Assessing partial defection in retail consumers and the role of private label in its prevention

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INGEGNERIA GESTIONALE

Agenda

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"Churn" refers to the instant when the customer stops purchasing the product or service from the company under analysis. This phenomenon can be identified as the **final stage of the customer relationship**.

Purchase context

Contractual setting:
customer-firm relationship is defined by a contract that regulates the supply.

Non-contractual setting:
customer-firm relationship is not ruled by a contract.

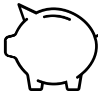
Why churn matters: a healthy and long-lasting customer relationship grants to the company consistent and stable cashflow generated from that relationship (firm value perspective).

Introduction: private label products

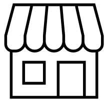
Private label products are directly sold by the retailer as an attempt to **differentiate itself from competitors**, thus introducing a switching cost. Quality of those products is guaranteed by retailer's ability to select suppliers, know-how derived from its core business.

3 TIERS OF PRIVATE LABEL

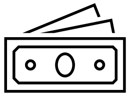
First price:
Cost saving and entry level quality



Retailer:
Good price-quality ratio



Premium:
Premium price for best quality



Literature review

1560 ARTICLES

FILTER ON SUBJECT AREA AND PUBLICATION YEAR

206 ARTICLES

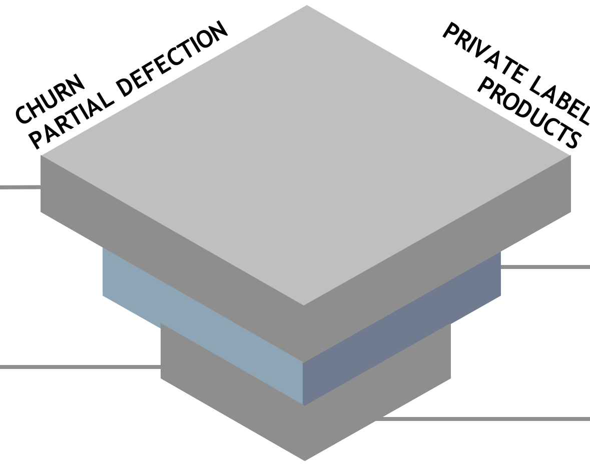
SORT BY ABSTRACT

62 ARTICLES

SORT BY FULL READING

28 ARTICLES

SELECTED



SUPERVISED PREDICTION MODELS IN CHURN ANALYSIS

FINDINGS

THE ROLE OF PRIVATE LABELS IN CUSTOMER RETENTION

01 Need for a probabilistic classification of churn risk, instead of a qualitative one in non-contractual setting scenario.

02 Need to investigate on possible customer relationship deterioration signs (i.e., churn predictors).

03 Investigate the impact of private label products on customer retention, this study will be conducted on 3 private label's tiers.

Main authors:

- **Kusum L. Ailawadi** (*"Private-Label Use and Store Loyalty"*)
- **Peter S. Fader** (latent class modelling, customer retention)
- **Wouter Verbeke** (churn contractual settings)
- **Koen Pauwels** (private labels)

Research questions

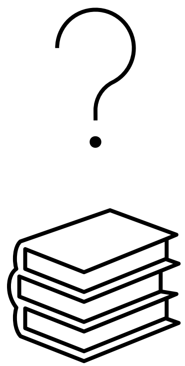
01 Develop a data-driven risk classification model to model partial defection in non-contractual settings.

02 Identify purchasing behaviours that can act as churn predictors.

03 Understand the role of private label products in churn prevention and churn prediction.

04 Compare our model performances with the most traditional and widely adopted RFM models.

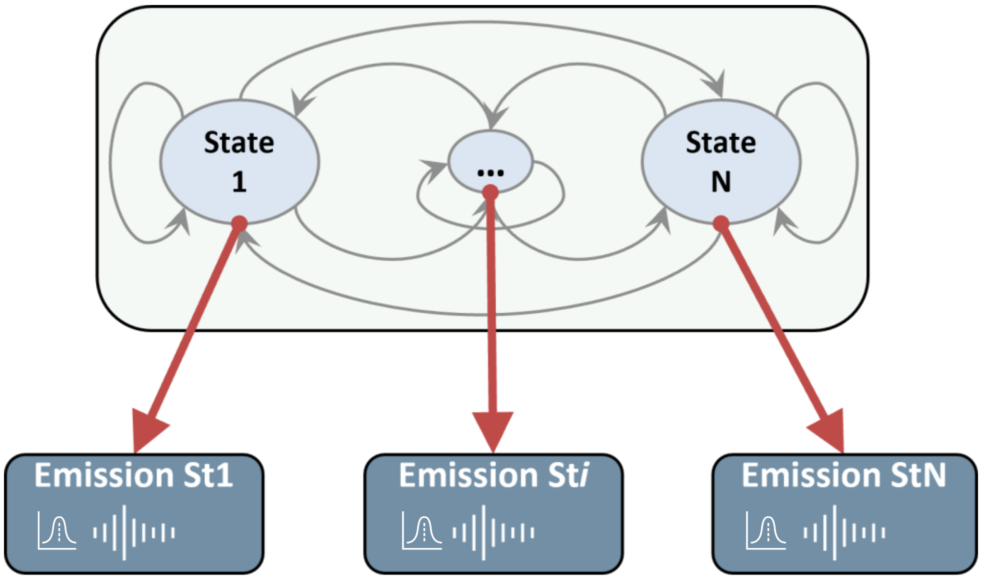
05 Provide implications derived from our model implementation.



Model presentation: hidden Markov model

Markov models are used to model random processes where the transition between the states of the system at time t are ruled by transitions probabilities that only depends on the state in which the system was at time t-1 (**Markovian assumption**).

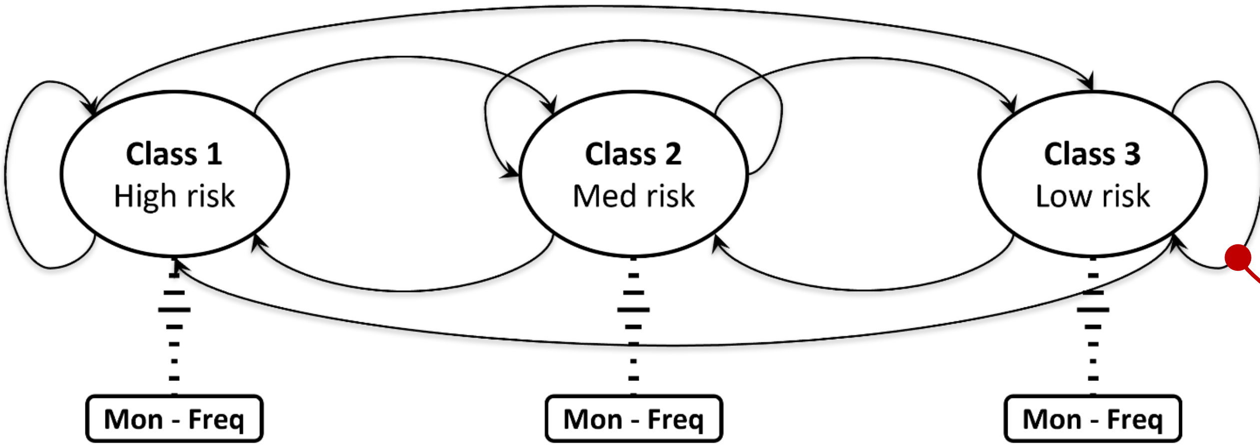
HMM representation



Latent classes → Relationships

Hidden Markov Models are an evolution of Markov models where the underlying Markov chain is hidden from the observer. Instead, at every time it can be observed the emissions the system produces and those emissions depend on the state of the system. **Depending on the emission it is possible to calculate the probability the system has of staying in each state (posterior prob).**
Also, from the observed emissions it is possible to rebuild the Markov model behind.

Conceptual Hidden Markov Model



Covariates

$$T = f(Mon, Freq, C1, C2, C3)$$

TPM	Class 1	Class 2	Class 3
Class 1	Tp11	Tp12	Tp13
Class 2	Tp21	Tp22	Tp23
Class 3	Tp31	Tp32	Tp33

Mon and Freq values were chosen as emission variables of a 3-states HMM. Each state is associated to a class representing a churn risk level from Low to High. The underlying idea is to **crate a model able to map customer into risk segment in order to recognize possible partial defections.**

We introduced a multinomial logit model on transition probabilities using percentage of pvl product bought as covariates. In this way it was considered the **impact of covariates on transition probabilities** and consequentially also on **posterior probabilities.**

Data and analytical choices

Dataset Presentation:

Data were retrieved from the data warehouse of one of the largest FMCG players in the Italian market. The time range goes from August 2020 to September 2022, and the data contains all transactions made by a pool of customers during that period. Data are structured at ticket line level and cover: **card number**, **tot sold**, EAN code, quantity, **ticket date** and **product description**.

Analytical choices

- Why Mon e Freq and a 3 states model?
- Why time bucket of one month?
- How private label products as covariates?

Focus on analytical choices

Emission variables

Mon [€/period] and **Freq** [#groceries/period] variables are actually approximations of customer relationship. A **3-states** model produces 3 risk classes that can easily be related to consistent marketing cluster: **distinguishable and actionable**

Time bucket

- Wide time bucket → too aggregated data (**loss of information**)
- Tight time bucket → too much variability and absenteeism (**churn/partial defection is less meaningful**)

Private label products covariates

The 3 covariates regarding the private labels (one for each tier) are calculated by period as the percentage of pvl products respect the tot number of products bought. Number of products does not involve quantities, rather is the number of different EANs. This to better **grasp the underlying choice done by the customer in selecting that specific product**. The goal is analyse a **distinguishable customer behaviour** that can act as **churn predictor**, and can be exploited to **foster loyalty**

Results disclosure: HMM vs RFM

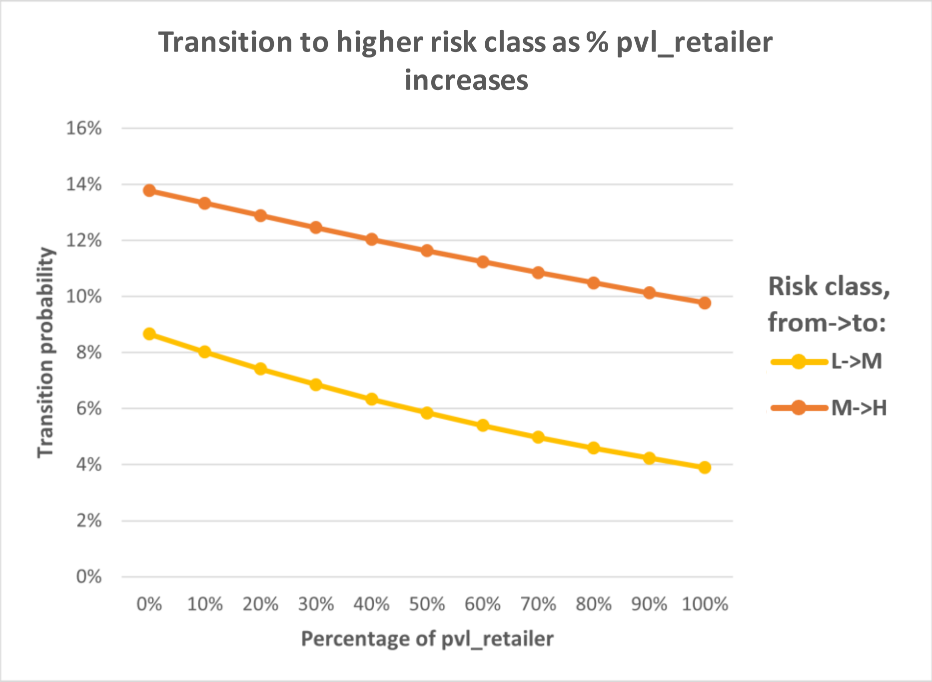
Staying Prob	High risk class	Med risk class	Low risk class
RFM	77.5%	47.2%	73.4%
HMM	80.5%	83.7%	91.6%

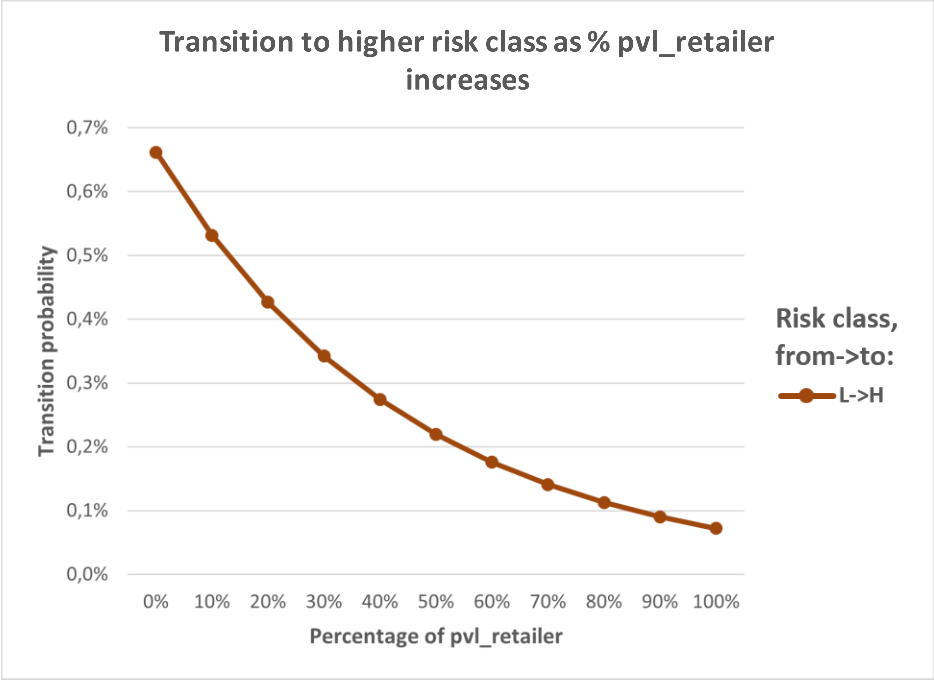
Mean Monetary	RFM	HMM	Mean Frequency	RFM	HMM
Low risk class	358.8€	394.4€	Low risk class	13 t/m	14 t/m
Medium risk class	187.8€	153.5€	Medium risk class	5.3 t/m	4.7 t/m
High risk class	43.9€	19.7€	High risk class	1.4 t/m	0.8 t/m
Tot expense € per period			*[t/m] = tickets per month*		

Class 1 in the HMM has lower mean values of Mon and Freq respect to the corresponding class in the RFM model. High Mon and Freq for Class 1 means that customers classified as churn or partial defection might in fact be out of risk (**problem of a priori thresholds**).

Staying probability of HMM are always higher than their respective in the transition matrix of RFM model. This means that the **classes in the HMM are more stable and consistent.** As a matter of fact, Class 2 of the RFM model turns out to be highly unstable: staying probability corresponds to 47.2% while the probability of changing class (i.e., moving to Class 1 or Class 3) is 52.8%, thus making it more likely to change class than to stay in it.

Results disclosure: Impact of "*retailer*" private label



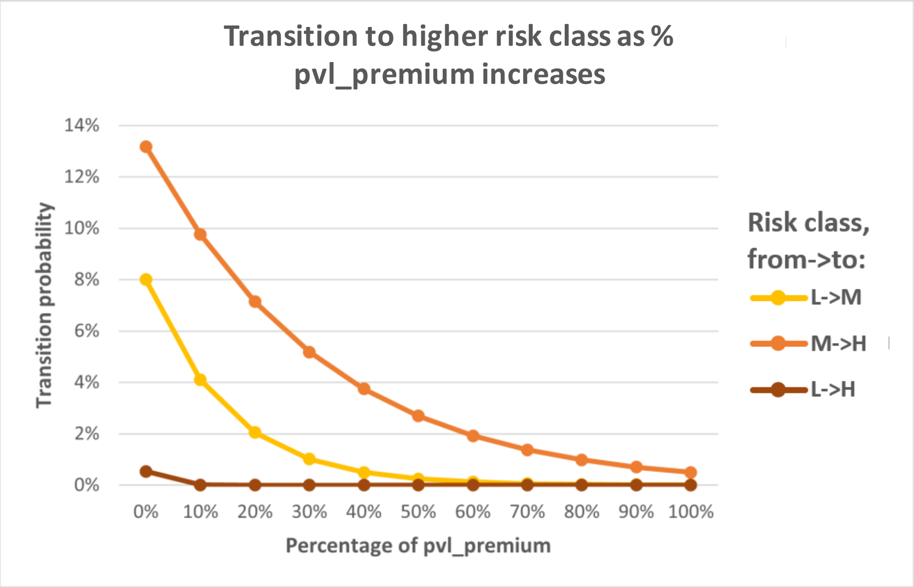


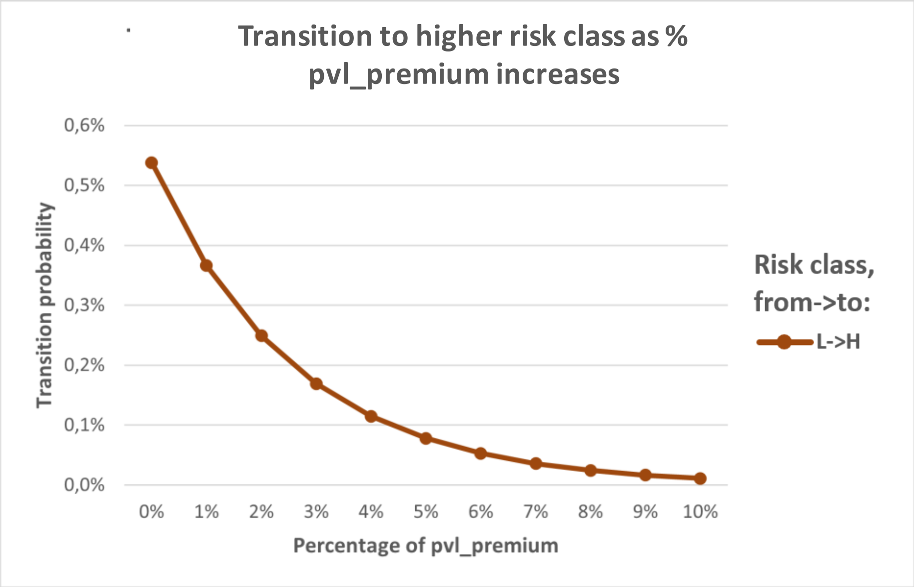
Perc_pvl_retailer = $\frac{\#\ product\ types\ pvl_{retailer}}{tot.\#\ of\ product\ types}$

Pvl_retailer products are sold as an alternative to well-known brand products that the retailer sales under his own brand. Usually these products rely on value for money. The **quality is guaranteed by the retailer's ability in selecting suppliers.** Customers keen on purchasing pvl_retailer products proved to be **more loyal** and to have a **decreased probability** of churn/partial defection respect to base case.

1 → 2 → 3 → 4 → 5 → 6 → 7 → 8 → 9

Results disclosure: Impact of "*premium*" private label

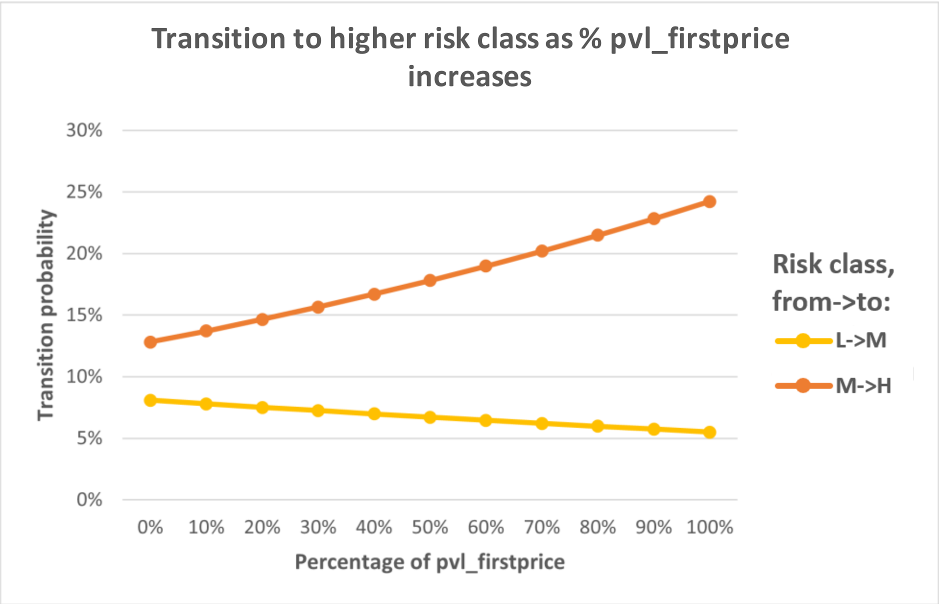


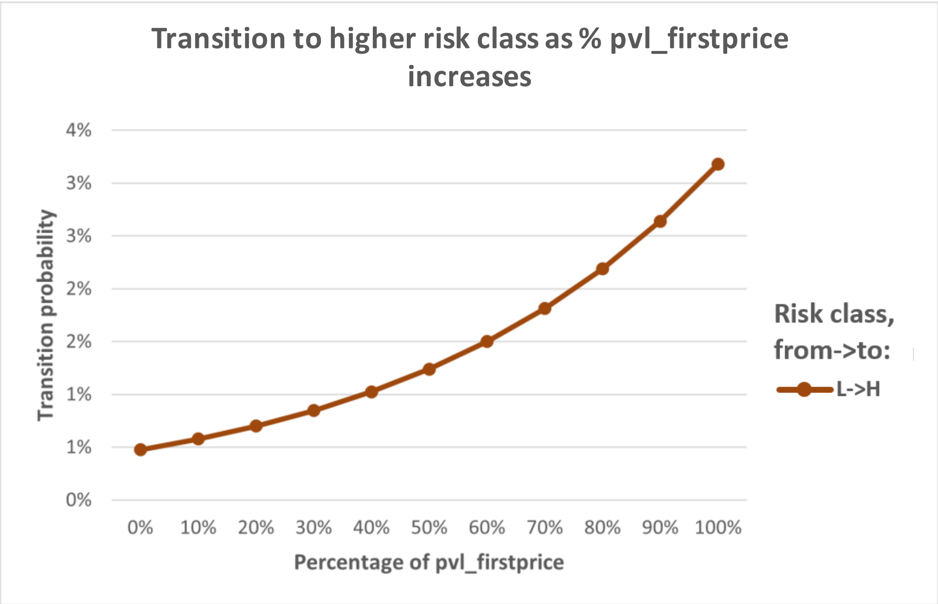


$$\text{Perc\_pvl\_premium} = \frac{\#\ product\ types\ pvl_{premium}}{tot.\#\ of\ product\ types}$$

Pvl_premium products are characterized by high prices and uncompromized quality. A customer who is used to buy those products proved strong trust in the retailer to the extent of paying a premium price. The **choice of pvl_premium is a conscious one**: the customer pays more because he/she recognizes the quality of the products and he/she knows that it meets his/her needs. Customers committed to buying pvl_premium are unlikely to end up being little loyal. Pvl_premium impact is **stronger than pvl_retailer** one.

Results disclosure: Impact of "*first price*" private label





$$\text{Perc\_pvl\_firstprice} = \frac{\#\ product\ types\ pvl_{firstprice}}{tot.\#\ of\ product\ types}$$

Pvl_firstprice products are sold as an economic with entry level quality. Customers keen on purchasing pvl_firstprice products search for the lowest price, and they will switch retailer when they find a competitor offering lower prices. Their loyalty is limited to the economic convenience.

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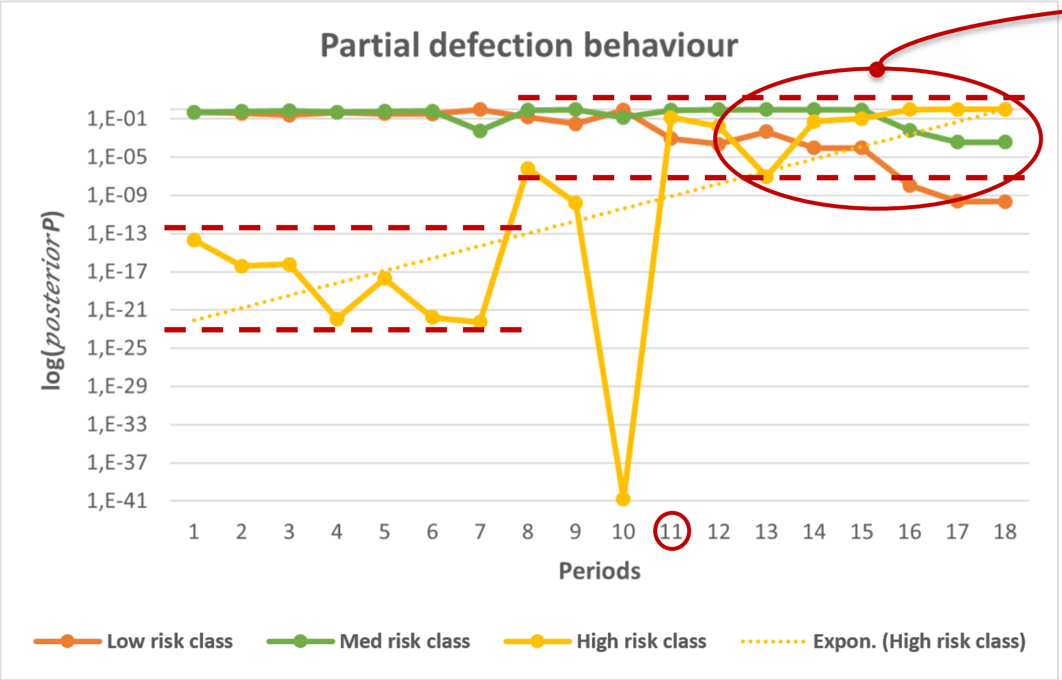
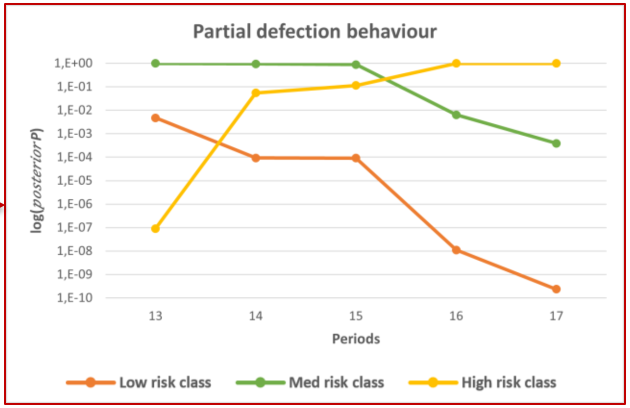
Results disclosure: model reaction to typical customers

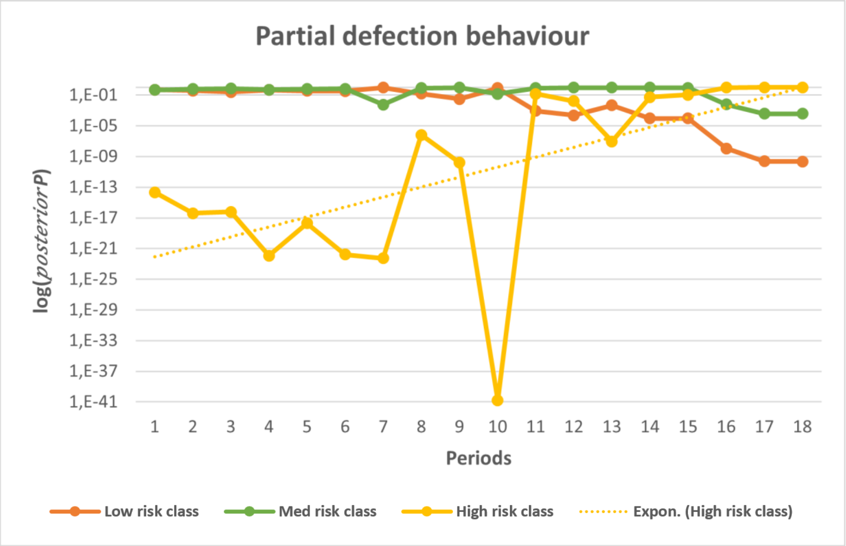
Posterior graph interpretation

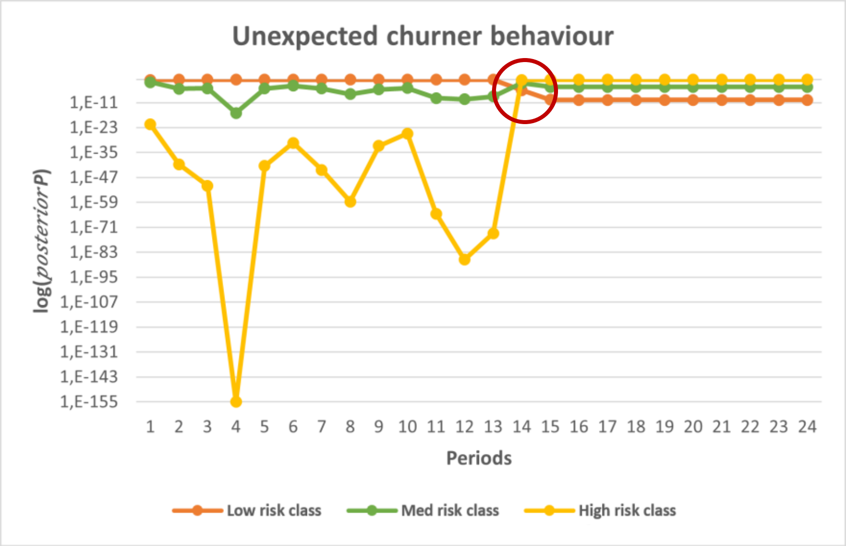


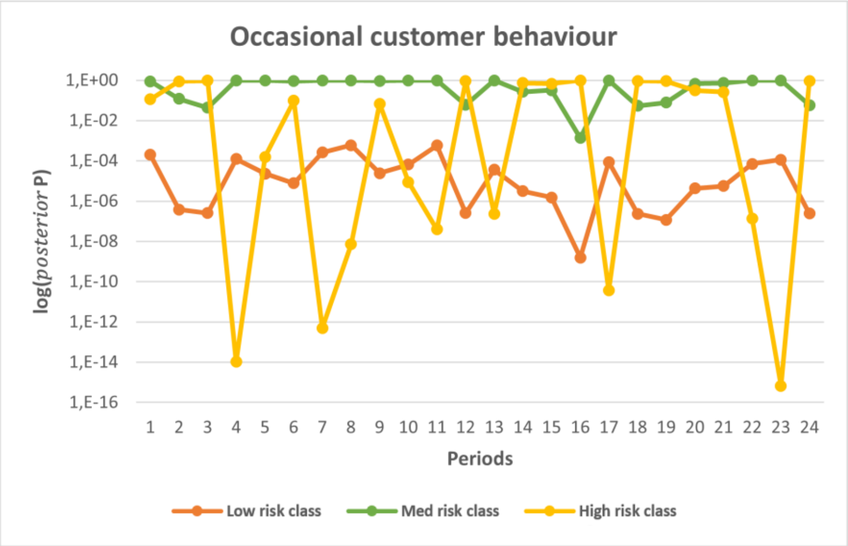


The posterior probabilities graph in logarithmic scale magnifies posterior probabilities variations. The example graph shows a partial defection. **Probability of belonging to highest risk class increases (note the trend)**, while in the same time probabilities of belonging to low and medium risk class decreases.

Results disclosure: model reaction to typical customers



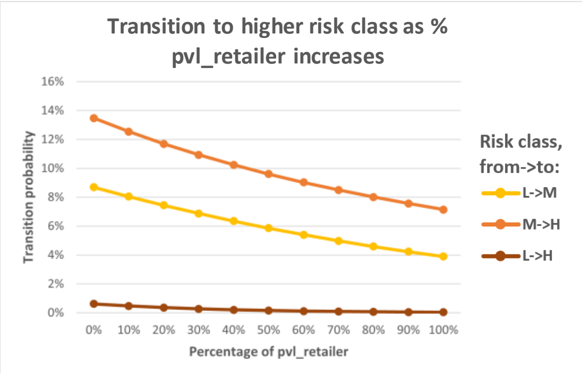


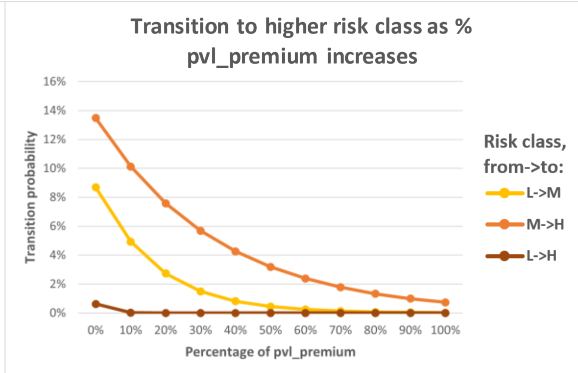


1 2 3 4 5 6 7 8 9

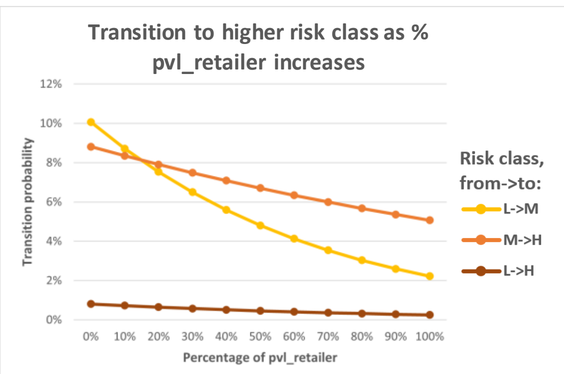
Model validation

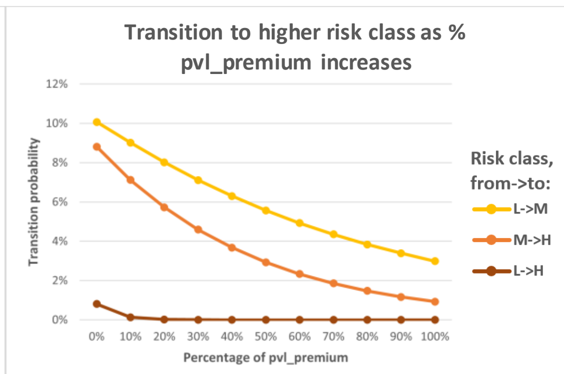
Master model





Test model





HMM test	Mean Monetary	Monetary Variance
Class 3:	246.078	144.208
Class 2:	130.675	80.738
Class 1:	26.342	23.584

HMM test	Mean Frequency
Class 3:	16.5
Class 2:	7.0
Class 1:	2.3

Recognition of three risk classes

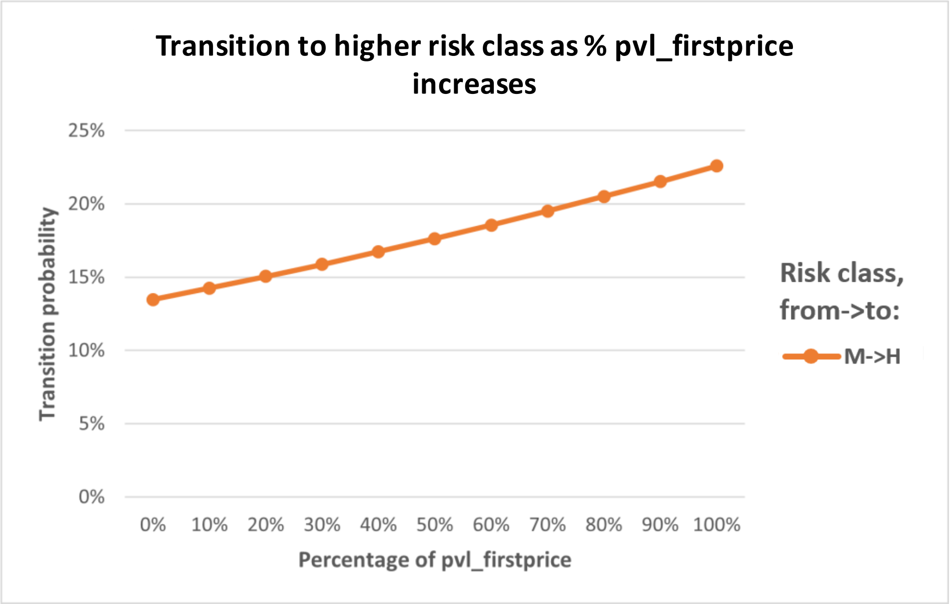
Consistency between classes of risk and their Mon and Freq values

Lowest class is well representative for churn of bad performing customers

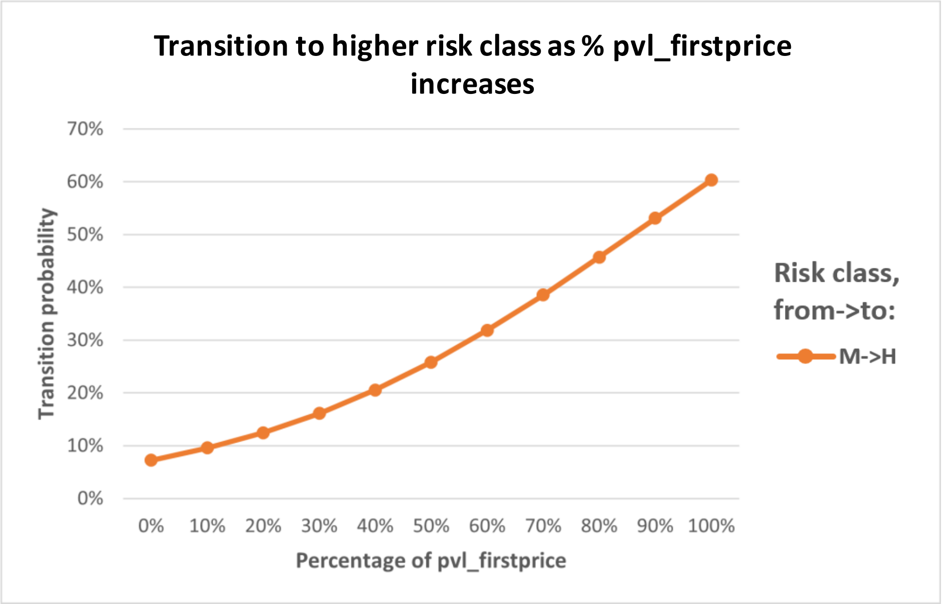
Covariates related to private label products have similar trend to Master model's one

Model validation: Focus on "first price" private label

Master model



Test model



Implications

Contribution to churn modelling → The model improves the non-contractual churn modelling respect to RFM. The validation step proved the model's reliability. Furthermore, KPIs and the statistical method used are such that the model can be used also for other retailers.

Model's predicting power → Using class transition probability this model can measure the specific risk of the singular customer

Private label products as churn predictors → The purchase of private label products (differentiated by tier) can be exploited to better evaluate the evolution of churn risk.

Private label products for churn prevention → Different pvl tiers demonstrated different impact on customer retention: they can be exploited as churn prevention instruments.

Research boundaries and future improvements

Data cleaning enhance model's performance

Gamma distribution instead of Normal distribution to model Monetary response

Test other covariates to find new churn predictors and customer retention booster

Thanks for the attention

Lorenzo Perego
Mirko Leoni