Demographic Models for Predicting Future Markets

We demonstrate the capability of cohort analysis as a tool to study the evolution of markets and their decomposition into demographic subcomponents using aggregate market penetration data in four fast moving consumer good categories. This paper introduces, benchmarks, and empirically evaluates a Bayesian age-period-cohort approach which overcomes the problem of non-identifiability of parameter estimates in an innovative way. An empirical study shows that this approach newly applied to marketing also allows the analyst to condition the derived model parameters on demographic scenarios for future population projections. Our findings suggest that models which ignore cohort effects tend to underestimate variations in age group-specific forecasts which in turn might result in misleading managerial conclusions. From a methodological perspective, this is one of the first contributions which integrate cohort analysis into demographic population projections in a coherent way to explore and to forecast future trends of consumer markets. We discuss marketing implications and draw conclusions for further research.

Key words: Age-period-cohort decomposition, Bayesian cohort analysis, generational marketing, demographic research, market forecasting

1 Introduction

Demographic shifts, like the aging population in Europe and North-America are reported to have a considerable impact on currently observable (Reisenwitz and Iyer 2009, Pitta and Gurau 2012, Moore 2012, Parment 2013, Pitta et al. 2012) and most likely also on future consumption patterns (Rentz et al. 1983, Rentz and Reynolds 1991, Fukuda 2010). In extreme cases, and in particular if paralleled by ground-breaking technological innovations (e.g., the rise of online media), such demographic shifts entail the potential consequence of vanishing industries and/or product and service categories just to take-off.

To study and to forecast such long-term changes of aggregate purchasing patterns, marketing researchers and analysts traditionally rely on a set of approaches including expert estimates and judgmental methods (Goodwin and Wright 1993, Lim and O'Connor 1996, Rowe and Wright 2001), time series analysis (Dekimpe and Hanssens 2000, Brodie et al. 2001), or diffusion models for the case of new product introductions (Mahajan et al. 1990, Sood et al. 2012). Most of these techniques assume some underlying structural process (like social contagion between innovators and adopters) that drives historical data and utilize this process to carry them forward into the future.

However, even accurate projections on the aggregate level may mask inherent processes that drive substantial changes in the composition of market segments and related customer needs and preferences at the disaggregate level (Noble and Schewe 2003, Schewe and Noble 2000). For example, the ongoing process of so-called "baby boomers" (age cohorts born in the post WW2 era between 1946 and 1964) reaching retirement ages has strong marketing implications, since they are substantially bigger and different in terms of their customer needs, attitudes, and media consumption as compared to prior age groups of the so-called 50+ segment (Musico 2008, Williams and Page 2011). Likewise, the green-movement and related age cohorts are becoming of age, digital natives are becoming adult and gaining importance as consumer groups for many products, etc. All these demographic changes continue to challenge marketing strategists and media planners in many industries. In order to carefully evaluate such changes in the consumer populations and to derive implications for the marketing plans of the products and services they offer, strategic planners and marketing managers require decent forecasts on the direction and magnitude of such demographic changes.

Cohort analysis can serve as one possible modeling framework to assist analysts with such forecasts. As we will describe in more detail below, cohort analysis is a method designed to decompose age (A), period (P), and cohort (C) effects to examine consumer behaviors. A cohort can be defined as a group of individuals with the same age location over time (Ryder 1965) contrary to the definition of age that considers individuals at the same period in time. The method was first introduced to the marketing literature by Reynolds and Rentz (1981) and was further recognized in a number of subsequent applications (Rentz et al. 1983, Rentz and Reynolds 1991). Although a number of descriptive contributions have used the concept of cohort effects to study the dynamics of consumption patterns for a variety of goods (for example, market segmentation based on cohorts; Schewe and Noble 2000, Noble and Schewe 2003), there are only few applications of APC analysis in economics and marketing. (Chen et al. 2001, Fukuda 2010)

A number of recent developments justify the further exploration of cohort analysis in the context of strategic marketing planning: First, more long-term tracking data is becoming available to marketing analysts at low cost. Aside from a rich set of publicly accessible data provided by central bureaus of statistics, many companies track the consumption patterns of their clients and systematically record customer interactions with the brands and product/service categories they offer over time. Second, recent methodological advances allow business analysts to overcome some of the limitations (e.g., model identification problems, cf. Rentz and Reynolds 1991) traditional approaches to cohort analysis are confronted with and refrained cohort analysis from further diffusion into practice. Finally, recent research in disciplines like demography provide analysts with well-grounded scenarios on projected demographic changes of consumer populations which can serve the framework of cohort analysis as a perfect starting point to simulate future long-run developments of markets (cf., e.g., Lutz et al. 2008).

In this paper, we show how cohort analysis and demographic research can be combined in one coherent approach to explore future developments of consumer markets. Using the formal framework of a Bayesian version of an age-period-cohort (APC) model presented in this research, market analysts are able to decompose consumption patterns and to derive long-term forecasts conditional to alternative future demographic scenarios. In our empirical study, we illustrate this property for a selection of fast moving consumer good (FMCG) categories using panel data collected over a time horizon of 17 years.

2 The Age-Period-Cohort Model

Cohort analysis comprises a class of modeling techniques which trace back inter-temporal change to the population's aging process (Ryder 1965, Palmore 1978). In sociology, these changes are typically explained by tracking individuals by age location (i.e., the date of birth) rather than by focusing on age and period alone. This general concept is also known as APC analysis. Its primary aim is to disentangle age, period and cohort effects to determine which is dominant in driving behavioral variations over time. It is common practice in APC analysis to explain changes on the aggregate population level using rates or proportions as dependent variables. Following Reynolds and Rentz (1981), Rentz et al. (1983), Rentz and Reynolds (1991), we focus in our subsequent analysis on the penetration rate (PR), which is defined as

$$PR_{ij} = \frac{I_{ij}}{P_{ij}}, \tag{1}$$

where I_{ij} measures how many households within a certain age group i have consumed a certain product or product category within a specific time period j at least once and P_{ij} is the population of relevant households in the same age group i and period j. The corresponding PRs are arranged in a rectangular array, with age intervals defining the rows and time periods defining the columns. The diagonal elements of the matrix correspond to the birth cohorts. Based on this data structure, a commonly adopted approach to cohort analysis fits a linear regression of the PRs on the model parameters (Mason et al. 1973):

$$PR_{ij} = \mu + \alpha_i + \beta_j + \gamma_k \tag{2}$$

where μ denotes the intercept, α_i the ith row age effect $(i = 1, \ldots, I)$, β_j the jth column period effect ($j = 1, \ldots, J$) and γ_k the kth diagonal cohort effect, as a function of the age index i and period j such that $k = (I - i) + j$.

The key in APC modelling is to obtain unbiased estimates of the main effects. Due to the definitions of age, period and cohort the effect parameters are linearly dependent which implies that the conventional APC model in its general form 2 cannot be uniquely identified. This well-known non-identifiability problem (Fienberg and Mason 1979, Kuang et al. 2008) can be resolved by constraining the APC model's intercept and by imposing constraints on the effect levels (O'Brien 2011). However, the problem with this approach is that these linear substitutes lead to biased estimates by arbitrarily choosing linear constraints on combinations of age, period and/or cohort for identifying the respective main effects (Mason et al. 1973, Rentz and Reynolds 1991, Chen et al. 2001). In the present research we adopt the approach proposed by Riebler et al. (2012) by imposing second-order random walk priors as smoothing priors on the main effects incorporated in a Poisson model to obtain unbiased estimates. It can be shown that the second-order differences penalize deviations from a linear trend and are not affected by the non-identifiability problem (Berzuini and Clayton 1994). For example, the second-order random walk prior for age can be written as

$$\pi(\alpha \mid \delta_\alpha) \propto \delta_\alpha^{\frac{I-2}{2}} exp\left(-\frac{\delta_\alpha}{2} \sum_{i=3}^{I} ((\alpha_i - \alpha_{i-1}) - (\alpha_{i-1} - \alpha_{i-2}))^2 \right) \tag{3}$$

$$\pi(\alpha|\delta_\alpha) \propto \delta_\alpha^{\frac{I-2}{2}} exp\left(-\tfrac{1}{2}\alpha^T R^{(2)} \alpha\right) \tag{4}$$

with precision matrix $\mathbf{R}^{(2)}$ where $\delta_\alpha \sim \Gamma(a,b)$ determines the degree of smoothing for the age effect (the higher the precision, the smoother the estimated parameter vector). Due to the functional form of the prior and because the observational model belongs to the class of generalized linear models, the model can be incorporated into a Gaussian Markov Random Field (GMRF; Fahrmeir and Lang 2001) and estimated via Integrated Nested Laplace Approximation (INLA; Rue et al. 2009). INLA is an approach to perform fully Bayesian inference on GMRFs and provides a deterministic alternative to MCMC sampling which is computationally fast and more accurate. In the following empirical study, estimation and forecasting of the APC model parameters are accomplished using R 3.2.2 (R Core Team, 2015) and the add-on package R-INLA (Rue et al. 2009).

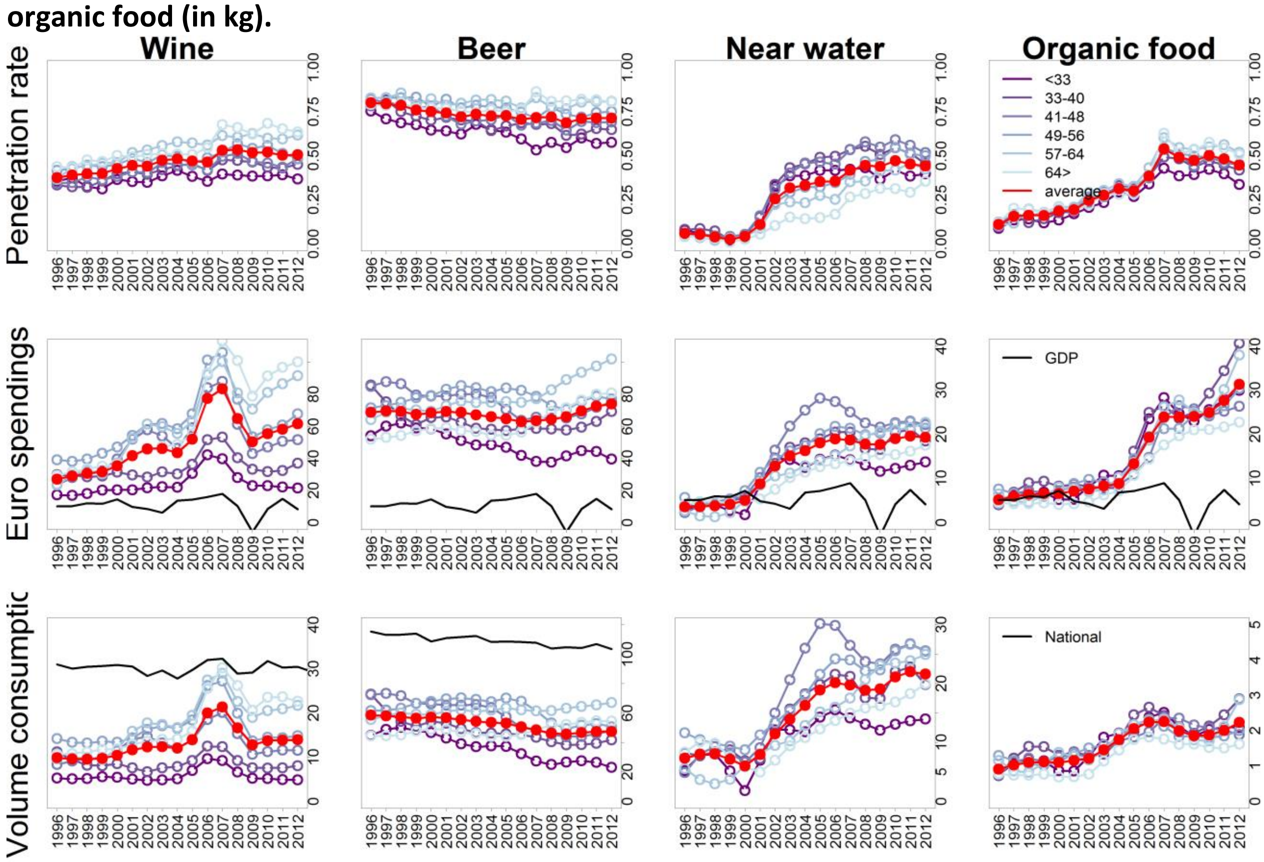
3 Empirical Study

To illustrate the empirical performance of the previously introduced methodology, we use household panel data obtained from GfK Austria which tracks the purchase behavior of a representative sample of around 3,000 households[1] in four different FMCG categories for an

[1] Note that GfK panel services replace panel members every two years by new households with similar characteristics. Thus, the effective number of reporting households varies between 2,405 and 3,477 throughout the observation period.

observational period of 17 years (January 1996 until December 2012). The product categories used in our study are (1) *wine*, (2) *beer*, (3) *near water* and (4) *organic food*. We selected these categories to reflect two different types of environmental conditions: While the wine and beer categories are established markets with slightly increasing (in the case of wine) or relatively stable market volumes, so-called "near water" and organic food products are emerging markets with high growth rates in the early 2000s (World Health Organization 2014, Wier and Calverley 2002). The dependent variable we wish to explain (and to predict for a future holdout period) by using the APC model are the yearly PRs we calculated for the four product categories.

Figure 1: Overall and age group specific penetration rates, mean per capita spending in Euro and mean per capita consumption volumes for wine, beer and near water (in litres) and organic food (in kg).



Note: Percentage changes in the Gross Domestic Product (GDP) and the national consumption volume (National) are obtained from Statistik Austria. Around 40% (60%) of the overall national wine (beer) consumption is represented by the GfK household panel. The changes in GDP were multiplied by the factor 5 for graphical scaling convenience.

3.1 Data Description

For each of the four selected categories Figure 1 represents the respective PRs, the corresponding average per capita spending (in Euro) and consumption volumes. The overall yearly rates are broken down into six specific age groups covering 8-year intervals and ranging from "aged 32 years or younger" to "65 years and older" (notice that the official retirement age in most European countries is around 65 years). Since GfK panel households can consist of several persons we defined the respective reporting person as consumer unit. With respect to the product categories under study, a couple of observations can be made:

- Austria, the county under investigation in our empirical study, is among those European countries with highest per capita wine consumption in litres (World Health Organization 2014). There is a peak in volume consumption as well as in terms of spending in 2006-2008 which can be explained by a general increase in consumption combined with a record wine crop (in terms of both quality and prices). Notice that the decrease afterwards goes in line with the decline of the GDP in 2009 and 2010.
- Our focal country has a very strong beer culture too, with a per capita consumption of approximately 108 litres in 2012 and experienced at least some volume growth (World Health Organization 2014). Similar to the wine category, however, the aggregate trend does no longer hold if it is broken down into age groups. Generally, PRs and spending are increasing with age, but this does not hold for the youngest age group where a general downward trend is visible. Interestingly, as GDP goes down, Euro spending for beer is increasing, which is contrary to wine spending. This might be due to a temporary substitutional effect.
- The near water category comprises mineral water based beverages flavored with fruits or herbs and are typically less sugared than soft drinks. The strong lift in PRs and spending

across all age groups since 2000 is clearly reflecting the healthy life style trend (Polaki and Yarla 2014). Notice that the two largest national beverage companies started producing and marketing near water beverages in 2000/2001.

- The trend toward a health conscious lifestyle is also reflected in the evolution of the organic food category (Thogersen 2010)[2]. In Europe, Austria is a country with one of the highest per capita consumption volumes of organic food. Figure 1 clearly shows that PRs and spending are increasing over time, but the market apparently reflects a considerable degree of heterogeneity across age groups since 2005. This observation is consistent with other empirical evidence that mainly younger people (<45 years) and/or families with children showing higher propensities to consume organic products (Hughner et al. 2007, Steenkamp 1997).

3.2 Model Estimation and Model Selection

To estimate the APC models for the four selected product categories, following Schmid and Held (2007) and Riebler et al. (2012) we assume that the number of consuming households I_{ij} in equation 1 is *Poisson* distributed with

$$I_{ij} \mid \eta_{ij} = Poisson(P_{ij} \exp(\eta_{ij})) \tag{5}$$

$$\eta_{ij} = \mu + \alpha_i + \beta_j + \gamma_k \tag{6}$$

The specific arrangement of yearly penetration rate data (i.e., unequal length of period and age groups) requires to cope with another identifiability problem which induces artificial cyclical patterns in the parameter estimates (Holford 2006). To adequately address this issue, we defined cohorts as proposed by Heuer (1997) which results in our empirical applications in

[2] As "organic" we considered food products sold in conventional supermarkets under the label BIO (short for "biological") or an organic seal certified by the National Ministry of Agriculture (warranting that all raw materials were grown organically).

$k = M \times (I - i) + j$ cohorts (i.e., the cohort index appears only every $M = 8$ years yielding 57 cohorts). Subsequently to determine the relative importance of including the effects in the full APC model, we fitted sub-models for only one or two of the three dimensions under consideration. To evaluate the in-sample model fit, we use the logarithmic scoring rule (log Score; Dawid 2007). To assess the predictive performance of the model specifications, we calculate the root mean squared error (RMSE) between the predicted and the observed values for a holdout period of 8 years.

Our findings reported in Table 1 suggest that the full APC model fits the data best for wine and near water according to the log Score criterion. For the beer and organic food categories the CP model performs only slightly better. For long-term forecasts the full APC model performs best for wine, beer and organic food. For near water it is not clear weather age or cohort have the strongest impact. However the full APC model still fits better for long term forecasts than our suggested benchmark models. Notice, that the PRs in the organic food category show a level shift in the hold-out period, which is hard to predict.

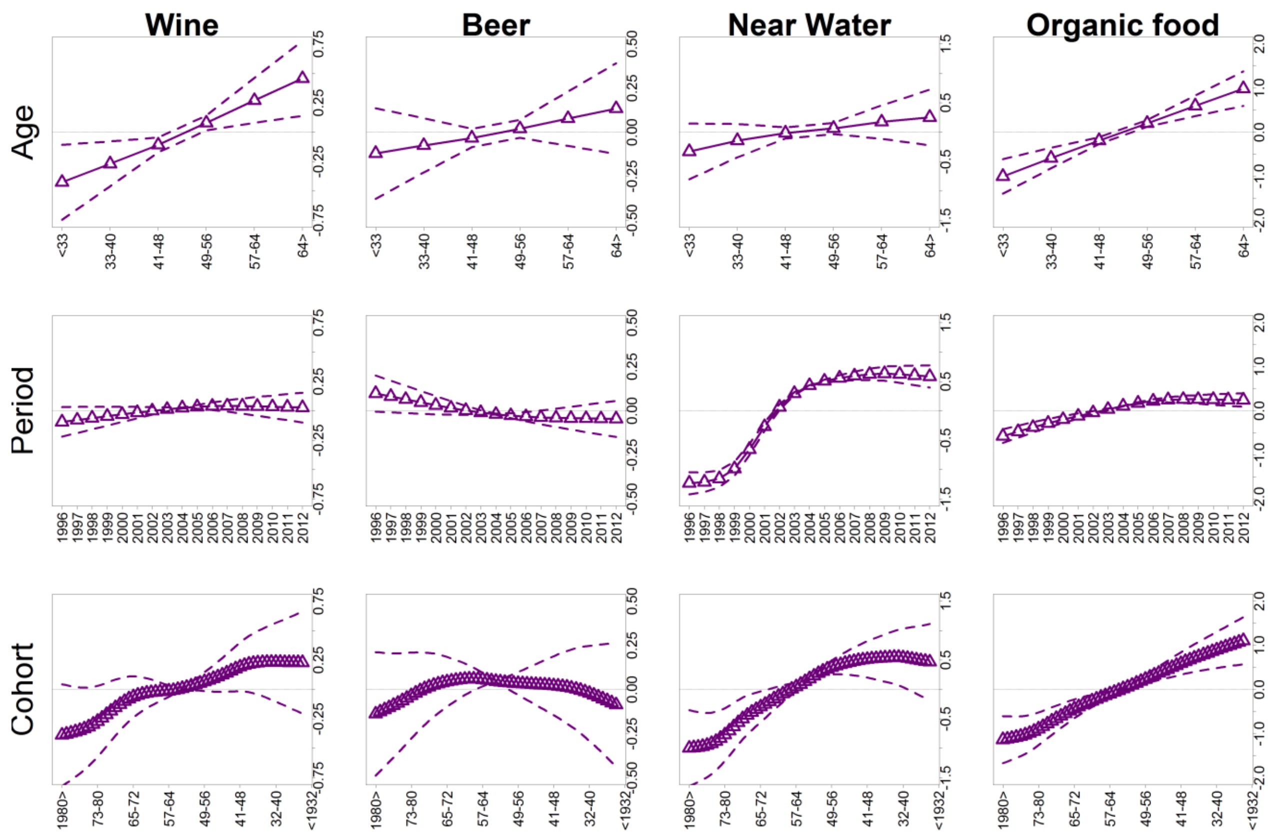
The visual inspection of the effect estimates depicted in Figure 2 reveals almost linear effects in age and period parameters for the wine and beer category, which is generally easy to interpret and to extrapolate (since the age effect quantifies differences in the age groups and period reflects a trend component). However, the cohort effect is generally of a non-linear fashion, except for organic products, where non-linearity is captured only in the period and not in the cohort effect. Thus, the cohort effect is not necessarily required to be added in this case, as suggested by RMSE criterion according to Table 1. For the wine category we find an increasing cohort effect, with older cohorts showing higher PRs, but there is a “plateau” in the middle. For the beer and near water product categories we find an inverse U-shaped cohort effect implying that the age cohorts in the middle show highest PRs in these categories. In the case of near water the period and cohort effects are needed in addition to capture the level shift in the holdout period which explains the result in Table 1 for the RMSE.

Table 1: Logarithmic scores (log Score) and root mean squared error (RMSE) for the holdout period of 2007-2012.

		A	P	C	AP	CP	AC	APC
Wine	log Score	1.7395	2.0410	1.9886	1.0170	0.9131	0.9246	0.9100*
	RMSE	0.0954	0.1060	0.1184	0.0489	0.0297	0.0416	0.0280*
Beer	log Score	1.5406	2.1113	1.2060	1.3395	1.1791*	1.1961	1.1896
	RMSE	0.0521	0.0751	0.0187	0.0369	0.0127	0.0274	0.0114*
Near Water	log Score	3.8290	2.7992	3.6725	1.8279	1.5238	2.7951	1.5012*
	RMSE	0.0478*	0.0657	0.0488	0.0830	0.1056	0.0607	0.0916
Organic food	log Score	3.1108	1.6054	3.0988	1.0650	1.0418*	1.6024	1.0472
	RMSE	0.3913	0.1380	0.3705	0.1172	0.1096	0.1645	0.1047*

Note: The best fitting models are marked with (*). Due to scaling of the marginal likelihood for the log Score smaller values indicate better model fit.

Figure 2: Decomposition of effect estimates for wine, beer, near water and organic food categories.

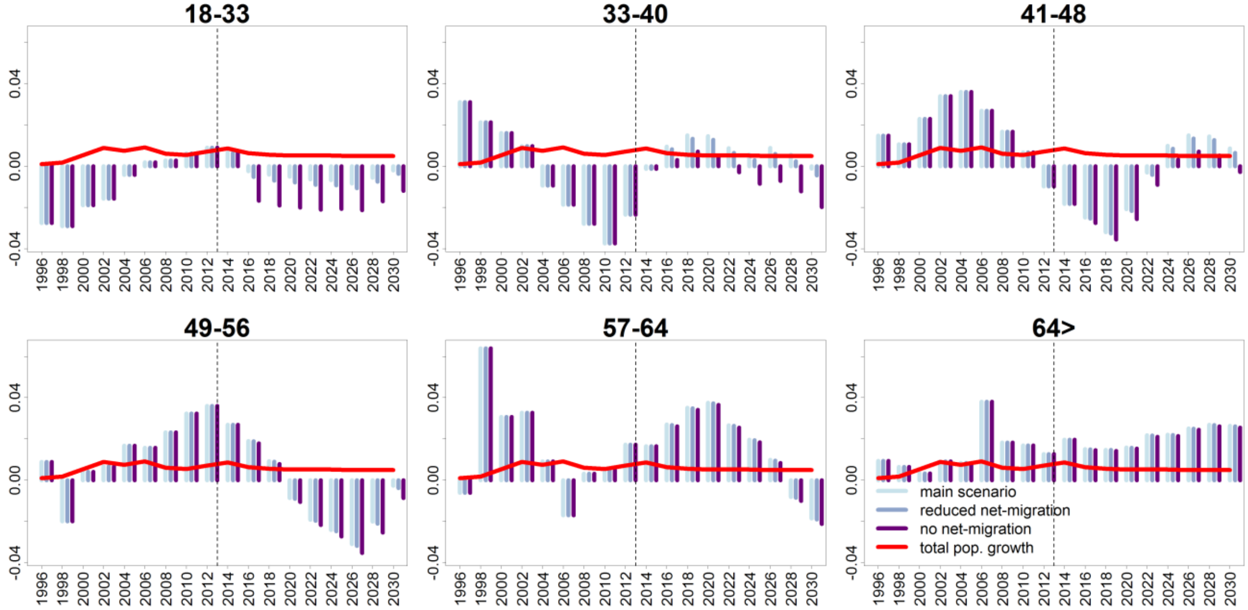


Note: The solid line depicts the posterior median of the effect parameters, the dashed lines indicate the corresponding 95% confidence regions.

3.3 Conditional Market and Age Group-Specific Forecasts

The usage of as dependent variable in the APC models allows us to condition on actual and potential population sizes of the respective age groups. Thus, conditional forecasts along different population growth scenarios are feasible. In the following, we use different demographic scenarios according to the *Europop2013* population projection up to 2030 published by European bureau of statistics EUROSTAT (European Commission and Economic Policy Committee 2014). Figure 3 shows the empirical (up to 2012) and projected percentage changes (using two year increments) of the Austrian population both on the aggregate and age group-specific levels.

Figure 3: Percentage changes in the age distribution and total population growth (solid line) in Austria based on three different demographic scenarios.



Note: The dotted vertical line indicates the projection period 2013-2030 according to the Europop2013.

While the (1) *main scenario* essentially assumes a continuation of recent net-migration levels, the (2) *reduced net-migration* scenario assumes a reduction of international net migration by 20% and the (3) *no net-migration scenario* a net migration of zero. Figure 3 clearly shows significant population aging in all three scenarios with a considerable decline of the population share in the youngest age group and a steadily growing older age groups. Since migration is concentrated at young adult age, the differences among the three scenarios are most clearly visible for the younger adult age groups.

To predict the expected number of consuming households I_{ij}, we used the estimated parameter sets for the four analyzed product categories and plugged them into equation 6 together with the respective population sizes P_{ij} in equation 6 according to the three above-described demographic scenarios. The model parameters were estimated for a calibration period of 17 years ranging from 1996 to 2012.

Several conclusions can be derived from inspecting the graphs shown in Figure 4[3]: There is considerable variation across age groups, and this variation is expected to increase in the future (in particular for the "established" categories wine and beer) if we include a cohort effect in the model (see APC vs. AP forecasts). This implies that ignoring cohort effects for forecasting markets can result in misleading conclusions regarding any segment-specific marketing actions and communications devoted to these age groups. Furthermore, older age groups generally show higher PRs as compared to younger age groups. In the near water product category this finding only becomes apparent if a cohort effect is included in the model; forecasts based on an AP-model would result in a different conclusion. In addition, the "spread" between PRs forecasted for the $64>$ and the <33-year age groups is much higher both in the wine and beer category, but also in the organic food category. This observation becomes even more apparent if we evaluate the PRs with the corresponding per capita consumption volumes (see the plots in Figure 4, rows 3 and 4). Apparently, the future of these markets (particularly the wine market) will be expected to be extremely dominated by older age groups. Finally, notable differences in the forecasted PRs between the projected scenarios of population changes can only be detected for younger age-groups. In Figure 4 these instances are visualized by the grey shaded areas deviating from the main scenario. Because the population shares in younger age groups are expected to decrease already according to the main scenario, the major driver of the age-specific composition of future markets is clearly the "aging effect" in the Austrian society.

4 Conclusion and Discussion

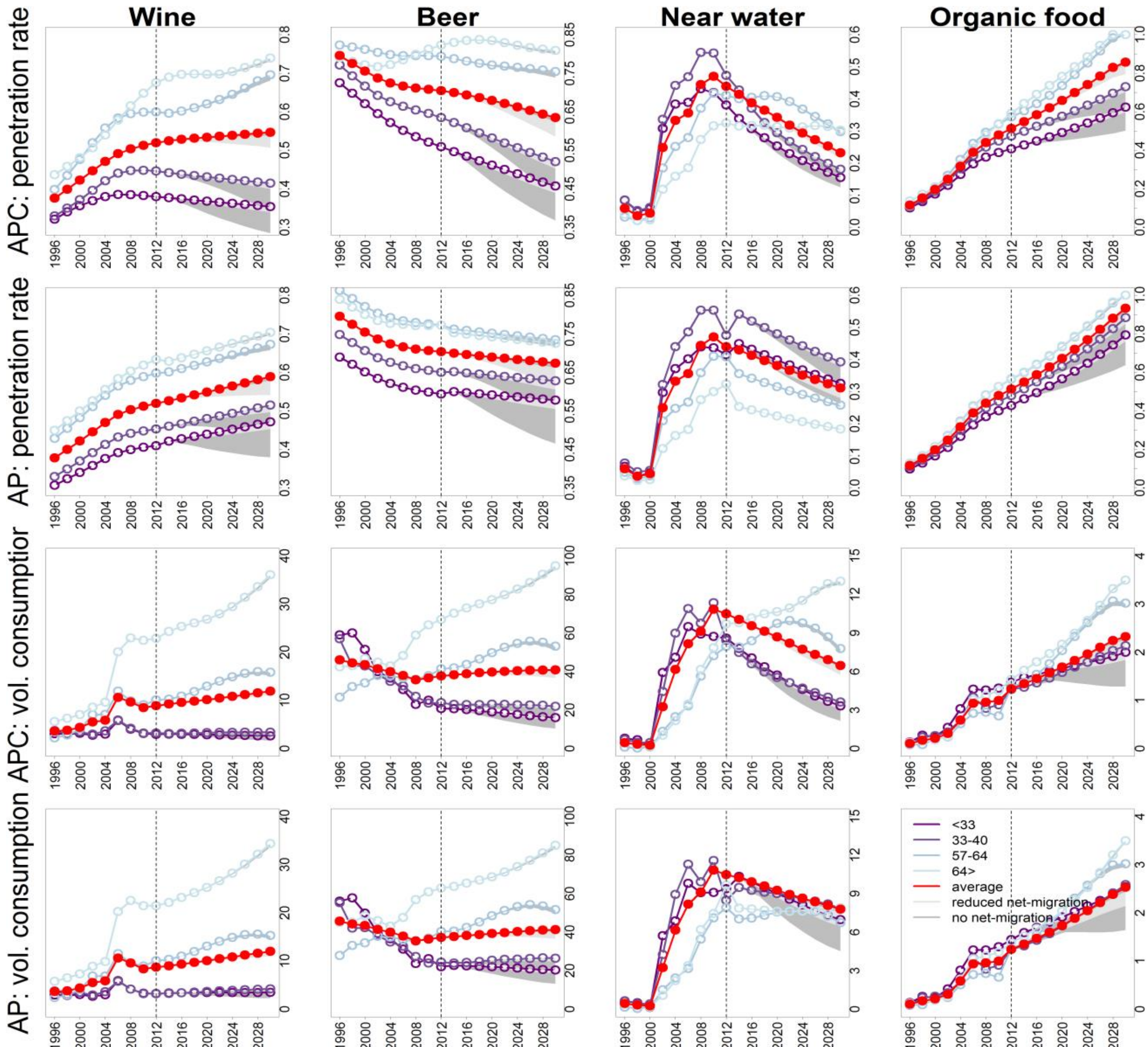
Our research contributes to the market forecasting and planning literature by combining a

[3] The contrasts between the observed PRs from Figure 1 and the corresponding "predicted" PRs in Figure 4 are due to data smoothing prior to estimation of the corresponding models. In addition, notice that we used 2-years increments in Figure 4 to facilitate the visual inspection of the time series.

novel APC modeling approach with scenario-based demographic forecasting. We introduce a novel Bayesian approach to APC modeling, which avoids identification problems more traditional approaches are typically struggling with, in an efficient manner. In our empirical application study, we demonstrate how the APC model estimates can be used to derive conditional expectations based on alternative projections of future demographic scenarios.

In summary, our empirical findings in four FMCG product categories suggest that models which ignore cohort effects tend to underestimate the variation of age group-specific forecasts. Our empirical findings clearly show that — at least in the categories we studied — future market volumes are dominated by the demand of "aged" population groups. Thus, the ageing trend in many societies can be expected to being translated into consequences for future market demands. Such developments clearly call for adequate marketing actions targeted to the various cohort-specific segments. On the other hand, marketing managers might also consider alternative strategies to stimulate stagnating (or even declining) markets in younger subgroups of the population. This finding is also consistent with various industry reports and sentiments which continue to see the age-groups of Boomers and Generation Xers as the most important wine consumers (e.g., McMillian 2015, pp. 28). Marketing managers, but also public policy makers need to design their future communication strategies accordingly to respond to the projected generational shifts in consumption behavior.

Figure 4: Conditional forecasts of age group-specific penetration rates across four product categories based on the APC and the AP model.



Note: The corresponding volume consumption is given in million liters or thousand kilos (for organic food), respectively. Per capita volume consumption for the forecasting period is assumed to be constant at 2012 levels. For sake of simplicity only the two youngest and oldest age groups are displayed.

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