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Title

Consumers preferences through as multilevel latent class models: the case of Italian market of sparkling wine

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Conference Presentation

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Keywords

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Research Question

How the sparkling wine purchasers behave on the Italian market? Are there any segmentation and what are the significant segments on this market?
This paper is aimed at evaluating the

Methods

The consumer segmentation is done through the traditional latent class analysis and the multilevel latent class modelling which assumes that some model parameters can vary across groups or clusters.

Results

Latent class models reports 5 clusters while the MLLC model draws groups or classes which encompasses three or more clusters confirming the complexity of segmentation .

Abstract

The Italian market of sparkling wine has undergone a strong expansion driven by what can be defined as "Prosecco phenomenon". The strong growth of the Prosecco market was in fact accompanied by an expansion of the supply aimed at reaching new markets and meeting the needs of a new and large circle of consumers. The supermarket shelf of sparkling wines has therefore been enriched with multiple variations of product and price: a consumer can choose among many appellations and different types for residual sugar (dry, extra dry, brut etc.) for blend (cuveé), cru rather than opting for the organic version. The increase in competition has led the wineries to create new brands and to try to reposition their brand in new market segments.
Accordingly, the sparkling market growth has extended the consumption reaching new and more complex segments. While in the past the sparkling wine consumption was mostly seasonal and pulled by Christmas holidays; nowadays, the purchase occasions are larger and distributed along the year. More specifically, the wide offer of appellations, brands, prices has strongly increased the market penetration which is around 50% of Italian wine

drinkers having different loyalty (Rossetto and Gastaldello, 2019) and consumption (Rossetto and Gastaldello, 2018).
This paper is aimed at evaluating the sparkling market to identify and to evaluate the features and size of consumers segments.
Firstly, we identify homogeneous groups of purchases. These results shed light on customers' preferences since they draw patterns of associations among brand and product features. Customers' preferences are recognized on the base of their buying behavior that is observed on a panel sample over a period of two years. Then, the consumers were segmented with reference to their observed behavior in the market. In order to perceive these goals with apply the latent class (LC) approach. This approach has indubitable advantages over traditional clustering methods (Bassi, 2007 and 2009). LC analysis attempts to explain the observed association between the factors that make up a multiway contingency table (Goodman, 1974a) by introducing unobservable underlying classes (clusters).
Second, a multilevel latent class modelling (MLLC) (Vermunt, 2003) was applied. This approach is based on the assumption that some model parameters can vary across groups, clusters or level-2 units (Bassi, 2013). As an example of hierarchical data, operations are nested in a bank's customers: operations are level-1 units, clients are level-2 units. This is different from traditional latent class modelling, which assumes that the parameters are the same for the whole sample. The MLLC approach allows for variation across level-2 units for the intercept (threshold) of each latent class indicator. This makes it possible to examine how level-2 units influence the level-1 indicators that define latent class membership (Vermunt, 2003; Bassi, 2013). This method adopts a random-effects approach rather than a fixed-effects approach, enabling the effects of level-2 covariates to be verified on the probability of belonging to a given latent class (Vermunt, 2003).

Data for the analyses comes from a panel of 9,000 Italian households who recorded their purchases over a two-year period: 2015 and 2016. This sample is representative of the population with reference to the area of residence, family size, monthly income, age of the purchaser, family features. The survey is done by ACNielen, which collects longitudinal data with continuous time, data is also hierarchical since each household may perform multiple purchases in a selected reference period. The key element identifying each purchase is the Stock Keeping Unit (SKU) and the family code.
The database includes 22,362 purchases within unspecialized stores such as supermarkets, supermarkets, minimarkets and discounts, which account 5,155 purchasers representing a portion of the entire panel that made at least one purchase in the reference period.

The latent class models were introduced by Lazarsfeld and Henry (1968) to express latent attitudinal variables from dichotomous survey items, then they were extended to nominal variables by Goodman (1974a, 1974b), who also developed the maximum likelihood algorithm for estimating latent class models that serves as the basis for many software with this purpose. Later, these models were extended to include observable variables of mixed scale type, like ordinal, continuous and counts.
The probability structure defining a simple LC model may be expressed as follows:
(please look at the attached file for the equation and its eplanations)

As specified in the equation, the probability of observing a particular response pattern is a weighted average of class-specific probability weight being the probability that unit i in group j belongs to latent class t. As the local independence assumption implies, indicators are assumed to be independent conditional on LC membership.

The MLLC model (Vermunt, 2003) consists of a mixture model equation for level-1 and level-2 units, in which a group-level discrete latent variable is introduced so that the parameters are allowed to differ across latent classes of groups:
(please look at the attached file for the equation and its eplanations)
The above equation contains the additional assumption that nj members' responses are independent of one another conditional on group class membership.
A natural extension of the multilevel LC model involves including level-1 and level-2 covariates to predict membership, like an extension of the LC model with concomitant variables (Dayton & McReady, 1988).

LC results show 5 clusters. Cluster 1, 2, 3 represent about 30% each of the purchasers while clusters 4 and 5 refer mainly to Champenois sparkling wines. Cluster 1 includes mainly medium-low income families living in Centre and

South Italy buying mainly low price sparkling wine, especially sweet without appellation. Cluster 2 include families living in Northern Italy, single or couples, high age and income; this segment buys medium price sparkling wine with appellation. The cluster 3 is about Prosecco purchases; it includes purchasers living in the North-east and Center of Italy, couples, age between 35 and 54, with medium and high level of income.
The cluster 4 is small (8.5% of purchases) and it refers to classic method sparkling wines such as Franciacorta and Trento appellation having high price while purchasers are living mainly in North Italy, they are single or couple whit high income. The cluster 5 is the smallest one and it includes Champagne's purchasers.
The MLLC model was, then applied, and it figured out five segments or classes.
While 3 classes correspond to one cluster (class 1: cluster 1, class 3: cluster 3; class 5: cluster 2) 2 classes encompass 3 or more clusters (class 2: cluster 1,2,3; class 4: 1,2,3,4).
In particular, class 2 represents about 27% of purchases and it includes purchasers that look like the one in cluster 1 (low income families) together with some purchasers in cluster 2 (young buyers, medium income) and some in the cluster 3 (the Prosecco's cluster). The class 4 is less important as size (about 13% of purchases) but it is quite heterogeneous since it is extended to four clusters (except the Champagne one)
The MLLC models express and better performance respect to the LC one while showing a greater complexity of consumers in the Italian sparkling wine market.

REFERENCES
Bassi .F (2013) Analysing markets within the latent class approach: an application to the pharma sector. Applied Stochastic Models in Business and Industry, 29(3), 199-207.
Bassi F. (2007) Latent class factor models for market segmentation: an application to pharmaceuticals, Journal of Statistical Methods and Applications, 2, 279-287.
Bassi F. (2009) Latent Class Models for Marketing Strategies: an Application to the Italian Pharmaceutical Market, Methodology. European Journal of Research Methods in the Behavioural and Social Sciences, 5 (2), 40-45.
Dayton, M. C., & McReady, G. B. (1988). Concomitant-variable latent class models. Journal of the American Statistical Association, vol. 83, pp. 173-178.
Goodman, L.A. (1974a) The analysis of systems of qualitative variables when some of the variables are unobservable: Part I. A modified latent structure approach, American Journal of Sociology, 79, 1179-1259.
Goodman, L.A. (1974b) Exploratory latent structure analysis using both identifiable and unidentifiable models, Biometrika, 61, 215-231.
Lazarsfeld, P.F. & Henry, N.W. (1968) Latent structure analysis. Boston, Houghton Mifflin.
Rossetto L. and Gastaldello G., (2018). La fedeltà del consumatore al Prosecco sul mercato italiano degli spumanti. In (Boatto, Barisan, and Pomarici eds) Rapporto annuale 2018. Distretto del Conegliano Valdobbiadene. Consorzio di tutela Conegliano-Valdobbiadene Prosecco Superiore Docg.
Rossetto L. and Gastaldello G., (2019). The Loyalty Structure of Sparkling Wine Brands in Italy. Journal of Wine Economics (forthcoming)
Vermunt J.K. (2003) Multilevel latent class models. Sociological Methodology, 33(1), 213-239.