Predicting Volatile Markets Using Simulations

Reach and Limits

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Consumer Packaged Goods Markets

Characteristics

- Inherently noisy with volatile market share movements
- Very frequent competitive interventions by firms through pricing and promotional activities
- Heterogenous consumer base, wide variation in tastes and preferences
- Potential non-linearities in the form of network effects, WoM, feedbacks etc.

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– Can we predict such systems?

– To what extent and how?

Consumer Packaged Goods Markets

Volatility

- Volatility may arise due to heterogeneity in tastes and preferences (Allenby and Rossi, 1998; Jager, 2007)
- Volatility may arise due to frequent marketing interventions by firms, pricing/promotions, packaging, advertising (Blattenberg and Wisniewski, 1989; Ailawadi et.al., 2001)
- Emergent phenomena as a result of non-linearities (Gilbert et.al. 2007; Jager, 2007) (more likely to be longer term than short term)

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Use of Simulations

ConsSims: Roach and Gilbert (2007), North et.al. (2009), Sengupta and Glavin (2010), Sengupta and Glavin (2011)(in progress)

Background

- Traditional approaches - Logit/Probit/Nested Logit models
- Focus on effects of promotions on sales, market structure in the short term
- Difficult to incorporate dynamics over time
- Fail to explicitly account for individual level heterogeneity; don't allow household level predictions
- Poor out of sample performance
- Do not incorporate non-linearities

Aim of Today's Talk

- Illustrate the use of agent based simulations to model typical CPG markets
- Introduce a validation methodology, to test models at multiple levels
- Show such models can capture noisy dynamics accurately
- Show how validated models can be used to make out of sample predictions and carry out what-if-scenarios
- Provide a flavor of the potential of simulation based models for multidisciplinary applied research

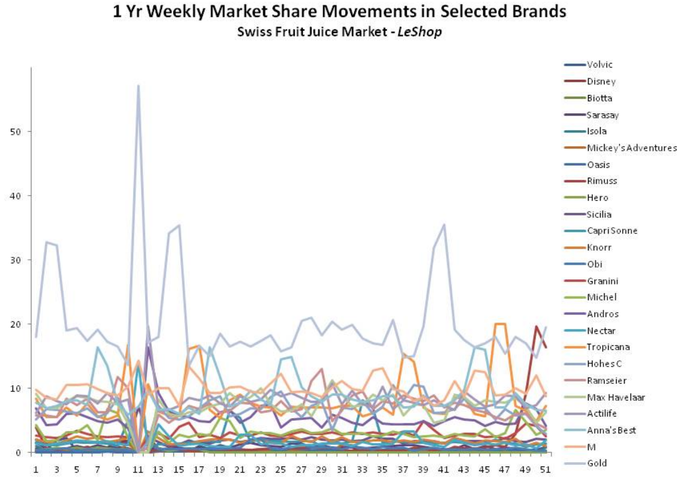
Outline of Today's Talk

1. Present a simple behavioral model relevant for consumers of general CPG markets with **Rational Agents**
2. Introduce a validation methodology and prediction results
3. Present an enhanced model of behaviour incorporating the more interesting **Shopping Strategies**
4. Predictions using enhanced model
5. Conclusion, future work and general discussions

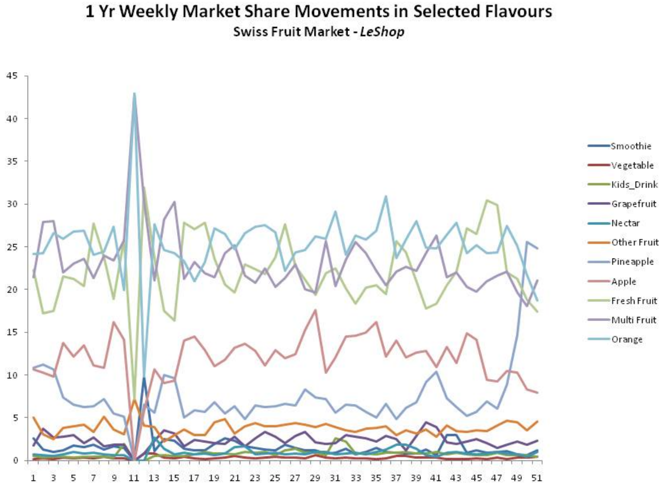
Models

Case Study Fruit Juice Market in Switzerland

Fruit Juice Brands



Fruit Juice Flavours



Rational Agents

Assumptions

- Product characteristics and portfolio remains unchanged in the given time period
- Individual level tastes and preferences remain unchanged in the given time period
- All agents act rationally and able to rank alternatives consistently
- Ranking is done based on a subjective utility function
- Social networks and word of mouth effects are absent

Rational Agents: Model

- Industry with K distinct *products*
- Each product $k \in K$ has M attributes, *address vector* in characteristics space

$$X_k = (x_k^1, x_k^2, \ldots, x_k^M) \qquad \forall k \in K$$

- Each agent has a *preference vector*, the best product or the *ideal point*

$$\lambda_i = (\lambda_i^1, \lambda_i^2, \ldots, \lambda_i^M) \qquad \forall i \in I$$

Rational Agents: Model

- Utility of i for product k, whose net price is P_k:

$$U_i(k) = \omega^i d_k^i + (1 - \omega^i) p_k \quad \text{where, } \; 0 \le \omega_1^i \le 1$$

$$d_k^i = -\frac{D_k^i}{\max\limits_{j \in K} D_j^i}, \quad D_k^i = \sum_{j=1}^{M} |x_k^j - \lambda_k^i|$$

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- Agent specific parameters: ω^i, $\vec{\lambda}^i$
- Utility is ordinal – for comparing products only

Data

- Loyalty card transactions data within the fresh fruit juices category, from Jan 2006 to Dec 2006 (52 weeks)
- 55 total products (SKU), 2435 households and 28179 transactions
- Each transaction records – household ID, SKU, week number, net price and discount, quantity bought
- Source: *LeShop*, largest *online* supermarket in Switzerland

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Model...

- 3 major product characteristic dimensions – brand, flavor, pack size
- $K = 55$, $I = 2435$, $M = 3$

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- *Calibration.* Transactions from Weeks 25 to 38 (Partition II). Fix agent specific weighting parameter ω^i.
- *Testing.* Transactions from Weeks 39 to 52 (Partition III). Use parameterized agents to make out of sample predictions using Monte-Carlo method to test predictions at micro and macro levels. Market share based random choice model used as benchmark.

Validation - Initialization

Products in Characteristics Space

- Each dimension of characteristic space normalized to [0, 1]
- Within each dimension, each component is assigned a value based on relative sales volume within initialization data
- The component with highest sales volume is assigned a value of 1, the lowest with 0 and the rest are equi-spaced based on relative sales volume
- The combination of all 3 dimensions define unique products within characteristics space

Validation - Initialization

Agents' Ideal Pts in Characteristics Space

- A proxy for each agent's ideal point is estimated using agent's purchase history in Part I
- Within a given dimension, the weighted average of all categories purchased, with purchase frequency as the weight, fixes the ideal for that dimension
- Repeated for every dimension to provide a 3-dimensional ideal point vector
- Repeated for all agents

Validation - Calibration

Strategy

- Identify the best ω^i for every i
- Carried out at macro (market share) and micro (household) levels
- **Macro** Capture market share movements of product groups
- **Micro** Capture household specific choice of SKUs and product characteristics over time
- Separate fitness metrics for each level
  - Macro – *binary matching*
  - Micro – *city block metric*
- The parameter space of ω^i discretized

Binary Matching

Optimize SKU Choice

- For every agent i, find the set of ω^is which results in best match of SKUs bought by i, for all weeks in Partition II
- Define a *weekly binary matching score* per value of ω
- The binary matching score is an average of *weekly* values
- Ω_b^i is the set of ωs which give the best fit for agent i

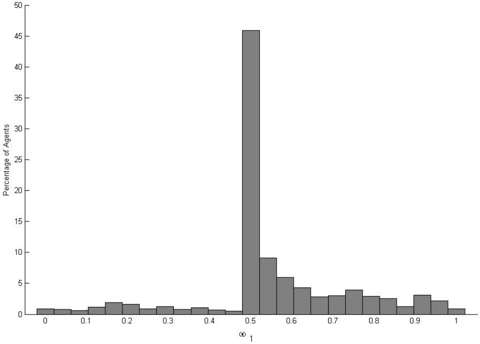
City Block Metric

Optimize Product Characteristic Choice

- For every agent i define a *weekly city block score*, which rewards for every characteristic choice matched per week
- Each dimension is treated independently
- ω's corresponding to best overall city-block scores are included in set Ω_c^i

Optimal Parameters

Distribution across all agents – Binary matching and City block metric



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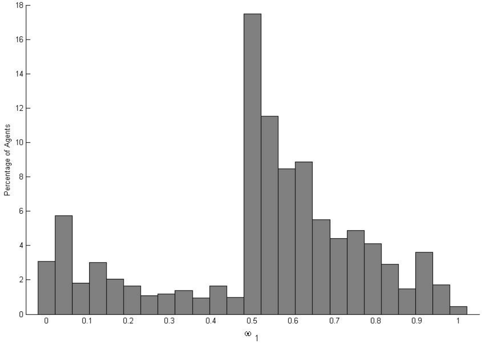

Validation - Test

- Carried out at both macro and micro levels
- Parameterized agents used to make out of sample predictions
- Monte-Carlo type simulations using multiple runs, where each run corresponds to a draw from the optimized parameter set of each agent (100 runs per agent)
- Results compared against benchmark – a market share based random model

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Benchmark

- A random choice model built using Partitions I and II
- The probability of any SKU being chosen is the relative frequency of purchase in the data
- Ignores individual heterogeneity but captures average market level preferences

Simulation Setup

- 2435 agents, each representing a household in the data
- At every time step, each agent chooses exactly one product from available choice
- Available choices and corresponding prices derived from data
- *Quantity* is not modelled here, but copied from data
- Software - Netlogo and Matlab

Results - Macro Levels

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- Significantly outperforms the benchmark

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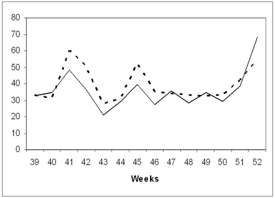

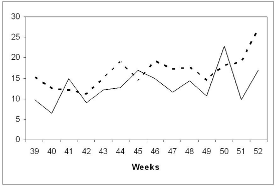

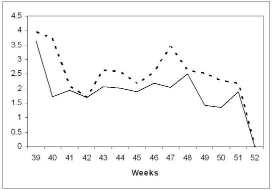

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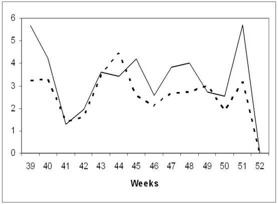
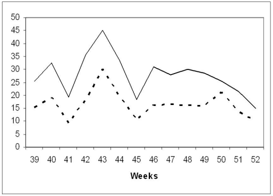
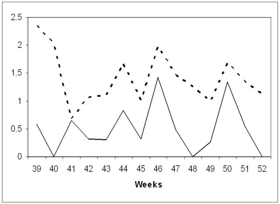
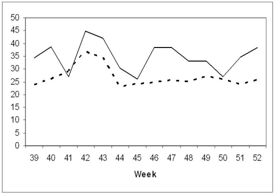
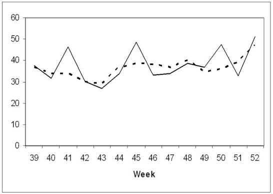


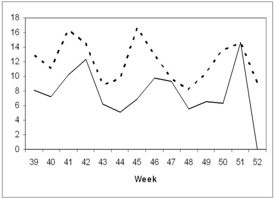




Results - Flavours







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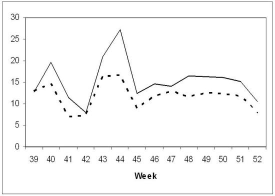

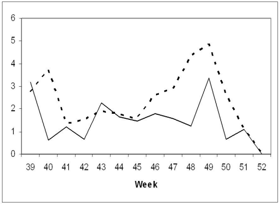

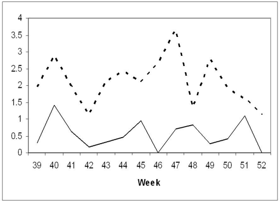

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Results - Micro Levels

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- Measures *joint* predictions along subsets of dimensions
- Model works very well at individual level, outperforming the benchmark
- Characteristic choice accuracy superior over product choice accuracy
- 36% accuracy in household specific SKU choice
- 62%, 73%, 40% accuracy in predicting brand, flavour and pack size respectively

Introducing Strategies

- Rational agents model performs well, but behavioral model is "artificial"
- Introduce bit more realism in agent level behaviour through Shopping Strategies
- **Loyalty** Shopper tend to be biased towards product attributes they usually buy
- **Change of Pace** Shopper ignores attributes they usually buy
- **Consumer Memory** plays an important role
- Both strategies help define the *consideration set* of individual shoppers

Strategies and Product Choice Rules

- Strategies act on product attributes rather than on SKU
- Loyalty – choose the attribute bought most frequently in memory
- CoP – ignore the attribute bought most frequently in memory
- Define probability α_i^m as the probability of choosing CoP over L for attribute m
- Once *consideration set* is defined for a shopping instance, use utility function to make final choice

Validation

- Same 3 stage process – initialization, calibration and testing
- Additionally initialize a switching parameter α_i^m per agent per dimension, estimated from switching frequencies in the Partition I of data
- Memory lengths are fixed at same integer value for all agents
- Two values of memory length experimented with - 4, 8
- Benchmark - Rational Choice model (No strategies)
- 3 year transactions data used: 171 products, 9379 households

Key Results

- Models with strategies perform significantly better at macro level than benchmark
- Longer memory lengths do not improve predictions significantly – non retention? discounting?
- Micro level results support the above as well

Conclusion

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- Agent level variation in tastes/preferences/strategies help capture the volatile nature of the market
- Quite accurate micro level predictions are possible in many cases
- Easy to incorporate deviations from mainstream rational choice type models into more fuzzy domains

To be done...

- Markets have been assumed to be stationary, but in reality they are not
- How do we handle discrete events in the market - or even paradigm shifting changes?
- New products with new features?
- Shifts in consumer psychology...
- Can the accuracy of predictions be maintained in markets where strong social networking/WoM effects are present?