The impact of competitive interactions on category penetration and purchase frequency of mature FMCG categories

Laurent Rochat
Consultant, Rue de Grenus 12, 1201 Geneva, Laurent@innovationatelier.com

Ann Van Ackere
Faculté des Hautes Etudes Commerciales (HEC), Université de Lausanne, 1015 Lausanne, Ann.VanAckere@unil.ch

Many fast moving consumer goods (FMCG) categories like laundry detergents, diapers or cereals are mature and rather stable, so the interest is high for manufacturers to make diagnostics on the category and their brand to find growth opportunities. Attempts to model mature category dynamics have mostly been based on probabilistic models. The most famous one is the "NBD-Dirichlet" model, which was first presented in 1984 and has subsequently triggered significant research in the area. The model has limitations as it assumes stable marketing and promotional activity and stable category dynamics. This paper uses a system dynamics model to relax some of these stability assumptions and explain how competitive dynamics impact the total category penetration, purchase frequency and volume size over time.

Background

Over the past decade, many fast moving consumer goods (FMCG) categories like laundry detergents, diapers or cereals have reached a plateau; although the average transaction size is increasing, the actual consumption has remained mostly unchanged, penetration is stable, an total category volume size even eroding. The consumer purchase dynamics explaining these observations from household panels (HHP) data are still not very well understood. New insights in this area could tremendously help FMCG business managers to shape brand strategy and identify growth opportunities.

FMCG category dynamics are well described through mathematical models like Fourt-Woodlock (1960), NBD-Dirichlet (Goodhardt, Ehrenberg & Chatfield 1984), Eskin (1973) or Kalwani & Silk (1980). These models are incredibly helpful to pose a diagnostic on a specific category or brand, but offer limited insights to understand the underlying factors influencing category dynamics without additional mathematical

complication. Their low applicability for brand strategy elaboration has been highlighted by Ehrenberg, Barnard & Sharp (2000). System dynamics is better suited to explaining the complexity of category dynamics. Though somewhat criticized with regard to validity and validations (Forrester & Senge 1980, Martinez & Richardson 2001), system dynamics does not seem to carry lower objectivity than mathematics-based sciences. The latter models actually make parameters interpretation more difficult (Fader & Hardie 1999), while system dynamics models leverage simple bivariate relationships, have the ability to produce a wider range of *mathematical curves* as output and can be more accurate for forecasting purposes (Lyneis, 2000).

There are some system dynamics based purchase behavior models which help to understand new product introduction dynamics, but they tend to be either too simple (Sterman 2001, Morecroft 2007) or too broad for practical use for marketers (Maier 1998). Also, they focus on the diffusion of new products and do not explain the evolution of mature categories over time.

The model presented here aims to provide a better representation of the market dynamics of a mature consumer goods category. In particular, our model aims to capture how competitive activity, market share objectives (Armstrong & Green 2007) and promotion support (Bell, Chiang & Padmanabhan 1997) lead to this evolution. To our knowledge, this model is the first one to link consumer consumption, category penetration and purchase frequency to capture mid-term and long-term category evolution.

Model description

The starting point to the model is the "NBD-Dirichlet" theory for mature, stable categories. The "NBD-Dirichlet" model uses a negative binomial distribution (NBD) for consumers' purchase distribution of a given FMCG product category, and a Dirichlet distribution to integrate brand choice to the purchase dynamic. The core assumptions of the model can be summarized as follows:

(1) Each household is either a stable product category user or a non-user. The split between both groups is given by category penetration (B). A glossary of household panel metrics and concepts is available in Appendix 2.

(2) The probability of purchase by a category user follows a Poisson process with the purchase frequency (w_P) as parameter. The average purchase frequency for the category across all category users is denoted by W.

(3) The distribution of w_P across households follows a Gamma distribution, with parameters K and A which can be computed from Household Panel (HHP) data. A useful tool to find K and other "NBD-Dirichlet" parameters using VB and Excel has been made available by Z. Kearns (2002). It can be downloaded from http://marketing-bulletin.massey.ac.nz/ (Dirichlet VB.xls link)

(4) The choice of each brand at any purchase act follows a multinomial distribution, with a probability assigned to each brand and the sum of probabilities totaling 1.

The conjunction of assumptions (2) and (3) is called a Gamma-Poisson mixture and gives a negative binomial distribution (NBD).

While the he "NBD-Dirichlet" model is a good predictor of aggregated category dynamics and brand purchase, two of its core hypotheses make it impossible to capture the drivers of some dynamics observed in consumer behavior:

I. The category penetration is time-invariant in the "NBD-Dirichlet" model. This hypothesis is not confirmed in practice; category penetration can evolve over time.
II. The purchase frequency is modeled using a Poisson process, which is a discrete process. Consequently, households who do purchase the product cannot have a purchase frequency lower than once per year. This assumption may look trivial at first, yet it fixes an unnecessary lower bound for light buyers and has an impact on the evolution of category penetration.

Using a system dynamics model, we remove these hypotheses and are thus able to explain the drivers of category penetration evolution and category purchase frequency evolution. An overview of the full model structure can be found in Appendix 1.

As a starting point to build the system dynamics model, we use three mathematical properties of the "NBD-Dirichlet" model to tackle the limiting hypothesis as follows:

(i) The algorithm to determine A and K:

$$B = 1 - \frac{1}{(1+A)^K} \qquad (1)$$

This is based on Goodhardt et al. (1984), where A is the scale parameter and K the shape parameter of the negative binomial distribution (NBD) for category purchases. The parameters capture households' purchasing heterogeneity. A more detailed description of the parameters used in the "NBD-Dirichlet" model can be found in Carl Driesener (2005).

(ii) The relationship between the parameters A and K:

$$A = \frac{W*B}{K} \qquad (2)$$

A is a function of the annual buying rate per household in the total population ($W*B$) and of K.

(iii) The linear relationship of the scale parameter A with time:

$$A_T = T * A \qquad (3)$$

HHP data provides annual values for B and W, so K and A can be computed for the category using equations (1) and (2). Changing A to A_T to reflect a longer time period as per equation (3) and feeding the results back into equation (1) while keeping K constant, we can determine the % evolution of the penetration over periods longer than 1 year.

As the penetration computed over a longer time period exceeds the 52-week penetration level, we refer to the difference as the excess penetration. This excess penetration comes from households who buy the category less than once a year. For instance, consumers buying once every two years would only be included in the annual penetration every other year. We refer to these consumers as light buyers and denote the excess penetration by B_L. This interpretation is compatible with the "NBD-Dirichlet" hypothesis that the annual penetration is stable: the number of light buyers who purchase during a 52 week period remains constant.

The dynamic model divides the light buyers representing the excess penetration B_L into two groups:

1. Stable light buyers. These are consumers that are committed to the category (category users) but consume little and only need to purchase the category less than once a year. These consumers are considered as stable users not driven by promotions; they will buy the category regardless of promotions, though they would buy on promotion if there is one in the store the day they shop the category.

2. Opportunistic new buyers. New buyers that are exclusively buying on promotion. In a stable category with stable promotional activity, the percentage of these promotion/impulse driven consumers is assumed stable and total category penetration (B) is stable. The dynamic model here considers this group of consumers separately in order to understand how changes in the promotional activity in the category affect category penetration and purchase frequency.

Looking at these two groups independently is key to assess the promotional impact on overall category penetration. The overall dynamic of these two groups and their relation to promotional activity is shown in Figure 1, which provides a simplified view of the model for visual convenience.

The increase in the *52W Rolling User base* is determined by the light buyers (buying regardless of promotion) and the opportunistic new buyers (buying through promotions). These will leave the user base 52 weeks later (*Lapsed Users*). The proportion of *lapsed users* under stable conditions is calibrated using the "NBD-Dirichlet" theory and is a fraction of yearly B_L (split linearly over 52 weeks).
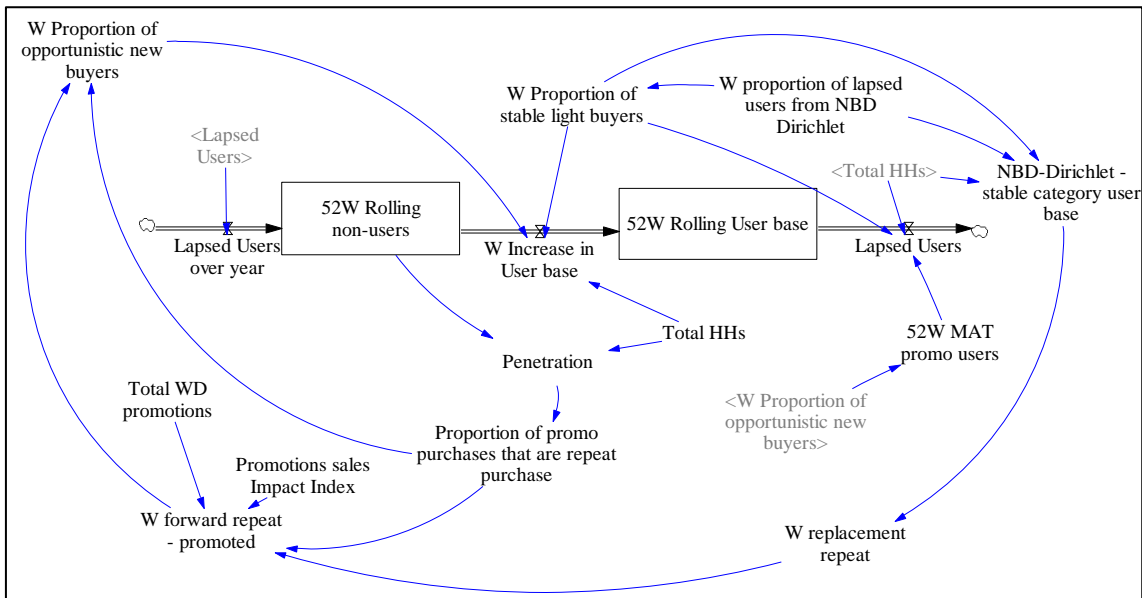
Figure 1. The user base dynamic.

The impact of promotions on the *W proportion of opportunistic new buyers* is derived from a *promotions sales impact index* which is considered as a known input (it can be found from econometric trade promotions analysis done by IRI, Nielsen ...etc.). The model splits the *promotion sales impact index* into transaction size driven volume, extra forward purchase acts (*W forward repeat – promoted* from stable category users) and extra trial acts (from opportunistic new buyers). The proportion of trial purchases from promotions is negatively impacted by the level of category penetration; the less available users there are, the less new buyers there can be. This is a stabilizing feedback loop in the model (similar to diffusion curves).

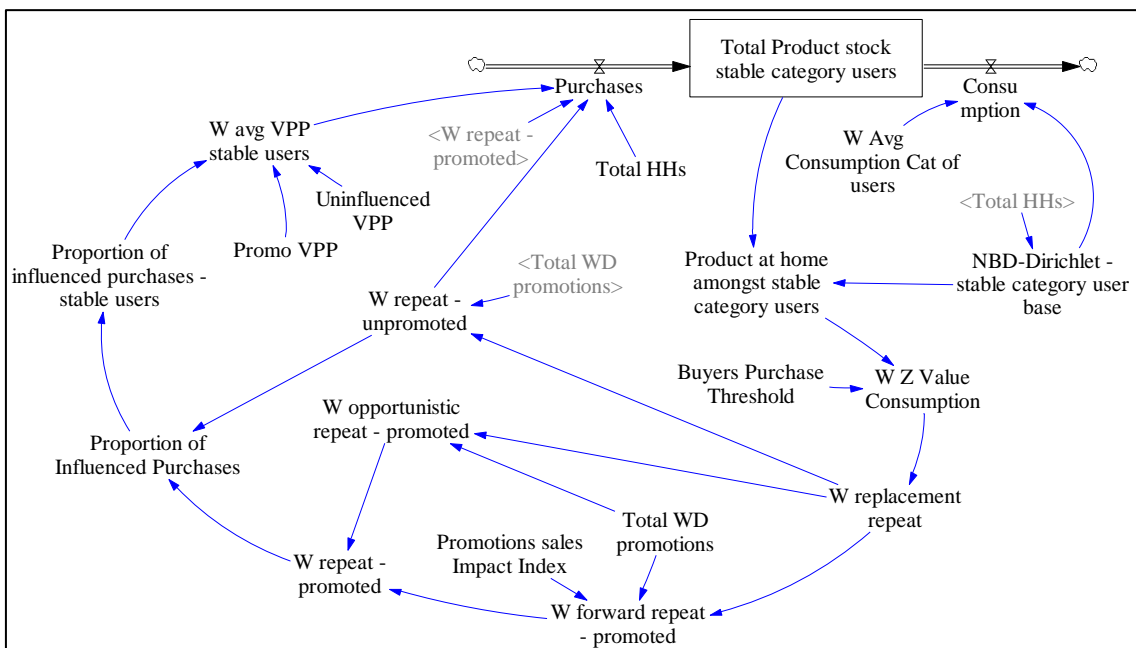Figure 2 shows the simplified dynamic of repeat purchases and promotions.

Figure 2. The repeat purchases dynamic.

Every week, a certain proportion of category buyers go to the store and purchase the category to keep a certain level of stock at home. These purchases are repeat purchases as they occur amongst households that have already bought the category in the past. Only stable category users are taken into account for repeat purchasing and their penetration (B- B_L) is invariant even under unstable category dynamics. The dynamics of stable users' repeat purchases (*W replacement repeat*, bottom right of figure 2) are based on the average product they have left at home (*Product at home amongst stable category users*), which depends on their *consumption* and the average transaction size (*W avg VPP stable users*) of their purchases (figure 2).

Product at home amongst category users triggers repeat purchases when a certain threshold is reached, under which they will purchase the category to keep an acceptable stock of product at home and continue consuming. The proportion of consumers that fall below the threshold and therefore make a category purchase in a given week is assumed to follow a normal distribution for modeling simplicity. The variance of the normal distribution is derived from the "NBD-Dirichlet" purchase acts distribution and adjusted for average consumption using equations (4) and (5):

$$\sigma^2(x) = K * M^2 \qquad (4)$$

$$\sigma(ax) = |a| * \sigma(x) \qquad (5)$$

Where K is the "NBD-Dirichlet" parameter and M is given by $W*B$. Note that despite this modeling approach, the model remains deterministic: distributions are used to predict replacement repeat purchases without uncertainty.

In most mature categories, manufacturers impose larger sizes in promotions to load consumers with their product (in our beer example, the promotion would be a 10-can pack compared to the usual 8-can pack). This strategy works well for manufacturers as they can offer a higher absolute deal in promotion (i.e. a bigger monetary discount, which is more interesting for consumers) and the bigger size mechanically increases their brand's volume share of requirement.

We assume consumption to be stable. This implies that category users buying bigger sizes build product stock and do not need to shop for the category as early as if they had bought their regular size (it will take them longer to reach the threshold at which they go purchase the category). In fact, there is evidence that consumption is influenced by pack size (Wansink 1994), but the effect on purchase frequency is small enough to not be taken into account in the current version of the model.

This is a second stabilizing feedback loop in the model: as promotion purchases increase, stable users buy a bigger size (volume per purchase, VPP), which increases their product stock, decreases their natural replacement purchases and consequently their promotion purchases.

For conceptual convenience, the model limits the transaction size variability to two options: the uninfluenced (usual) volume per purchase (*uninfluenced VPP*) and the promotion volume per purchase (*promo VPP*).

Finally, the model includes a simple dynamic of competitive interactions that captures variations of promotional intensity. Promotional dynamics do not reflect a store model (analyzing where consumers shop) but a category model (analyzing when consumers buy and how much). Two competitors are considered; Brand A and Brand B, equally liked by consumers (50% preference share for each brand), and 100% substitutable.

The model assumes that competitors know the impact of promotions on their market share and can adjust promotions to the exact level so as to reach their target market share under current conditions – with a certain delay. Promotions are expressed as a % of weighted distribution. The weighted distribution of promotions is defined as the % of all stores having a promotion, weighted by store sales of the product category. Weighted Distribution (WD) takes into account the stores' importance for category sales, which is not the case with Numerical Distribution (ND, the % of all stores).

These dynamics are shown in figure 3. Promotions (*W Brand A WD promotions*) are modeled as a stock as they take time to be adapted. This assumption is also made for the sake of consistency; high/low promotion activities over short time periods would be more difficult to capture in terms of decision making and would induce unnecessary fluctuations in the model which would confuse rather than help us in understanding the link with category penetration and purchase frequency evolution.
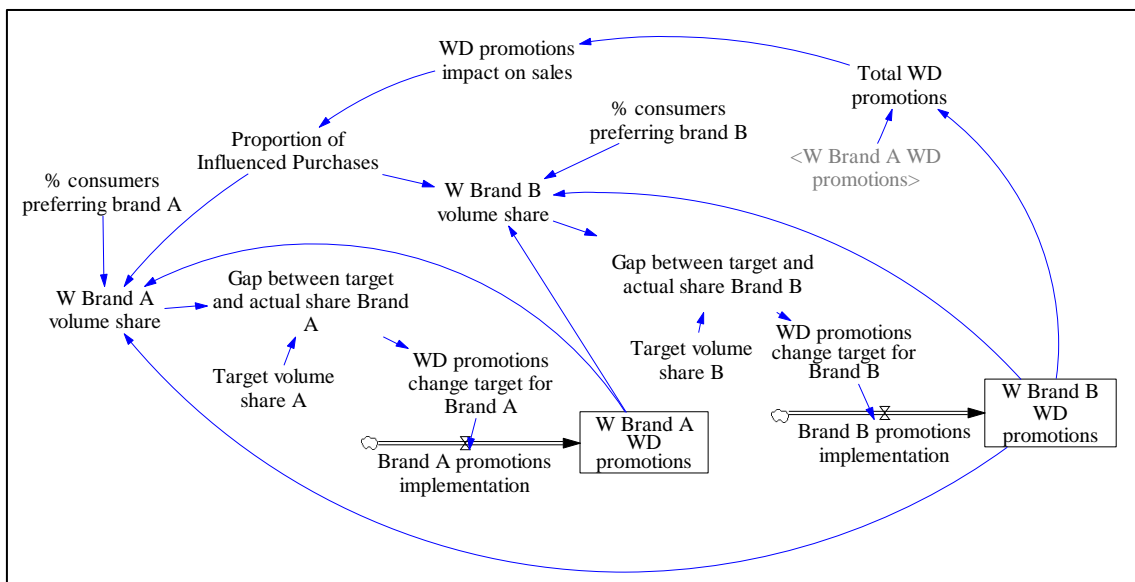

Figure 3. The competitive promotional dynamic

Figure 3 shows the competitive promotional dynamics. These promotional dynamics induces an oscillation of market shares and levels of promotions (weighted distribution of promotions) of Brands A and B. Equilibrium can be achieved if both competitors have a volume share objective equal to the natural consumer preference and their relative promotional pressure is equal to their relative market share.

The model admits that each competitor can increase his level of promotions to cover up to 100% of the stores. A different upper limit could be imposed in the model to take into account financial constraints or stores acceptance of extra promotions; however the model would show the same dynamics, so we decided to keep 100% as limit for promotions WD.

We assume that promotions of each brand are distributed independently across stores, so they can be found in the same store at the same time, in which case consumers buy brand A or B according to their natural preference ratio.

Model calibration and validation

The model is calibrated using publicly available household panel (HHP) data for the Beers/Ale/Alcoholic Cider category from the IRI Marketing Data Set of 2008: category penetration, purchase frequency and the volume sold on deal (VSOD), i.e. the proportion of total volume sales that is sold on promotion.

The promotion impact index has been set to deliver a VSOD in line with panel data. The consumption rate and the purchase threshold have been calibrated to reach model equilibrium (the steady state corresponding to the "NBD-Dirichlet" model).

In addition, the following numerical values are used for calibration:

1. The population of the theoretical case has been set to 10,000,000 households.
2. The proportion of trial purchases that come from non-promotion driven buyers (stable "NBD-Dirichlet" base in the model) has been set to 80%.
3. The transaction sizes have been set to 2.64 liters for regular (unpromoted) purchases and 3.3 liters for promoted purchases.
4. The promotions are initialized at 10% of the weighted distribution for each brand.
5. The brand preference ratio has been set to 50% for A and B respectively.

Weekly time periods are used, as they represent the shortest measurable period of time from household panels. The simulation time-step δt of ¼ allows delays as short as 1 week if need be. We run the simulation for a 3-year period (156 weeks), which is the minimum required to observe the patterns under investigation. Seasonality is excluded from the model to make interpretations easier. The model has been implemented in Vensim[®].

The model has been validated using Sterman's twelve model tests (Sterman 2000, 859-61). Two comments are worth highlighting:
1. Structure assessment: the simplification of competitive dynamics is consistent with the model objectives.
2. Dimensional consistency: purchases are assumed to be dimensionless as they are interchangeable with consumers for trial purchases.

All tests provide satisfactory conclusions regarding model robustness.

Results

We consider two scenarii:

1. The equilibrium scenario, which is a more granular application of the "NBD-Dirichlet" theory and is referred to as the base case.
2. Starting from the base case, we assume an increase in the market share target for one of the brands (brand A) at time 0.

Scenario 2 shows the competitive dynamic as a competitor (brand A) increases its market share target and relies on extra store promotions to reach his target. This creates disequilibrium in the competitive environment leading to an escalation of promotional activity of both competitors up to the maximum level (see Figure 4). As brand A gains market share thanks to higher promotional pressure than brand B, the second competitor increases his promotions to recover the loss, hindering the ability of brand A to build share with promotions and prompting for more promotions. As promotions are only constrained by the number of stores in the model, the escalation of promotions goes on until the maximum of 100% of the stores have a promotion for each brand.

The rise in promotions (figure 4) induces an increase in the category user base, fueled by the recruitment of promotion-driven buyers with no loyalty to the category. This shows how the category user base and overall category penetration are inflated by promotions (figure 5).
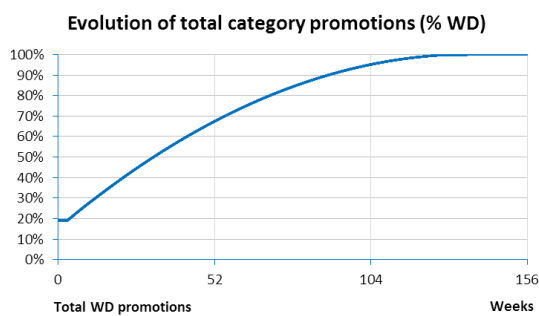

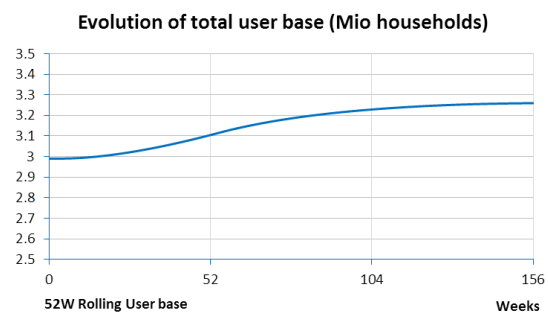**Figure 4. Total promotions of the category**   **Figure 5. Total user base**

In addition, promotions increase the average transaction size of regular buyers, which builds their product stock (see figure 6) and decreases the natural replacement repeat rate. The increase in user base due to these "one-off" buyers, combined with the drop in repeat rate amongst stable category users, induce a significant decline of category purchase frequency over time (figure 7).

Note that in the short term (up to week 6) we observe an increase in purchase frequency, driven by forward purchases by stable category users due to the additional promotions. However, this effect is quickly compensated by the increase in user base ("one-off" buyers) and the lower natural replacement repeat purchases, as mentioned above.
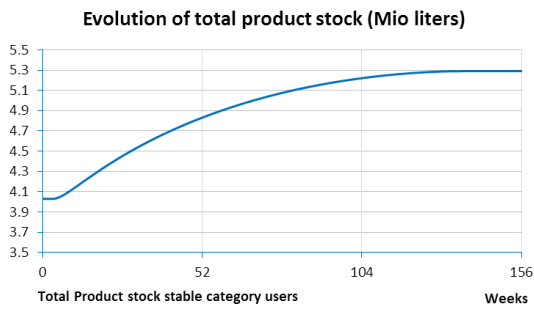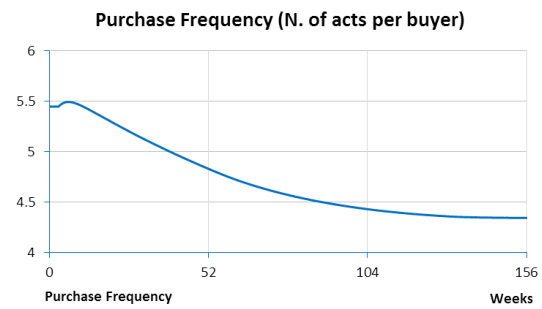
Figure 6. Total product stock

Figure 7. Purchase Frequency

The gradual drop of category purchase frequency from week 6 onwards makes competitors more dependent on promotions; as purchase acts occur less often in the category, it is more important for competitors to keep a high promotion pressure over time to divert purchases towards their brand. When promotions are on the rise, Brand A market share is ahead of Brand B as it is moving first on promotional pressure and Brand B is only reacting (figure 8). Note that the sum of the Brand A and Brand B promotion is not equal to the total category promotion (figure 4) because when computing the total, we subtract the duplicate promotions, i.e. the cases where both brands are on promotion in the same store at the same time. Duplicate promotions are close to 0 for low levels of promotion (time 0), and reach 100% when both brands advertise in all stores (towards the end of the simulation period).
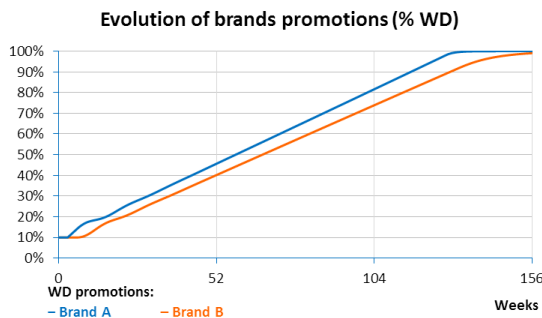

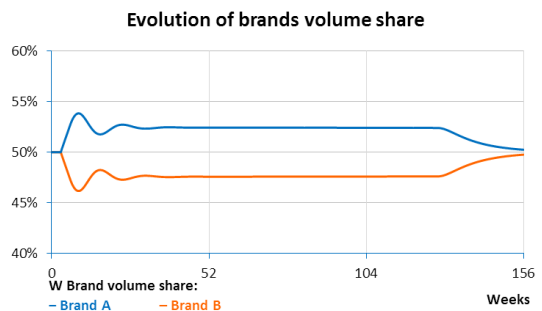**Figure 8. Brand A and Brand B promotions**

Figure 9. Brand A and Brand B volume share

Brand A benefits from this first mover advantage until he gets close to the maximum promotional pressure possible (in week 126, with 97% of weighted distribution). At that point Brand B is catching up on his promotional disadvantage and gaining market share back. As Brand B approaches the maximum promotional pressure, his promotional pressure gets very close to Brand A levels. Both brands lean towards similar competitive pressure, so promotions-based competitive advantage and market shares tend towards consumers' natural brand preference (50% in this case). Market shares converge to their original levels as of week 126, but with almost all volume sold on deal. These curves lead to a new equilibrium with equal maximum promotional pressure, 100% volume sold on deal and 50% market shares. At that point, a drop of promotional pressure by one of the competitors would result in him losing market share. Hence, this state is a Nash equilibrium.

In addition to market shares variations (figure 9), total category volume shows an interesting dynamic. As expected, category volume initially grows with the intensity of promotions in the category. However, category size is not following the evolution of promotions over the full period; category volume reaches a maximum at week 62 while promotions keep increasing beyond week 120. From period 62 to period 120, competitors continue to increase promotions, yet the yearly category volume (see figure 10) is going down in the simulation.
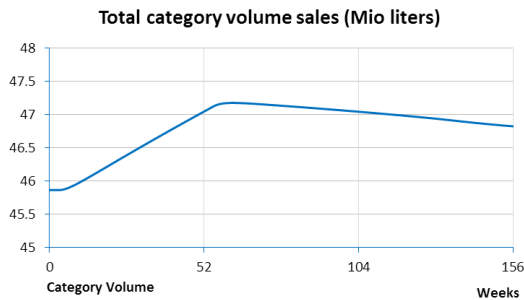
Total category volume sales (Mio liters)

Category Volume

Weeks

Figure 10. Total category size (volume)

While this observation is a priori counter-intuitive, it makes perfect sense in a dynamic context: category volume gains are slowed by the duplication of promotions and extra brand promotions have a declining marginal impact at category level (a new promotion for, say, Brand B is likely to be redundant in the store as there is already a promotion for Brand A). Also recall that stable consumers have increased their product stock (figure 6) and do not need to purchase the category as often, delaying some purchases. Thus, looking at the evolution over a 52 weeks moving average, category volume is decreasing while promotions for both competitors keep increasing.

As the first competitor increases his promotions, his actual market share remains below his new target as the second competitor is reacting, yet his volume sales are significantly increasing (see figure 11). However, competitors relying exclusively on market shares objectives will keep on increasing their investment in promotions despite increases in their volume sales – even though the actual volume sales get close to their share objective applied to the initial category size. Market share objectives rather than sales objectives fuel the escalation of promotions (Armstrong & Green 2007).
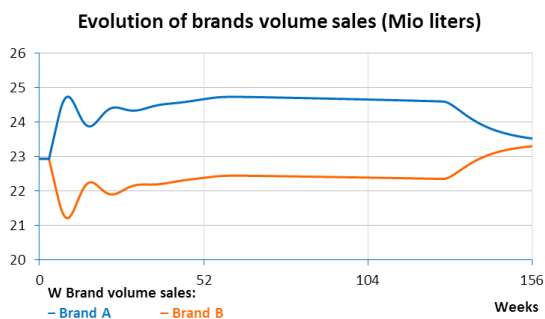
Evolution of brands volume sales (Mio liters)

W Brand volume sales:
– Brand A   – Brand B

Weeks

Figure 11. Brand A and Brand B volume sales

Interestingly, if the first competitor decreased his market share target back to the original level, the level of promotions of both competitors in the new equilibrium would remain well above the original level: the competitive escalation is not reversible if competitors rely exclusively on market share objectives as in the model.

Conclusions

The proposed model enables us to explain how competitive interactions in store promotions impact category size, penetration and purchase frequency evolution. Some restrictive hypotheses of the "NBD-Dirichlet" model can be relaxed through the use of system dynamics modeling. The model considers three groups of consumers that may make a purchase in the category: the stable yearly user base, the committed light buyers, and the opportunistic buyers. Under stability conditions (our base case), the dynamic model shows the same patterns as the "NBD-Dirichlet" model. However as competitors enter a promotional fight for market share, this stability condition is no longer fulfilled and category metrics change: we observe a gain of penetration as more opportunistic buyers enter the category and a reduced purchase frequency (due to the loading of stable users with extra stock as well as the extra light buyers that do not repeat their purchase). The model also explains why even if the promotion intensity is increasing in a category, the total category volume size can be decreasing. And this shows how market share objectives can lead to a higher reliance on promotions by competitors, which is healthy neither for competitors' financials nor for category growth in the long term.

The model described assumes stable consumption by stable category users; an interesting extension would be to include the transaction size as well as the price impact on consumption.

Appendix 1

Model description (simplified)
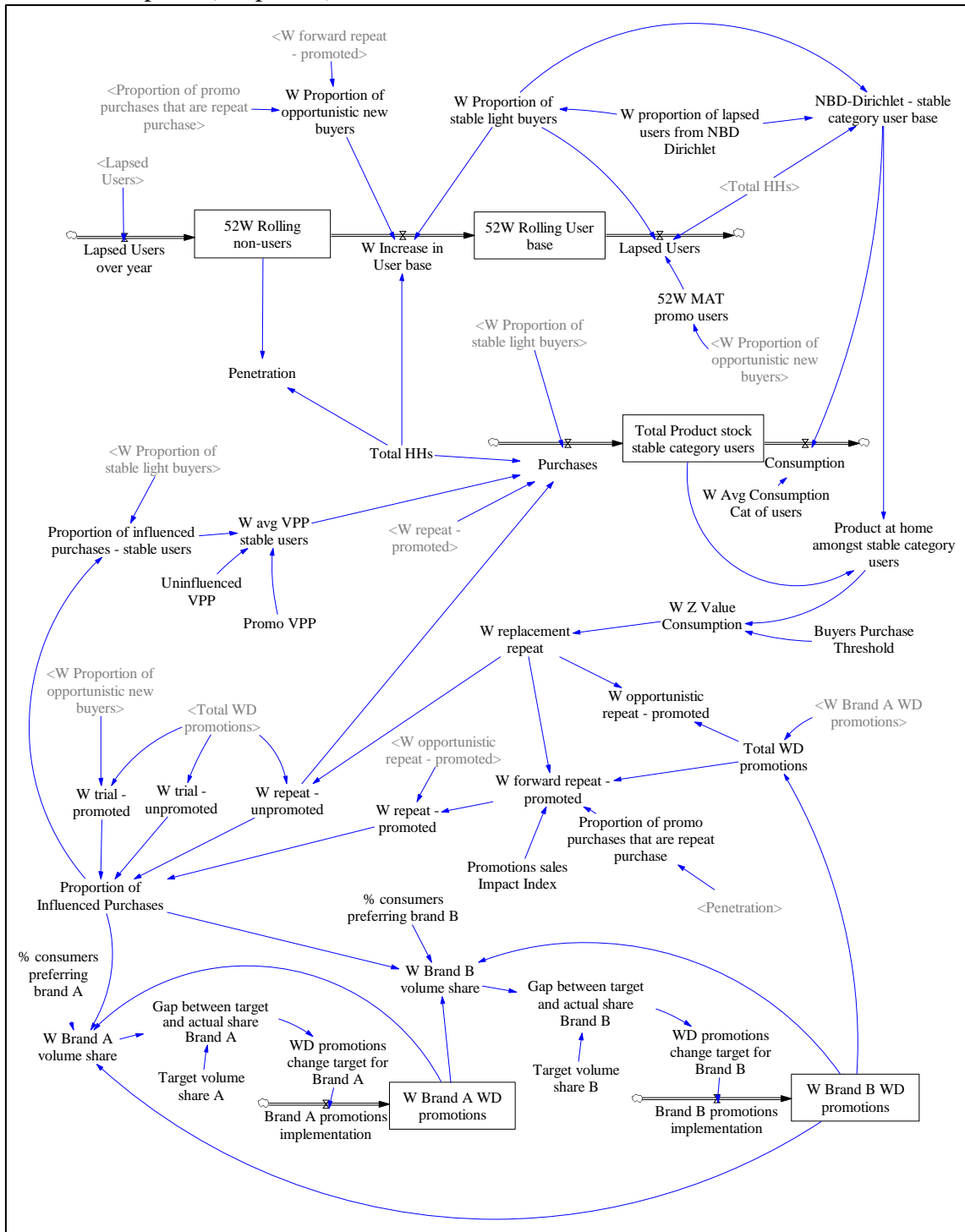
The complete list of equations is available from the author.

Appendix 2

Glossary

Penetration (*B*). The % of households in a particular area that have bought a brand or a product category over a 52 week period.

Trial. The % of households in a particular area that have bought a brand or a product category over a 52 week period for the first time.

Repeat / repeat rate. The % of households in a particular area that have bought a brand or a product category more than once if they have bought at least once over a 52 weeks period.

Purchase Frequency (*W*). The average number of purchases of a brand or a product category that households make over a 52 week period amongst households that have bought the brand or the product category at least once.

Promotions. All promotional activities (leaflets, displays, shelf material …etc.) that carry a price discount. The mix of promotional activities is assumed constant over time in the model.

Weighted Distribution. The % of all stores weighted by store sales of the category.

Promotions sales impact index. Volume sales when and where a promotion takes place divided by the normal sales level (i.e. without promotion).

Volume sold on deal. The volume sales that was made on promotion divided by total volume sales, i.e. the % of volume sold on promotion.

Volume per purchase (VPP). The transaction size expressed in consumption units (liters in the case of the Beers/Ale/Alcoholic Cider category).

Volume share of requirement. The average proportion of total category volume that a brand represents amongst buyers of that brand over a certain period.

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