SAMM-E™: The Little Algorithm That Can

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Meet SAMM-E. No relation to a lonely robot or a little blue engine, the acronym stands for Simplified Assessment of Multiple Market Events. SAMM-E is a synthesis of advanced experimental design and modeling techniques that addresses a growing need to investigate increasingly complex market scenarios. Theoretically, these complex scenarios may be modeled using traditional choice/conjoint designs but only at great cost, both financial and cognitive: large, complex designs require large samples and place an enormous cognitive load on the respondent. Setting aside financial considerations for the moment, few researchers would argue that increased task complexity does not negatively impact the reliability of data thus collected. At the same time, complexity is an enduring feature of modern markets and wishing it away in the research setting is not a reasonable option. The trick is to simplify the respondent task as much as possible with minimal loss in functionality and analytic rigor. SAMM-E represents one such "trick".

Background

So, what exactly is SAMM-E? To answer this, let us consider a typical business scenario where it may be applied.

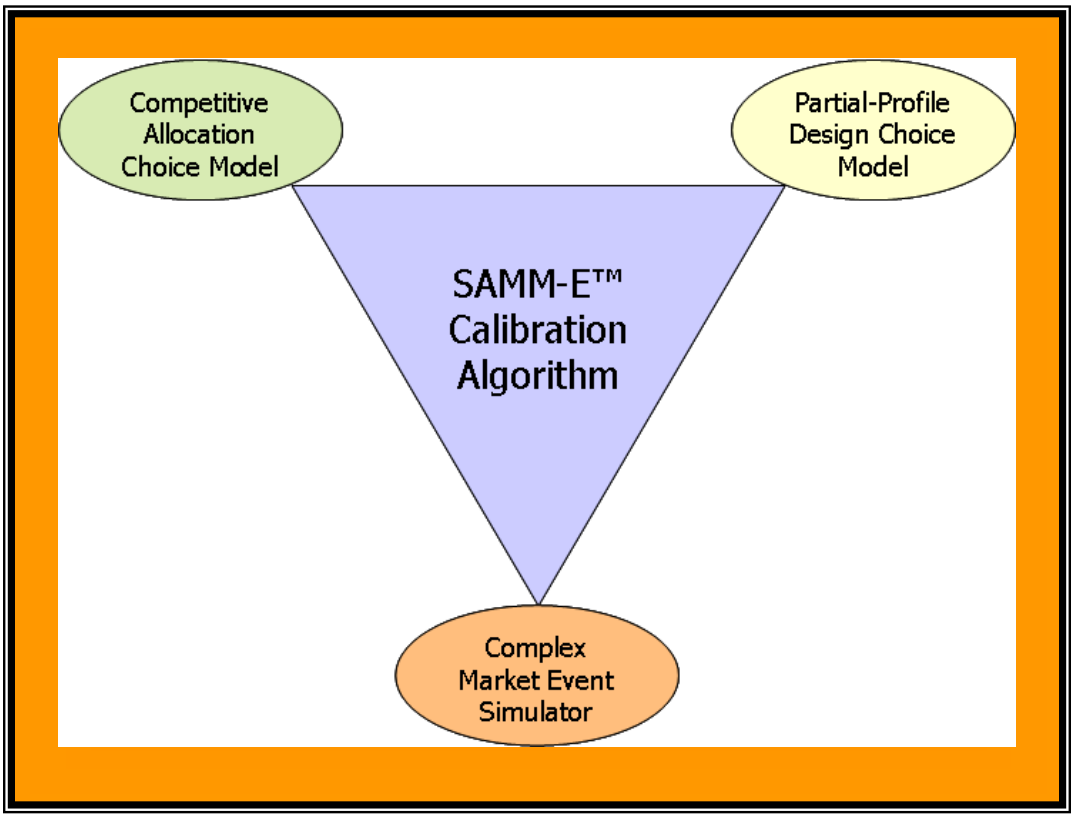
Company A has two pipeline products in a rapidly evolving therapeutic area. The market is characterized by the impending arrival of generics as well as four new competitors across multiple therapeutic classes. Company A needs to estimate the uptake for its own pipeline products *in the complete context of these market upheavals*. From a methodological standpoint, this implies that product profiles must be varied not only Company A's products, but for all possible market entrants. Can this be done with standard choice designs? Sure it can. The experimental design would vary the presence and absence of each new product and vary each of their profiles independently, thereby giving the brand team the ability to explore market scenarios with different competitive combinations of varying profiles. Great news for the brand team, but what of our hapless respondent? Consider that in a typical choice study involving a single product profile with eight attributes, a respondent evaluates anywhere from 8-12 choice cards where the profile of "Product X" varies per the experimental design: no easy task, especially given a large competitive set, multiple patient types etc. In the scenario we have laid out, this already complex task morphs into a monster with no less than 15 cards per respondent, each containing up to six *independently varying* new products! Even assuming the respondent doesn't quit half way in disgust, how much would you trust the data that came out of such a mind numbing exercise? There has to be a better way!

At this juncture, those of you with a few conjoint projects under your belt are probably wondering what the fuss is all about. Surely this isn't a new problem – you've dealt with analogous scenarios before without resorting to enormously complex choice designs, right? So, let's talk about how this issue is typically dealt with. One approach is to ignore the impending arrival of competitors in the conjoint exercise or, at most pay lip service to it "outside the model". Another, is to allow Product X to vary across a really wide range so that any possible product may be simulated, including potential competitive drugs. Let's focus on the latter as the former is

less an approach than an avoidance of the issues on hand. It is true that varying the Product X profile across a wide range of levels will allow it to take on the guise of any new product expected to enter the market. The problem is that these new "products" are never presented to the respondent all at once or even a few at a time: this means that the model cannot capture the competitive dynamic that exists among these new (and incumbent) treatments. To make an obvious point, my choice of Pepsi Cola at a Taco Bell is less a function of my relative preference for Pepsi over Coke and more a function of the restricted choice set presented to me at that establishment. The notion therefore, that physicians' preference structure across a wider competitive set can be estimated based on their preference for the individual items presented in a vacuum completely ignores the impact of competitive alternatives on prescribing decisions.

The SAMM-E Solution

As we saw in the previous section, current approaches to modeling multiple market events involve either very complex designs with an extremely laborious respondent task or simplifying assumptions that completely miss the competitive dynamic among all available treatments. SAMM-E gets around this dilemma by separating the competitive assessment portion from the measurement of attribute sensitivity and then integrating the two pieces analytically. Competitive relationships are estimated using a simple choice design where the only thing being varied is the presence and absence of competitors with fixed profiles. Attribute preference is measured with a partial profile choice model. A calibration algorithm integrates the two models into a single simulator with all the functionality of a full-fledged choice model. At the same time, the respondent task required for both components combined is far simpler than the single task required by a traditional choice modeling design with dozens of moving parts.



SAMM-E's First Component: Competitive Allocation Choice Model

The respondent is first exposed to a few experimentally designed scenarios which feature new competitive entrants with a fixed profile based on best-guess estimates. For example, the entry of 6 new products can be captured with a nine-card design, divided into three blocks. Thus, any one respondent would evaluate only three such choice cards. The respondent completes an allocation exercise based on each choice card. The resulting data is analyzed using a multinomial-logit choice model that captures the potential uptake for all existing and potential treatments. Note that this model will not allow us to vary the profiles of the new entrants; however, the value or "utility" of the specific end-points presented in the scenarios is captured by the model's brand constants[1]. The primary output from the model is the ability to simulate any combination of new players – only A, only B, A, B, C and D etc. The competitive dynamic is therefore explicitly addressed by the model. Now, all we need is a way to vary the profiles of these new market entrants so we can make realistic predictions of product uptake under all possible clinical outcomes. This leads us to the second component of SAMM-E.

SAMM-E's Second Component: Partial-Profile Choice Model

In a partial-profile choice model, products are described in terms of a partial profile. For example, if there are twenty relevant product attributes, each product profile may be described by no more than five attributes. Typically, each choice card will contain two partial profiles and the respondent is asked to pick the one product she is most likely to prescribe.

EXAMPLE PARTIAL-PROFILE CHOICE CARD

Please assume that the following two treatments are identical in all respects except as detailed below. Which product are you most likely to prescribe?

Median Survival: 27 months	Median Survival: 18 months
Time to Progression: 7 months	Time to Progression: 4 months
Time to Use of Opiates: 7 mths	Time to Use of Opiates: 5 mths
55% Skeletal Related Events	25% Skeletal Related Events
Easily Manageable Headaches	Some Injection Site Reactions

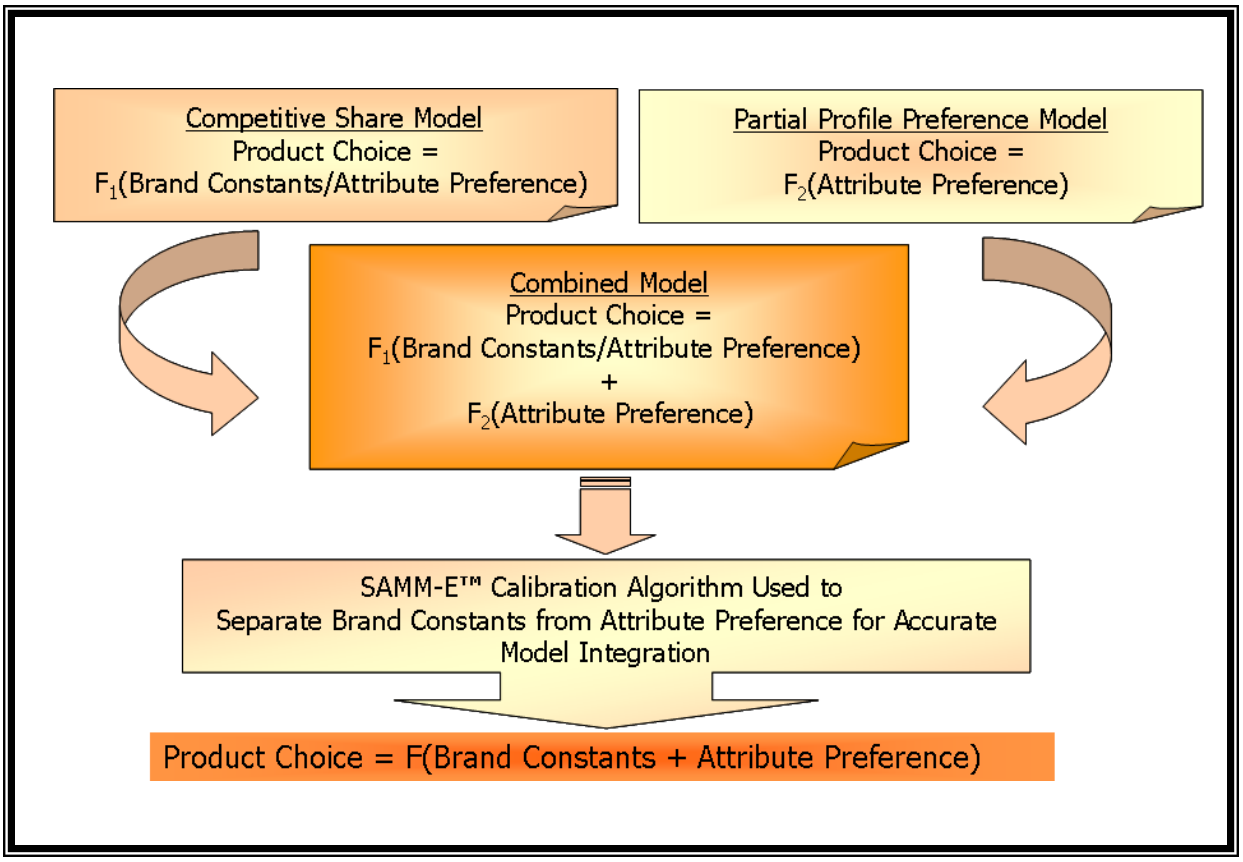
The respondent will evaluate several such cards with different combinations of attributes as determined by a sophisticated experimental design. With just 2 products that differ on no more than five attributes, the task is easy to complete, especially when compared to a full-profile choice task with multiple new entrants. The resulting model ignores competitive effects but yields

[1] Multinomial logit models yield an intercept term (constant) for each alternative in the choice set. These "alternative-specific constants" capture the intrinsic utility of the alternative that is not explained by the product attributes. In this case the intrinsic utility includes the value that respondents place on the fixed profile of each new product.

the attribute preferences necessary for sensitivity analysis. Now, armed with the competitive effects model from the first component and the attribute preference model from the second, we have all the pieces needed for an integrated, "full-function" choice model.

SAMM-E's Final Component: The Calibration Algorithm

As we saw earlier, the first component consists of a product-allocation choice model that outputs patient share estimates for all existing treatments as well as all possible combinations of new entrants of a given (fixed) profile. Technically, this is a model with only alternative-specific constants, where each constant contains information regarding both the intrinsic value of the product profile as well as the value of the fixed clinical end points shown. The second model, based on the partial profile design contains information on attribute preferences. If the parameters from these two models were combined into a single simulator, the value of the clinical attributes would be counted twice – once as part of the constants in the first model and second, from the partial profile model, as shown in the "Combined Model" box (see graphic).



The SAMM-E calibration algorithm essentially adjusts the constants from the first model in order to account for the double counting of attribute preference when these two models are integrated.

The idea is this: if we "turn on" the attribute levels to match the fixed profiles of the products in the first component, the product shares predicted by the combined model should match the shares predicted by the first share allocation model alone. A convergent algorithm is used to derive the calibration factors that make this possible. The end result is an integrated model that captures both competitive effects and attribute-preference, thus allowing us to investigate every possible scenario involving different combinations of players and clinical outcomes.

Concluding Thoughts

We have presented SAMM-E in the context of having to model extremely complex market scenarios. Recall however, that the strengths of this approach may be summarized simply as, *a)* Budget-Friendly, *b)* Respondent-Friendly, and *c)* Analytically Rigorous. None of these points suggest its use exclusively in projects of extreme complexity. The fact of the matter is that full-profile conjoint exercises start to break down when the number of product attributes exceed seven or eight, even when a single product is being tested. Partial-profile designs by themselves are an unsatisfactory solution as they lack competitive context and cannot provide accurate estimates of product uptake. SAMM-E's ability to synthesize the advantages of partial-profile designs with those of competitive allocation-based choice exercises makes it a powerful and versatile element of the sophisticated researcher's tool-kit.