dynamic segmentation methods instead of static ones.

Keywords: Country segmentation, dynamic segments, international new product growth, penalized splines, semiparametric modeling.

1. Introduction

Country segmentation is fundamental to any successful international marketing strategy (Steenkamp & Ter Hofstede, 2002). The globalization of firms and markets enhances the need for cross-border exchange of experiences and market research, accounting for (dis)similarity across markets. With globalization comes an increased understanding that some markets are similar while others are very different from one another.

Various segmentation bases have been suggested for international markets; particularly relevant for the present paper is the segmentation of countries based on sales, adoption or penetration patterns of new products over the life cycle (see e.g. Gielens & Steenkamp, 2007; Helsen, Jedidi, & DeSarbo, 1993; Kumar, Ganesh, & Echambadi, 1998; Sood, James, & Tellis, 2009). Such segmentation is often used to select the sequence of countries to enter (Tellis, Stremersch, & Yin, 2003). Grouping countries based on the penetration patterns new products show over time is especially relevant if one considers the high financial stakes involved in globally introducing a new product and the substantial differences new product growth patterns show across countries and country segments (Dekimpe, Parker, & Sarvary, 2000; Desiraju, Nair, & Chintagunta, 2004; Gatignon, Eliashberg, & Robertson, 1989; Mahajan & Muller, 1994; Stremersch & Lemmens, 2009; Stremersch & Tellis, 2004; Van den Bulte & Stremersch, 2004; Van Everdingen, Fok, & Stremersch, 2009). The idea of such segmentation is that penetration patterns of new products are likely to show regularities across countries because the latter share similarities at the demand (e.g. national culture) and supply side (e.g. regulation), as demonstrated by Stremersch and Lemmens (2009).

Prior research has cited multiple reasons why country segmentation on the basis of penetration patterns is relevant to companies. First, it enables cross-fertilization and experience sharing between managers of different countries of the same segment (Bijmolt, Paas, & Vermunt, 2004). Second, the sales evolution of a new product in a country can be used as reference point in another country that belongs to the same country segment (Steenkamp & Ter Hofstede, 2002). Third, international segmentation can improve forecasting accuracy regarding the growth of new products, especially prior to launch, similar in principle to analogical diffusion models (Bass, 2004; Ofek, 2005). A firm may also select a test country within a segment to explore the sales potential not only for that test market, but, by analogy, for the entire segment (Green, Frank, & Robinson, 1967). The benefits of country segmentation can be exploited by firms, both at the individual brand and at the product category level (e.g. brand diffusion versus category diffusion models or brand management versus category management).

A key shortcoming of the country segmentation methods in the marketing literature is their static nature (Steenkamp & Ter Hofstede, 2002). An implicit assumption is made that the segments are stationary in structure (segment composition or membership) and in characteristics (segment profiles). In other words, country membership to segments does not vary over the product life cycle. For instance, Helsen, et al. (1993) segment countries based on the time-invariant parameters of the Bass (1969) diffusion model in a mixture regression framework. Similarly, Jedidi, Krider and Weinberg (1998) cluster movies according to their share-of-revenue patterns over time. Recently, Sood, et al. (2009) propose a semiparametric version where they estimate diffusion curves, which they subsequently cluster using functional principal components (Ramsay & Silverman, 2005).

However, the non-stationary nature of new product adoption endangers the temporal stability of international segments, which are likely to show dynamics (Wedel & Kamakura, 2000). The combined studies of Tellis et al. (2003) and Stremersch and Tellis (2004) provide indirect evidence for the relevance of this time dependence. Using the same European diffusion data, they find that the factors that drive early growth (i.e., time-to-takeoff) are different from the factors that drive late growth (i.e., time-to-slowdown). Also, Golder and Tellis (2004) and Stremersch and Lemmens (2009) show that the influence of variables that affect new product growth varies over time.

In this paper, we demonstrate that country segments based on the penetration pattern of new product categories are not static but inherently dynamic. To accommodate dynamics, we develop a semiparametric Hidden Markov Model (HMM) that allows the country membership to segments to vary flexibly over time. The paper extends recent advances in time-varying household segmentation (e.g. Du & Kamakura, 2006; Paas, Vermunt & Bijmolt, 2007), dynamic customer value segmentation (Brangule-Vlagsma, Pieters & Wedel, 2002; Homburg, Steiner, & Totzek, 2009) or customer relationship dynamics (Netzer, Lattin & Srinivasan, 2008) to an international scope, and combine them with recent advances in semiparametric modeling of new product growth patterns with penalized splines (Stremersch & Lemmens, 2009).

We apply our semiparametric dynamic segmentation method to country-level penetration data of six product categories of ICT products and media devices, across 79 developed and developing countries, between 1977 and 2009. For this specific set of product categories, we identify three latent country segments, which show substantial dynamics in membership probabilities and size over time, especially at the beginning of the product life cycle. Dynamic segments provide a better fit than static segments or segments based on geographic area (e.g. North America and Western Europe). In addition, a semiparametric response function offers a better fit than a parametric specification. Our dynamic segmentation model also shows outstanding prelaunch forecasting performance, outperforming in most cases static and/or parametric segmentation methods. While we apply the model to product categories, it is trivial to apply it to brands, as - in contrast to (parametric) diffusion models such as the Bass diffusion model - our semiparametric approach does not impose a (behavioral) structure.

This paper has important implications for firms and international public policy bodies that use country segmentation methods. Many of them use an exogenously-defined regional segmentation criterion (see e.g. Ghauri & Cateora, 2006, p. 492), or if more sophisticated, a static model-based segmentation method. We show that both are inaccurate since segments are intrinsically dynamic.

Therefore, both may lead to inappropriate decision-making and imprecise forecasts, as compared to dynamic segments. We suggest that analysts change their current (i.e., static segmentation) practice and derive, for their respective industries and product categories, a dynamic segmentation of the countries they compete in.

The remainder of the paper is organized as follows. In the next section, we present a short overview of the recent developments in (international) segmentation modeling. The following section describes the methodological framework used to dynamically segment countries over time. We then turn to the data description and present the empirical findings. Managerial implications and conclusions are drawn in the last section.

2. Existing International Segmentation Methods

Most research uses established segmentation algorithms developed in the statistical literature, such as finite-mixture models (Helsen, et al., 1993; Ter Hofstede, Steenkamp, & Wedel, 1999) or variations of k-means clustering (Chaturvedi, et al., 1997; Homburg, Jensen, & Krohmer, 2008; Kale, 1995). Few international segmentation studies have focused on the development of new methodological frameworks. Recently, scholars have proposed several new methods for (international) segmentation. In particular, hierarchical Bayesian models with segment-specific response parameters (Ter Hofstede, Wedel, & Steenkamp, 2002) allow spatial dependence within and between segments. The multi-level finite-mixture model proposed by Bijmolt, et al. (2004) accounts for different levels of aggregation (e.g. consumer and country levels).

Another interesting on-going methodological development is functional data analysis and functional clustering, as in Sood et al. (2009) for product-country segmentation (or Foutz & Jank, 2010, for product segmentation). The main benefit of such approaches, beyond the flexibility that functional analysis offers as a nonparametric framework, is that the econometrician can cluster the growth curves of new products globally based on their functional shape. Any possible shape can be dealt with.

Time dependence remains an important concern in international segmentation. As raised by Steenkamp and Ter Hofstede, "over time, the number of segments, segment sizes and structural properties of international segments may change. [...] This issue has not received rigorous attention yet." (Steenkamp & Ter Hofstede, 2002, p. 209). From a managerial viewpoint, ignoring dynamics in international segments is likely to lead to suboptimal marketing strategies. From an estimation viewpoint, the violation of the assumption of stationarity may invalidate model estimation when the phenomenon under study is by nature non-stationary or when the data range spans a long time period, such as in diffusion studies. Recent methodological advances over the last decade in segment dynamics modeling are (hidden) Markov models (Brangule-Vlagsma, et al., 2002; Du & Kamakura, 2006; Homburg, et al., 2009; Liechty, Pieters & Wedel, 2003; Mongomery, Li, Srinivasan & Liechty, 2004; Netzer, et al. 2008; Paas, et al., 2007; Ramaswamy, 1997). Applied on a collection of time series, HMM can identify, for each time period, the segment to which a realization belongs to. They allow segment membership to dynamically vary over time. Existing marketing applications have focused on customer or household segmentation and have modeled the finite-mixture response function in a parametric way. Our research extends the use of HMM to international country segmentation and proposes to use a semiparametric framework where time series are not restricted to a specific functional form.

3. Semiparametric Hidden Markov Model for Dynamic Country Segmentation

This section first describes the semiparametric hidden Markov model we propose to dynamically segment countries. Then, we explain how we use this approach to make new product growth forecasts and we present a number of alternative benchmark models.

3.1. A New Dynamic Segmentation Framework

For every country i, with $i = 1, \dots, n$ and product category j, with $j = 1, \dots, J$, we observe a penetration pattern $y_{ij1}, y_{ij2}, \dots, y_{ijT_{ij}}$, where T_{ij} is the number of sample points available for this product-country combination. In our application, we define penetration in percentage as the number of devices or subscriptions used by a population divided by the number of users (see data section). Prior to launch, we have $y_{ijt} = 0$ up to $t = 0$. Note that we consider duration time – rather than calendar time – as the goal of the analysis is to pool penetration data of multiple product categories launched at different calendar times and extract from it regularities or commonalities in diffusion patterns across countries. Let $\boldsymbol{y_{it}} = (y_{i1t}, \dots, y_{ijt}, \dots, y_{iJt})$ be the vector containing the penetration data in country *i* at time *t* of all product categories under consideration. As the number of observed sample points can differ per product category, the number of components in the vector $\boldsymbol{y_{it}}$ is allowed to vary over time. Denote $T_i = \max_j T_{ij}$ and write, for notational convenience, for every country $T_i = T$.

We model the penetration of product *j* in country *i* at time *t* using a semiparametric hidden Markov model. A hidden Markov model is a probabilistic model of the joint probability of a collection of random variables, here $\{\boldsymbol{y_{i1}}, \dots, \boldsymbol{y_{iT}}\}$. The distribution of $\boldsymbol{y_{it}}$ depends on the value a hidden (or latent) state variable takes in the set $\{1, \dots, S\}$ of possible states, with *S* the total number of hidden states. We denote $s(i, t)$ the value of the hidden state variable for country *i* at time *t*. Countries that share the same value $s(i, t)$ belong to the same *latent segment* at time *t*. To allow for time-varying country membership to the latent segments, each country i follows a particular (hidden) sequence of states $s(i, 1), \dots, s(i, T)$, the *state path*. Using the time-varying segmentation basis $\boldsymbol{y_{it}}$, we can estimate the model and obtain the probability for each country to belong to each latent segment at any given time point of the product life cycle.

Hidden Markov Model

The model is composed of two parts: (i) a response component that connects the state variable to the observed responses at any given time point, and (ii) a structural component modeling changes in latent segments across time periods.

We model the penetration of product *j* in country *i* at time *t*, given that country *i* belongs to latent segment $s(i,t)$ as

$$y_{ijt} = f_{s(i,t)t} + g_{s(i,t)jt} + \varepsilon_{ijt} \qquad \text{with } \varepsilon_{ijt} \sim N(0, \sigma_t^2). \tag{1}$$

For every segment *s*, with $1 \leq s \leq S$, we have that f_{st} is a segment-specific function and g_{sjt} is the corresponding product-specific deviation from the segment function. Product-specific deviations vary between segments and capture the heterogeneity between products. These functions can be modeled in a parametric or semiparametric fashion. In order to keep our segmentation method as flexible as possible, we opt for a penalized spline semiparametric specification for both f_{st} and g_{sjt}, as detailed in the next subsection. Another option would be to specify f_{st} and g_{sjt} as parametric functions of the time *t* (e.g. Bass, 1969). Both possibilities are compared to each other in the empirical analysis. Furthermore, we allow the error term in (1) to be heteroscedastic with $\sigma_t^2 = \sigma^2 t$ and each ε_{ijt} to follow a first-order autoregressive process with a common autoregressive parameter. This specification accounts for the fact that penetration curves are cumulative time series and provides better fit to the data than a model with homoscedastic errors and/or without autocorrelation.[1] For a fixed time point, equation (1) can be interpreted as a finite mixture model, defining a country segmentation based on the observed penetration values across product categories at that time period. Figure 1 proposes a graphical representation of our semiparametric HMM in the case of three states or segments.

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[1] Note that one could apply the logit transformation to the penetration data to ensure that the estimated penetration levels are between 0 and 1. In our particular application, all fitted values were in this interval.

Insert Figure 1 about here

The structural component follows a first-order Markov chain. In particular, it assumes that membership to the latent segment at time t is affected only by segment membership at $t-1$, but not by latent segment membership at earlier periods. The initial latent segment probability $\pi_s = P(s(i,1) = s)$ is the probability of belonging to segment s at $t = 1$ while the time-varying transition probability $\pi^t_{s_t s_{t+1}} = P(s(i,t+1) = s_{t+1} | s(i,t) = s_t)$ denotes the probability of switching from segment s_t at t to segment s_{t+1} at $t+1$, for $t = 1, \dots, T-1$. The above probabilities are the same for all countries and are referred to as the prior probabilities. The prior probability that a country follows the *state path* $s_1, \dots s_T$ is then given by $\pi_{s_1} \pi^1_{s_1 s_2} \dots \pi^{T-1}_{s_{T-1} s_T}$ for any $s_1, \dots, s_T$, using the first-order Markov property.

In our approach, the transition probabilities are time-varying (or *time-heterogeneous*). In the non-stationary new product growth context, one can indeed easily conceive that transition probabilities in the period right after the new product is launched are likely to differ from transition probabilities when the product matures. For instance, the first years after launch tend to show higher variability in state membership (lower stickiness of the states) than later years when the total market potential is almost reached. We allow these transition probabilities to vary freely over time. One could possibly extend this formulation by letting the probabilities depend on available (time-varying) covariates, as proposed by Paas, et al. (2007). To identify segments' labels, we use the restriction $f_{1t} < f_{2t} < \cdots < f_{St}$ at each time. It allows us to identify the segment with the largest value of the index *s* as the segment with the highest penetration level. A similar identification restriction was made in Netzer, et al. (2008). Note that this restriction does not prevent that a country would move from the high- to the low-penetration segment, while another would move from the low- to the high-penetration segment, thus resulting in crossing penetration patterns.

Combining the semiparametric response model given by equation (1) and the first-order Markov model yields a semiparametric hidden Markov model. The total likelihood function is given by

$$\prod_{i=1}^{n} \sum_{s_1=1}^{S} \dots \sum_{s_T=1}^{S} \pi_{s_1} \pi_{s_1 s_2}^{1} \dots \pi_{s_{T-1} s_T}^{T-1} \quad L(\boldsymbol{y_{i1}}, \dots, \boldsymbol{y_{iT}} | s_1, \dots, s_T), \tag{2}$$

with $L(\boldsymbol{y_{i1}}, \dots, \boldsymbol{y_{iT}} | s_1, \dots, s_T)$ the conditional likelihood of the series for country i given the state path. This conditional likelihood is easy to compute. For instance, in absence of serial correlation in the error terms in (1), we have $L(\boldsymbol{y_{i1}}, \dots, \boldsymbol{y_{iT}} | s_1, \dots, s_T) = \prod_{t=1}^{T} L_t(\boldsymbol{y_{it}} | s_t)$, where $L_t(\boldsymbol{y_{it}} | s_t)$ is the likelihood of a normal distribution with mean $\boldsymbol{\mu_{st}} = (\mu_{s1t}, \dots, \mu_{sJt})$ and covariance matrix R_t. Here, $\mu_{sjt} = f_{st} + g_{sjt}$ is the expected penetration level of product *j* in segment *s* at time t and the matrix R_t is the covariance matrix of the error terms $\boldsymbol{\varepsilon_{it}} = (\varepsilon_{i1t}, \dots, \varepsilon_{iJt})'$. If we allow for autocorrelation in the error terms, the expression for the likelihood becomes slightly more complex since the distribution of $\boldsymbol{y_{it}}$ does not only depend on the state where it belongs to anymore, but also on $\boldsymbol{y_{i,t-1}}$ and the previous state.

Semiparametric Modeling using Penalized Splines

To ensure full flexibility in the choice of the time-varying segmentation basis, we model the segment-specific function and the product-specific deviations in a semiparametric fashion, using penalized or *p*-splines. Previous diffusion research has indeed argued that parametric diffusion models suffer from several limitations, which semiparametric modeling can address. For instance, parameters tend to be biased when the observed time window is too short (Bemmaor & Lee, 2002; Van den Bulte & Lilien, 1997) or when data contain repeat purchases (Hardie, Fader & Wisniewski, 1998; Van den Bulte & Stremersch, 2004). Penalized splines constitute a highly flexible and modular approach to model how a response variable is affected by covariates, in this case by duration time (Ruppert, Wand & Carroll, 2003). Splines have become increasingly popular in medicine (e.g. Durban et al., 2005), finance (e.g.

Jarrow, Ruppert and Yu, 2004), and recently, in marketing (Kalyanam & Shively, 1998; Sloot, Fok, & Verhoef, 2006; Stremersch & Lemmens, 2009; Van Heerde, Leeflang, & Wittink, 2001; Wedel & Leeflang, 1998).

We can construct a *spline* as a linear combination of K linear *bases*, which are broken lines $(t-\kappa_k)_+$ truncated at knot κ_k with $0 \leq \kappa_k \leq T$ for $k = 1, \ldots, K$ (i.e. the knot is the location where the broken lines are tied together).[2] If we combine such bases with different knots ranging from 0 to T, and assign weights $u_1, \ldots, u_K$ to each, we can fit any non-linear, smoothed curve $h(t) = \sum_{k=1}^{K} u_k(t-\kappa_k)_+$. To ensure smoothness of the curve, these weights are *penalized*, i.e. they are subject to the constraint $\sum_{k=1}^{K} {u_k}^2 < U$, for some constant U (see Ruppert, et al., 2003, pp. 65-67, for more details). This weighting mechanism is the reason why splines are called penalized splines. The number of knots K is taken large enough to ensure the flexibility of the curve. The level of smoothing of the penalized splines is controlled by the variance of u_k, i.e. σ_u^2 . A large variance corresponds to a wiggly function, while a small σ_u^2 yields a smooth function. Note that the variance is estimated using maximum likelihood (Wand, 2003).

The segment-specific function f_{st}, see Equation (1), is written as a penalized spline

$$f_{st} = \beta_s t + \sum_{k=1}^{K} u_{sk}(t-\kappa_k)_+ \tag{3}$$

with fixed slope parameters β_s and random coefficients $u_{sk} \sim N(0, \sigma_u^2)$. It can be interpreted as the average penetration pattern observed in the country segment *s*. This component reflects the regularities in the penetration patterns that new products exhibit in this specific country segment. In turn, deviations for product *j* from the segment-specific function are modeled similarly as

[2] The notation $h(x) = (x)_+$ indicates that the function h equals zero when $x < 0$ and equals x for $x \geq 0$.

$$g_{sjt} = \alpha_{sj} t + \sum_{k=1}^{K'} v_{sjk}(t - \kappa_k)_+ \tag{4}$$

with the random parameters $\alpha_{sj} \sim N(0, \sigma_\alpha^2)$ and $v_{sjk} \sim N(0, \sigma_v^2)$.

The above formulation treats products as being nested into segments and therefore accounts for product-segment interaction effects. It allows the product-specific deviations to vary across country segments. Controlling for the product deviations allows us to define an international segmentation solution generalizable to the set of product categories considered, making abstraction of the product-specific peculiarities, as well as the non-informative variation in the data (e.g. measurement error). Note that the resulting country segments may be different if one considers a different pool of product categories (e.g. high tech products versus kitchen and laundry appliances). For firms, the best approach would be to consider their product divisions and pool across all products of each respective division.

Parameter Estimation

The model parameters are estimated using maximum likelihood and computed using the Expectation-Maximization (EM) algorithm. We refer to Zucchini and MacDonald (2009) for details on the EM algorithm applied to the hidden Markov model.[3] The outline is as follows. Denote $\boldsymbol{\theta}$ the vector collecting all unknown parameters of the model, including the initial state probabilities and the transition probabilities, and the unknown f_{st} and g_{sjt}. Assume that, at the k^{th} step of the algorithm, we have an estimate $\boldsymbol{\theta_k}$ at our disposal. In addition, P_k and L_k are the probabilities and likelihood assuming that $\boldsymbol{\theta} = \boldsymbol{\theta_k}$. In the E-step, we compute (i) the *posterior segment membership probabilities*, $P_k(s(i,t) = s | \boldsymbol{y_{i1}}, \dots, \boldsymbol{y_{iT}})$, i.e. the probability to belong to segment s at time t for country i, conditional on the observed time series and (ii) the *posterior segment transition probabilities*. These posterior probabilities can be computed efficiently using the Baum-Welch forward-backward algorithm (Baum et al. 1970, see

[3] Most textbooks only present the homogenous version of the HMM, where the transition probabilities are not time-dependent. We carefully adapted all formulas – in particular of the Baum-Welch algorithm - to the non-homogeneous case. For brevity, we only report here the most important ingredients of the EM algorithm. Full details are available from the first author upon request.

also Paas et al., 2007). By averaging the posterior probabilities $P_k(s(i,1)=s|\boldsymbol{y_{i1}},\dots,\boldsymbol{y_{iT}})$ over all countries, we obtain an update of the estimates of the initial state probabilities π_s for $s=1,\dots,S$. Similarly, by averaging the posterior segment transition probabilities over all countries, we get an update of the transition probabilities $\pi^t_{s_t s_{t+1}}$. In the M-step, we maximize the expected log-likelihood, leading us to maximize

$$\sum_{i=1}^{n}\sum_{s_1=1}^{S}\dots\sum_{s_T=1}^{S}P_k(s(i,1)=s_1,\dots,s(i,T)=s_T|\boldsymbol{y_{i1}},\dots,\boldsymbol{y_{iT}})\log L_k(\boldsymbol{y_{i1}},\dots,\boldsymbol{y_{iT}}|s_1,\dots,s_T) \tag{5}$$

with respect to the unknown parameters f_{st} and g_{sjt} appearing in the likelihood, and yielding a new estimate $\boldsymbol{\theta_{k+1}}$. Maximizing the expected log-likelihood corresponds to computing a weighted maximum likelihood estimator. Alternatively, the observations can be randomly assigned to the latent states, according to the posterior probabilities of the state paths. The standard estimators are then computed from the data allocated to the different states. This approach is called the Stochastic Expectation-Maximization (SEM) algorithm, and was first proposed by Celeux & Govaert (1991). We then iterate the E and the M steps until convergence of the model fit criteria. We start the algorithm with equal posterior latent segment membership probabilities $1/S$, and equal latent posterior transition probabilities $1/S$, for $t=1,\dots,T-1$.

Note that our model-based segmentation provides richer information than "hard" clustering algorithms (e.g. *k*-means), as it gives probabilities for each country to belong to each of the various segments at every time point.

Model Fit Criteria and the Optimal Number of Segments

As commonly done in segmentation analysis (see e.g. Wedel & Kamakura, 2000), we evaluate the fit of the model by computing the Bayesian Information Criterion (*BIC*) based on the estimated likelihood given in equation (2) and the total number of free parameters in the model (Greene, 2003, p. 160). The latter include the transition probabilities and starting probabilities, and the parameters in the specification of the segment curve (equation 3) and the product-deviation curve (equation 4). In the context of our semiparametric mixed-effect model, we compute the number of free parameters following the approach proposed by Vaida and Blanchard (2005, see also Ruppert, et al., 2003), yielding a number ranging between the sum of the number of fixed effects and variance components and the sum of the number of fixed and random effects.

In addition to the Bayesian information criterion, we also evaluate the separability of the segments as well as the stability of the segmentation to changes in the data (i.e. its robustness). The normalized entropy criterion (NEC) can be computed to investigate the degree of separation in the posterior probabilities (Grover & Vriens, 2006, pp. 402-403, 416). The lower the NEC, the better the segments are separated from each other. In addition, a value smaller than one indicates that the segmentation structure found does exist (Biernacki, Celeux & Covaert, 1999).

To study the stability of the segmentation to changes in the data, we apply the model explorer algorithm of Ben-Hur, Elisseeff & Guyon (2002), which makes use of the following cross-validation. We randomly split 10% of the countries and apply the model to the remaining 90%. Repeating this operation 10 times, we obtain 10 different segmentations, of which pairwise similarity indices are computed using the popular Adjusted Rand Index (ARI) generalized to probabilistic segmentation (Hubert & Arabie, 1985; Anderson, et al., 2010). It takes values between -1 and 1, where 0 means that the clustering is due to chance, and 1 indicates a perfect similarity. A high average similarity index translates a high stability of the segmentation.

To select the optimal number of segments, we compute these statistics for different numbers of segments S and the model yielding the most satisfactory fit, separability and stability is selected.

3.2. Forecasting Procedure

Country segmentation can be a powerful instrument for prelaunch forecasts. Prior to its first launch, firms do not observe any product-specific information on actual adoption of the new product or product category. In those cases, they can either rely on test market data, consumer surveys or "clinics" (Blattberg & Golanty, 1978; Urban, Hauser, & Roberts, 1990), on advance purchase orders (Moe & Fader, 2002), and/or on available sales or adoption history of similar products introduced in the past using analogical diffusion models (Lee, Boatwright, & Kamakura, 2003; Ofek, 2005). For international markets, one can also pool the information on similar products across multiple countries, rather than using the information in the single country (Talukdar, Sudhir, & Ainslie, 2002). In such context, country segments should indicate the relevant set of countries to be considered in prelaunch forecasting. If the premise we made above – information that is contained in dynamic segments of countries is richer than information contained in static segments of countries or in single countries – is correct, then the dynamic segmentation method we introduced above should outperform alternative methods based on static segments of countries or past patterns in single countries. This idea is similar to the spatial model proposed by Bronnenberg and Sismeiro (2002) that infer data in markets where no or little data is available using information available in other geographic locations.

Segments can be used to make prelaunch forecasts in the following two ways, depending on (i) whether forecasts are made before a new product (category) is launched for the very first time (i.e. is not available in any country yet), or (ii) whether forecasts are made before a new product (category) is launched in a given country (*local launch*) but has been already launched in other countries before.

Forecasts before First International Launch

Before a new product (category) j_0 is launched for the very first time, we predict its penetration in country i at duration time t (i.e. t years after launch) as the value at t of the segment-specific curve country i belongs to. Forecasts can be obtained for all prediction horizons in this fashion. In case of dynamic segments, the set of similar countries used to build forecasts changes over the product life cycle as segment membership is now time-varying. If the segmentation is probabilistic as it is the case for our proposed HMM, the predicted curve for the focal country i refers to a weighted average of all segment-specific curves. That is,

$$\hat{y}_{ij_0t} = \sum_{s=1}^{S} w_{ist}\,\hat{f}_{st}, \tag{6}$$

where $\hat{f}_{st}$ is the estimate of the segment-specific curve for segment s. The weights w_{ist} are the posterior probabilities for the focal country i to belong to the given segment at the corresponding time t, so $w_{ist} = P(s(i,t) = s|\boldsymbol{y_{i1}}, \dots, \boldsymbol{y_{iT}})$ as resulting from the EM algorithm.

Forecasts before Local Launch

Companies often make use of waterfall entry strategies, by spreading national introductions over a given time span. In this context, it is possible to use experience from previously-entered markets to improve our forecasts. Specifically, in case the focal country i is not the first international entry and the product (category) j_0 has been introduced in similar countries, i.e. in countries belonging to the same segment, we make forecasts in focal country i using penetration data of the segment's member countries. Again, in case of dynamic segments, the set of similar countries used to build forecasts changes over the product life cycle. Denote $\bar{y}_{sj_0t}$ the average penetration level in all previously-entered countries that belong to segment s for product j_0, and for which data is available at time t. We predict the penetration of product j_0 in country i at time t as the following weighted average

$$\hat{y}_{ij_0t} = \sum_{s=1}^{S} w_{ist}\,\bar{y}_{sj_0t}. \tag{7}$$

where the weights are defined as in equation (6).

3.3. Benchmarks

We evaluate the fit and forecasting performance of our semiparametric hidden Markov model for dynamic segmentation against a number of benchmarks. Benchmarks are chosen such that we can assess the contribution of each of the dimensions characterizing our approach:

(i) *Semiparametric vs. parametric response model*;

(ii) *Multi-country vs. single-country segments*;

(iii) *Model-based vs. a priori-defined segmentation*;

(iv) *Dynamic vs. static segments*.

The various benchmarks are listed in Table 1 and are subsequently described in turn.

Insert Table 1 about here

Semiparametric vs. parametric response model

First, we assess whether our semiparametric splines-based HMM yields a better fit and forecasting performance than a parametric variant. To do so, we replace the segment-specific and product-deviation response functions in equation (1) by parametric equivalents. We use the Bass (1969) mixed-influence model. For completeness, we also implement each of the methods below in a parametric and semiparametric way, such that we can assess the systematic contribution of the *p*-splines approach, through all approaches.

Multi-country vs. single-country segments

Second, we assess whether grouping countries into segments (multi-country segments) yields a better fit and forecasting performance than considering each country as a separate segment (single-country segments). A so-called *single-country segments* model with one country per segment can be represented by equations (3) and (4), where the segment-specific parameters are replaced by country-specific parameters. A parametric and a semiparametric version are considered. Note that the parametric version is equivalent to the multi-product, multi-country, Bass model proposed by Talukdar et al. (2002), without covariates. The resulting segmentations are static, as the segmentation membership is constant over time.

Model-based vs. a priori-defined segmentation

Third, we assess whether model-based segmentation yields a better fit and forecasting performance than a-priori segmentation. To do so, we replace in equations (3) and (4) the segment-specific parameters by geographic region indices, yielding *a priori-defined segments*. We follow the geographic classification established by the United Nations Statistics Division: Africa, (South-Eastern) Asia, Eastern Europe, Latin America, Middle East (Western, Central and Southern Asia), North America, Oceania, and Western Europe. Table 2 depicts a list of all countries in our study according to geographic region. Segments are static as the segmentation membership is constant over time.

Insert Table 2 about here

Dynamic vs. static segments

Fourth, we assess the relevance of allowing for segment dynamics by comparing the proposed hidden Markov models to finite-mixture models, further denoted as *static segments*. Countries are not allowed to change segment membership over time. We implement a parametric finite-mixture Bass model as proposed by Helsen, et al. (1993) as well as a semiparametric finite-mixture splines model, in the same spirit as the functional clustering approach suggested by James and Sugar (2003).

Note that all models are implemented within the same framework. The parametric models are obtained by replacing in (1) the segment (and product) curves by the Bass diffusion function, depending on 3 segment- (and product-) specific parameters. The *single-country segments* approach corresponds to $S = N$ segments; i.e. each country is a singleton segment. The a-priori segmentation replaces the probabilities in (2) by an indicator of the known cluster membership. Finally, the finite-mixture model is a special case of the HMM, where the transition matrix is diagonal. In total, 8 different models are obtained and cover all possible cases. Note that we do not need a full factorial design of 2^4 combinations as the 8 omitted combinations of factors are impossible cases (e.g. single-country segments are by nature not model-based segments, nor dynamic; a priori-defined segments are not dynamic). When the segmentation is model-based, the number of segments, as reported in the second column of Table 5, is selected according to the BIC criterion.

4. Data

We gathered annual data on the percentage penetration of six new product categories, among households, in 79 countries. The data source is Euromonitor. The new product categories are ICT products and media devices, and we therefore expect them to exhibit similarities in their penetration patterns. They include CD players, DVD players (including DVD recorders), home computers, Internet subscriptions, mobile phones, and cable television. As we define penetration as the number of devices or subscriptions used by a population divided by the number of users (member households or individuals), penetration can supersede 100% (i.e., when users own multiple devices) and can decrease (i.e., when users disadopt). The set of 79 countries (see Table 2) is global – consisting of Western and Eastern European, North and Latin-American, African and Middle East countries – and thus contains both developing and developed countries as recommended by Burgess and Steenkamp (2006).

The database covers the period 1977-2009. Since the various technologies are introduced at different times during this period, the starting date of each series differs across product categories and countries. Note that we observe a maximum of 25 years of data per product-country combination.

Several technologies have presumably not reached half of their market potential in 2009 as there is no inflection point within the data range. In total, we have data on 398 product-country combinations. We have full country coverage for DVD players, Internet subscriptions and home computers while some countries are missing for CD players, mobile phones and cable television.

5. Results

In this section, we first present the results of the dynamic segmentation model applied to the aforementioned set of new product categories. Next, we demonstrate the superior fit and forecasting accuracy of the dynamic segmentation method, as compared to the benchmark methods introduced above.

5.1. Dynamic Country Segments in New Product Growth

We estimate the semiparametric hidden Markov model for different numbers of segments. In order to determine the appropriate number of segments, we compute various model performance statistics (see the methodology section), including (i) the overall fit using the Bayesian information criterion (BIC), (ii) the separability of the segments using the normalized entropy criterion (NEC) and (iii) the stability of the segmentation solution using adjusted Rand index (ARI). All results are reported in Table 3. The lowest BIC and NEC are obtained using a 3-segment solution. As to the ARI, the 2-segment and 3-segment solutions give the highest stability to changes in the data. Therefore, we opt for the 3-segment solution.

Insert Table 3 about here

Figure 2 shows the segment-specific penetration pattern for these three latent segments. We subsequently label the segments according to the level of the dependent variable as "low-penetration" (segment 1), "mid-penetration" (segment 2) and "high-penetration" (segment 3) segments. The low-penetration segment exhibits a slow growth during the complete time range, with penetration levels reaching about 40% of the households 25 years after introduction. The mid-penetration segment shows higher growth rate than the first segment, in particular when the product category is for more than 8 years on the market. Finally, the high-penetration segment shows a substantially faster and higher diffusion during the complete time range. Penetration in the high-penetration country segment accounts for 80% of the households after 25 years.

To assess the reliability of the estimates of the segment-specific functions, we use the parametric bootstrap procedure described in Zucchini and McDonald (2009, p. 55). The bootstrap procedure captures both the uncertainty in the segment membership as in the estimation of the segment-specific curves. We obtain an estimate of the covariance matrix of the estimator and compute the standard error of the difference between each pair of estimated curves. The resulting t-statistic values over the product life cycle (see Appendix) confirm that the high-penetration segment exhibits consistently superior penetration levels than the other segments during the complete time range, while the low- and mid-penetration segment curves only become significantly different from each other for a time horizon longer than 8 years after introduction. At early stages of diffusion, the information in the data is still too scarce to be able to clearly distinguish segments; penetration is low in both segments. This is confirmed by Table 4, where transition probabilities between these two segments are higher than 40% during the first 5 years after launch. As time goes by, these two segments become more distinct. This is confirmed again by Table 4, where we can see that the transition probabilities between 6 and 15 years after introduction become much lower.

Insert Figure 2 about here

Specific to our dynamic segmentation approach, we observe countries changing segments over the product life cycle. Those changes are governed by the time-varying transition probability matrices. Table 4 reports average transitions probabilities (in percentage) between segments, as well as their standard deviations, during three consecutive time spans: year 1 to year 5, year 6 to year 15, and year 16 to year T(=25). The matrices provide information on the *stickiness* in each segment over time. In particular, diagonal elements indicate how likely countries are to stay in the same segment over the product life cycle. In contrast, the non-diagonal elements capture the existing dynamics in segment membership. We find that dynamics in international market segmentation of new product is most pronounced at the beginning of the product life cycle. When product categories become more mature, the dynamics in segment membership decreases. In comparison to the low- and mid-penetration segments, the high-penetration segment shows little dynamics. Most segment switches occur between the low- and mid-penetration segments and most switches occur between neighboring segments, e.g. between segment 1 and 2 but rarely from segment 1 to 3.

Insert Table 4 about here

As countries switch segment over the product life cycle, segment membership probabilities evolve, as depicted by Figure 3. Figure 3 reports the evolution of the prior membership probabilities among the three segments. Interestingly, we find that the high-penetration segment (segment 3) is small (in terms of the number of members) during the first years of the product life cycle and gradually gains in size as product categories mature. In contrast, the low-penetration segment starts as the largest segment and gradually loses members over time. Finally, the size of the mid-penetration segment shows much less variability. For mature product categories, country segments have similar sizes.

Insert Figure 3 about here

Beyond the prior segment membership probabilities, we also estimate for each country in our data the time-varying posterior segment membership probabilities per country, i.e. the probability for each country i to belong to segment s at time t. Figure 4 reports these membership probabilities among 6 leading industrial nations: USA, United Kingdom, Japan, Germany, France and Italy, while Figure 5 reports the probabilities among 6 leading emerging markets: Brazil, Russia, India, China, South Africa and Mexico, often referred to as the BRICS+M countries. Collectively, these 12 countries capture more than half of the world's population and economic activity.

Those figures nicely illustrate how countries stochastically switch between segments over time and allow the reader to visualize the most likely state path of each country. In general, we observe three different types of paths in our data set. Some countries belong to the high-penetration segment with a very high probability during the complete time span (except maybe for the first few years after introduction), therefore showing little membership dynamics over time. This is the case of the 6 leading industrial nations in Figure 4, but also of most West European countries (Austria, Belgium, Finland, Ireland, the Netherlands, Norway, Portugal, Spain, Sweden and Switzerland), Canada, Australia and New Zealand, and the most developed South East and Middle East nations (Bahrain, Hong Kong, Israel, Kuwait, South Korea, Taiwan, United Arab Emirates).

Another set of countries tend to switch between the low- and mid-penetration segments during the first 6-7 years after introduction and subsequently end up in the mid-penetration segment in later periods. This is the case of Russia, China and South Africa in Figure 5, but also of many Eastern

European countries (Bosnia-Herzegovina, Bulgaria, Czech Republic, Estonia, Hungary, Lithuania, Slovenia), but also a few other nations from the Middle and South East (Kazakhstan, Qatar, Saudi Arabia) and Latin America (Columbia and Costa Rica).

Finally, a last set of countries show comparable probabilities to belong to (and therefore tend to switch between) the low- and mid-penetration segments during the first 6-7 years after introduction but then tend to remain in the low-penetration segment after this period. This is the case of Brazil, India and Mexico in Figure 5, but also of the less-developed or developing economies from various parts of the world mostly Latin American countries (Argentina, Chile, Dominican Republic, Peru and Venezuela), but also many African countries (Algeria, Cameroon, Egypt, Morocco, Nigeria, Tunisia), and some Eastern European (Belarus, Croatia, Georgia, Poland, Romania, Slovakia and Ukraine), Asian (Indonesia, Philippines and Vietman) and Middle Eastern countries (Iran, Jordan, Pakistan, Turkey and Turkmenistan). Our results are in line with Dekimpe, Parker and Sarvary (2000), Van den Bulte and Stremersch (2004), and Van Everdingen et al. (2009), among others, who find adoption timing of new products to be negatively correlated with Gross Domestic Product.

Insert Figures 4 and 5 about here

To conclude the investigation of the results, we compare the fit of our dynamic segmentation model with the alternative specifications described in section 3.3 and summarized in Table 1. In Table 5, we report the Bayesian Information Criterion (*BIC*), log-likelihood and the number of segments chosen for each model. First, our results show that a semiparametric specification leads to a better fit performance in terms of BIC than its parametric counterpart. The flexibility of semiparametric models pays off. The only exception is for the *single-country segments* case because of BIC penalizes for the high number of country-specific parameters involved in the semiparametric model. However, the fit performance of the *single-country segments* models remains inferior to the performance of all *multi-country segments* models.

Second, our results clearly indicate that the model-based segmentation approaches (i.e. the static and dynamic segments) outperform in fit the a priori-defined regional segments, both for the parametric and semiparametric versions. Such findings support current knowledge in marketing research that domain-based segmentation bases should be favored in comparison to general segmentation bases (Steenkamp & Ter Hofstede, 2002).

Third, the fit comparison also shows that the semiparametric dynamic segmentation approach yields the best fit performance of all specifications.

Insert Table 5 about here

To conclude, the semiparametric dynamic segmentation we propose shows superior in-sample fit, as compared to the other models. In the next section, we will assess the hold-out predictive performance of our approach.

5.2. Prelaunch Predictive Performance

We assess the relative predictive performance of the dynamic segmentation against the alternative approaches described in section 3.3. The prediction task consists of forecasting the future penetration levels reached by a new product category in each country before its launch time in this country. All forecasts are made prior to introduction and for various prediction horizons (further denoted h), where h ranges from 1 year until 5 years after launch (i.e., 5 years-ahead forecasts).

For forecasts made before the first international launch, no information on the actual adoption of the new product is available yet. If we denote $\tilde{t}_{ij_0}$ the year when a new product j_0 is introduced in country *i*, the *estimation sample* to forecast penetration of product j_0 in country *i* at prediction horizon *h* only includes the penetration data of other products available prior to $\tilde{t}_{ij_0}$. In other words, we cut our data sample according to calendar time at $\tilde{t}_{ij_0}$. All data corresponding to the years after product j_0 has been launched in country *i* do not belong to the estimation sample.

For subsequent entries (all countries entered later than the first country entered), some information on the product's actual adoption becomes available. More specifically, the *estimation sample* to predict penetration of a new product j_0 in a subsequent entry i' at prediction horizon *h* also includes penetration data on product j_0 in previously-entered countries up to the introduction time in the focal country i'. As *hold-out sample*, we use the penetration of product j_0 in the focal country for all available years. Thus, for each product-country combination, we construct a different estimation and hold-out sample, divided according to calendar time. Such a framework replicates the data context practitioners face when making prelaunch forecasts.

As the idea is to use penetration data of older product categories to forecast penetration of new product categories, we focus in the analysis on the most recent product categories in our data set, that is DVD players and Internet, which have been both introduced in the nineties. We assess the predictive accuracy of each method by computing the mean absolute deviation (*MAD*) between the predicted value and the actual value across all countries per prediction horizon. Table 6 reports the average MAD of the prelaunch forecasts for all methods per product category over various prediction horizons, from *h* = 1 to *h* = 5. In practical terms, the MAD can be interpreted as the average absolute deviation from the actual penetration level. For instance, a MAD = 1.00 indicates that our forecasts deviate from the actual penetration level with 1.00 unit(s). If the actual penetration is 20 (% of the households), the corresponding forecast are on average between 19 and 21 (% of the households). The best method is reported in bold for each product category. Note that, in Table 6, the results for the forecasts made before the first international launch and before a local launch are lumped together in order to compute the MAD.

Insert Table 6 about here

The out-of-sample forecasting comparison supports four main conclusions. First, semiparametric models give more accurate forecasts than parametric models based on the Bass specification. Second, relying on multi-country segments rather than single countries generally improves prelaunch forecasts. This indicates that segmentation allows identifying similar countries and helps the analyst to decide how to account for data available in other countries. Information is thus gained by pooling across countries. For DVD players, forecasts made at the multi-country segment level mostly outperform forecasts made using country-specific information in one country only. For Internet subscriptions, it is also the case for the semipararametric models, while all parametric models perform quite poorly. Third, we do not find substantial differences in forecasting performance between the a priori-defined segments and the static model-based segments. Fourth, dynamic segments give better forecasts than static segments, confirming that there is substantial dynamics in country segment membership, which static segmentation approach do not account for.

In practical terms, our dynamic segmentation method yields low average absolute forecast deviations both for DVD players and Internet subscribers. For the former, we find that our forecasts deviate with only .64 unit(s) (i.e. 0.64 % of the households in the country) from the actual penetration levels 5 years after introduction. As for Internet subscriptions, the dynamic segmentation offers forecasts that deviate with 2.22 units (i.e. 2.2 % of the households in the country) on average from the actual penetration level 5 years after introduction.

In sum, the semiparametric dynamic segmentation approach offers the lowest forecast errors for all prediction horizons for both product categories, suggesting that country segments show substantial dynamics and that the flexible semiparametric specification of the penetration pattern is appropriate. These results are particularly encouraging knowing that forecasting the first five years after launch is probably the most crucial for managers when they plan to launch a new product on the market.

6. Conclusions and Discussion

Recent calls in the marketing literature advocate the need for a dynamic modeling framework when approaching non-stationary marketing phenomena (e.g. Pauwels et al., 2004; Lemmens, Croux & Dekimpe, 2007), such as new product adoption. Also in the country segmentation literature, Steenkamp and Ter Hofstede (2002) have cautioned that the static nature of the current international segmentation methods limits their usefulness.

In this paper, we apply a new dynamic segmentation methodology, based on semiparametric modeling, to six new product categories in 79 countries and show that, in this sample, country segments in new product growth are dynamic and not static. Our approach makes it possible to identify markets that are homogeneous during a given part of the product life cycle. We find that country membership to segments varies over the product life cycle and that accounting for this time variation provides superior prelaunch forecasts. Therefore, we recommend international firms and international public policy bodies, such as, e.g. analysts at the European Commission or at the United Nations, interested in understanding cross-national differences in innovativeness and in making global forecasting reports, to reconsider their current practice, and adopt a dynamic segmentation instead of an exogenously-defined regional segmentation, or if more sophisticated, a static model-based segmentation method. To do so, they should also consider cautiously the set of products or product categories to use as reference (i.e. estimation sample) when deriving dynamic segments. This choice is likely to affect the outcome of the segmentation and should therefore be made with care. In our data, we find a substantial amount of heterogeneity across products, which we captured by the product-deviation function.

Our research can be extended in multiple ways. First, our dynamic segmentation is done at the aggregate level, and our method identifies countries, rather than consumers, that share similar penetration patterns. Country-level analysis conveys a number of advantages, such as the excellent availability of data at the country level and the good accessibility and cost-effectiveness through centralization of the resulting country segments. At the same time, country segments also suffer from a number of limitations. They overlook the differences that exist between consumers within these countries and ignore potential horizontal consumer segments that cross national borders. Country segments also tend to be less responsive to marketing efforts than disaggregated consumer segments (Steenkamp & Ter Hofstede, 2002). An interesting avenue for future international segmentation research is to collect individual (adoption) data for an international sample of consumers for cross-national dynamic segmentation purposes. One could also extend our methodology, in the same spirit as Bijmolt, et al. (2004) in order to combine country and consumer segments.

Second, our approach makes abstraction of the role of country-specific and product-specific characteristics that might partially underlie the diffusion processes. For instance, the observed penetration level in one country can be influenced by the adoption in neighboring countries (cross-country spillover effects, lead-lag effects, etc.). Similarly, influences can also occur between products, as it would for instance be the case in presence of competitive or substitution effects for multi-generational technologies (Islam & Mead, 2010). While such effects are out of the scope of the present research, it would be a fruitful research goal to study their role on diffusion by including them at two levels of the hidden Markov model: (i) either in the response component of the HMM, as additional covariates and/or (ii) in the specification of the transition probabilities, in the same manner as proposed by Netzer et al. (2008).

Third, we show that country segments are intrinsically dynamic, but the question remains how the complexity of the segments that these methods yield can be absorbed by managerial practice. Therefore, more research is needed to apprehend how organizations could structure themselves conveniently to have more dynamic international structures.

Overall, our dynamic segmentation framework opens multiple opportunities to tackle non-stationary phenomena in marketing where segmentation is needed. As the increasing number of studies in this area testifies, modeling marketing dynamics is without any doubt one of the important research areas in marketing science in the next decade.

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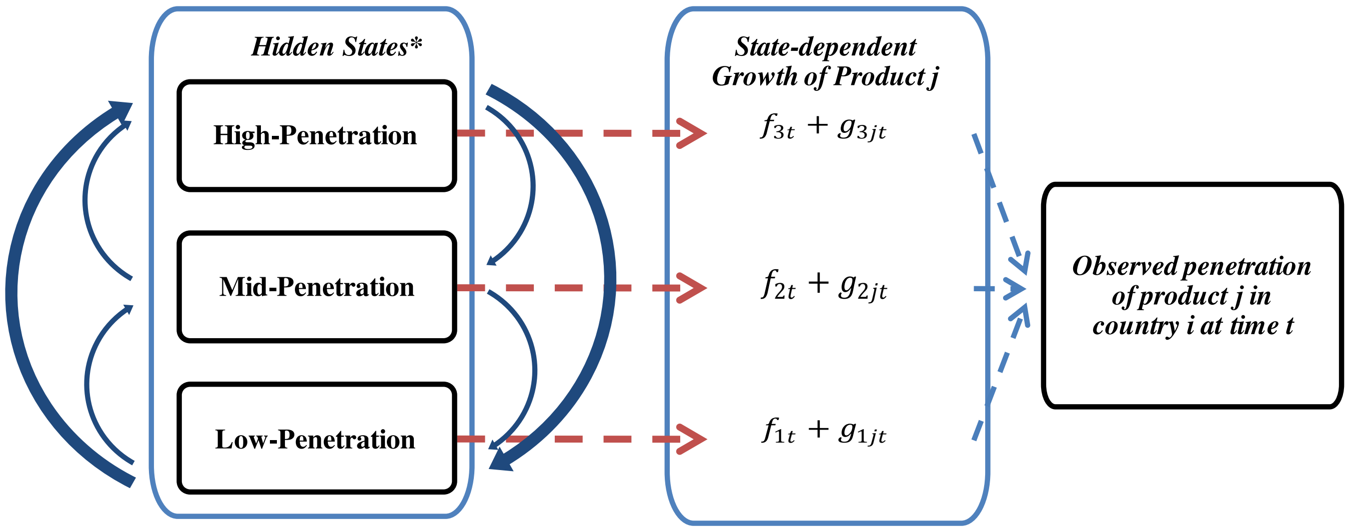
Figure 1:

A Three-States Hidden Markov Model of New Product Growth



* Example of a 3-states hidden Markov model. The curved solid lines represent the transitions between states.

Figure 2:

Segment-Specific Penetration Patterns of the High-, Mid- and Low-Penetration Segments

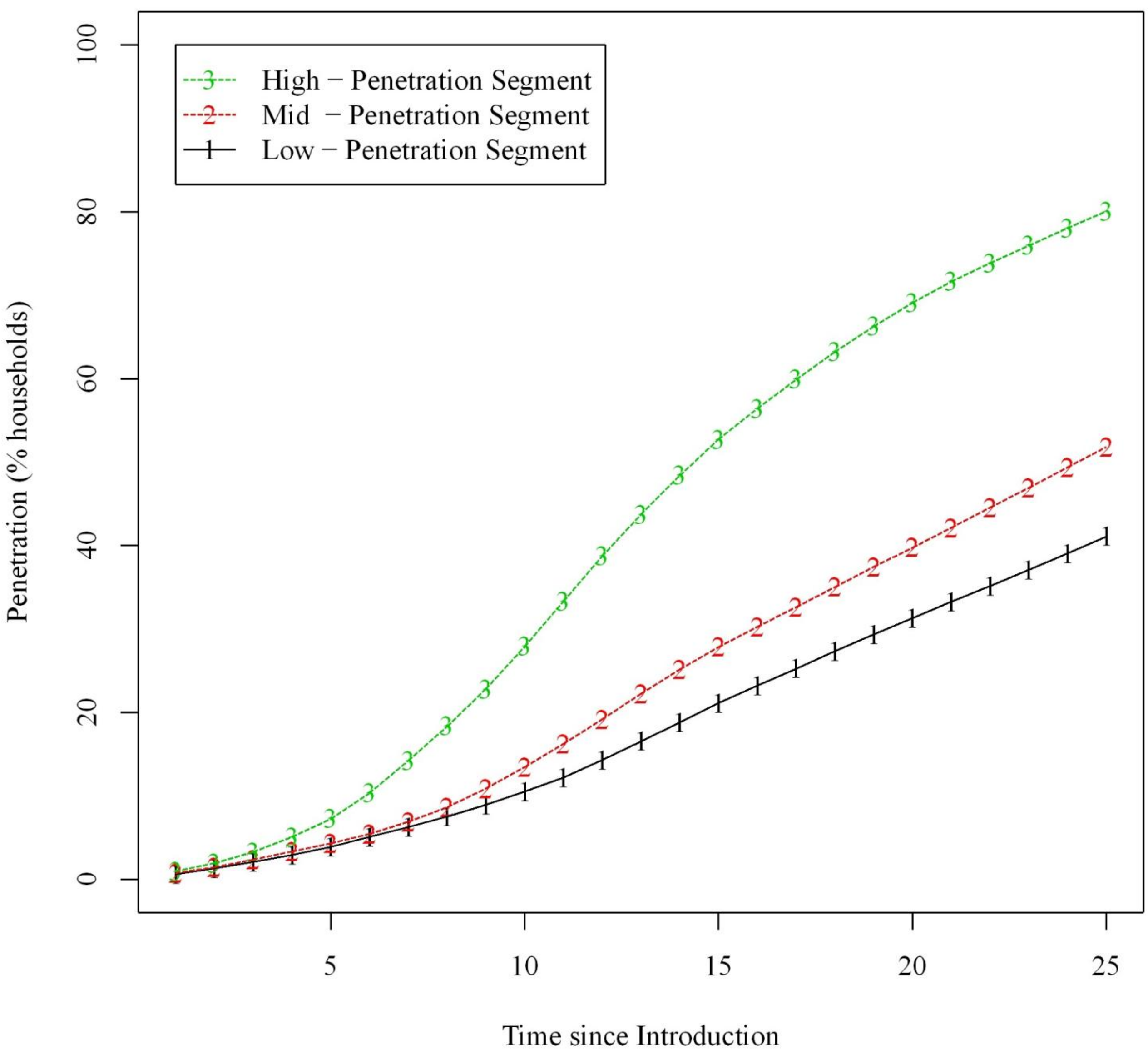


Figure 3:

Evolution of the Prior Segment Membership Probabilities

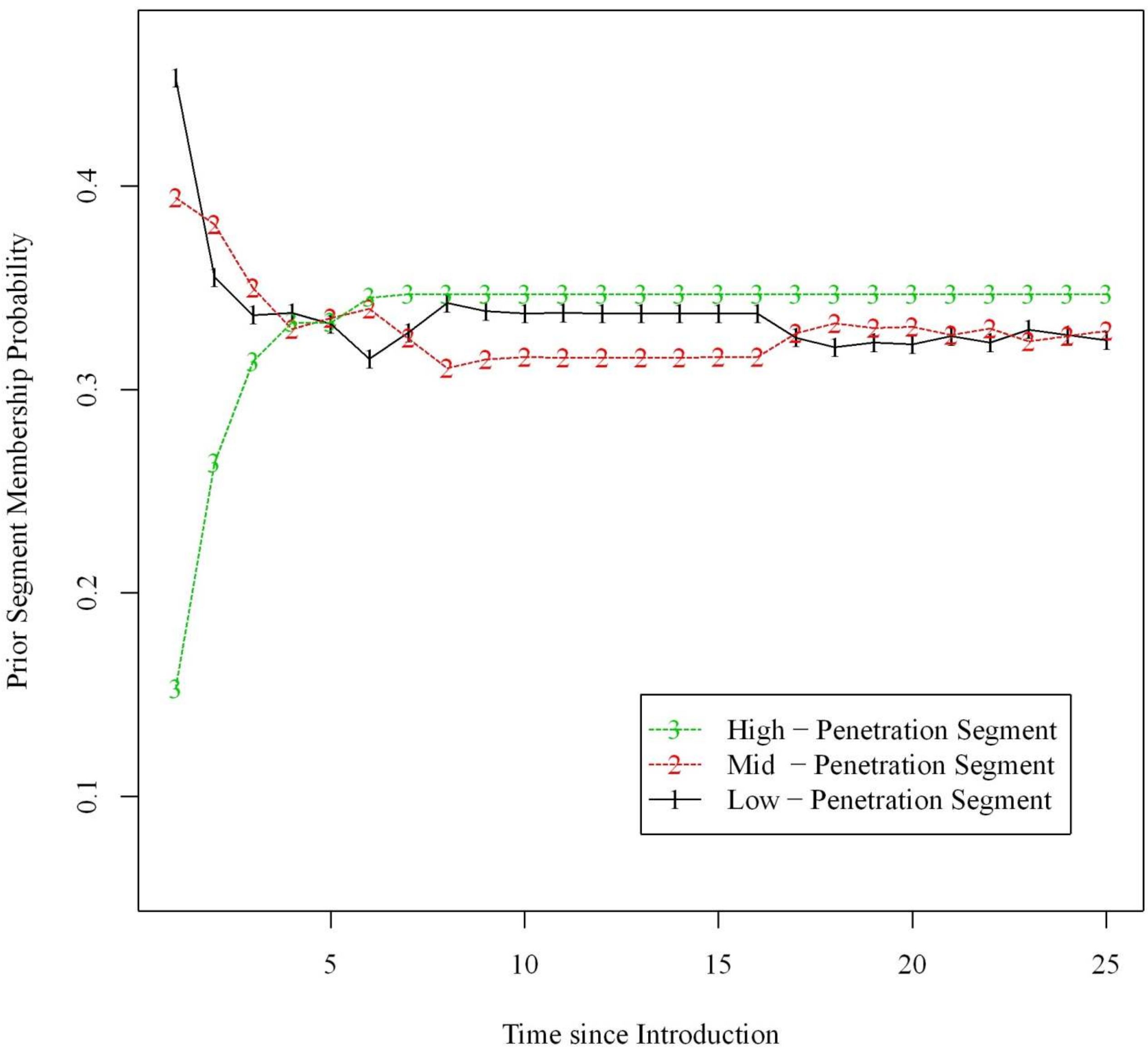


Figure 4:

Dynamic Segment Membership Probability Path for 6 Leading Industrial Nations: USA, United Kingdom, Japan, Germany, France and Italy. Labels indicate (1) the low-penetration segment, (2) the mid-penetration segment and (3) the high-penetration segment.

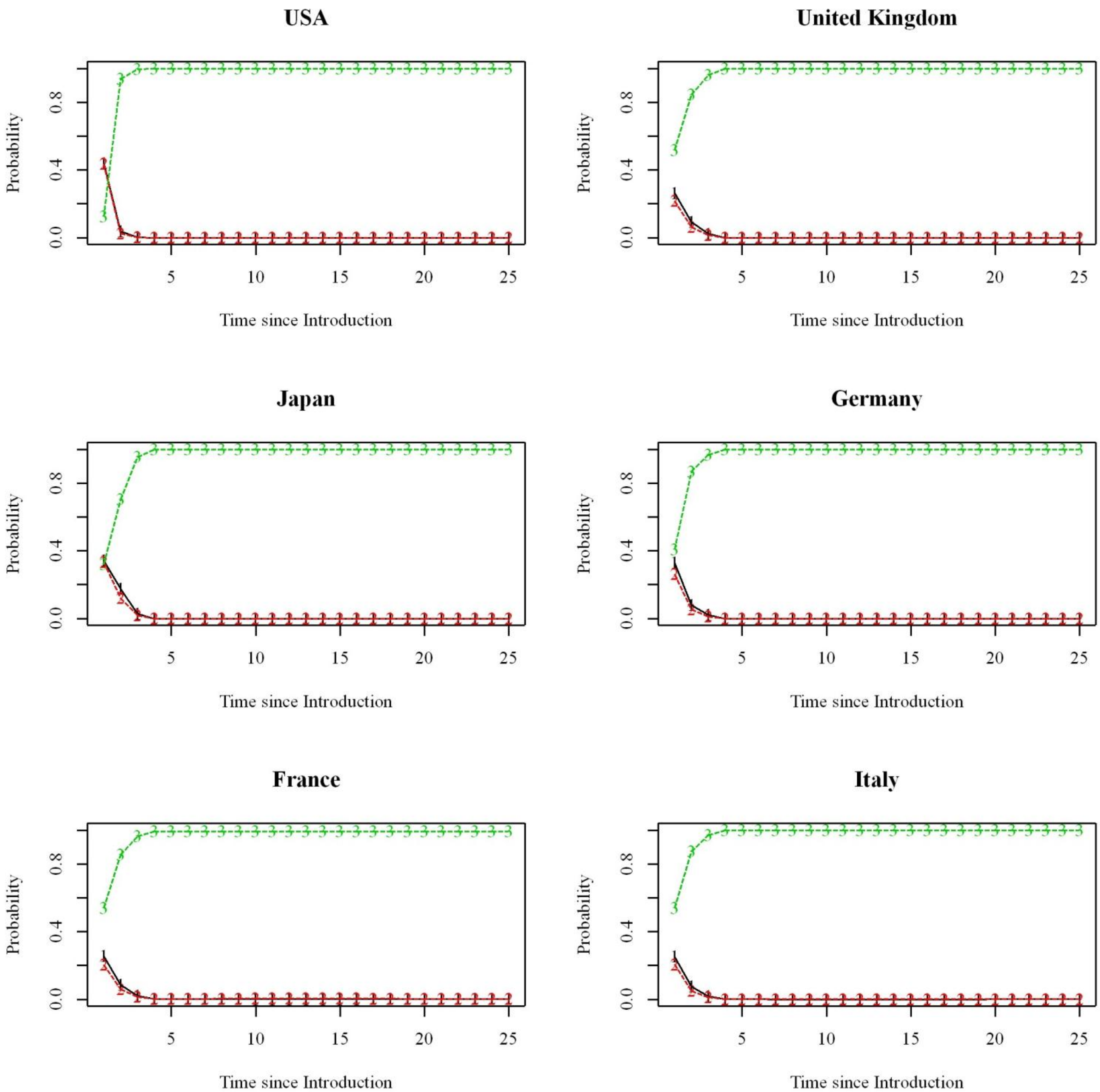


Figure 5:

Dynamic Segment Membership Probability Path for 6 Leading Emerging Markets: Brazil, Russia, India, China, South Africa and Mexico. Labels indicate (1) the low-penetration segment, (2) the mid-penetration segment and (3) the high-penetration segment.

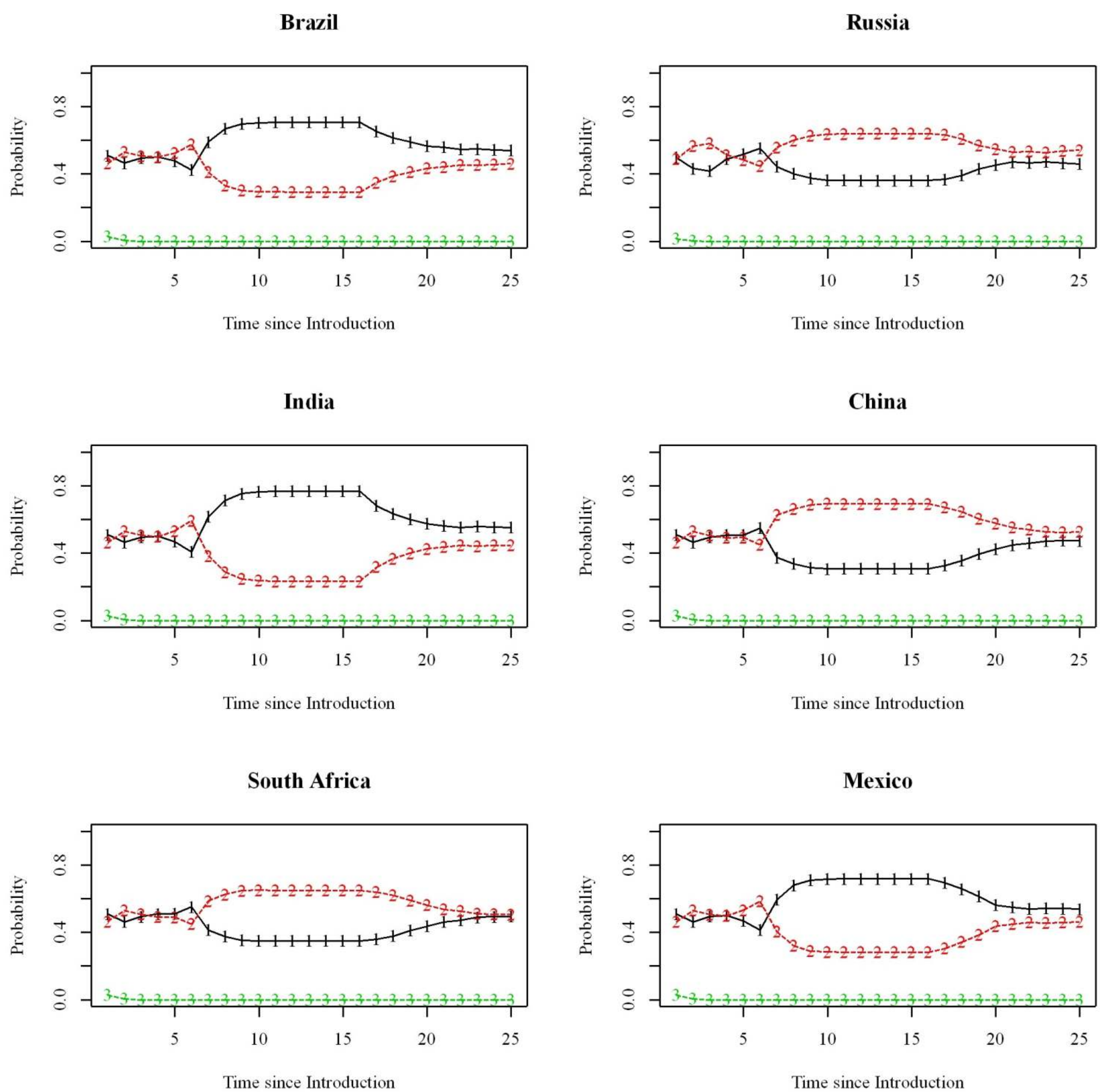


Table 1:

Model Comparison

Models	***Semiparametric vs. Parametric Response Model***	***Multi-Country vs. Single-Country Segments***	***Model-Based vs. A Priori-Defined Segmentation***	***Dynamic vs. Static Segments***
<u>Benchmarks</u>				
Single-country segments	Parametric	Single-Country	A Priori	Static
	Semiparametric	Single-Country	A Priori	Static
A priori-defined segments (geographic regions)	Parametric	Multi-Country	A Priori	Static
	Semiparametric	Multi-Country	A Priori	Static
Static segments	Parametric	Multi-Country	Model-Based	Static
	Semiparametric	Multi-Country	Model-Based	Static
Dynamic segments	Parametric	Multi-Country	Model-Based	Dynamic
<u>Our Proposal</u>				
Dynamic segments	**Semiparametric**	**Multi-Country**	**Model-Based**	**Dynamic**

Table 2:

Included Countries by Geographic Region

Africa	*Asia*	*Eastern Europe*	*Latin America*	*Middle East*	*North America*	*Oceania*	*Western Europe*
Algeria	China	Belarus	Argentina	Azerbaijan	Canada	Australia	Austria
Cameroon	Hong Kong	Bosnia Herz.	Bolivia	Bahrain	U.S.A	New Zealand	Belgium
Egypt	India	Bulgaria	Brazil	Iran			Denmark
Morocco	Indonesia	Croatia	Chile	Israel			Finland
Nigeria	Japan	Czech Rep.	Colombia	Jordan			France
South Africa	Malaysia	Estonia	Costa Rica	Kazakhstan			Germany
Tunisia	Philippines	Georgia	Dom. Rep.	Kuwait			Greece
	South Korea	Hungary	Mexico	Pakistan			Ireland
	Taiwan	Latvia	Peru	Qatar			Italy
	Thailand	Lithuania	Uruguay	Saudi Arabia			Netherlands
	Vietnam	Macedonia	Venezuela	Turkey			Norway
		Poland		Turkmenistan			Portugal
		Romania		U.A.E.			Spain
		Russia					Sweden
		Slovakia					Switzerland
		Slovenia					United Kingdom
		Ukraine					

Table 3:

Model Fit, Segment Separability and Stability for Various Number of Segments

Number of Segments (S)	*Bayesian Information Criterion (BIC)*	*Normalized Entropy Criterion (NEC)*	*Adjusted Rand Index (ARI)*
1	41818	1.00	-
2	38111	0.43	**0.31**
3	**36187**	**0.25**	0.29
4	39441	0.58	0.07
5	46049	5.62	0.02
6	48127	5.17	0.04

Table 4:

Average Transition Probabilities over 3 Successive Time Ranges

(and Standard Deviations within Brackets)

***From t* = 1 to 5 years after introduction:**

	Period *t*		
***t* - 1**	**Segment 1**	**Segment 2**	**Segment 3**
Segment 1	52.06% [0.08]	41.70% [0.03]	6.24% [0.06]
Segment 2	40.89% [0.04]	54.12% [0.08]	4.98% [0.07]
Segment 3	1.68% [0.03]	1.66% [0.03]	96.66% [0.06]

***From t* = 6 to 15 years after introduction:**

	Period *t*		
***t* - 1**	**Segment 1**	**Segment 2**	**Segment 3**
Segment 1	91.42% [0.18]	8.55% [0.18]	0.03% [0.00]
Segment 2	8.94% [0.18]	91.05% [0.19]	0.02% [0.00]
Segment 3	0.00% [0.00]	0.00% [0.00]	100.00% [0.00]

***From t* = 16 to *T years after introduction*:**

	Period *t*		
***t* - 1**	**Segment 1**	**Segment 2**	**Segment 3**
Segment 1	82.63% [0.04]	17.37% [0.04]	0.00% [0.00]
Segment 2	16.79% [0.05]	83.21% [0.05]	0.00% [0.00]
Segment 3	0.00% [0.00]	0.00% [0.00]	100.00% [0.00]

Table 5:

Model Fit Comparison

	Number of segments	*BIC*	*Log-Likelihood*
Parametric Models			
Single-country segments	79	56198	-21680
A priori-defined segments (geographic regions)	8	48658	-23643
Static segments	4	44601	-21926
Dynamic segments	2	44712	-22060
Semiparametric Models			
Single-country segments	79	70211	-11808
A priori-defined segments (geographic regions)	8	41118	-18866
Static segments	4	36331	-17125
Dynamic segments	3	**36187**	-16883

Table 6:

Prelaunch Mean Absolute Forecast Errors (MAD) per Product in the Hold-Out Sample, for Various Prediction Horizons from h = 1 to h = 5 for all Models*

DVD Players:

	h = 1	***h = 2***	***h = 3***	***h = 4***	***h = 5***
Parametric Models					
Single-country segments	0.78	1.14	1.49	1.83	2.15
A priori-defined segments	0.52	0.85	1.30	1.80	2.45
Static segments	0.43	0.70	1.20	1.76	2.55
Dynamic segments	0.37	0.71	1.22	1.77	2.44
Semiparametric Models					
Single-country segments	0.68	1.00	1.32	1.68	2.04
A priori-defined segments	0.27	0.45	0.75	1.07	1.48
Static segments	0.28	0.45	0.72	1.05	1.49
Dynamic segments	**0.15**	**0.23**	**0.32**	**0.48**	**0.64**

Internet Subscribers:

	h = 1	***h = 2***	***h = 3***	***h = 4***	***h = 5***
Parametric Models					
Single-country segments	0.80	1.11	1.41	1.87	2.58
A priori-defined segments	**0.00**	1.35	2.27	3.12	4.03
Static segments	**0.00**	1.58	2.72	3.72	4.75
Dynamic segments	**0.00**	1.16	1.86	2.43	3.06
Semiparametric Models					
Single-country segments	0.68	1.00	1.25	1.62	**2.22**
A priori-defined segments	**0.00**	0.65	1.11	1.66	2.42
Static segments	**0.00**	0.66	1.19	1.84	2.68
Dynamic segments	**0.00**	**0.33**	**0.69**	**1.31**	**2.22**

* The lowest mean absolute deviations (MAD) are given in bold.

Appendix:

Value of the t-Statistic for Testing the Equality between Every Pair of Segment-Specific Curves over Time. The Horizontal Line is the 5% Critical Value.