Validating Agent-based Marketing Models Using Conjoint Analysis

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Abstract

Validation issues have received little attention by agent-based modelers in marketing research. In this paper we provide a definition of validation relevant for this community of modelers. Using the foundation of a history-friendly model for simulation calibration (Malerba, et al., 1999), we demonstrate how conjoint analyses can be used to instantiate and calibrate an agent-based marketing model. Model instantiation can be accomplished using conjoint partworths, and the conjoint first-choice rule can be used to calibrate these initial model settings. When the model matches the results of the first-choice rules for consumer preferences, a modeler can feel more confident that calibration is complete. When verification replicates stylized facts on a macro-level, the model is one step closer to being validated. 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 using in agent-based marketing models.

Key words: conjoint analyses, agent-based modeling, validation, calibration, history-friendly model
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1.0 Introduction

Validation of computational models has long been an area of concern to simulation modelers (Conway, 1963; Knepell and Arangno, 1993; LeBaron 2006). This extant research has introduced 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). Further confounding validation tasks of empirically-based agent-based models (ABMs) is the difficulty of validating a model that typically includes feedback loops, path dependencies, sensitivity to internal conditions, and unpredictability of agent adaptation (Fagiolo, et al., 2005). Important questions being posed by agent-based modelers, especially those investigating ‘real-world’ systems are: Which methods of validation are best? What levels should be considered? How does one know a model is correct?

Validation issues have received little attention by agent-based modelers in marketing research. Thus, our goal in this paper is 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. We first provide a definition for validation and for validation levels that are important to this community of agent-based modelers. Then drawing upon reviews by Carley (1996) and Fagiolo, et al. (2005) that are grounded in agent-based computational economics (ACE), we briefly present three methodologies that can be used to seek validity in ABM simulations. We use this foundation to demonstrate how conjoint analysis can be used to calibrate an agent-based marketing model.

In the next section, we establish definitions for validation. Here we introduce three calibration methodologies; indirect calibration, the Werker-Brenner calibration approach (Werker and Brenner, 2004), and the history-friendly calibration approach (Malerba, et al., 1999). Finally, using an example of a history-friendly approach based in the wine industry, we demonstrate how conjoint analysis can be used
to calibrate an ABM. We henceforth refer to ABMs that focus on marketplace behavior as agent-based marketing models (AMM).

1.1 Validation Defined

Although numerous definitions for ‘validation’ exist, we specifically focus on ‘empirical validation’ of a computerized marketing model. A validated model will possess a satisfactory range of accuracy, matching the simulated model to a ‘real-world’ model that is the intended focus of the study (Fagiolo, et al., 2005). AMMs usually include individuals, either at a consumer level or a firm level, that are observed at the marketplace or industry level. Thus, when validating AMMs, matching should occur on both a micro and macro level. In addition, an empirically validated model is grounded on qualitative and/or quantitative data collected from the system being investigated. We refer to validation as determining 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) suggest 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 vested-interest parties. In establishing face validity, the model should set forth how the simulation represents the real-world and should delineate the scope of the model based on qualitative and quantitative empirical data. Parameter validity examines if the characteristics and initial conditions assigned to an agent appear realistic. Process validity examines if the overall model simulation on a macro level ‘makes sense’. The process should include the appropriate players, and these players should interact in a realistic manner. A causal model as demonstrated in Figure 1 is often good for establishing process validity. During grounding, boundaries should be established both on a micro and 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. In our model, which we explain in the following sections, we incorporate the conjoint data during grounding analyses, but we tune the model to this data during calibration analyses.

Calibration, the next step, is the process of tuning a model to fit detailed empirically-supported data (c.f. 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 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 if 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, model verification should occur at both the individual and industry level. Specifically, if the purpose of the model is to explain individual-level phenomena based on generic agents, the model should be also be verified at the industry level. If the purpose of the model is to examine industry-level (organization-level) phenomena based on specific actions of heterogeneous agents, then the model should be also 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 validation of a simulated model’s inputs and verification can be thought of as validation of a model’s outputs.

If the model is to be predictive, a final step in validation is harmonization, which is used to show that theoretical assumptions embodied in the simulated model are in harmony with the real-world 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 – model development should increasingly become 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. Sensitivity analyses would be conducted in the first three levels of validation but would not be consistent with the goals of harmonization unless the hypotheses explicitly called for sensitivity analyses. Evaluating all levels should be considered in order to have a sufficiently validated model, and the modeler will have greater confidence that the model correctly achieves the intended goal of the model. Methodologies to accomplish validation are considered next.

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). Stylized facts, a term commonly used in economic theory, are observations that are widely 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, it also adds an additional step that uses Bayesian inference procedures to verify that the output of the model matches the real-world data (Werker and Brenner, 2004). Two sets of empirical data are required: one to calibrate the model and one to verify the model. The results of a single empirical study can be split into two sets to accomplish this goal.
The history-friendly approach uses a specific historical case study in an industry to model parameters, agent interactions, and agent decision rules. Like the indirect calibration approach, the goal of this method is to reduce the dimensionality of a model as guided by empirical evidence. This approach is done by combining the results of qualitative and quantitative data collection. Ethnographic research on a particular industry can be used to guide specification of the agents’ behaviors, their decision rules, and interactions between agents and the environment in which they conduct marketing transactions. Quantitative data can be used 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 the computer and pharmaceutical firms to inform the researcher in model building, analysis, and validation of the dynamic evolution of the entire industry (Malerba, et al., 1999; Malerba and Orsenigo, 2002).

We use the history-friendly approach to look at a specific issue within an industry: the diffusion of screw cap closures on fine wines within the New Zealand wine industry. This approach is most appropriate when an episodic event (Malerba, et al., 1999), such as the diffusion of screw caps into the wine industry, is to be modeled. There are typically four steps in developing an agent-based model using HFM: describing the industry background, delineating the main theoretical issues to be explored, developing the computational model, and presenting the results of the model. In the remainder of this paper, we complete steps 1-3 but do not report on step 4, the results of the fully validated model. We leave that detailed account for future reporting in order to give the appropriate focus on calibration methodologies for agent-based marketing models. In the next section, we use the history-friendly approach to demonstrate the development and calibration of the AMM based upon this case study.
2.0 A History-friendly model of the New Zealand Wine Industry

As noted, the goal of history-friendly models (HFM) is an attempt to bring together the empirical analyses, general theories, formal modeling, and stylized facts observed within an industry. We base our HFM on an episodic event set within the New Zealand wine industry. This is a rapidly expanding industry that grew over 150% from 1995 to 2005; there are now more than 500 wineries in New Zealand. Despite the low barriers to entry in this industry, the ready acceptance of the global marketplace for New Zealand wines has resulted in increasing market size allowing 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 in the 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 the industry is the high quality and distinctive Sauvignon Blancs of New Zealand, which make up 45% of the total harvest. A major concern for 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. It has been reported that 2-15% of all wine bottles using natural cork closures are plagued with “cork taint,” where poor quality corks cause a bottle of wine lose its 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 in lost revenue and 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. Screw caps were tested for feasibility as a wine closure in the late 1950s and early 1960s and introduced in the late 1970s to the Australian marketplace by Yalumba Wine Company. 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) making them highly suitable closures for white wines. Between 1976 and the early 1980s, approximately 20 million wine bottles were sealed with the screw cap closure in Australia and New Zealand (Courtney, 2001). By 1984, the Australasian producers had stopped using the Stelvin because of consumer resistance to accepting 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).

However, the innovation did not completely die out with these failed introductions. Driven by 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. Gaining insights from the failure over the previous twenty years, this collaborative of Australian wineries launched a marketing campaign, ‘Riesling with a Twist’ in which it communicated to the media, consumers, and retailers the quality aspects of the seal. The success of the Australian launch motivated 27 New Zealand wineries to form the New Zealand Wine Seal Initiative (www.screwcap.co.nz/), which was 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 had more than 40 member wineries representing premium producers from New Zealand. Both large and small companies were represented. Today, according to estimates, 80% of wines bottled in New Zealand use screw cap seals (Sogg, 2005).

The issue of consumer resistance to innovative closures in the wine industry is interesting because of the stark contrast between high performance of new closures such as screw caps and their 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 perceptions or misperceptions. In the remainder of the paper, we discuss model
development starting with theory formulation and ending with simulation results.

2.2 Theoretical Foundation of New Zealand Wine Industry HFM

In our simulation model, we consider a single stylized episode that can be summarized as follows. With a growing domestic market in an increasingly competitive global market, New Zealand wineries were concerned about delivering a distinctive, quality product to wine consumers around the world. A growing concern for wine makers worldwide was the diminishing availability of high quality cork closures due to limited natural cork resources. An alternative to cork closures was the Stelvin closure, which had previously been rejected by fickle consumers. Traditional marketing techniques had not been effective for diffusing this resistant innovation into the marketplace (Garcia and Atkin, 2005). Buoyed by the success of an alliance of Australian wineries, a group of New Zealand wineries formed their own collaborative with the specific goal of promoting the use of screw caps by wineries and promoting the benefits of these types of closures to consumers and to the media.

We propose that a strategy of co-opetition was used to diffuse the Stelvin to resistant customers. Co-opetition 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 co-opetitive 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 co-operating firms can maximize 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 co-opetition strategy for diffusing a resistant innovation into the marketplace.
The above discussion presents 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 specification of the model dynamics. In order to capture the co-opetitive environment, we model the wineries as seeking to maximize market share, $MS_i$.

$$MS_i = \frac{S_i}{\sum_{k=1}^{K} S_k} \quad (1)$$

where $S_i$ is the number of bottles sold with Stelvin closures by firm $i$ and $\sum_{k=1}^{K} S_k$ 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;

$$\Pi = Np - Nk - N_i l \delta_{ia} \quad (2)$$

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, $N_i$ is the number of bottles sold with a Stelvin closure and $\delta_{ia}$ is 1 if the firm is in the alliance, 0 otherwise. (As a first-order model, Equation 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 production costs constant across all types of wines produced. Even though the screw cap closure itself is less expensive than a cork closure, the threaded necks of wine bottles necessary for screw caps results in no difference in manufacturing costs.

Consumer demand drives manufacturing decisions of firms. When making a purchase decision, the consumer is presented with product offerings from randomly selected 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. Or, in other words, they choose the product that maximizes their utility, such that:

\[ U_{ij} = f(p_j) + \sum_{m=1}^{M} \omega_{imj} \delta_j + \omega_{ij} \delta_j \]  

\[ \omega_{i\delta_j}(t) = \omega_{i\delta_j} + [\omega_{\text{max NZ}} - \omega_{i\delta_j}] \rho(\phi) \]

where \( i \) represents the individual, \( m \) the attribute, \( j \) the product offering, \( \omega_{ij} \) refers to the initial Stelvin partworth for the \( j \)th product (with a Stelvin closure) and \( \omega_{i\delta_j}(t) \) refers to its value at time \( t \), \( p_j \) is the price of product \( j \) and \( \delta_j \) is 1 for the product choice being evaluated, 0 otherwise. Equation 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 maximum for NZ.

Product \( j \) can be a ‘none’ product with a higher utility than the options in the choice set that leads to no purchase of wine. Price is modeled as a function to capture scaling issues in the definition of “utility.” In the simulation, price points for different types of wine fluctuate endogenously based on demand. That is, firms select their prices to maximize profits: when products don’t sell, prices are decreased; when the demand for a product is high, prices are adjusted up.

Because price is endogenous, we begin the simulation at reasonable starting prices and run the simulation until price reaches equilibrium. The simulation continues until diffusion of Stelvins also reaches market equilibrium. We now consider the policy in which wineries form an alliance to spread the gospel of screw caps. When the alliance is formed, consumers’ Stelvin partworths are altered based on (1) number of Stelvin product offerings considered in the choice set, (2) positive word of mouth by other consumers, and (3) advertising impact of alliances. These components are captured in the rate of change,\( \rho(\phi) \):

\[ \rho(\phi) = \frac{e^c}{1 + e^c} \]  

where
\[ c = C + v_{\text{stel-wineries}}n(t)_{\text{stel-wineries}} + v_{\text{consumer-network}}n(t)_{\text{consumer-network}} + v_{\text{adv}}n(t)_{\text{alliance_firms}} \]  

(6)

The \( n(t) \)s change every iteration as driven by the number of wineries using Stelvins and number of consumers in an agent’s network that have adopted the Stelvin. We assume that the constants are non-negative. This assures that \( \rho(\phi) \) is bounded on \((0, 1)\) and increases with increased marketing activities.\(^1\)

The magnitude of evolution described by Equation 4 is determined by the difference between the highest partworth for Stelvin closures by a New Zealand respondent and the average partworth for Stelvins \( \omega_{\text{max_NZ}} - \bar{\omega}_{\text{NZ}} \). By adjusting the partworths, demand is influenced by individual preferences for the type of wine, origin, price, and winery as well as by the advertising efforts of producers and word of mouth between consumers. In the next section, we present the computation model based upon the HFM just described, and then we introduce how conjoint analysis results can be used to validate this model.

3.0 Computational Model

The purpose of this agent-based model is to gain insights into how co-opetition 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, wineries determine price, production levels, and product attributes based on customer demand. Similarly, each period based on individual preferences consumers purchase the products manufactured by the wineries. A generalized causal model, as shown in Figure 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) initialized with heterogeneous characteristics (as determined by the conjoint results).

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\(^1\) Equation 6 allows \( c \) to increase or decrease. \( c \) might decrease if consumers return to corks from Stelvin closures. An alternative model might require partworths to never decrease. This can be accomplished by suitable modification of Equation 6.
Step 2. Wineries decide whether to join an alliance of wineries that exclusively produces wines with Stelvin closures and markets these products jointly with its competitors.

Step 3. Wineries ‘produce’ wines 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 an agent’s preference for Stelvin closures.

Step 5. Consumers ‘purchase’ wine based on individual utility maximization of product choices. If no wine is found that provides 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.

Step 7. The goal of the wineries is to maximize profit through meeting customer demand while minimizing inventory. Profit maximization is accomplished first through adjusting prices and then through adjusting production levels.

Profit maximizing wineries adjust the price of their offerings based on how much stock is left over at the end of the month. Excess stock results in lowered price; depleted stock results in higher prices. (See Figure 3 for an illustration of the rapidity by which we obtain the price equilibria.) Under fairly general conditions, this iterative procedure finds the price equilibria (fixed point) as a function of model parameters. Based on the price equilibria, wineries are then allowed to change their production levels to maximize profits. After approximately 24 months (or iterations, in this model) demand for screw caps begins to reach equilibrium.

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2 In this paper we provide no formal proof that price equilibria exist or are uniquely determined for the markets that we model. However, our simulations using different initial conditions suggest that the prices converge to equilibria in our market simulation and that they appear to be unique. We make no claims about either existence or uniqueness for market simulations based on different assumptions or structure.
To simulate alliances we randomly select 27 wineries to ‘form’ an alliance. 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 bear the costs of the campaign, decreasing their short-term profits. As the marketing campaign is initiated, consumers' conjoint partworths are adjusted as described in equations (5) and (6).

We used Netlogo (v3) (1999) to simulate this model. It is available upon request from the first author for those interested in reviewing the model structure and simulation results. Now that we have described the basic underpinnings of the model, we will describe the tasks undertaken in model validation, which include using conjoint analysis results to calibrate the model.

3.1 Calibration of New Zealand Wine Industry AMM

A wide range of parameter settings can be used to initialize the AMM. Knowing which parameters to use is a conundrum for agent-based modelers. Some, but not all, parameter settings lead to patterns of industry evolution that, in effect, ‘replicate’ the episode being 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 to realize an abstraction (in this case, the real world). In this study, we choose to use conjoint analysis results to instantiate the simulation so it ‘realistically’ models consumer choice decisions. The partworths determined from the conjoint study are used to initialize consumers’ preferences and thus provide a platform from which to calibrate the model. We explain how this is accomplished after briefly describing the conjoint data collection.

We recruited 2,255 leading-edge wine consumers from the US, Australia, and New Zealand to complete a conjoint web-based survey. Respondents were subscribers to wine-related e-newsletters and could be expected to be knowledgeable about wines. We obtained 1,203 respondents in the US, 667 in
Australia, and 385 in New Zealand. In this study, we focus only on the New Zealand (NZ) data. The conjoint design included five features at four levels each (see Figure 4):

- closure type: traditional cork, synthetic cork, Metacork\textsuperscript{TM} (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 was given two separate conjoint tasks to complete: they were asked about purchase preferences for an informal occasion and a formal occasion. Accordingly, we had conjoint results from 770 different responses. Survey results show that New Zealand consumers have equal preferences for Stelvins and natural cork closures. On average, respondents preferred red wines over white wines and they preferred wines from regional and boutique wineries over international conglomerates. These consumers prefer wine from their home country. Questions in addition to the conjoint questions revealed that respondents rely on wine-related periodicals and wine-related functions to gather knowledge about wines. Methodology and detailed results of this study are reported in Toubia, et al. (2006) and Garcia and Atkin (2005).

Consumer agents were assigned partworths only for two wine-type attribute levels (red wine/white wine), two closure attribute levels (screw cap/cork), two wine origin attribute levels (NZ-AUS/US), but all four levels of winery-type (boutique, regional, national, international) and price ($7, $12, $20, $25).\footnote{Price partworths for these prices are estimated from the conjoint study in which we used price ranges.} These levels were chosen in order to focus the model on the stylized facts of interest and to simplify the model. In the conjoint study we measured conditional choice and therefore did not include a ‘none’ alternative (Orme, 2005). Instead we modeled into the AMM an alterative choice where no wine purchase would occur. To set this ‘none’ choice, we calculated the least preferred choice of the agent to
find a minimum ‘threshold’ for which a purchase would be made. A purchase of wine by the agent would only occur if the threshold utility was exceeded.

To instantiate the wineries we need to assign the following parameters: (1) type of wine (red or white), (2) region of winery (US or Australia/New Zealand), and (3) type of winery (boutique, etc.). To ease 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 wines priced at $20; national wineries priced at $12; international wineries priced at $7. These ‘initial’ prices were then adjusted to reach a price equilibrium, which has previously been explained.

Winery parameters were also driven by the conjoint analysis results. For example, the first setting to instantiate was the percentage distribution of each type of winery in the marketspace (boutique, regional, national, international). Using the first-choice rule from the conjoint results, it was determined 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 between two different types of wineries. This small difference did not impact the model outcomes and consequently were not considered in model instantiation. Thus, we used these percentages to set the initial distribution of types of wineries.

However, winery type instantiation is not complete until we calibrate the model. Using sensitivity tests, we evaluated how prices would change based on changing the ratio of different types of wineries. It is easy to see that starving the market of the most commonly preferred wine (national wines) would drive the price up for these wines, but it would also glut the marketspace with less preferred options since the winery-type allocations percentage must equal 100%. The goal in this step of calibration was to adjust the percentages until the equilibrium prices sufficiently matched real-world prices for these types of wines. ‘Real world prices’ for NZ wines were obtained from industry partners. Table 1 shows the starting allocation percentages initialized during instantiation and also the final allocation percentages as determined during model calibration. The final price points reached after equilibrium are also shown.
The percentage of red wine versus white wine that is 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-to-white wine production obtained through sensitivity testing. For example, first-choice rule results showed that 58% of the respondents preferred red wine over white wine; using sensitivity analysis to reduce excess inventory of red and white wines resulted in model setting of 55% red wine production and 45% white wine production. The final instantiation setting driven by the conjoint results was percentage of Australian/New Zealand wineries versus US-based wineries. Although we also collected preferences for French and South American wines in the conjoint study, partworth evaluations showed that New Zealand respondents had the least preferences for these types of wines, and thus, to simplify the model they were excluded from the analyses. First-choice rule results showed that ninety-two percent of New Zealand respondents preferred Australian/New Zealand wines over US wines. To summarize the instantiation and calibration method, we used the conjoint partworth results to instantiate the overall preferences of consumers and then the first-choice rule to calibrate these initial setting 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 who 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 that needed to be set were number of wineries in the marketspace and production level of each winery. Using sensitivity analyses, we settled upon 52 wineries in the marketspace of 770 consumers. Consumers evaluated 16 different wineries when choosing a wine to purchase. This number was chosen as it increased the probability of a boutique winery being evaluated since they were in limited number (3 out of the 52 wineries). Production was set initially to be equal among the 52 wineries.

3.1.1 Stelvin Production
The next step in model validation was to verify that the model has face validity. We do this by evaluating a baseline model, where alliance memberships, advertising, and word-of-mouth impacts are excluded. This allows us to examine model sensitivity by setting the micro variables (agent characteristics driven by the empirical data) constant and observing how well the macro-environmental variables match the true market place (for example, market share for 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 of the model parameters are required. Macro-level results which not match the known empirical data require re-calibrating the model.

Initially, the percentage of Stelvin-closed wines was arbitrarily set at 10%. After initiation, wineries were allowed to adjust production level of Stelvins based on overall market share. Wineries produced Stelvin-closed wines to maximize profit based on market demand. The conjoint analysis first-choice rule showed that 55% of the New Zealand respondents preferred Stelvin closures over cork closures. Thus, in model verification, we have a calibration goal that the market share for Stelvins would reach 55% without any exogenous shocks to the model. Results show (Figure 5) market share for Stelvins reaches 53.5% (based on 50 runs of 50 iterations each, or 2500 total iterations). This simulation output (53.5%) adequately matches the conjoint results (55%) so that we conclude that this important test of model calibration and face validity has been achieved.

4.0 The Simulation Results

As earlier described, we propose that a strategy of co-opetition was used to diffuse the Stelvin to resistant customers in the New Zealand wine industry. We briefly describe early simulation results. We collected data in 2004, which was three years after the formation of the Wine Seal Initiative in New Zealand. Thus, our data does not allow us to present ‘real-world’ pre-alliance Stelvin market share and diffusion results. Instead, for illustration, we model market equilibrium as driven by the existing data and then introduce the alliance as if this was the actual pre-alliance equilibrium. Thousands of test runs were
conducted to establish face, parameter, and process validity as dictated by the empirical results of the conjoint study.

Because we allow price (as well as advertising and production levels) to be set endogenously by rational agents (wineries) in response to economic decisions by consumer agents (buy what and from whom), we begin with a burn-in period until prices reach a pre-alliance equilibrium. In oligopolistic competition, wineries make market share maximizing, but myopic, decisions to introduce Stelvins. It is only after we have reached both a price and production equilibrium do alliance effects come into the model. The results in Figure 5 show market penetration when no alliances have been formed and consumers’ partworths are not allowed to change (no effect of word of mouth or advertising). We can see that at approximately t=30, the market becomes saturated and Stelvin market share reaches only 53% as dictated by consumers’ partworths. It is after this period that we model alliances.

In Figure 6 we demonstrate how market penetration changes when alliances are formed. In this figure, we see that market share has increased to 76.5% and diffusion is 97.6% (all consumers have bought at least one Stelvin-closed product). We find this consistent with actual marketplace response four years after the alliance formation; approximately 80% of wines are bottled with Stelvins in New Zealand (Sogg, 2005). In our model the primary factor which changes consumers’ awareness of and preference for Stelvins is advertising by the alliance firms. Word of mouth can also positively impact adoption as consumer agents ‘communicate’ with one another based on a small world structure (Watts and Strogatz, 1998), thus aiding (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 impact the rate of diffusion of the screw cap. This finding supports the qualitative data collected from New Zealand wineries, which have stated that at least a dozen committed wineries were necessary to ‘get the ball rolling’. The need for a minimum number of alliance members seems to be necessary to spread advertising and media expenditures across members and obtain economies of scale in bottling costs. Our model also suggests that too large of an alliance results in lower profits for the firms in the alliance because consumers are not ‘ready’ to accept the innovation and sales go to the wineries that stayed
committed to cork closures. Later, wineries not in the alliance can free-ride on the Stelvin-coalition’s initial investments. Continuing analyses are planned to explore the profit impact of competition vs. co-opetition.

5.0 Summary

In this study, we have outlined the levels necessary to validate agent-based marketing models (AMMs). We demonstrated a history-friendly model (HFM) approach (Malerba, et al., 1999) that incorporates qualitative and quantitative data to create a ‘real-world’ replication of an episodic event in the New Zealand wine industry. We showed how conjoint data results can 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 for guiding calibration and verification of the model. An important take away from this study is that model instantiation can be set using conjoint partworths, and conjoint first-choice rule can be used to calibrate these initial model settings in this type of market. When the model matches the results of the first-choice rules for consumer preferences, a modeler can feel more confident that calibration is complete. When verification replicates stylized facts on a macro-level, the model is one step closer to being validated. 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 for AMMs. Empirical results that are reported on an aggregate level (such as regression analyses) do not lend themselves as well to grounding an AMM. The next step for our model is harmonization. Calibration and verification are not meant to be substitutes for harmonization, or guarantee accurate predictions. For details on how to conduct harmonization refer to Carley (1996).

Early model results of our HFM indicate that the market place becomes saturated for a resistant innovation, such as screw cap closures on high-end wines. Exogenous forces such as coalitions are required to adjust consumers’ preferences away from the status quo. One method of doing this was co-opetition, or the cooperation of competing wineries to jointly promote the benefits of the screw cap to a
resistant marketplace. Early results show that too few wineries will not cause the necessary ‘shock’ to the marketplace and too many wineries dilute the message so that profit and market share suffer for all the firms in the alliance.

Acknowledgements

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Table 1  Initial and Final Model Settings

<table>
<thead>
<tr>
<th>Type of Winery</th>
<th>Initialization¹</th>
<th>Model Setting²</th>
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<tbody>
<tr>
<td>Boutique</td>
<td>4%</td>
<td>5%</td>
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<tr>
<td>Regional</td>
<td>24%</td>
<td>18%</td>
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<tr>
<td>National</td>
<td>45%</td>
<td>39%</td>
</tr>
<tr>
<td>International</td>
<td>27%</td>
<td>38%</td>
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1. based on conjoint first-choice rule when evaluating type of winery at set price
2. after verification

<table>
<thead>
<tr>
<th>Type of Wine</th>
<th>Initialization¹</th>
<th>Model Setting²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Red wine (boutiques)</td>
<td>58%</td>
<td>55%</td>
</tr>
<tr>
<td>Red wine (regional)</td>
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<td>60%</td>
</tr>
<tr>
<td>Red wine (national)</td>
<td>59%</td>
<td>60%</td>
</tr>
<tr>
<td>Red wine (international)</td>
<td>59%</td>
<td>60%</td>
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</table>

1. based on conjoint first-choice rule when evaluating red versus white wine
2. after verification

<table>
<thead>
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<th>Region of Wine</th>
<th>Initialization¹</th>
<th>Model Setting²</th>
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</thead>
<tbody>
<tr>
<td>Australian/New Zealand</td>
<td>92%</td>
<td>92%</td>
</tr>
<tr>
<td>US</td>
<td>8%</td>
<td>8%</td>
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</table>

1. based on conjoint first-choice rule when evaluating AUS/NZ vs. US
2. after verification

<table>
<thead>
<tr>
<th>Price of Wine</th>
<th>Initialization¹</th>
<th>Model Setting²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Boutique (high priced)</td>
<td>$25.00</td>
<td>$21.50</td>
</tr>
<tr>
<td>Regional (mid-high priced)</td>
<td>$20.00</td>
<td>$17.50</td>
</tr>
<tr>
<td>National (mid priced)</td>
<td>$12.00</td>
<td>$11.50</td>
</tr>
<tr>
<td>International (low priced)</td>
<td>$7.00</td>
<td>$5.00</td>
</tr>
</tbody>
</table>

1. based on conjoint attribute levels
2. after price equilibrium achieved (approx. 24 iterations [months])
Figure 1. Causal Model

Production Levels of Screw Caps
Consumers Evaluate Screw Caps
Sales of Screw Caps
Marketshare of Screw Caps
Alliance Membership
Advertising
Winery Adopts Screw Caps
Price Adjustment (until pre-Stelvin equilibrium)
Sales of Screw Caps

Figure 2. Framework for Empirical Calibration of AMMs (based on Madey, et al. 2002)

Model/Theoretical Foundation
Empirical Data
Simulation
Test
Develop
Structure
Enrich
Instantiate
Replicate
Figure 3. Price Adjustments

Netlogo output

Figure 4. Conjoint Design (from Toubia, et. al., 2006)
Figure 5. Pre-Alliance Market Penetration

![Graph showing Stelvin Market Penetration](image)

Netlogo output: average of 50 runs of 50 iterations

Figure 6. Post-alliance Market Penetration

![Graph showing Stelvin Market Penetration](image)

Netlogo output: average of 50 runs of 50 iterations