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Validating agent-based marketing models through conjoint analysis☆

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Abstract

Agent-based modelers in the field of marketing research have paid little attention to validation issues. This paper provides a definition of validation relevant for this community of modelers. On the basis of a history-friendly model for simulation calibration [Malerba, F., Nelson, R., Orsenigo, L., and Winter, S. (1999). 'History-friendly' models of industry evolution: the computer industry. Industrial and corporate change, 8(1), 3–40.], the authors demonstrate how conjoint analyses can be used to instantiate and calibrate an agent-based marketing model. Methods for model instantiation using conjoint partworths and model calibration using the conjoint first-choice rule are demonstrated. When the model matches the results of the first-choice rules for consumer preferences, the modeler can feel more confident that calibration has been achieved. When verification replicates stylized facts on a macro-level, the model is one step closer to validation. Because conjoint data results are meaningful on an individual level as well as on an aggregate level, this type of empirical data collection is ideal for agent-based marketing models.

Keywords: Conjoint analyses; Agent-based modeling; Validation; Calibration; History-friendly model

1. Introduction

Validation of computational models is an area of concern to simulation modelers (Conway, 1963; Knepell and Arangno, 1993; LeBaron, in press). Different types of validation (Knepell and Arangno, 1993), different levels of validation (Carley, 1996) as well as different methodologies for conducting validation (Carley, 1996; Fagiolo et al., 2005) have resulted. These differing studies, along with feedback loops, path dependencies, sensitivities to internal conditions, and the unpredictability of agent adaptation (Fagiolo et al., 2005) associated with empirically based agent-based models

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(ABMs), easily confound the task of validation. Important questions asked by agent-based modelers, especially those investigating real-world systems, are: which methods of validation are best? Which levels should be considered? How does one know a model is correct?

Agent-based modelers in the field of marketing research have paid little attention to these validation issues. The goal of this paper is therefore two-fold: to provide a definition of validation relevant for agent-based modelers in marketing research and to introduce a calibration method based on conjoint analysis that incorporates real-world data into a marketing-oriented agent-based simulation. The paper first provides a definition for validation and for validation levels that are important to this community of agent-based modelers. Drawing upon reviews grounded in agent-based computational economics (ACE) by Carley (1996) and Fagiolo et al. (2005), the authors then briefly present three methodologies used to seek validity in ABM simulations. This foundation serves to demonstrate how conjoint analysis can be used to calibrate an agent-based marketing model.

The next section establishes definitions for validation and introduces three calibration methodologies; indirect calibration, theWerker–Brenner calibration approach (Werker and Brenner, 2004), and the history-friendly calibration approach (Malerba et al., 1999). Finally, by using an example of a history-friendly approach based on the wine industry, the paper demonstrates how conjoint analysis is used to calibrate an ABM. Henceforth, the authors refer to ABMs that focus on market behavior as agent-based marketing models (AMM).

1.1. Defining validation

Although numerous definitions for validation exist, this study specifically focuses on the empirical validation of a computerized marketing model. A validated model will possess a satisfactory range of accuracy matching the simulated model to the real-world model (Fagiolo, et al., 2005). AMMs usually include individuals, either at a consumer level or a firm level, who are being observed at the market or industry level. Thus, when validating AMMs, matching should occur on both a micro and a macro-level. In addition, an empirically validated model is grounded on qualitative and quantitative data collected from the system being investigated. Validation determines that the conceptual simulation model (as opposed to the computer program) is an accurate representation of the real-world system under study (Kennedy et al., 2005), as supported by empirical data.

Carley (1996) suggests four validation levels – grounding, calibration, verification, and harmonizing – in order to properly investigate both micro and macro economic levels. Grounding, which includes establishing face validity, parameter validity, and process validity, should occur first (Carley, 1996). Face validity pertains to whether the output looks valid to vestedinterest parties. In establishing face validity, the model should set forth how the simulation represents the real-world and should delineate the model's scope based on qualitative and quantitative empirical data. Parameter validity examines if the characteristics and initial conditions assigned to an agent of the model appear realistic. Process validity ascertains whether the overall model simulation makes sense on a macro-level. The process should include the appropriate players, and these players should interact in a realistic manner. A causal model, as demonstrated in Fig. 1, is often good for establishing process validity. During grounding, boundaries should be established on both a micro and a macro-level. For example, in a model of diffusion, individual consumers will purchase a set limit of products monthly, and overall, diffusion will typically follow an S-shaped curve. Limiting consumer purchase amounts is an example of setting parameter boundaries on a micro-level and monitoring the diffusion rate is an example of obtaining face validity on a macro-level. The model investigated in this study incorporates conjoint data gathered during grounding analyses, and is tuned to these data during the calibration process.

Calibration, the next step, is the process of tuning a model to fit detailed empirically supported data (Levitt et al., 1994; Carley, 1990). During calibration, model parameters and initial conditions are tested and tweaked so that the behaviors of individual agents in the model are consistent with empirical micro-level characteristics of the modeled agents (Carley, 1996). The

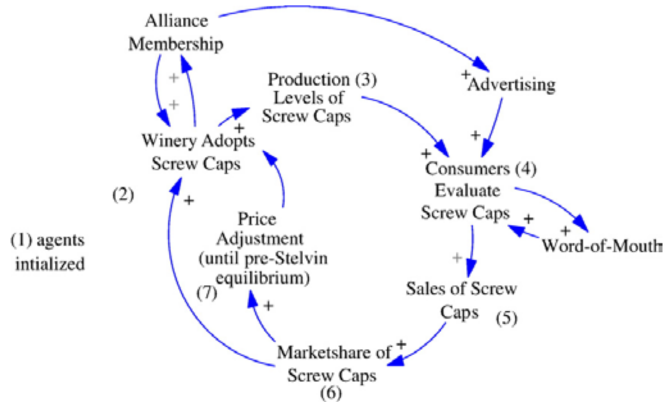

Fig. 1. Causal model.

model is considered to be calibrated when the simulated model matches some particular, unrelated features of historical data that are drawn from macro-level data (Fagiolo et al., 2005).

Verification, which occurs after calibration, establishes whether the macro-individual simulated model captures the intent of the real-world model. During verification, parameters are not adjusted to fit the model. The focus is on the validation of the model's results, not on its internal workings. To verify a model, the model's outcomes are compared graphically or statistically with empirical data. With multi-agent marketing models, verification should occur at both the individual and the industry level. Specifically, if the purpose of the model is to explain individual level phenomena based on generic agents, the model should also be verified at the industry level. If the purpose of the model is to examine industry level (organizationlevel) phenomena based on specific actions of heterogeneous agents, then the model should also be verified at the individual level (Carley, 1996). Although calibration and verification often become synonymous with validation, they are both separate tasks that occur during validation procedures. Calibration can be thought of as the validation of a simulated model's inputs and verification can be thought of as the validation of a model's outputs.

For the model to be predictive, the validation step of harmonization is used to show that theoretical assumptions embodied in the simulated model are in harmony with the realworld based on quantitative data (Carley, 1996). One method of establishing harmony is by comparing the predictive outputs of the computative model with the predictions of a linear model (Stone, 1994).

As the modeler moves through each level of validation (grounding, calibration, verification and harmonization), the model becomes more refined. Grounding sets up the model, calibration fine-tunes the model, verification matches the model to real-world phenomena, and harmonization tests the model to the proposed hypotheses developed. In order to have the model validated sufficiently, evaluating all levels of validation should be considered. This will increase the modeler's confidence that the model is sufficiently suitable for achieving the intended goal. The following section will discuss the methodologies to accomplish validation.

1.2. Calibration methodologies seeking validation

Fagiolo et al. (2005) proposed three different types of validation-seeking calibration methodologies: the indirect calibration approach, the Werker–Brenner empirical calibration approach (Werker and Brenner, 2004), and the history-friendly approach. The indirect calibration approach uses a combination of stylized facts and empirical data to build a model where the micro-level description is modeled in a not-too-unrealistic fashion (Fagiolo et al., 2005, pg. 23). Stylized facts, a term commonly used in economic theory, are observations generally understood to be empirical truths to which theories must fit. The stylized facts are used to restrict the parameter space and initial conditions. The goal of the indirect calibration approach is to establish a realistic model.

The Werker–Brenner approach also uses stylized facts and empirical data to establish the model. However, this method adds an additional step that makes use of Bayesian inference procedures to verify that the output of the model matches the real-world data (Werker and Brenner, 2004). This approach requires two sets of empirical data: one to calibrate the model and one to verify the model. This can be accomplished by splitting the results of a single empirical study into two sets.

The history-friendly approach uses a specific case study set in a particular industry to guide modeling of parameters, agent interactions, and agent decision rules. Like the indirect calibration approach, the goal of this method is to reduce a model's dimensionality on the basis of empirical evidence. This approach combines the results of qualitative and quantitative data collection. Ethnographic research conducted in a particular industry is used to specify the agents' behaviors, their decision rules, and interactions between agents and the environment in which they conduct marketing transactions. This approach uses quantitative data to establish initial conditions and initialize parameters. Model validation compares the model output with the actual history of the case study. Malerba et al. (1999) note, "It is worth emphasizing that it is not the purpose of history-friendly modeling to produce simulations that closely match the quantitative values observed in the historical episode under investigation. The goal is to match overall patterns in qualitative features, particularly the trend behavior of the key descriptors of industry structure and performance", (pg. 4). Examples of history-friendly models (HFMs) have focused on computer and pharmaceutical firms to provide the researcher with knowledge of model building, analysis, and validation of the dynamic evolution of the entire industry (Malerba et al., 1999; Malerba and Orsenigo, 2002).

This study uses the history-friendly approach to look at a specific issue within an industry: the diffusion of screw cap closures on bottles of fine wines within the New Zealand wine industry. This approach is most appropriate when modeling an episodic event (Malerba et al., 1999), such as the diffusion of an innovation. Four steps typically occur in developing an HFM agent-based model: describing the industry background, delineating the main theoretical issues to be explored, developing the computational model, and presenting the results of the model. The remainder of this paper completes steps 1–3 but does not report on step 4, the results of the fully validated model. A detailed account of step 4 is reserved for future reporting in order to maintain appropriate focus on calibration methodologies for agent-based marketing models (AMMs). The next section demonstrates the development and calibration of the AMM using the history-friendly approach, based upon this case study (see Fig. 2).

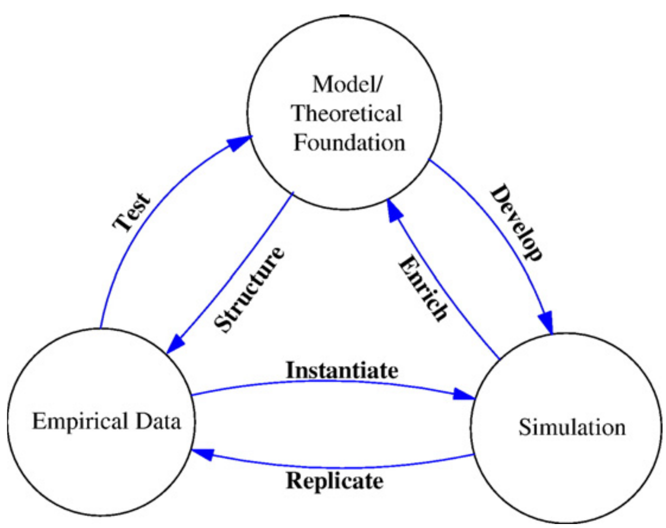

Fig. 2. Framework for empirical calibration of AMMs (based on Madey, et al. 2002).

2. History-friendly model of the New Zealand wine industry

History-friendly models (HFMs) attempt to bring together empirical analyses, general theories, formal modeling, and stylized facts observed within an industry. The HFM of this study is based on an episodic event staged within the New Zealand wine industry. This is a rapidly expanding industry with a growth rate of over 150% from 1995 to 2005; there are now more than 500 wineries in New Zealand. Low entry barriers and global market acceptance of New Zealand wines has allowed even new entrants to be profitable. The New Zealand Winegrowers, an organization established in March 2002 to represent both independent grape growers and wineries, suggest that the economic growth of their industry reflects the "value of a united approach to industry issues. Innovation, learning, cooperation and quality have been at the heart of the New Zealand wine industry's rapid development in past years", (New Zealand Grape and Wine Industry Statistical Annual, 2005).

One of the factors driving the growth of this industry is the high quality and distinctive Sauvignon Blancs of New Zealand, which make up 45% of the total harvest. A major concern of the wineries producing white wines is the freshness and fruitiness of these delicate wines. A problem that has surfaced in this growing industry is the availability of bottle closures that preserve the true quality and taste of New Zealand wines. Industry analysts report that 2–15% of all wine bottled with natural cork closures are plagued by cork taint, a condition where poor quality corks cause the wine to lose flavor (Sogg, 2005). Often the consumer does not realize that the poor taste is due to cork taint and blames the offending flavor on a poor vintage or a cheap brand. Hence, the wine manufacturer potentially loses a customer in addition to incurring the cost of replacing the bottle. The result is millions of dollars of lost revenue as well as brand-name erosion when consumers attribute the poor wine quality to the winery rather than to the closure.

One solution to the problem of cork taint is to use screw cap closures. The screw cap was tested for feasibility as a wine closure device in the late 1950s and early 1960s, after which the Yalumba Wine Company introduced the innovation into the Australian market in the late 1970s. Screw caps (often called by their brand-name, Stelvin) have been found to eliminate cork taint and other problems found with cork closures, such as crumbling and leakage (Murray and Lockshin, 1997). Stelvins are said to allow consistent, reliable, aging characteristics, showing the wine's development as the winemaker intended (Courtney, 2001), which makes them highly suitable closures for white wines. Between 1976 and the early 1980s, the screw cap closure served to seal approximately 20 million wine bottles in Australia and New Zealand (Courtney, 2001). By 1984, the Australasian producers had stopped using the Stelvin because of consumer resistance to a screw cap closure. The effect on Yalumba's Pewsey Vale Riesling, an early Australian introduction, almost killed the brand as a prestige product (Bourne, 2000).

This unsuccessful introduction, however, did not completely destroy the innovation. Driven by belief of the superiority of screw caps over cork closures, especially for white wines, a group of 15 winemakers from the Clare Valley of Australia selected the Stelvin for closing their premium Rieslings in 2000. Having gained insights from previous introduction failures over the previous twenty years, this collaborative of Australian wineries launched a marketing campaign, "Riesling with a Twist", which communicated to the media, consumers, and retailers the quality aspects of the innovative seal. The success of the Australian launch motivated 27 New Zealand wineries to form the New Zealand Wine Seal Initiative (www.screwcap.co. nz/), launched in August 2001. Key roles of the Initiative were to promote the use of screw caps, to provide technical education and support to members regarding the use of screw cap wine seals, and to educate the wine trade, wine press, and wine consumers about the benefits of using screw caps. In 2005, the Initiative consisted of more than 40 members wineries, representing the best of New Zealand's premium wine producers. The Initiative represented both large and small wineries and today, according to estimates, 80% of wines bottled in New Zealand use screw cap seals (Sogg, 2005).

The issue of consumer resistance to this innovative closure for the wine industry is interesting in terms of the stark contrast between the high performance of the new closure and its lack of acceptance by consumers. Although screw caps perform well in preserving the quality of wine (Hart and Kleinig, 2005), some consumers still prefer the romance of the cork (Courtney, 2001). Accordingly, the screw cap is often referred to as a resistant innovation because the consumer resists using or purchasing the innovation due to particular perceptions or misperceptions. The remainder of this paper discusses model development, starting with theory formulation and concluding with simulation results.

2.1. Theoretical foundation of the New Zealand wine industry HFM

The simulation model of this study addresses a single stylized episode that can be summarized as follows. With a growing domestic market in an increasingly competitive global market, New Zealand wineries shared a concern with respect to the ability to deliver a distinctive, quality product to wine consumers around the world. This concern mainly focused on the diminishing availability of high quality cork closures due to limited natural cork resources. Fickle consumers had previously rejected the alternative to cork closures, the Stelvin closure. Traditional marketing techniques had not been effective in diffusing this resistant innovation into the marketplace (Garcia and Atkin, 2005). Buoyed by the success of the alliance of Australian wineries, a group of New Zealand wineries formed their own collaborative with the specific goal of promoting the use and benefits of the screw type closure (Stelvin) to consumers and the media.

This paper proposes that the New Zealand collaborative used a strategy of coopetition to diffuse the Stelvin among a population of resistant customers. Coopetition is a form of a strategic alliance in which two or more interorganizational firms in the same industry, who normally compete against each other, instead cooperate to accomplish a specific goal (Brandenburger and Nalebuff, 1996; Gomes-Casseres, 1996; Harbison and Pekar, 1998). Firms have embraced coopetitive alliances in order (a) to exchange patents and other knowledge, (b) to undertake collaborative research and development activities, (c) to build market alliances for setting new standards, and (d) to establish collaborative agreements to integrate existing businesses (Garraffo, 2002). By working together cooperating firms can maximize their resources, stimulate knowledge development and utilization, and expand market opportunities (Jorde and Teece, 1989). By forming the New Zealand Wine Seal Initiative, 27 innovative wineries utilized a coopetition strategy for diffusing a resistant innovation into the marketplace.

The above discussion gives a broad outline of what one would expect to see in a simulated industry history and points to some of the stylized facts that need to be treated in the specification of the model's dynamics. In order to capture the coopetitive environment, the model typifies the wineries as seeking to maximize their market share, MS_i.

$$\mathrm{MS}_i = \frac{s_i}{\sum_{k=1}^{K} s_k} \tag{1}$$

where S_i is the number of bottles sold with Stelvin closures by firm *i* and ΣS_k is the total number of Stelvins sold in the marketplace. The primary goal is to introduce the resistant innovation into the marketplace and to gain market share in an increasingly competitive industry. For the firm, profits are calculated each period, *t*, as;

$$\Pi = N_p - N_k - N_s l \delta_{iA} \tag{2}$$

where N is the number of total bottles sold, p is the price of the wine to the consumer (distribution channels are not modeled in), k is the production cost of a single bottle, N_s is the number of bottles sold with a Stelvin closure, and δiA is 1 if the firm is in the alliance and 0 if otherwise. (As a first-order model, Eq. (2) does not model economies or diseconomies of scale.) Each winery that joins the alliance is required to pay a per bottle levy, l, to the alliance for the cost of the advertising program. Product offerings include both cork closures and Stelvin cap closures with constant production costs for all types of wines produced. Although the screw cap closure itself is less expensive than the cork closure, the costs of manufacturing the threaded necks of wine bottles necessary for screw caps equal the manufacturing costs of the cork.

Consumer demand drives the manufacturing decisions of firms (wineries). When making a purchase decision, the consumer chooses product offerings by randomly selecting firms; these product offerings become the choice set. Consumers then refer to their combined partworths to evaluate the product offerings within the choice set, and to then select the most preferred offering. In other words, they choose the product that maximizes their utility, such that:

$$U_{ij} = f(p_j) + \sum_{m=1}^{M} \omega_{im}\delta_j + \omega_{iS}\delta_j \tag{3}$$

$$\omega_{iS}(t) = \omega_{iS(t-1)} + [\omega_{\max \mathrm{NZ}} - \overline{\omega}_{\mathrm{NZ}}]\rho(\Phi) \tag{4}$$

where i represents the individual, m the attribute, j the product offering, $\omega_{is}(t)$ the Stelvin partworth for the jth product (with a Stelvin closure) at time t, p_j the price of product j, and δ_j is 1 for the product choice being evaluated, and 0 if otherwise. $[\omega_{maxNZ} - \overline{\omega}_{NZ}]$ is a constant, which is the difference between the highest Stelvin closure partworth for a New Zealand respondent and the average partworths for Stelvins by all New Zealand respondents. Eq. (4) captures the evolution of the partworth for Stelvin closures. The evolution function, $\rho(\phi)$, represents the rapidity with which each consumer's partworth evolves from the current NZ average to the NZ maximum.

Product j also can be a product with a higher utility than the options in the choice set, leading to no purchase of wine. Price is modeled as a function to capture the scaling issues in the utility definition. In the simulation, price points for different types of wine fluctuate endogenously based on demand. In other words, firms set product (wine) prices to maximize profits: when products do not sell, prices decrease, and when the demand for a product is high, prices are adjusted upward.

Because price is endogenous, the simulation begins at reasonable starting prices and runs until prices reach equilibrium. Price is then set and the simulation continues until the diffusion of Stelvins also reaches market equilibrium. When the wineries have formed their alliance to spread the gospel of screw caps, the consumers' Stelvin partworths are altered on the basis of (1) the number of Stelvin product offerings considered in the choice set, (2) positive word of mouth by other consumers, and (3) the impact of alliance advertising. These components are captured in the rate of change, $\rho(\phi)$:

$$\rho(\phi) = \frac{e^c}{1+e^c}\text{; where,} \tag{5}$$

$$c = C + v_{\text{stel-wineries}} n(t)_{\text{stel-wineries}} + v_{\text{consumer-network}} n(t)_{\text{consumer-network}} + v_{\text{adv}} n(t)_{\text{alliance\_firms}} \tag{6}$$

The $n(t)$s change every iteration as driven by the number of wineries using Stelvins and the number of consumers in an agent's network that have adopted the Stelvin. The model assumes that the constants are non-negative. This assures that $\rho(\phi)$ is bounded at (0, 1) and increases with increasing marketing activities. Eq. (6) allows c to increase or decrease; c might decrease if consumers again prefer corks to Stelvin closures. An alternative model might set the partworths constant. A suitable modification of Eq. (6) can accomplish this. The next section presents the computational model based on the HFM described above and explains how conjoint analysis results can be used to validate this model.

3. Computational model

The purpose of this agent-based model is to gain insights into how coopetition strategies can affect the diffusion of Stelvin wine bottle closures (a resistant innovation). The model utilizes two different types of interacting agents: wineries and consumers. Each period, the wineries determine the price, production levels, and product attributes based on customer demand. Similarly, each period the consumers purchase the products manufactured by the wineries on the basis of their individual preferences. A generalized causal model, as shown in Fig. 1, demonstrates the sequence of how the two types of agents, wineries and consumers, interact with each other. A seven-step process summarizes these interactions:

Step 1. Agents (wineries and consumers) are initialized with heterogeneous characteristics as determined by the conjoint results.

Step 2. Wineries decide whether to join an alliance of wineries that exclusively produces wines with Stelvin closures and markets these products jointly with their competitors.

Step 3. Wineries produce wines with attributes based on market demand and membership in the alliance.

Step 4. Consumers randomly choose a set of wineries from which to evaluate product offerings. Networking with other consumers (word of-mouth) and winery advertisements can also increase a consumer's preference for Stelvin closures.

Step 5. Consumers purchase wine based on individual utility maximization of product choices. If no wine is found to provide sufficient utility, the consumer does not make a purchase. If the purchase choice includes a Stelvin closure, the consumer has adopted the innovation.

Step 6. Market share is calculated. Wineries record sales and inventory any unsold wine. Stored wine is available for future periods, but wineries incur holding costs. The goal of the wineries is to maximize profit through meeting customer demand while minimizing inventory. Profit maximization is accomplished by first adjusting prices and then by adjusting production levels.

Profit maximizing wineries adjust the price of their offerings based on how much unsold stock remained at the end of the month. Excess stock results in lowered prices; depleted stock results in higher prices. (See Fig. 3 for an illustration of the rapidity with which the price equilibrium is obtained.) Under fairly general conditions, this iterative procedure finds the price equilibrium (fixed point) as a function of model parameters. In this paper, the authors provide no formal proof that price equilibria exist or that prices are uniquely determined for the markets modeled. By using different

Netlogo output

Fig. 3. Price adjustments. Netlogo output.

initial conditions, however, the simulations suggest that the prices converge to equilibria and appear to be unique. The authors make no claims regarding the existence or uniqueness of market simulations based on different assumptions or structure. Based on price equilibrium, wineries are then permitted to change their production levels to maximize profits. After approximately 24 months (or iterations in this model), the demand for screw caps begins to reach an equilibrium.

To simulate an alliance, 27 randomly selected wineries were designated members. Alliance members use only Stelvin closures and jointly conduct an advertising campaign to educate the consumer on the benefits of screw cap closures. The members of the alliance share the costs of the campaign, decreasing their short-term profits. As the marketing campaign is initiated, consumers' conjoint partworths are adjusted as described in Eqs. (5) and (6).

The authors simulated the model with the aid of Netlogo (v3) (1999). Those interested in the structure and simulation results of the model can obtain a review from the first author upon request. Having described the basic underpinnings of the model, the following section will give a description of the steps taken towards model validation, including the use of conjoint analysis to calibrate the model.

3.1. Calibration of the New Zealand wine industry AMM

A wide range of parameter settings can be used to initialize an AMM. Knowing which initialization parameters to use is often a conundrum for agent-based modelers. Some, but not all, parameter settings lead to patterns of industry evolution that, in effect, replicate the episode modeled. One method of parameter instantiation is to use the empirical results from quantitative data collection. Instantiation (a term used by Java programmers) is synonymous with the creation or initialization of a model used to realize an abstraction (in this case, the real-world). This study used conjoint analysis results to instantiate the simulation in order to realistically model consumer choice decisions. Partworths, as determined from a conjoint study, were used to initialize consumers' preferences, and thus, provided a platform for model calibration. An explanation on how this was accomplished follows the brief description of the conjoint data collection given next.

The study recruited 2255 leading edge wine consumers from the US, Australia, and New Zealand to complete a conjoint web-based survey. The 1203 respondents from the US, 667 from Australia, and 385 from New Zealand were subscribers to wine-related e-newsletters and were considered knowledgeable about wines. In this study, the focus is only on the New Zealand (NZ) data. The conjoint design included five features at four levels each (see Fig. 4):

Fig. 4. Conjoint Design (from Toubia, et. al., 2006).

- Closure type: traditional cork, synthetic cork, Metacork™ (closure combining a screw cap and a cork), screw cap.
- Type of wine: dry white, aromatic white, dry red, blush red.
- Origin of wine: New Zealand/Australia, France, Sonoma/Napa, Chile/Argentina.
- Vintner type: small boutique, mid-size region winery, large nationally recognized winery, international conglomerate winery.
- Price: $7, $12, $20, $25 in the respondents' currency (e.g., New Zealand dollars).

Each respondent completed two separate conjoint tasks by indicating their wine purchase preferences for an informal and a formal occasion. Accordingly, this resulted in 770 different responses. The survey results showed that New Zealand consumers have equal preferences for Stelvins and natural cork closures. On average, the respondents preferred red wines to white wines and preferred wines from regional and boutique wineries to international conglomerates. These consumers preferred wine from their home country. Questions in addition to conjoint queries revealed that the respondents relied on winerelated periodicals and wine-related functions to gather knowledge about wines. The methodology and detailed results of this study are reported in Toubia, Hauser, and Garcia (2006) and Garcia and Atkin (2005).

Consumer agents were assigned partworths only for two of the four wine-type attribute levels (red wine/white wine), two closure attribute levels (screw cap/cork), two wine origin attribute levels (NZ-AUS/US), all four levels of winery-type (boutique, regional, national, international) and price ($7, $12, $20, $25). These levels were chosen in order to focus on the stylized facts of interest and to simplify the model. The conjoint study measured conditional choice and therefore did not include a none-alternative (Orme, 2005). The AMM, instead, included the none-alternative choice of no wine purchase. To set this choice of none, the least preferred choice of the agent was calculated to find a minimum threshold for which a purchase would be made. Consumer agents purchase wine only when this threshold utility is exceeded.

To instantiate the wineries the following parameters were assigned: (1) type of wine (red or white), (2) region of winery (US or Australia/New Zealand), and (3) type of winery (boutique, etc.). To simplify model validation steps, each type of winery only produced wines at a single price. Thus, boutiques offered products at a starting price of $25; regional wineries priced at $20; national wineries priced at $12; international wineries priced at $7. During the first few iterations of a model run, these initial prices are adjusted to reach price equilibrium, as explained above.

Conjoint analysis results defined the winery parameters. For example, the first setting to instantiate was the percentage distribution of each type of winery in the marketspace (boutique, regional, national, international). The first-choice rule based on the conjoint results indicated that 4.4% of the NZ respondents preferred boutique wines, 23.9% preferred regional wines, 44.7% preferred national wines and 22.8% preferred international wines. These percentages do not add up to 100% because 4.2% of the respondents were indifferent with respect to two different types of wineries. This small difference did not influence the model outcomes and therefore is not considered in model instantiation. These percentages formed the basis for setting the initial distribution of types of wineries.

The winery-type instantiation, however, is not complete until the model is calibrated. Using sensitivity tests, the study evaluated how prices would change based on changing the ratio of different types of wineries. Starving the market of the most commonly preferred wine (national) would drive the wine's price up and consequently glut the marketspace with less preferred options. The goal of this step in the calibration process was to adjust the percentages until the equilibrium prices sufficiently matched real-world prices for these types of wines. Industry partners provided real-world prices for NZ wines. Table 1 shows the starting allocation percentages initialized during instantiation and the final allocation percentages as determined during model calibration. The table also shows the final price points reached after equilibrium.

Table 1
Initial and final model settings

Type of winery		
	Initialization[a]	Model Setting[b]
Boutique	4%	5%
Regional	24%	18%
National	45%	39%
International	27%	38%
Type of wine	Initialization[c]	Model Setting[d]
Red wine (boutiques)	58%	55%
Red wine (regional)	59%	60%
Red wine (national)	59%	60%
Red wine (international)	59%	60%
Region of wine		
	Initialization[e]	Model Setting[f]
Australian/New Zealand	92%	92%
US	8%	8%
Price of wine		
	Initialization[g]	Model Setting[h]
Boutique (high priced)	$25.00	$21.50
Regional (mid-high priced)	$20.00	$17.50
National (mid priced)	$12.00	$11.50
International (low priced)	$7.00	$5.00

[a] Based on conjoint first-choice rule when evaluating type of winery at set price.
[b] After verification.
[c] Based on conjoint first-choice rule when evaluating red versus white wine.
[d] After verification.
[e] Based on conjoint first-choice rule when evaluating AUS/NZ vs. US.
[f] After verification.
[g] Based on conjoint attribute levels.
[h] After price equilibrium achieved (approximately 24 iterations [months]).

The percentage of red wine versus white wine produced by the wineries is set in a similar manner. Table 1 shows the initial percentages of red and white wine determined through the conjoint results and the final calibrated percentage of red-towhite wine production obtained through sensitivity testing. For example, first-choice rule results showed that 58% of the respondents preferred red wine over white wine; sensitivity analysis resulted in a model setting of 55% red wine production and a 45% white wine production. The percentage of Australian/New Zealand wineries versus US-based wineries also needed to be set for the model. Although preferences for French and South American wines were also collected in the conjoint study, they were excluded from the analyses to simplify the model because partworth evaluations showed that New Zealand respondents had the least preferences for these types of wines. First-choice rule results showed that 92% of New Zealand respondents preferred Australian/New Zealand wines to US wines. Sensitivity analyses confirmed this setting for the model.

To summarize the instantiation and calibration method, conjoint partworth results were used to instantiate overall consumer preferences and the first-choice rule was used to calibrate their initial settings using sensitivity analyses to replicate stylized facts. Table 1 shows that after calibrating these three parameters (types of winery, region of winery, red–white wine), 5% of the wineries were boutique wineries that produced 55% red wines and 45% white wines. Of these boutique wineries, 92% were Australian/New Zealand wineries and 8% were US wineries.

Additional parameters set were the number of wineries in the marketspace and the production level of each winery. Sensitivity analyses led to a model with 52 wineries in a marketspace of 770 consumers. In order to increase the probability of including a boutique winery in the selection process, which was limited to 3 out of the 52 wineries, consumers evaluated 16 different wineries when selecting a wine to purchase. Production levels were initially set to be equal among the 52 wineries.

The next step was to verify the model's face validity by evaluating a baseline model that excluded alliance memberships, advertising, and word of-mouth impacts. This allowed for the examination of model sensitivities by setting the micro variables (agent characteristics driven by the empirical data) constant and observing how well the macro-environmental variables match the true marketplace (for example, the market share of Stelvins, red wines, white wines, etc.). When the simulations do not replicate the known facts about the macro system as revealed in the empirical data, adjustments to the model's parameters are required. Macro-level results that do not match the known empirical data require a re-calibration of the model.

Initially, the percentage of Stelvin-closed wines was arbitrarily set at 10%. After reaching initial price equilibrium, wineries were permitted to adjust their production level of Stelvins based on their overall market share. Wineries produced Stelvin-closed wines to maximize their profits based on market demand. The conjoint analysis first-choice rule showed that 55% of the New Zealand respondents preferred Stelvin closures to cork closures. Thus, in model verification, market share of Stelvins needed to reach 55% without any exogenous shocks to the model in order to achieve the calibration goal. The results show (Fig. 5) that the market share of Stelvins reached 53.5% (based on 50 runs of 50 iterations each, or 2500 total iterations). This simulation output (53.5%) adequately matched the conjoint results (55%), which led to the conclusion that this important test of model calibration and face validity had been successful.

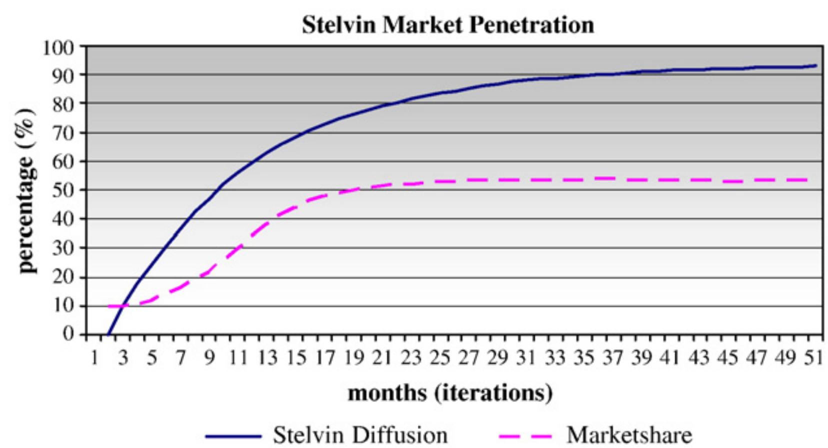

Fig. 5. Pre-alliance market penetration. Netlogo ouput: average of 50 runs of 50 iterations.

4. The simulation results

This study proposes that a strategy of coopetition served as an instrument to diffuse the Stelvin amongst resistant consumers in the New Zealand wine industry. The authors collected the data for this study in 2004, three years after the formation of theWine Seal Initiative in New Zealand. The study therefore does not present actual pre-alliance Stelvin market share and diffusion results. Instead, for illustration purposes, the data gathered in 2004 drove the pre-alliance market equilibrium and was used to simulate subsequent market results. Thousands of test runs were conducted to establish face, parameter, and process validity as dictated by the empirical results of the conjoint study.

By allowing price (as well as advertising and production levels) to be set endogenously by rational agents (wineries) in response to economic decisions made by consumer agents (buy what and from whom), the model begins each run with a burn-in period until prices reach a pre-alliance equilibrium. In oligopolistic competition, wineries make myopic marketsharemaximizing decisions to introduce Stelvins. Only after both price and production equilibrium are reached, do alliance effects come into play in the model. The results in Fig. 5 show market penetration when no alliances are formed and the consumers' partworths are not allowed to change (no effect of word of mouth or advertising). The results show that at approximately t=30, the market becomes saturated and the Stelvin market share reaches only 53%, as dictated by the consumers' partworths.

Fig. 6 demonstrates how market penetration changes when alliances are formed. This figure shows that the market share for Stelvins has increased to 76.5% and the diffusion is 97.6% (all consumers have bought at least one Stelvin-closed product). This is consistent with actual marketplace response four years after the alliance formation; in New Zealand approximately 80% of wines are bottled with Stelvins (Sogg, 2005). In the model, the primary factor that changes consumer awareness and preference for Stelvins is advertising by the alliance firms.Word of mouth can also positively (or negatively) impact adoption, as consumer agents communicate with one another based on a small-world structure (Watts and Strogatz, 1998), thereby stimulating (or inhibiting) the diffusion of Stelvins.

Early results of this model indicate that the size of the alliance (number of firms committed to screw caps) can significantly affect the rate of diffusion of the screw cap. These findings support the qualitative data collected from New Zealand wineries, indicating that at least a dozen committed wineries were necessary to get the ball rolling. A minimum number of alliance members seem to be necessary to spread advertising and media expenditures across members and obtain economies of scale in bottling costs. The model also suggests that if an alliance is too large, winery's profits of those in the membership will be lower because supply exceeds demand. In this case, more sales go to wineries that remained committed to cork closures. Later, wineries not in the alliance can free-ride on the Stelvin-coalition's initial investments. Continued analyses are planned to explore the profit impact of competition versus coopetition.

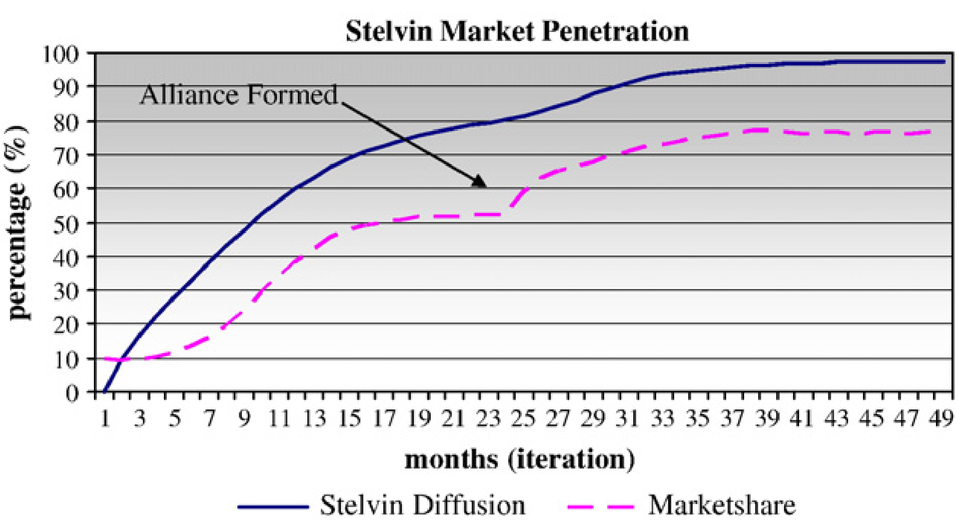

Fig. 6. Post-alliance market penetration. Netlogo output: average of 50 runs of 50 iterations.

5. Summary

This study outlined the levels necessary to validate agentbased marketing models (AMMs) and demonstrated a historyfriendly model (HFM) approach (Malerba et al., 1999) that incorporates qualitative and quantitative data to create a realworld replication of an episodic event in the New Zealand wine industry. Research showed how conjoint data results could be used to instantiate, calibrate, and verify an AMM to achieve model validation. Conjoint data provides a grounding foundation for instantiating the model, which naturally lends itself to guiding calibration and verification.

Two important conclusions of this study are that AMM instantiation can be set with conjoint partworths and the conjoint first-choice rule can be used to calibrate initial model settings. When a model's results match the results of the firstchoice rule for consumer preferences, a modeler can feel more confident that model calibration is complete. When verification replicates stylized facts on a macro-level, the model is one step closer to validation. Because conjoint data results are meaningful on an individual level as well as on an aggregate level this type of empirical data collection lends itself nicely to AMMs. Empirical results that are reported on an aggregate level (such as regression analyses) are less suitable for grounding an AMM. The next step in the model is harmonization. Calibration and verification are not substitutes for harmonization, nor do they guarantee accurate predictions. For details on how to conduct harmonization, refer to Carley (1996).

Early model results of the HFM indicate that diffusion can stagnate with a resistant innovation, such as screw cap closures on high-end wines. Exogenous forces, such as coalitions, are required to move the consumers' preferences away from the status quo. One method of moving consumers' preferences is through coopetition, where competing wineries cooperated to jointly promote the benefits of the screw cap to a resistant marketplace. Early results show that an alliance of too few wineries will not cause the necessary shock to the marketplace and an alliance of too many wineries dilutes the message, resulting in loss of profits and market share for all wineries in the alliance.

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