New Markets as New Products: Adaptation of the Bass Diffusion Model and System Dynamics Modeling for Forecasting Agri-Food Exports

Vincent Amanor-Boadu[1]

December 2021

Abstract

Finding effective forecasting tools in the absence of historical data has been a challenge for analysts, industry leaders, and policymakers in the agri-food trade environment for many years. This paper contextualizes this challenge and adapts the Bass Diffusion Model using system dynamics modeling as a solution. It draws on practitioners' knowledge and insights to develop a decision support tool to enhance forecasting in the absence of data. The interactive tool enables decision-makers to identify, understand, and leverage the dynamic interactions of the principal variables in their decision environment. US exports of distilled spirits to Morocco is used as a case example to illustrate the decision support model. The tool allows the identification of the feedback loops in the model, the critical loops that influence model behavior, and in so doing helps decision-makers to develop appropriate responses to potential challenges.

Keywords: Bass Diffusion Model; System Dynamics Model; Feedback Loops; Forecasting; Agri-Food Exports

Introduction

The Bass Diffusion Model (BDM) is exquisitely simple, demanding only three parameters: coefficient of innovation; coefficient of imitation; and potential market size (Bass 1969). Because of this simplicity, it has been employed to forecast the diffusion of numerous products (Steffens 1998). The power of its broad applications rests on lending itself to empirical generalizations, defined by Bass (1995, p.G7) as "a pattern or regularity that repeats over different circumstances that can be described simply by mathematical, graphic, or symbolic methods."

System Dynamics Modeling (SDM), developed by Jay Forrester (1968) and advanced by his acolytes and students, including Barry Richmond (Chen and Stroup 1993), is useful when studying problems with dynamic variables or components in nature and character. The implicit difficulty of dealing with problems with dynamic components is their delayed impact relationships, otherwise referred to as feedback loops. For example, imposing a trade tariff generally presents a delayed impact as existing inventory in the system is exhausted and new imports enter the market. The feedback loop of the new tariff could be changes in levels or patterns of imports or substitution with new products from the same market or different markets. This bedrock of SDM is so essential in decision making it has been applied to school finance (Baker and Richards 2002), leadership (Shaked and Schechter 2013), and total quality

[1] Dr. Vincent Amanor-Boadu is an agribusiness economics and management professor at Kansas State University's Department of Agricultural Economics. He may be reached by email at vincent@ksu.edu.

management (Ehrenberg and Stupak 1994). Amanor-Boadu et al. (1999) used it in assessing the net benefits of trade liberalization for the Canadian agri-food sector and Ross and Amanor-Boadu (2006) employed it to assess new functional food introduction in the US. Recently, Zhang (2019) used SDM to explore the reinforcing boost effect on regional transoceanic trade driven by industrial clustering in Qingdao, China.

The BDM has been applied traditionally to durable goods. However, there have been attempts over the years to incorporate repeat purchasing (Rao and Yamada 1988; Chaudhary, Kumar and Mehta 2018) and price into the Bass Diffusion Model (Mesak and Berg 1995). Rao and Yamada (1988) focus on novel prescription medication while Chen and Chen (2010) explicitly use a system dynamics model and a modified BDM incorporating prices and consumer characteristics to forecast sales of room air conditioners and clothes dryers. Guo (Guo 2014) employed the BDM to model first-time purchasing and the Novelty-Loyalty Based Consumer Utility theory to model repeat purchases for product life cycle analysis. Likewise, Chaudhary et al. (2018) explores the theoretical dimensions of repeat purchasing effect on the BDM using stochastic differential equations.

Exporting to a new market may be considered analogous to the introduction of a novel product to the market. In both cases, the product has no history in the target market and follows a diffusion path not dissimilar to that presented under the BDM's. Despite this strong similarity, the BDM has not been employed either alone or in conjunction with a system dynamics model to forecast agri-food exports. The closest the BDM and SDM have been applied to a novel food product entry into a new market is Horvat et al. (2020) and their forecast of the radically new insect-based foods in the Netherlands. The low application of these tools to new agri-food products in new markets may be attributed to the disconnected between the domains of researchers forecasting agri-food trade does those using SDM and BDM to forecast product diffusion. This research, therefore, seeks to bridge the two fields, providing a means for trade forecasters to expand their toolbox by employing BDM and SDM. This is necessary when data is sparse, and/or when the diffusion path involves dynamic loops that are fundamental to appropriate sensemaking in problem conceptualization and solution development.

For the analogy of novel product to work with agri-food exports to new markets using the BDM, potential customers must perceive the product as unique with enduring identity and be non-substitutable. Let us illustrate this by letting Q_{xy} be a Country X product about to be exported to Country Y for the first time. The necessary product characteristics require that Q_{zy}, an identical product from Country Z in Country Y is perceived as different by Country Y consumers. Exporting firms are able to create these necessary characteristics by bundling their products with inimitable resources when entering new markets (Lancaster 1966; Kim and Mauborgne 2005).

Against the foregoing background, the paper is presented in the following order. The foundations of the BDM and SDM are presented in the next section. The section focuses on building understanding of the tools for the uninitiated so that their value in the toolset of forecasters can be appreciated. The section following that provides a framework for employing SDM-based BDM to forecast agri-food exports to novel destinations. The application of the SDM-based BDM to US distilled spirits exports to Morocco is them presented. The paper's appendix provides the summary of the structured conversations undertaken with leaders of US agri-food companies currently exporting. The conversations focused on identifying factors influencing their selection of potential export markets and their responses to changes in their selected markets after entry. These conversations provide insights into the designing the model structure to reflect the sensemaking processes practitioners use in their pre- and post-market entry decisions.

Bass Diffusion Model: A Brief Overview

Conceptualization of the Bass Diffusion Model in this paper's context begins with a population of potential buyers (adopters), *m*. Their probability of purchasing (adopting) at time *t*, $f(t)/[1-F(t)]$, may be presented as follows:

$$\frac{f(t)}{[1\text{-}F(t)]}=p+qF(t), \tag{1}$$

where *p* and *q* are both greater than 0 and are defined respectively as the coefficient of innovation (external effect), and the coefficient of imitation (internal effect). They are also defined as advertising effectiveness and word of mouth adoption fraction. Equation (1) may be re-written as:

$$\frac{n(t)}{[m\text{-}N(t)]}=p+\left[\frac{q}{m}\right]N(t), \tag{2}$$

where $n(t)=mf(t)$ and $N(t)=mF(t)$ is the cumulative number of buyers at time *t*. Reorganizing Equation (2) produces:

$$\begin{aligned} n(t)=\frac{dN(t)}{dt}&=[m-N(t)]\left[p+\frac{q}{m}N(t)\right] \\ &=pm+(q-p)N(t)-\left[\frac{q}{m}\right][N(t)]^2, \end{aligned} \tag{3}$$

which produces a nonlinear closed form solution that describes the time pattern of purchasing the new product. The number of buyers and cumulative buyers at time *t* may be determined as follows:

$$\begin{aligned} N(t)&=mF(t)=m\left[\frac{1-e^{-(p+q)t}}{1+\alpha e^{-(p+q)t}}\right], \\ n(t)&=mf(t)=m\left[\frac{p(p+q)^2e^{-(p+q)t}}{(p+qe^{-(p+q)t})^2}\right], \end{aligned} \tag{4}$$

where $\alpha=q/p$.

Bass (1969) uses an ordinary least squares approach to estimate the parameters in Equation (4), regressing sales on cumulative sales and cumulative sales squared, treating time as discrete when it is, in fact, continuous, and in so doing, introducing a bias in the estimates (Schmittlein and Mahajan 1982). Srinivasan and Mason (1986) noted that while the Schmittlein and Mahajan (1982) solution eliminated the time interval bias by using aggregation of the continuous time over time intervals, because they did not consider other error sources apart from sampling errors, their computed standard errors may be underestimated. The error sources they ignored include the impact of excluded variables, and misspecification of the density function. To address this gap, Srinivasan and Mason (1986) proposed a non-linear least squares (NLS) estimation for the BDM parameters using an additive, instead of a multiplicative, error term, which yielded a superior predictive validity. Thus, they restated Equation (4) in terms of time interval with an error term, μ_t, that has zero mean and a variance of σ^2. Their model is summarized as follows:

$$N(t)=m\left[\frac{1-e^{-(p+q)t_1}}{1+\alpha e^{-(p+q)t_1}}-\frac{1-e^{-(p+q)t_{t-1}}}{1+\alpha e^{-(p+q)t_{t-1}}}\right]+\mu_t \quad \forall\, t=1,2,...,T. \tag{5}$$

The assumptions about the additive error term create negative sales risk, which Srinivasan and Mason argue is low and acceptable given the benefits of the reformulation.

The risk of density function misspecification in Bass (1969) is discussed by Easingwood et al. (1983), who show that using a non-uniform influence model relating imitation to cumulative adoption, *N*(*t*), improves predictive validity. Their estimated non-linear least squares (NLS) model is presented as:

$$\begin{aligned} G(t) &= \gamma N(t)=\frac{c(1-e^{-\beta t})}{(1-\alpha e^{-\beta t})}, \\ L(\alpha,\beta,\gamma,\{n_t\} &= [1-G(t_{T-1})]^{nT}\prod_{t=1}^{T-1}[G(t_t)-G(t_{t-1})]^{n_t}, \end{aligned} \tag{6}$$

where $\beta=p+q, \gamma=m/M$, the probability of eventually adopting the product, m is the cumulative number of buyers at each time and M is the total number of potential buyers, while L is the likelihood function, and all others are as previously defined. Srinivasan and Mason's estimated non-linear least squares method produces the parameters *p*, *q*, and *m*, and their standard errors were found to be superior to the maximum likelihood estimation approach suggested by Schmittlein and Mahajan (1982).

A major limitation of the BDM, regardless of how the parameters are estimated, is that it focuses on durable goods, does not recognize competitor reactions to innovation, and does not include decision variables. Durable goods are often purchased once by consumers in the diffusion process, and therefore, do not capture the repeat purchasing characteristic of non-durables. The earliest work on repeat purchase diffusion model was done by Lilien et al. (1981), and was validated by Rao and Yamada (1988) using prescription pharmaceutical product as the focus product. Prescription product' diffusion is unique because the consumption decision involves the prescribing physician and the consuming patient. In that prescription role, the physician is the principal decision-maker in the product's diffusion. This explains why drug manufacturers target physicians in the promotion of their new products (Güldal and Şemin 2000; Gönül et al. 2001).

Chaudhary et al. (2018) consider the repeat buying situation with a focus on stochasticity of the adoption rate. They note that successive increases in number of adopters may consist of first-time buyers and repeat buyers, and if the novel product has a long-life cycle, then the number of adopters increases at a decreasing rate over time compared to the potential adoption population. They modify Equation (3) to include the proportion of adopters who repeat their purchase of the product at time *t*. Because there is no guarantee that a customer who has purchased the product would repurchase it, Chaudhary et al. introduce randomness resulting from promotional expenditure, perceptions about product quality, changes in customer preferences, and competitor responses to the innovation. These thoughts are employed in the application of the model to forecasting the exports of agri-food products, the quintessential repeat buying product, to new markets.

Overview of SDM

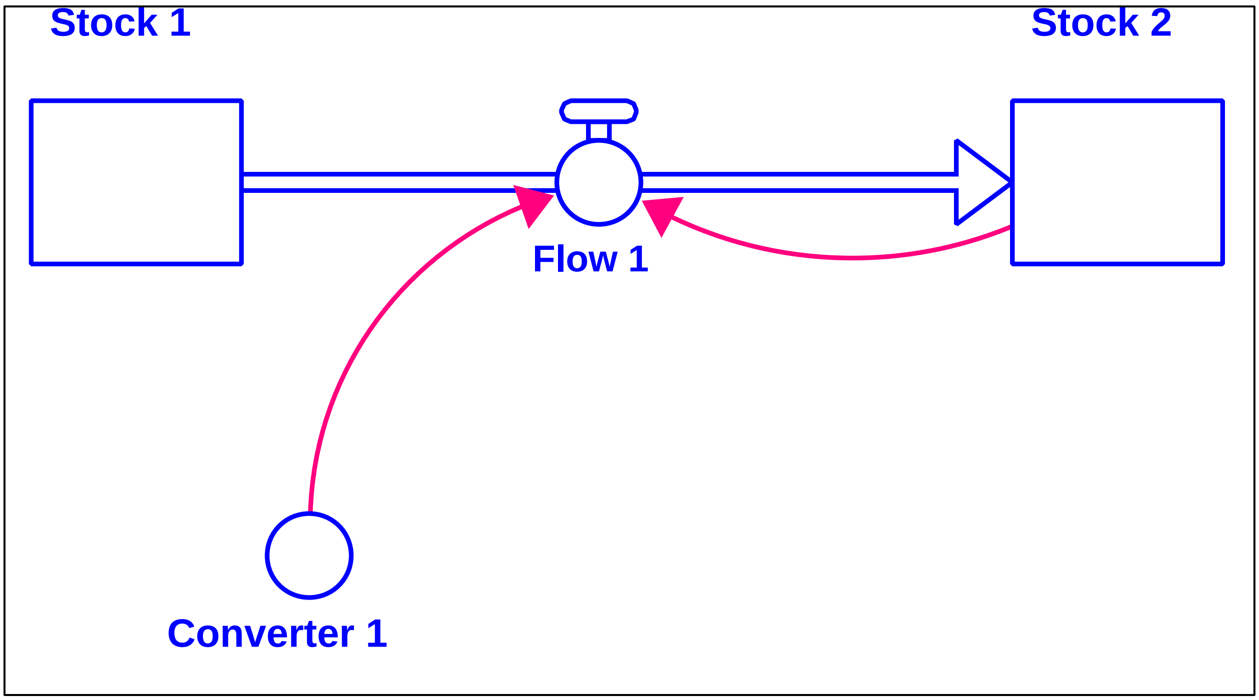
System dynamics (SD) models provide a lucid modeling approach born of the need to improve understanding and sensemaking of complex problems. They are part of the many system approaches that share a perspective of a world described by complex dynamic processes. They have become useful in numerous fields: from teaching different subjects from kindergarten to university, and in corporate boardrooms, to improving public policymaking. Thanks to Forrester (1969), who discovered that all changes propagate themselves through stock and flow sequences, and user-friendly SD modeling software, such as iThink®, Stella®, Vensim®, and others, SD models have increasingly become available for facilitating learning, improving decision making, and undertaking more accurate forecasts.

SD models attempt to describe, explain, design, build, and/or influence the systems they study. Therefore, they offer both a sensemaking theory, a way of thinking (systems thinking), and a method for dealing with systems issues (Richardson 2009). Their effectiveness has been enhanced by using graphical representation of complex, multi-loop, and non-linear relationships among important and critical variables in the system, and then using computers to simulate the resulting models under alternative conditions to provide new perspectives, modify mental models, and improve decision-makers' thinking about solutions to the problems being modeled.

Developing SD models that produce useful insights depends on what Richmond (2010) describes as horizontal and depth thinking skills. These thinking skills help define what to include in and exclude from mental models representing the phenomena of interest. Richmond (2010) classifies these thinking skills into three types: 10,000-meter; system-as-cause; and dynamic thinking skill. The 10,000-meter thinking skill enables the structural representation of the system, which may be likened to the view one gets from the window seat of an airplane – expansive with very little depth. The system-as-cause thinking skill provides depth to the 10,000-meter thinking's by incorporating the simplest details and the best explanations, organizing them to contain only those elements whose interactions produce the phenomenon of interest. Dynamic thinking skill focuses on the behavioral representation of the phenomenon of interest, filtering all nonessential elements of reality from the mental model. It encourages looking for patterns in order to understand activities that lead to observed events, thereby providing richer mental models. Richmond (2010) recommends starting from the 10,000 meter thinking level and working to the dynamic thinking level to enable the development of the most accurate perspectives and sensemaking. By accurately understanding the problem's structural representation, Richmond argued, that relevant elements and their accurate interactions can be developed to represent their dynamics and reveal their underlying challenges. Focusing on critical elements defining a problem minimizes distractions from inconsequential variables. Therefore, mastering these three thinking skills enables the effective translation of mental models into computer models, which facilitate further elucidation through simulation, discussion, and assessment of alternative solutions to modelled challenges. The purpose, then, of SD models is to improve understanding and provide insights into better solutions to identified problems through simulations by focusing on their key structural components and relationships.

SD models have four "grammatical elements"(Figure 1): stocks; flows; converters; and connectors, which are universal and independent of discipline (Richmond 2004; Richmond 2010). Stocks, represented by rectangles in model diagrams, are state variables that accumulate or deplete in the system. Flow variables are represented by valves and define the changing accumulation or depletion rate of stocks. When the flow is from a stock, as in Stock 1 in Figure 1, then the stock is depleting, and when it is to a stock, as in Stock 2, then the stock is accumulating. Converters are used to capture parameters and intermediate calculations that neither accumulate nor contribute directly to accumulations. For example, line speed in a manufacturing facility may be captured with a converter. Finally, connectors are the pink arrows in Figure 1, and they show model structures' cause-and-effect links. These four elements together facilitate the translation of invisible mental models of physical systems into visible computer models, enabling challenging of assumptions that are otherwise unarticulated, contributing to improving understanding of the system. This translation also fosters the computer simulations that engender learning and improvement in assessing alternative policies.

Figure 1: "Grammatical Elements' of System Dynamics Model



Ease, transparency, participation, and ability to explore alternative futures with SDM are their principal advantages. Their ability to absorb other models, such as the BDM, allowing them to overcome some of the major limitations of statistical forecasting models, is another non-trivial advantage. For example, econometric models require modelers to make two major decisions. First is the selection of variables assumed to produce the outcome of interest, which is often based on theory, on observation, or both (Mass and Senge 1978). The other decision is choosing the structure of the relationships among the variables and between the variables and the outcome of interest. In doing this, the modeler implicitly imposes all the assumptions of the Markov-Gauss approach (Shostak 2002; Greene 2018) and often not testing their validity (Spanos 2021). Also, because of their intense dependence on quantitative measurements, they tend to ignore factors that cannot be measured, no matter how important to the structural relationships of the model (Lyneis 2000). Finally, statistical tools and way they are structured to be used often keep the ultimate beneficiary (the practitioner) of the tools' outputs from intimately participating in the modeling process, making it a "black box" whose processes are hidden from the uninitiated. The ultimate importance of feedback loops in determining system behavior is another critical limitation of statistical tools when the purpose is to mimic the system being studied so that effective decision options may be considered. The highlighting of the limitations of statistical methods in forecasting does not in any way negate their importance. They only seek to draw attention to aligning the model to its purpose. If the purpose is to make decisions in a dynamic environment, then the model supporting the decision-making process must replicate the decision environment as close as possible. And feedback loops and dynamics are integral to all decision choices (Forrester 1976).

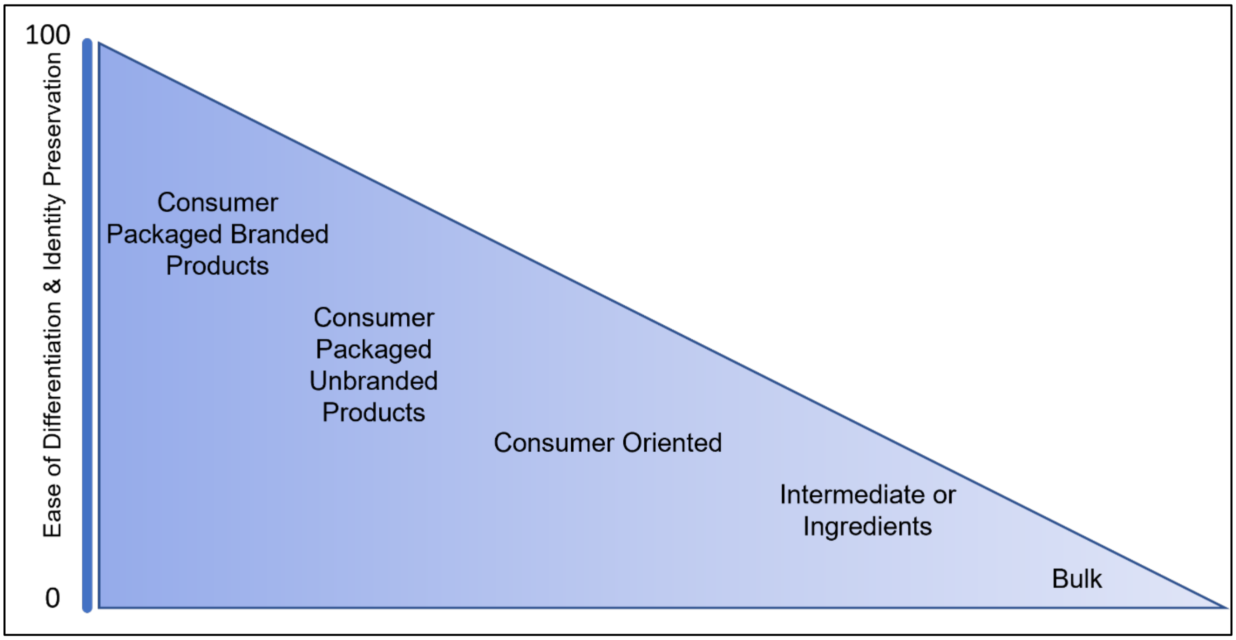
System dynamics modelers have been modeling the Bass Diffusion Model for a long time. It has been used as the framework for simulating disease infection rates (Homer and Hirsch 2006; Supriatna and Anggriani 2012). Devahli et al. (2020) provide an extensive review of the literature on the application of simulation methods, including system dynamics, to healthcare issues. They observe that system dynamics has been used extensively in epidemiology and disease prevention studies. With a few exceptions, such as Amanor-Boadu et al. (1999), Horvat et al. (2020), and Ross and Amanor-Boadu (2006), system dynamics and the Bass Diffusion models have not been very popular among new agri-food product diffusion and trade researchers.

Assumptions for Using of the BDM and SDM for Agri-Food Exports

The preceding two sections provided overviews for the Bass Diffusion Model and System Dynamics and their potential employment in forecasting agri-food exports to new markets. Successfully doing this requires some enabling assumptions. First, it is assumed that entering new markets are motivated by profit enhancement opportunities. These opportunities may be exploited only if the exporter has lower production costs and/or higher value proposition in the target markets. The higher value proposition is realized by exploiting revealed consumer preferences for certain inherent characteristics or attributes of products from certain foreign suppliers (Lancaster 1966). That is, products from certain countries/brands offer some consumer segments specific utility they do not get from similar products originating from other countries. This implies that there may be consumer segments in the target market who do not prefer the imported product/brand. Thus, different consumer segments with very different affinities for the same product may coexist in the same market.

It is next assumed that potential exporters are able to identify the relevant consumer segments for their products and assess their potential to produce their expected performance results within projected time frames. The potential is directly influenced by the size, social and economic characteristics that influence first time purchasing and repeat purchasing of the exported products. The foregoing also involves target product value curves and strategy canvas construction to confirm the value innovation supporting success (Kim and Mauborgne 2005). Figure 2 illustrate the ease with which the exported product may be differentiated, and its identity preserved. Bulk products are more difficult to be differentiated while consumer-oriented products have wider differentiation and identity preservation opportunities.

Figure 2: Ease of Differentiation and Identity Preservation for Different Types of Exported Products



Market expansion and profit enhancing opportunities are the assumed motivations for exporting. The foundations for these opportunities are production cost advantages and/or higher quality. Production cost advantages allow firms to price products below competitors' while high-quality allows them to price products above competitors' prices. In planning exports, firms invest in discovering destinations and the specific market segments at those destinations most likely to be attracted to their products. They assess the size and analyze the characteristics of the identified market segments in multiple candidate countries. This enables them to determine the alternative destinations' relative ability to meet their business objectives. The most promising destinations given firms' resources and capabilities to be successful are selected and strategies developed to enter and grow in those markets. Effective strategies for sustained performance, measured by the motivations for exports, are developed to enable firms swim in Kim and Mauborgne's (2005) "blue ocean."

The type and nature of exported products influence the ease of executing blue ocean strategies. Exporters of branded differentiated consumer-oriented products have the advantage of their products' identity facilitating differentiation from competing products. Yet, they can enhance non-substitutability and inimitability of their value contribution to sustain performance by extending customer engagement beyond their products. Exporters of unbranded non-differentiated bulk commodities or intermediate products, on the other hand, need special relationships with customers in destination countries and service providers along their supply chains to execute non-price focus strategies that make price competition irrelevant. These relationships may be built on quality, service, and other non-substitutable and inimitable variables that provide customers an advantage in their own markets.

Using BDM and SDM for forecasting exports to new markets facilitate the incorporation of sustained performance strategies into the forecasting model. This is because performance is predicated on strategy and strategies influence performance, i.e., there is a feedback loop between performance and strategy. The BDM provides the framework for assessing the diffusion pathways in the new markets through the deployment of alternative marketing mix over products' lifecycle (Mahajan, Muller and Bass

1990). The SDM provides the ability to evaluate export performance under alternative assumptions about the selected market – competitor response, trade, and other policy changes, changing customer preferences, and other influencing variables of interest over time. Its ability to incorporate feedback loops and discover critical loops can enhance insights into how to modify strategies to increase the probability of achieving the desired strategic objectives.

The fused BDM and SDM models could broaden the domain of trade disputes from individual products or industries to assessing their system implications. In this way, they contribute to export policy conversations that could motivate firms to export to new markets while reducing trade dispute risk. This may be achieved through the simulation of alternative policies and their potential system's effects and appreciation of potential feedback loops. More importantly, recognizing the natural feedback loops may reveal unintended consequences emanating from anticipated policies, such as tariffs, engendering reconsideration of such policies, and in so doing contribute to less interventions in trade. Apart from this, a system's perspective on trade policy has the potential to expand dispute boundaries to cover the net benefits from trade in clear and compelling ways, which can accelerate settlement and improve trading regimes. It could reduce the current expensive zero-sum approach to dispute settlement.

Underscoring the foregoing is the fact that employing the BDM and SDM as export forecasting tools challenges the traditional homogeneity assumptions about agri-food products and markets. If products are truly homogenous, then theoretically, the lowest price supplier should always be selected. Yet, the evidence is that importers may buy from numerous countries and from multiple sellers at different prices. Recognizing that buyers and sellers leverage products and relationships' idiosyncratic characteristics provide opportunities to develop forecasts of relevance to exporters and improve policymakers' effectiveness to achieving their policy objectives. Buyers and sellers do not automatically select each other for exchange purposes. Rather, they form and nurture relationships based on trust, reputation, and reciprocity determine selection of trading partners at the firm level (Anderson and Gatignon 1986; Rho and Rodrigue 2016). These allow buyers (importers) and sellers (exporters) to incorporate extrinsic characteristics of the product as well as their relationship and the exchange processes into their choice decisions. These relationship-based factors can evolve over time in ways that make products inseparable from the relationships between a specific buyer and supplier, thereby making the product inimitable and non-substitutable (Wernerfelt 1995). The nature and complexity of these exchange relationships influence how trading partners respond to changes in the competitive environment and extrinsic product characteristics, such as prices.

Food and beverage products are unique, even among nondurables. They are purchased and consumed more frequently in fixed quantities. Compared to other household expenditures, food and beverage exhibit lower relative prices, but their shares of those household expenditures are relatively stable across time within households but can vary significantly across households. Therefore, it is assumed that for any given population segment, food and beverage consumption increases are determined almost entirely by increasing segment size. Increasing incomes do not increase consumption but cause shifts from the consumption of perceived lower quality to higher quality products as predicted by Bennett (1941) and Engel (Lades 2013; Banks, Blundell and Lewbel 1997). Such shifts increase total expenditure on the selected perceived higher quality product even as expenditure on the lower quality products decline. This general statement notwithstanding, there are certain goods that may be necessities at certain income levels and luxuries at others, and good models match patterns of consumer and supplier behaviors across a population of households to provide the requisite insights (Banks et al. 1997).

Strategic Exporters and their Market Selection

This research dichotomizes exporters into two major groups: (1) Opportunistic exporters; and (2) Strategic exporters. Opportunistic exporters are tactical in their engagement with export markets, essentially behaving as arbitrageurs. They view exports as transactional, temporary, and atomistic, and do not commit resources to develop export markets. They service their export customers out of existing surplus production capacity or inventory, and hardly accommodate idiosyncratic requests from these customers. They are the true excess supply suppliers in traditional trade models.

Strategic exporters, on the other hand, approach exports as part of a strategic plan to grow their businesses, diversify their markets, manage performance risks, and/or insulate themselves from local disruptions. They are deliberate in assessing and selecting their export markets, ensuring prevailing characteristics match their expectations. They commit the requisite resources to their selected markets to secure the appropriate growth-oriented foothold upon entry. Strategic exporters often take years to build the necessary relationships and infrastructures before shipping their first load. Because their market development investments are strategic, their decisions tend to be focused on structural changes instead of short-term *noise* in market conditions. This research focuses on strategic exporters because it is for them that forecasting is necessary and important input into their decision choices (Rho and Rodrigue 2016).

It is not uncommon for strategic exporters to assess the potential sizes of the relevant market segments in their destination countries and compare the characteristics of the buyers in those segments against their potential to achieve their strategic objectives. Among the variables of importance are socio-economic characteristics and potential purchase quantity and frequency. They also evaluate simultaneously the attractiveness of the intrinsic and extrinsic attributes of their product to the identified population segments in the selected markets. These analyses define the identified population segments' willingness and ability to be bona fide customers. It is not uncommon for strategic exporters to develop specialty products with the desirable intrinsic and extrinsic characteristics to enhance their attractiveness to specific market segments. They would employ the increasingly ubiquitous certification agencies to give them the desired legitimacy. There are now certification agencies for agronomic, seasonality, and geography, among others. For example, agronomic and husbandry practices such as organic and meat from purebred livestock might attract the interest of some consumers, making them more willing to purchase, and become customers. Likewise, specific foods from certain places may be desired in certain places in certain seasons, For example, German *stollen* and Danish butter cookies during Christmas. Geography may influence the consumption decisions of some consumers for certain products, using it as a proxy for quality and safety. For these consumers, "Product of USA," for example, may be a product attribute that justifies paying a higher price for the higher perceived quality and safety. Similarly, consumers may consume certain products in order to belong to certain social classes. For the consumers in communities where US food products carry an intrinsic value of social class, the higher product price is defined to include the class status achieved through consumption. This underscores the reconsideration of heterogeneity even when exporting bulk commodities.

The BDM/SDM forecast tool for agri-food exports to new markets assumes constant household consumption in each purchase period, and flexible purchase frequency to reflect changing affinity with the products. Increasing consumer affinity with the product increased purchasing frequency, and vice versa. It is also assumed that competitors are able to enter the market that an exporter creates by imitating the product offering, albeit imperfectly, but compensates consumers with lower prices to lure them away from the primary exporter. This incorporates natural obsolescence into the model, challenging strategic agri-food exporters to make investments in market leadership innovation.

Developing the BDM/SDM for Agri-Food Exports

Industry leaders were interviewed to develop their 10,000-meter view of a new export destination. As hypothesized above, they indicated exploring the socio-economic and demographics of alternative markets and selecting the most-promising as a beachhead. They also indicated exploring the consumption patterns for analogous products to determine their potential market share and revenue timelines. Once a decision has been made about the potential market to tackle, they begin to make investments in building relationships along their product's supply chain – transporters, customs agents, local distribution agents, destination warehousing, customers, regulation, etc. They see these investments as "priming the pipes" for their success. They also signal their commitment to their local partners, separating strategic exporters from opportunistic exporters.

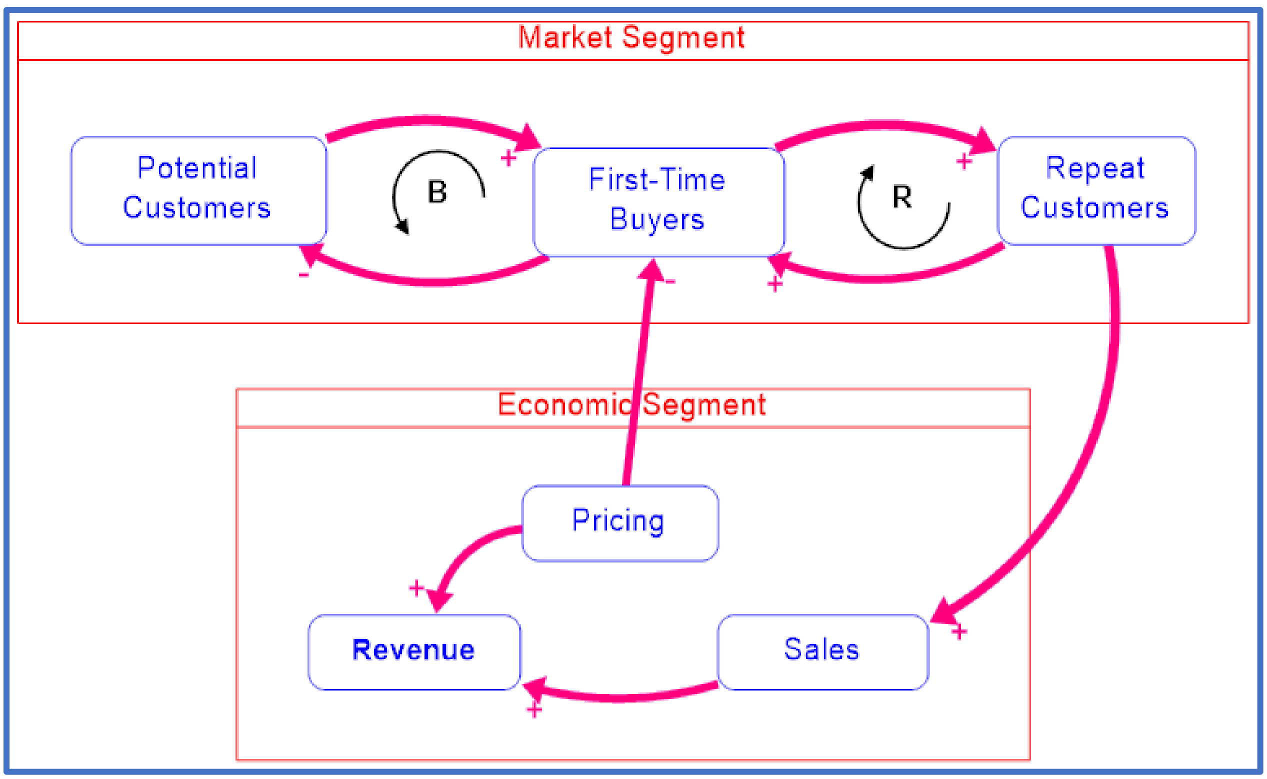
These market development (sunk) costs produce a more serene response to market changes that would cause opportunistic exporters to bolt away. The serenity emanates from strategic exporters commitment to playing the long game, which is focused on long-term growth and profitability (Antràs 2016; Anderson and Gatignon 1986). "Short-term price changes are noise in our business," observed the vice president of international trade for a major US meat products exporter. "We focus on the long-term objectives of our programs. . . our return on investment in each of our markets," he explained. This is supported by evidence from the literature showing that including decision variables, such as price, does not have a significant impact on product diffusion patterns (Mahajan, Muller and Bass 1995). This insight is important in modeling the diffusion of exports because it constrains the theoretical expectations about price shifts, for example, allowing the nuanced response to be reflected in the model. Recognizing this nuanced response improves the performance of the model.

The system-as-cause and the dynamic thinking of the interviewed industry leaders were used to develop a general agri-food export casual loop diagram. Causal loop diagrams capture hypotheses about the causes of a model's dynamics and reveal the mental models driving problem understanding. The problem of focus in this research is defined as the diffusion of a new product in a new market (Figure 3). A loop is the set of interconnections or links between variables in a model that form a closed path from a variable back to itself. All loops need at least one state (stock) variable to avoid simultaneity. The causal loop diagram in Figure 3 is organized into two segments – market segment and economic segment. This dichotomy allows the reflection of the earlier observation about strategic exporters' principal participation objective being securing long-term sustained growth in sales in their selected destination country.

The market segment illustrates the relationship between potential customers and first-time buyers, and between first-time buyers and repeat customers. The positive polarity of the link between potential customers and first-time buyers indicates that if potential customers increase, first-time buyers will increase above where they would have been had potential customers not increased. The negative polarity between first-time buyers and potential customers indicates that if first-time buyers increase, then potential customers would decrease below where they would have been had first-time buyers not increased. This creates a balancing or negative loop, illustrated by an anticlockwise arrow with a "B" label. The link between first-time buyers and repeat customers is positive, i.e., an increase in first-time buyers would increase repeat customers above where they would have been without the increase. The link between repeat customers and first-time buyers is also positive, creating a reinforcing or positive loop, illustrated with a clockwise arrow with an "R" label. As indicated in the model, the link between repeat customers and first-time buyers is not direct. Rather, the link goes from repeat customers to their word-of-mouth activities influencing adoption by potential customers who then become first-time buyers.

The dynamics in the economics segment emanates solely from the dynamics in the market segment. As such, there is no feedback loop in the economic segment and between the economic and market segments in this illustration. Such a feedback loop is possible if it is assumed that increasing repeat customers, for example, not only influences sales but also influence pricing. Instead, the relationship between repeat customers and product sales is algebraic – the product of the number of customers and their assumed per capita consumption (parameter) and consumption frequency (parameter). Likewise, the revenue is a product of price (parameter) and sales (dynamic). Policies to increase performance in the new market are, therefore, resident in influencing the appropriate variables in dominant loops in the model.

Figure 3: Causal Loop Diagrams of New Product Diffusion



In summary, the decision to export a particular product to any market is dependent of the existence of a credible threshold of eligible customers with the characteristics to become the product's potential customers. These characteristics include income and an appreciation of the product's embedded value proposition. As a rule, staple food products have larger potential markets than specialty food products simply because of the number of people likely to consume them and their frequency of consumption. However, staple food product market tends to be more competitive mainly because of high degree of substitutability, and low degree of inimitability and rareness (Wernerfelt 1995; Lado et al. 2006).

Specialty products, demanded more for their intrinsic than extrinsic attributes, tend to insulate themselves from competition within their well-defined market segments. The challenge for organizations selling these products in domestic or export markets is defining and identifying their appropriate market segments into which to place them. Strategic exporters in the conversations supporting this study indicated spending significant resources deciphering their potential market, its size, and the characteristics of the potential customers in the segment. This, they argued, enables them to develop the appropriate local partners and requisite local relationships to forge their entry strategy.

The Case Example: Distilled Spirits Exports to Morocco

The modeling process presented above has language that is focused on the firm and not the industry or economic segment. This is because all ex-ante trade decisions are made by firms based on their individual expectations of potential payoffs. Ex-post analysis can aggregate these individual decisions to determine the aggregate outcomes. When exporting into a country where there have been no prior exports, aggregate analysis does not work well without some strong assumptions about firms that would be potentially interested in exporting and their engagement strategies with specific products to ensure their competitiveness. For policymakers with a trade expansion agenda, such aggregate analysis provides directional information and not strategic indicators *unless* they lead to specific conversations with industry stakeholder to help them assess their own unique opportunities. Such forward-looking analyses always demand action beyond the analyses. The essential benefit of the SDM is its ability to facilitate such conversations and enable individuals to formulate their individual strategies to achieve firm performance objectives and enable policymakers develop the appropriate support systems to help then firms in support of achieving their trade expansion objectives. The case example of distilled spirits exports to Morocco is conducted as the first step in the process of discovering market potential and assessing the macro environment to enable firms formulate their individual strategies.

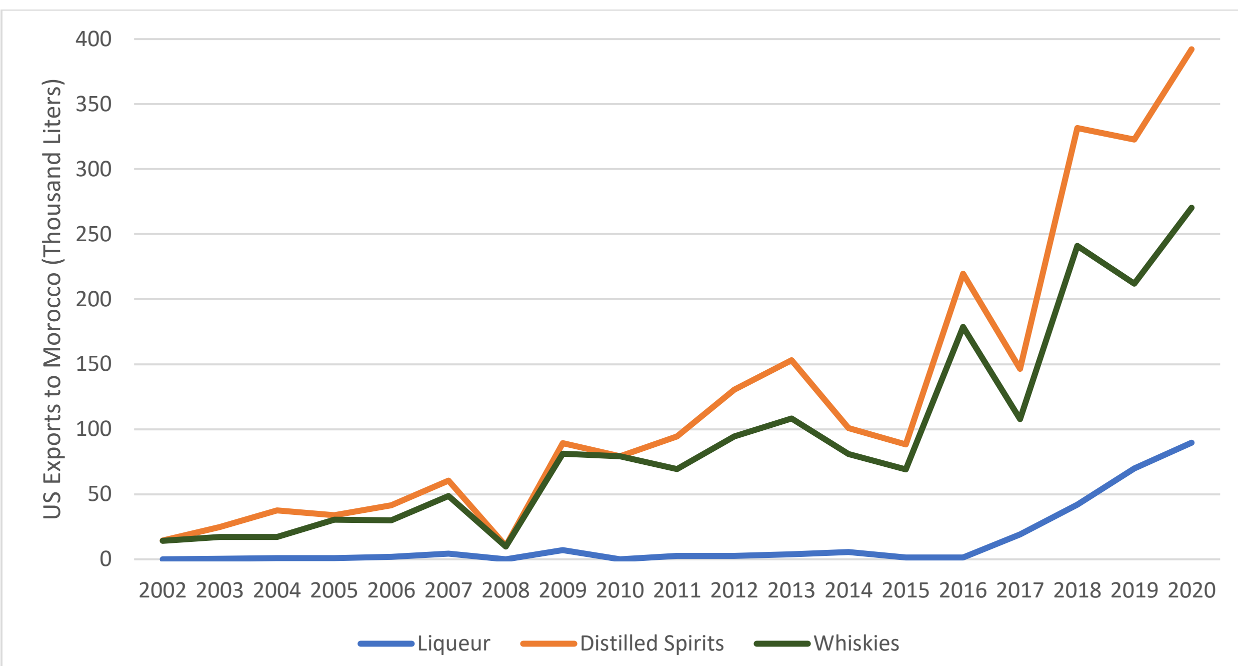
Consumption of alcoholic beverages in the US peaked in the mid-to-late 1970s when 71% of American adults reported drinking at least once in the week prior. It is currently at about 60% (Brenan 2021). US drinkers are more likely to consume beer, with 39% of adults 18 years and over indicating in 2021 that they drink mostly beer compared to 27% for liquor and 31% for wine. The distribution has not changed much since the 1990s but the proportion of drinkers indicating liquor as their preferred drink has been increasing steadily since the late 1990s (Brenan 2021). That consumption has peaked implies US manufacturers need to look to exports to expand their sales and profitability. The global consumption for liquor has been expanding worldwide, in both developed and developing countries. World Health Organization data show that global pure alcohol consumption was 6.2 liters per person 15 years or older in 2016, compared to 4.8 liters per person 10 years earlier, an increase of about 27% (World Health Organization 1999; World Health Organization 2018).

Morocco is a North African country characterized by its Berber, Arabian, and European influences. Although its constitution describes Morocco as a Muslim country, it also guarantees freedom to practice any religion (Office of International Religious Freedom 2018). Morocco's estimated population for July 2020 was about 35.6 million, and 27.04% of them was 14 years or younger (Central Intelligence Agency 2020). The World Health Organization (2018) reports that about 97.4% of Morocco's population 15 years and above do not drink alcohol, meaning the potential alcoholic beverage market size is about 2.6% of the population 15 years and above. This contrasts with the 60% of US adult population that indicated drinking (World Health Organization 2018). The population of drinkers in Morocco based on the 2020 population estimate is, thus, estimated at about 675,338.

Total alcohol per capita consumption is defined as the total of recorded and unrecorded alcohol consumed divided by the *population of drinkers* 15 years and older, adjusted for consumption by tourists. Morocco's average annual per capita consumption (pure alcohol) for its drinking population is estimated at 23.0 liters (World Health Organization 2021). Based on this and the 2020 drinking population, it is estimated that total alcohol consumption is about 15.5 million liters. Given alcoholic beverage distribution of 17% for spirits, 43% for beer, and 40% for wine (Masaiti 2017), this translates to an average annual spirits consumption of about 3.9 liters per person in the dinking population, or a total of about 2.6 million liters. Morocco has been importing about 4.7 million liters of its alcohol needs over the past decade, with US share accounting for about 4.2%. However, while total alcoholic beverage imports are trending down at about 3.6% per year, US alcohol exports have been increasing, averaging about 15.2% per year over the past decade. Similarly, Morocco's imports of liqueurs and cordials have also been declining at about 13.5% per year, but US exports have been increasing at an average of 42.7% per year. US share of Moroccan liqueur imports was about 1.5% between 2011 and 2016 but it has been increasing steadily since 2016 (1.6%) to 2020 (41.0%).

Morocco is small in the global alcohol import market. Its share of both global value and quantity of alcohol imports in 2020 was only 0.2% and 0.1%, respectively. Its share of the global liqueur import market is even smaller, 0.1% for both value and quantity. However, it is the growth opportunity for US exporters described above that makes Morocco an attractive market with potential. The estimated growth rates suggest US liqueur exporters are migrating from opportunistic to strategic exporters. This migration is exhibited by the small and irregular export volumes changing to a consistently significant and growing exports. Figure 4 shows that the overall US exports of distilled spirits to Morocco (including whiskies and liqueurs) have only in the last decade become strategic exports, making them a good candidate a BDM-SDM export forecasting case example.

Figure 4: US Distilled Spirits and Liqueur Exports to Morocco (2002-2020)

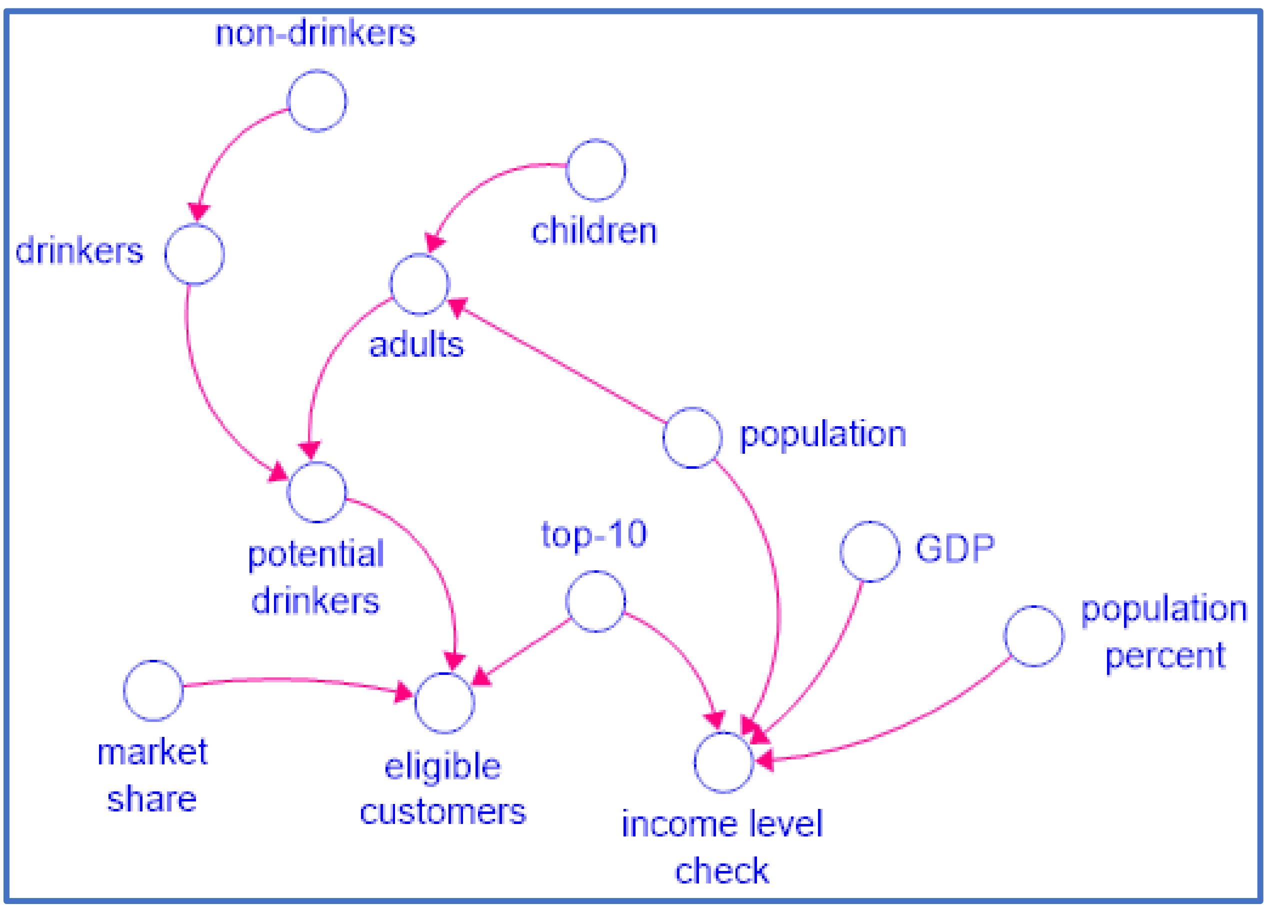


Source: UN Comtrade Database (https://comtrade.un.org/data/).

Morocco's 2020 gross domestic product (GDP) in current US dollars was estimated at about $114.7 billion, growing over the 2010-2019 period at an average rate of 2.1% per year. The top 10% of the population, equivalent to about 3.6 million people, control about 33.3% of the GDP (Central Intelligence Agency 2020). This would imply an average per capita income for this group is about $10,729. There is evidence that income and education are positively correlated with alcohol consumption (Jones 2015). Therefore, assume that the average consumption of spirits among the top 10% of drinkers by income is between 50% and 100% higher than the average per capita consumption estimated above, i.e., between 5.9 liters and 7.8 liters. This would be equivalent to between 395,061 liters and 526,748 liters per annum, or between 15% and 20% of the estimated total spirit consumption in the country. This provides the potential project volume sales in the country for both imports and domestic producers. The growth in these sales would be determined by changes in the population of drinkers and their incomes since the per capita consumption is kept fixed. Finally, assume that US exporters will ultimately seize between 30% and 45% of this market.

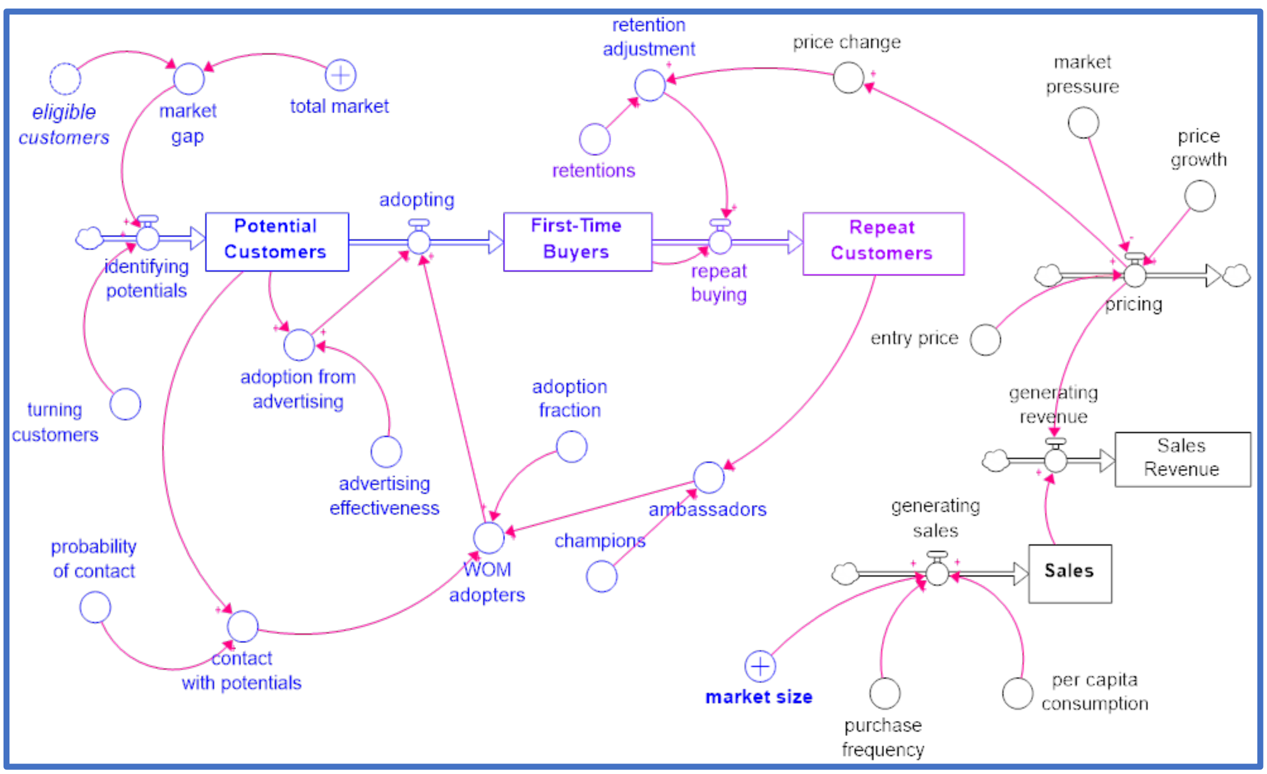
The converter and connector diagram used in developing the eligible customers in the selected market is presented in Figure 5. For example, drinkers is the proportion of the adult population that self-identified as drinkers in the World Health Organization (2018) study. The market segment of interest is defined as drinkers' population in the top 10 percent of income.

Figure 5: Developing the Eligible Customers in the Moroccan Distilled Spirits' Market to Establish a Market Potential for US Exporters



The stock-and-flow representation of the export market development for US whiskies and cordial in Morocco is presented in Figure 6. The model consists of five stocks, six flows, and 34 converters. It has 19 constants, 21 equations and 45 variables. The model equations and documentation are presented in Appendix 2. The model is built and simulated using Stella Architect™ (iseesystems 2020). Figure 3 (the causal loop diagram) and Appendix 2 provide the complete description of the Stella Architect™ model used in this research. Potential customers become first-time buyers, testing the product for expectation confirmation. Those whose expectations are confirmed become repeat buyers (Harmeling et al. 2015). Depending on their position in their networks, they become what Rogers (2003) describes as opinion leaders or the marketing profession labels influencers. They are described as product ambassadors in this research, representing the product to potential buyers in ways that may engender conversion to first-time buyers. Their ability to engender this transformation is influenced by the number of eligible consumers with whom they have contact and the proportion of their contacts who adopt. In general, it is expected that some first-time buyers may not purchase the product again because of expectation disconfirmation (Anderson and Sullivan 1993; Esper and Peinkofer 2017). This recognition supports distinguishing first-time buyers from repeat buyers to enable early and effective assessment of entry challenges and attrition factors. One potential cause of high first-time buyers' attrition rate is potential market misidentification or value proposition misspecification.

Figure 6: System Dynamics Model for Forecasting US Exports of Distilled Spirits to Morocco



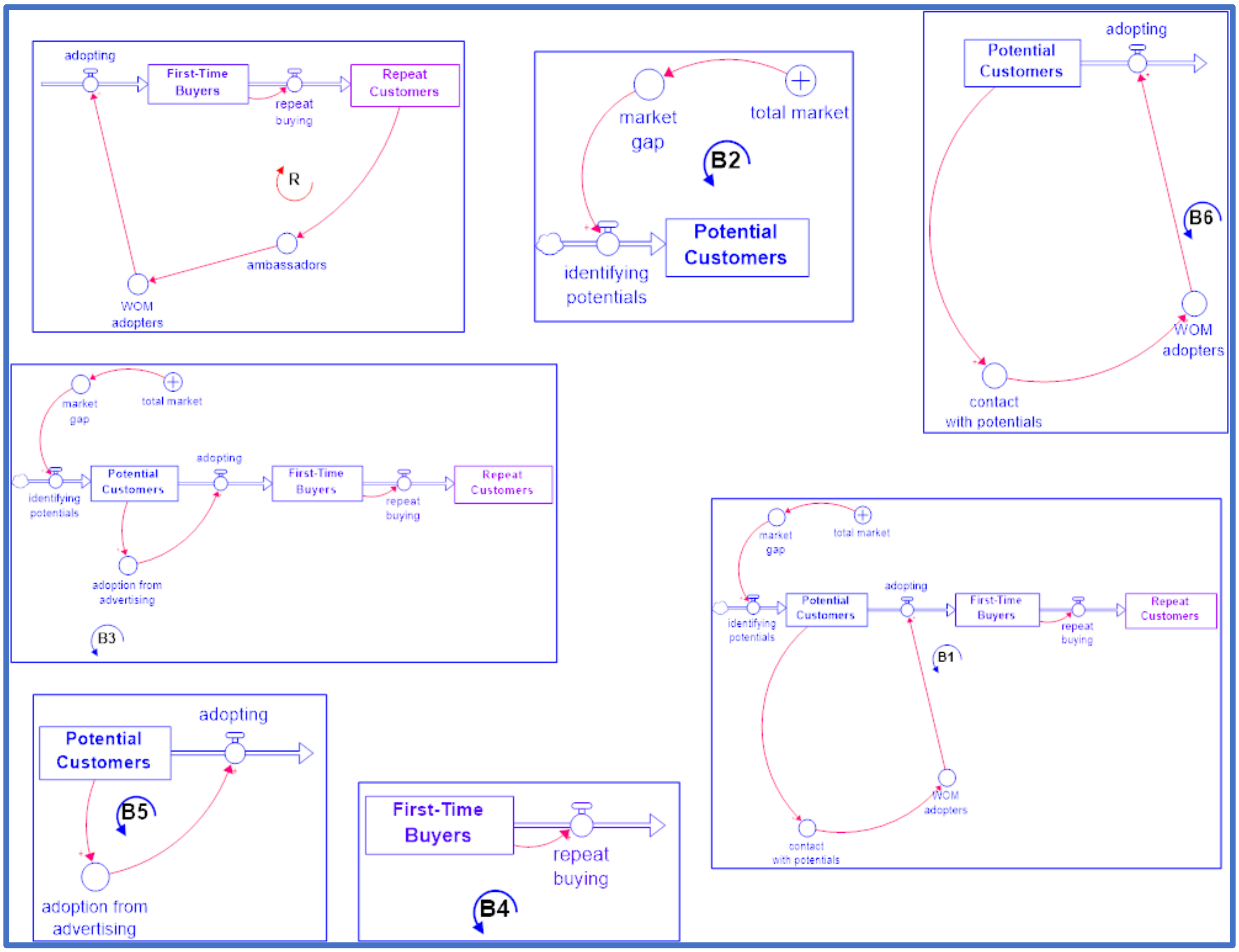
The six balancing loops and one reinforcing loop in the model presented in Figure 6 are isolated and presented in Figure 7. The reinforcing loop, as shown in Figure 7, starts with **WOM adopters** to **adopting**, then to **first-time buyers**, **repeat buying** and **repeat buyers**, who become **ambassadors**. In this loop, an increase in **WOM adopters** causes increases along the whole loop, reinforcing **WOM adopters**. The first balancing loop also begins with **WOM adopters**, through **adopting**, **first-time**

buyers, **repeat buying** and **repeat customers** to **total market** (first-time potential customers plus repeat customers). The difference between **eligible customers** and **total market** in each time period is the number of eligible customers remaining who are not yet potential customers or repeat customers, which is labeled as **market gap**. The B1 loop continues from **market gap** to **identifying potentials** who would be in contact with **repeat customers**. This is a very long loop, and its interpretation is similar to the reinforcing loop above, except going in the opposite direction. Because the **WOM adopters** reduce the **market gap**, which reduces the **potential customers**, the **number of contacts with potentials** also decrease. A similar effect is reflected in the B3 loop, which starts from the **adoption** from **advertising** and goes through **adopting**, **first-time buyers**, **repeat buying**, **repeat customers**, **total market**, **market gap**, **identifying potentials** and end with **potential customers**. The B4, B5, and B6 loops are the way they are because flows comprise two segments, before and after the tap. An increase in the flow decreases the stock before the tap while increasing the stock after the tap. The recognition of the nature of flows is critical in understanding the causal relationships in loops involving flows.

The model is designed such that potential customers initially adopt the product as a result of advertising, but word of mouth (WOM) from repeat customers begins contributing to adoption at a higher rate over time. **Advertising effectiveness** and **adoption fraction** in the model are equivalent to the coefficient of innovation and the coefficient of imitation in the Bass Diffusion Model. The literature indicates that the sum of these two coefficients must be no higher than one, with the coefficient of innovation defined to be less than 0.1 and the coefficient of imitation defined to be greater than 0.3. These parameters were not estimated for this model but parameterized using the literature as a guide. They were both set at 0.2 for the base scenario.

It has been argued that the translation of first-time buyers into repeat customers is influenced by the expectation confirmation. Industry participants in the modeling conversations noted that as they "age" in their export markets, they usually see an erosion of their niche protections, causing them to make price adjustments that were unnecessary in the early periods following entry. It also true that late adopters are more influenced by price than innovators and early adopters. Both these events mean that some price erosion become necessary as the product matures in its market and the market gap decreases. Based on this, prices are adjusted downwards to accommodate the higher confirmation threshold of later adopters, which it is assumed increases the retention rate of first-time buyers and increases the number of repeat customers. To this end, pricing is determined by the initial price, the market pressure, and the price adjustment (growth) factor. These are policy parameters within management's control, selected to achieve desired sales and revenue objectives. Additionally, the relationship between price and retention and the influence difference between advertising and word of mouth allows management to improve the advertising budget to improve customer acquisition and overall performance (Jones, McCormick and Dewing 2012; Berger 2013; Sernovitz 2006). Whitler (2014) reports seeing a good word of mouth marketing "campaign generate thousands of conversations, recommendations and triple sales in just a year." When to shift resources from advertising to encouraging customers to become product ambassadors may spell the difference between spectacular and mediocre performance in a new market. Adoption fraction and advertising effectiveness parameters are drawn from the literature in analogous locations. They may also be estimated from good data on the company's performance in other markets. The structural model for the pricing component of the model is shown in black in Figure 6.

Figure 7: Causal Loops in System Dynamics Model for US Exports of Distilled Spirits to Morocco

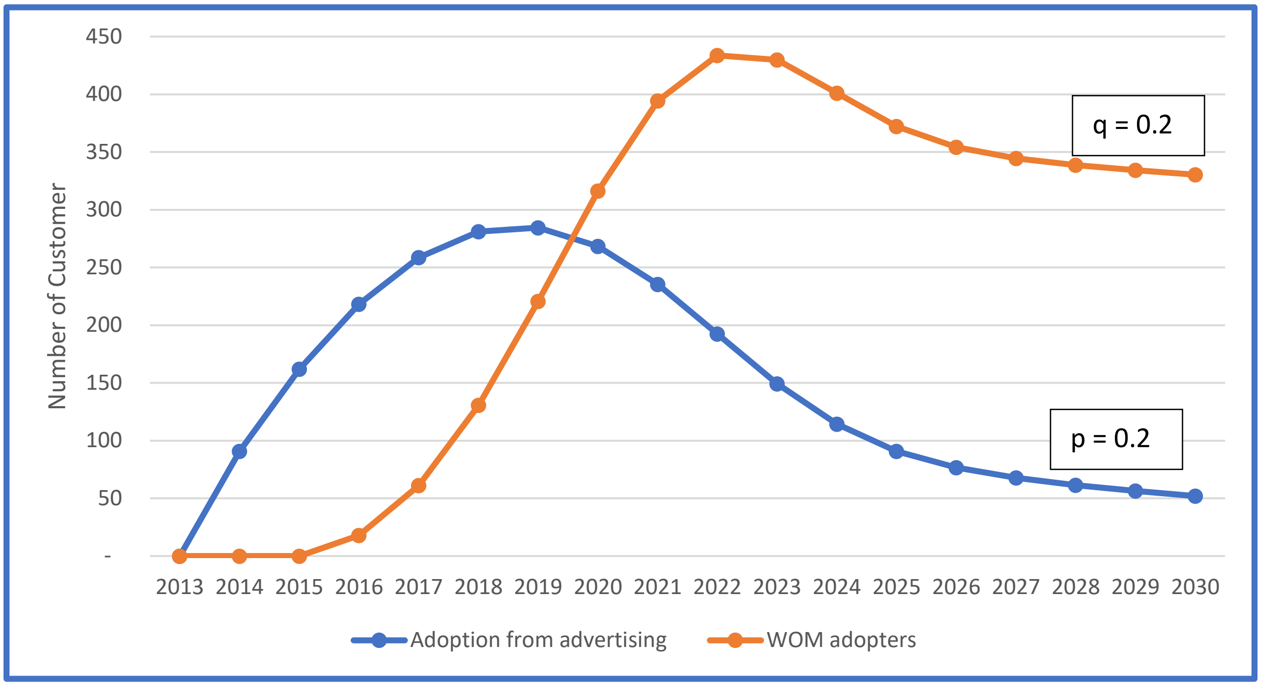


Base Scenario Simulation Results

The model treats the US distilled spirits industry as a single firm to forecast aggregate US liqueur exports to Morocco from 2013 through 2030. Therefore, the results are interpreted for industry level strategy, allowing industry associations and policymakers to evaluate a *collective* entry strategy in the Moroccan defined alcoholic beverage market. For the base run, the model was calibrated to produce the results observed in the years with export data, i.e. 2015 through 2019. The calibration focused only on the three principal Bass Diffusion Model parameters – market size, coefficient of innovation, and coefficient of imitation. These variables have been defined as potential customers, advertising effectiveness, and WOM adoption fraction in the model. Market gap is defined as the difference between eligible customers and total customers at each time. They are the eligible drinkers who have not yet been exposed to the US product in each time period. A proportion of them, defined as potential fraction in Figure 6, will become exposed and become potential customers. To reproduce the export data available from the Global Agricultural Trade System of USDA's Foreign Agricultural Service for distilled spirits exported to Morocco, the calibrated parameters are 1.35 per 1,000 untouched customers for potential fraction, and 0.2 each for the coefficients of innovation and imitation.

Based on these base parameters (and the other constants defined Appendix 2), Figure 8 shows the trend in the number of adopters generated from the two adoption mechanisms – advertising and word of mouth – in each period. It confirms the dynamic hypothesis that a shift in dominance from advertising to word of mouth adoption is necessary for sustainable diffusion of a new product. Under the stated conditions, the US is treated to be in a very niche market with adoption from advertising peaking at about 284 people per year in 2019. It is overtaken by WOM adopters soon after its peak, which in turn peaks in 2022 with 434 people. The figure shows that the difference between WOM adopters and adoption from advertising increases exponentially for the rest of the forecast period.

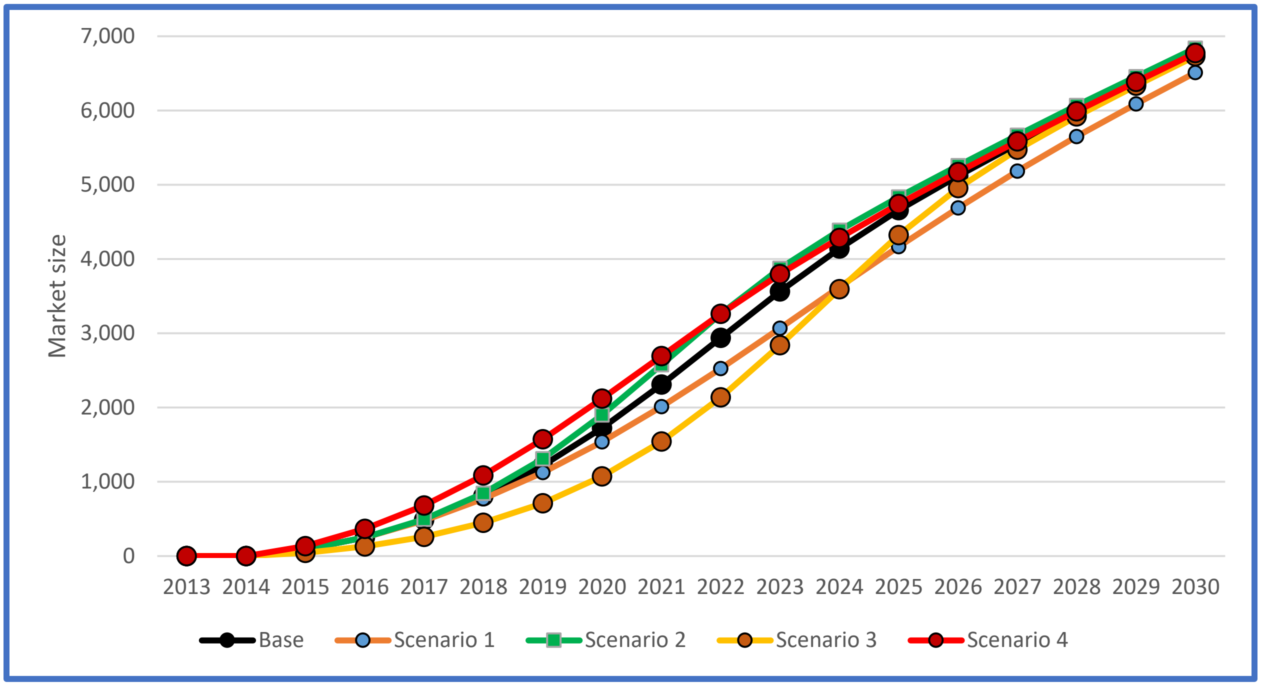
Figure 8: Trend of Simulated Number of Customers from Advertising and Word of Mouth (Base Scenario)



Recall that market size, defined as first-time buyers plus repeat customers, is influenced by both advertising effectiveness and WOM adoption fraction parameters. Figure 9 shows the sensitivity of cumulative market size to these two parameters. It shows that the diffusion, revealed through the market size, is differentially sensitive to both parameters. Obviously, the firm has more control over increasing its advertising effective, holding all things constant, by increasing its advertising dollars. Yet, no definitive positive relationship has been established between advertisement investment and sales (Lahiri 1974; Goddard and Amuah 1989; Edeling and Fischer 2016). That is, the relationship between higher advertisement expenditure and advertising effectiveness is, at best, spurious. There is an anecdote around marketing circles that attributes the following statement to an executive, but probably made up more by a marketing consultant: "I know that at least half of my advertising money is being wasted. My problem is I do not know which half." On the other hand, the positive effect of word of mouth on market size has been established, especially in these days of social networking (Whitler 2014). Figure 9 shows the trend of simulated market size under five alternative scenarios developed through the combinations of the two parameters. The scenarios are as follows: Base Scenario (p= 0.20 and q = 0.20); Scenario 1 (p= 0.20 and q = 0.10), Scenario 2 (p= 0.20 and q = 0.30), Scenario 3 (p= 0.10 and q = 0.20), Scenario 4 (p= 0.30 and q = 0.10).

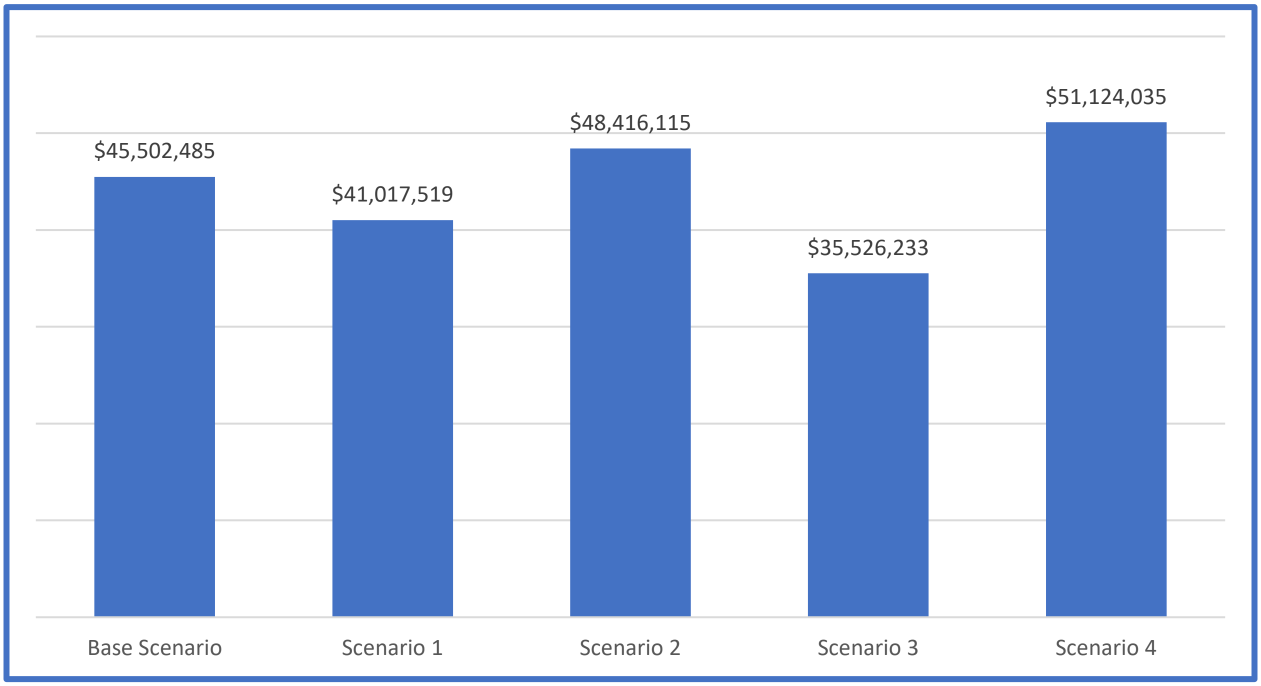
Figure 9 shows the absence of a clear dominance of any scenario. For example, the cumulative market size under the Base Scenario lies in the middle, above Scenario 1 and Scenario 3, and below Scenario 2 and Scenario 4. Scenario 1 dominates Scenario 3 in the first half of the simulation and is dominated by it in the second half. Similarly, Scenario 4 dominates Scenario 2 the first half of the simulation and is dominated by it in the second half. This suggests that higher advertising efficiency increases market size early in the diffusion process regardless of the WOM adoption fraction. This is not surprising since WOM adoption only takes effect after achieving a critical mass of repeat customers.

Figure 9: Sensitivity of Cumulative Market Size Trend to Word of Mouth (WOM) Adoption Fraction (q) and Advertising Effectiveness (p)



The relevance of the market size is revealed in the net present value (NPV) of the cash flows. This is even more important given the differences in the effect of advertising and WOM on the adoption rates. The NPV can be used to decide the level of advertising expenditure to invest to achieve a certain level of advertising effectiveness. The results, presented in Figure 10, show that a higher advertising effectiveness parameter produces a higher NPV than WOM adoption fraction of the same value, holding all others constant. This is not surprising since the market size density functions in Figure 9 show that advertising effectiveness dominates WOM adoption fraction in the early stages of the diffusion process and is dominated by WOM adoption fraction only in the latter stages. This outcome is true also for undiscounted cash flows.

Figure 10: Net Present Value of Sales Under Alternative Word of Mouth (WOM) Adoption Fraction (q) and Advertising Effectiveness (p) Parameters (Discount Rate = 5.00%)



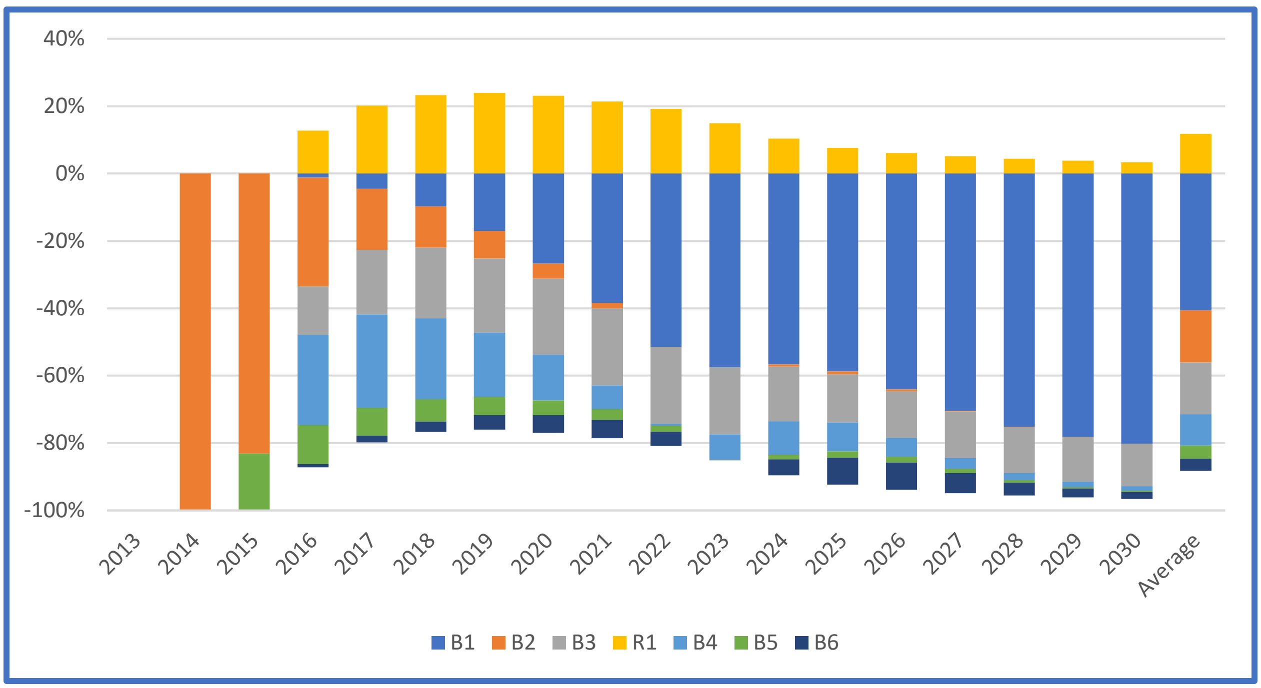
Loop Dominance Analyses

Stella Architect™ offers an analytical tool that allows for the assessment of the relative importance of the different loops in the model at each point in time during a simulation. This tool allows those with interest in the model's results to develop a deeper understanding of how the model's structure reproduces the problem being considered and helps improve the structure to develop effective solutions (Schoenberg, Davidsen and Eberlein 2019). Schoenberg et al. (2019) argue that a loop or a set of loops may be considered dominant if they describe at least 50% of the changes observed in the model's behavior across all stocks over the simulated duration. Their analytical method has its foundations neither in Forrester's (1982) eigenvalue elasticities nor the pathway participation method (Mojtahedzadeh 2008; Duggan and Oliva 2013). Schoenberg et al. (2019, p.6) explain that their approach, using chain rule and guaranteeing that the models' dynamic behavior is independent of their structural form, "does all of its calculations directly on the original model equations, walking the causal pathways between stocks through all intermediate variables making it easier to understand the measurements of loop contribution to model behavior and link contribution to feedback loop dominance." The loop dominance analysis produces the link score, which measures the contribution and polarity of the link between an independent and a dependent variable and the loop score which measures the contribution of the feedback loop to the model's behavior at each time interval. Negative loop scores refer to balancing loops while positive loop scores refer to reinforcing loops.

The most dominant of the seven loops in the base simulation model (described in Figure 7) is B1, contributing an average of about 38.3% to explaining model behavior over the total duration of the simulation. Both B2 and B3 contributed an average of 14.6% while the sole reinforcing loop, R1, had an average contribution of 11.1%. Figure 11 shows the contributions of the different loops in each simulation period. It shows that B2 dominated the model in the first two periods. The B2 loop, from

Figure 7, is shown to encompasses the following: **adoption from advertising → adopting → First-Time Buyers → repeat buying → Repeat Customers → total market → market gap → becoming potentials →Potential Custome**rs. However, its contributory role in understanding model behavior increasingly disappears by 2025. On the contrarily, B1, which encompasses **WOM adopters → adopting → First-Time Buyers → repeat buying → Repeat Customers → total market → market gap → identifying potentials → Potential Customers → contact with potentials**, begins contributing about 1.2% in 2016, and rises steadily to 80.1% by 2030, the final simulation period. On average over the simulation duration, B1, B2 and B3 contributed 38.3%, 14.6%, and 14.6%, respectively, while R1's contribution average 11.1%. These four loops together contributed about 78.6% of understanding the overall behavior of the model. Thus, the remaining three loops together account for less than 22% of understanding overall model behavior.

Figure 11: Loop Dominance Analysis for Base Scenario at Each Time Interval and the Average Over Simulation Duration



The Loop Dominance Analyses for the other four scenarios are presented Figure 12, Figure 13, Figure 14, and Figure 15 for Scenario 1 (p= 0.20 and q = 0.10), Scenario 2 (p= 0.20 and q = 0.30), Scenario 3 (p= 0.10 and q = 0.20), Scenario 4 (p= 0.30 and q = 0.10). Unlike the Base Scenario, which was dominated by B2 in the beginning, Scenario 1 was dominated by Scenario B3 in the first two periods of the simulation but disappeared by 2021. On the other hand, B1's influence in contributing to understanding model behavior started almost imperceptibly in 2017 and accelerated to account for 64.3% of loop contribution to model behavior by 2030. The average contribution of B1 was not statistically different under the Base Scenario and Scenario 1 (t = 1.011; p = 0.319). Loops B1, B2, B3, and R1 together contributed 77.8% of understanding the overall behavior of the model, which was not statistically different from the contributions they made as a group under the Base Scenario (t = 0.033; p = 0.974). While the contributions differed across the simulation durations under the different scenarios, the dominant loops remained unchanged, and the differences between their average and that of the Base Scenario were not statistically significant.

Figure 12: Loop Dominance Analysis for Scenario 1 at Each Time Interval and the Average Over Simulation Duration (p = 0.20, q = 0.10)

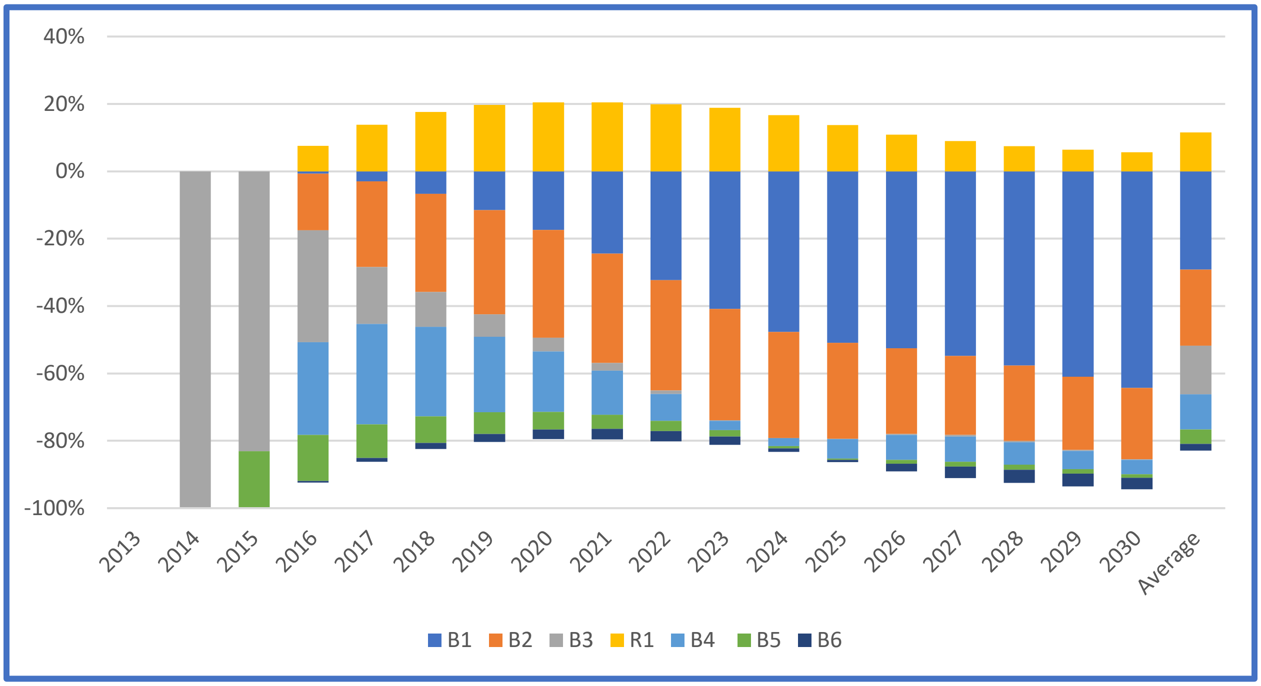


Figure 13: Loop Dominance Analysis for Scenario 2 at Each Time Interval and the Average Over Simulation Duration (p = 0.20, q = 0.30)

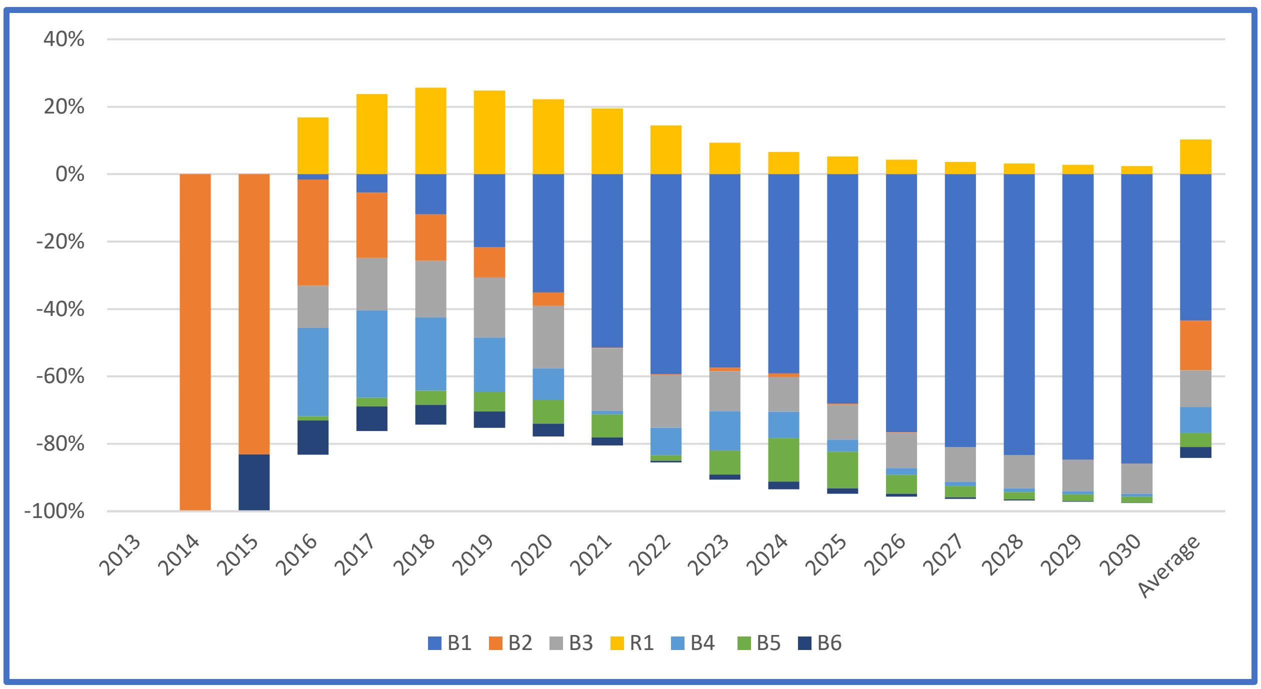


Figure 14: Loop Dominance Analysis for Scenario 3 at Each Time Interval and the Average Over Simulation Duration (p = 0.10, q = 0.20)

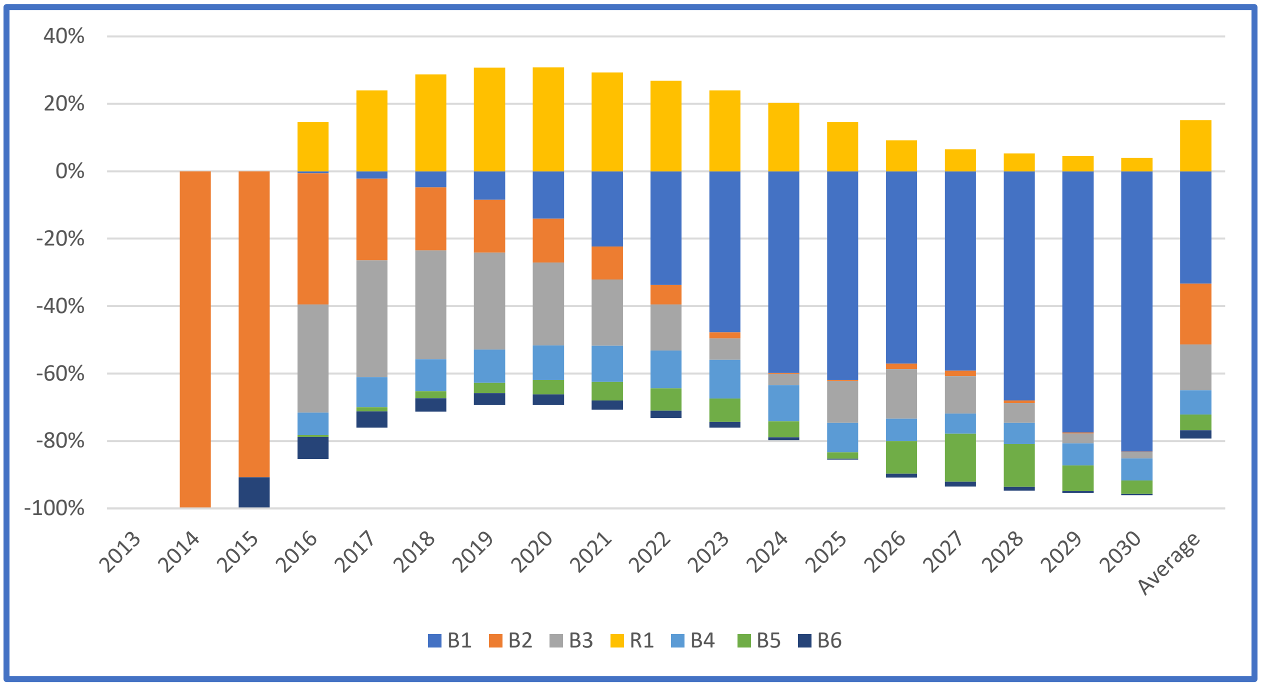
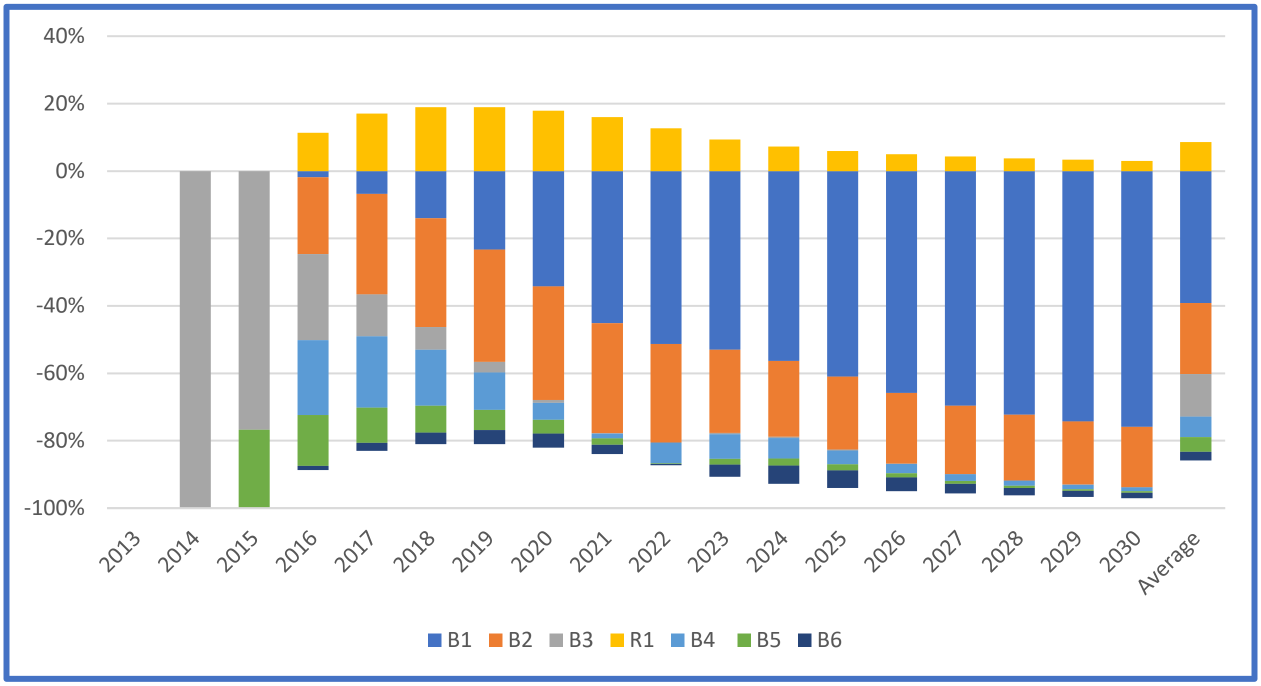


Figure 15: Loop Dominance Analysis for Scenario 4 at Each Time Interval and the Average Over Simulation Duration (p = 0.10, q = 0.30)



Conclusion

The purpose of this research was to provide another approach to forecasting export market opportunities in novel markets. It argued that US agri-food products could be considered novel products in these novel markets, which allowed the forecasting to utilize the Bass Diffusion Model as the theoretical framework and a system dynamics model as the simulation tool. The approach's principal advantage is its relatively small data footprint and its ability to provide immersive engagement with decision makers in both industry and in the policymaking environments. The modeling software of choice in this research was Stella Architect®, published by iseesystems.com.

It was argued that there were two types of exporters: opportunistic exporters, and strategic exporters. The latter were the focus of this research because they invested in their chosen destination markets in ways that ensured their success and long-term growth. It is not uncommon for strategic exporters to begin as opportunistic exporters. Strategic exporters' investments in market development produce very large price elasticities because they tend to perceive short-term price changes as noise that do not warrant any response in their strategic plans. To ward off competition, they focus on positioning their products as unique in well-defined market segments that can appreciate their product's intrinsic and extrinsic attributes that differentiate it from the competitions'. This approach to export market development suggests a careful assessment of potential points of differentiation, such as country-of-origin, exporter, and inherent product characteristics. This is even true when exporting bulk commodities which are undifferentiated in the product but can be differentiated by supplier and country attributes.

The system dynamics modeling approach using the Bass Diffusion Model focuses attention on three principal parameters: coefficient of innovation; coefficient of imitation; and market size. The market size is the careful identification and definition of the appropriate market segment which may be converted into consumers. This is finite at the entry point in time and may change as a result of changing socio-economic conditions in the target market. The BDM assumes that potential customers adopt the product initially to ascertain the congruence of their experience with their expectation, the so-called expectation confirmation (Lee and Yun 2015; Dimyati 2015). Only when expectations are confirmed do these customers become repeat buyers. A segment of these repeat buyers would become ambassadors for the product, using their social influence to motivate others to adopt the product. The number of repeat buyers becoming ambassadors may be influenced through strategic investments in repeat buyers. This makes this investment a decision variable exporting firms can use to motivate loyalty and expand their diffusion in target markets.

The coefficient of innovation, represented by the advertising effectiveness, is the effectiveness of the communication and promotion channels the firm uses to engage potential customers, and to persuade them to purchase the product. As indicated, although this parameter is critical in the BDM, it is extremely hard to pin down in practice. Although BDM researchers have used analogous products in analogous markets to estimate it using non-linear regression models (Bayus 1993; Rao and Yamada 1988), it was parameterized in this model. It is, therefore, treated as a decision variable, just as the word-of-mouth adoption fraction, allowing decision-makers to assess the sensitivity of their outcome variables.

In the model structure presented in this research, it was assumed that there is no attrition of repeat buyers. Competition-driven attrition risks are addressed using embedded price adjustments. These price adjustments also reduce the expectation threshold of first-time buyers, thereby encouraging their transformation to become repeat buyers. Other assumptions include decision-makers choosing the proportion of repeat buyers who become ambassadors and their probability of contact with potential customers. The proportion of first-time buyers who go on to become repeat buyers is another assumption decision-makers can make with the model structure used in this case example. The number of eligible customers is determined from the relevant population and the expected socio-economic characteristics of the consumer segments on which the firm seeks to focus.

The case example shows that the system dynamics with the Bass Diffusion Model structure can replicate and forecast US exports of distilled spirits to Morocco between 2013 and 2030. The model's results indicate that increasing the advertising effectiveness could produce superior overall results than increasing word of mouth adoption fraction in the early stages of the simulation. It would be strategically sound, therefore, to invest in communication and other promotion channels that enable a broad reach to consumers in the eligible customer segment early in the diffusion, and then scale back investments in these efforts, transferring them to word-of-mouth initiatives. This forecasting model, therefore, puts the forecasting process in the hands of decision-makers, offering them ways that allow them to interact with computer models of their mental models, and helping them adjust both their mental and computer models to produce superior decisions. After all, all decision models are about improving the decisions that at made.

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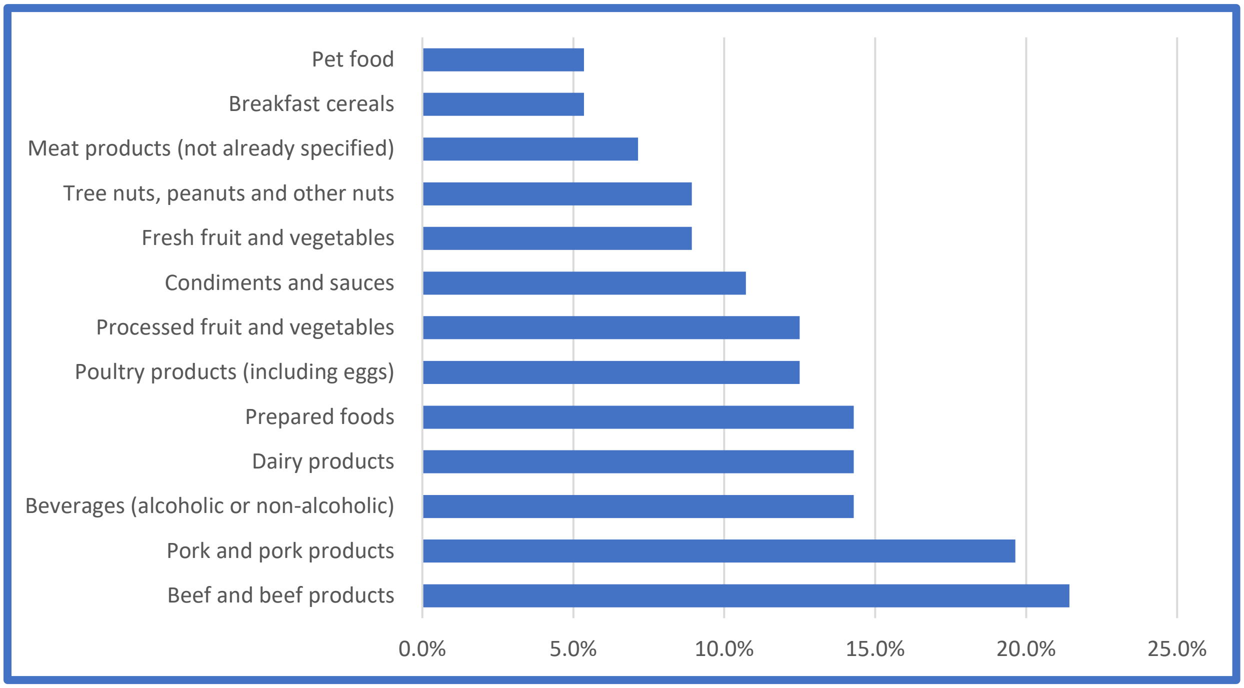
Appendix 1: Summary of Structured Conversation with Selected US Agri-Food Exporters

All exporters are not created equal. Two major groups of exporters are defined for the purposes of this research: (1) Opportunistic exporters; and (2) Strategic or committed exporters. Opportunistic exporters are tactical in their engagement with export markets, essentially behaving as arbitrageurs. This group of exporters respond to market opportunities opportunistically, viewing them as transactional, temporary, and atomistic, underscoring their rationale for not committing resources to market development. They service their export customers out of existing surplus production capacity or inventory. The Strategic or committed exporters approach exports as part of a strategic plan to grow their businesses, diversify their markets, and/or insulate themselves from local disruptions. Therefore, they are deliberate in assessing alternative markets, ensuring prevailing characteristics matching their expectations, and then committing resources to secure the appropriate foothold upon entry. Strategic exporters, therefore, approach exporting with long market development lead times, taking them years to build the appropriate relationships and infrastructures before shipping their first load. Their market development investments focus their business decisions on structural changes instead of short-term noise in market conditions. For the strategic exporters, exporting is a business they nurture and grow for sustainable, long-term, measurable performance. This research focuses on strategic exporters because it for them that forecasting is necessary and important (Rho and Rodrigue 2016).

To provide some context to the development of the forecasting tool, an electronic survey and telephone/Zoom interviews of a small group (58) of randomly selected agri-food companies across the US was conducted during the critical months June and August 2020, at the height of the COVID-19 pandemic. The results are not meant to be inferential but to illustrate some of the characteristics of agri-food exporters and perspectives guiding their export decisions. Nearly 88% of the firms participating in the interviews are currently exporting products to international markets. About 20% of the those currently not exporting plan to export in the future. However, 71.4% of them said the COVID-19 pandemic has adversely affected their export plans.

About 59% of the participants classified themselves as dealing with crops and crop-based products while 37% and 5% indicated being involved with livestock and animal products and fisheries, respectively. Using the Bulk, Intermediate, and Consumer-Ready (BICO) classification, the distribution was 16%, 16% and 67%, respectively. In the bulk group, there was representation from wheat, corn, soybeans, coarse grains, and rice. The intermediate group had soybean meal, soybean oil, vegetable oil, animal fats, animal feed, distillers grain, and planting seeds. Others were dairy ingredients and milled wheat. The distribution of those involved in the consumer-ready segment is presented in Exhibit 1. It shows that beef and beef product companies accounted for about 21.4% of participants compared to 19.6% for pork and pork product companies. Many participating companies were involved in more than one product. About 12.5% of participants each were involved with poultry products (including eggs) and processed fruits and vegetable products. Participants from the pet food and breakfasts cereal industry accounted for 5.4% each. All participants involved in pork and pork products, poultry products, condiments, and meat products were also exporting. Nearly 92% of participants involved in beef and beef product industry were also involved with exporting. About 87.5% of participants in the beverage, dairy and prepared foods industries were exporting compared to about two-thirds of participants in the breakfast cereals industry.

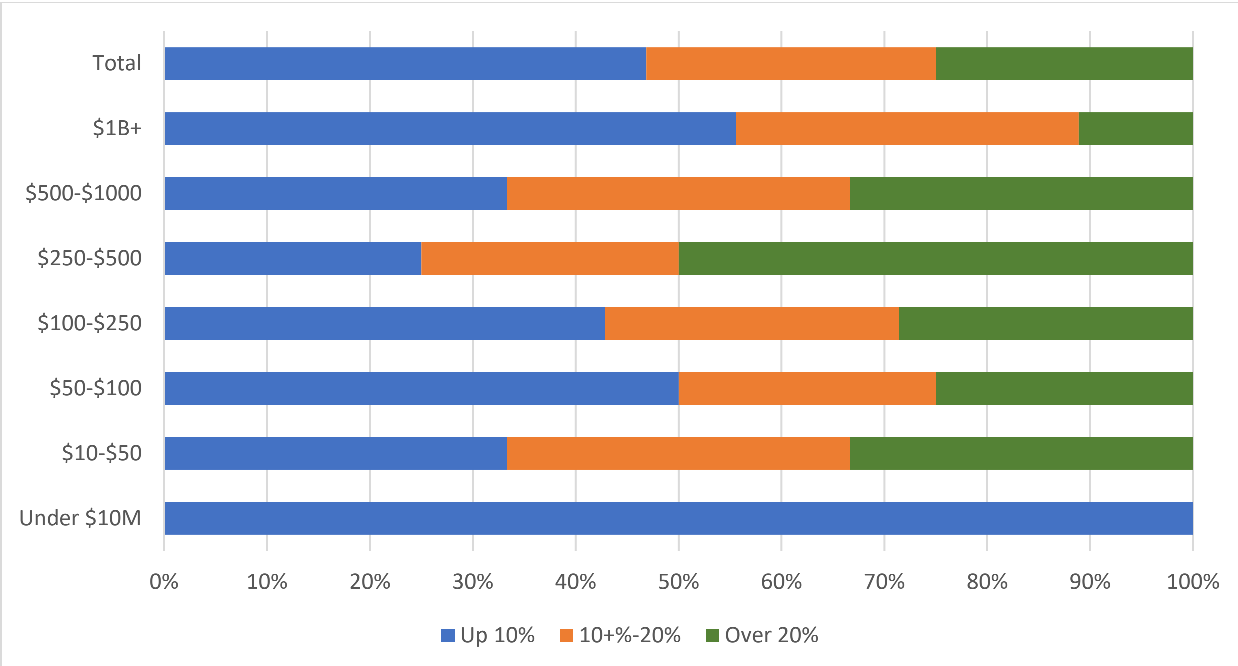
Exhibit 1: Distribution of Respondents by Consumer-Oriented Product



Participants who exported once or less than once a year, about 3% of participants in the conversations, were classified as opportunistic exporters. These participants indicated they exported only when a buyer called with an order and price that was "good enough". They also indicated they would often ship to a local agent of the client in the foreign country. As such, tactical exporters do not develop ongoing relationships with their buyers even if they deal with them multiple times. About 17% of participants in the conversations exported between twice and four times a year, 8.6% exported every two months, and 11.4% every month. About 60% of participants indicated exported more than once a month. These are the strategic exporters.

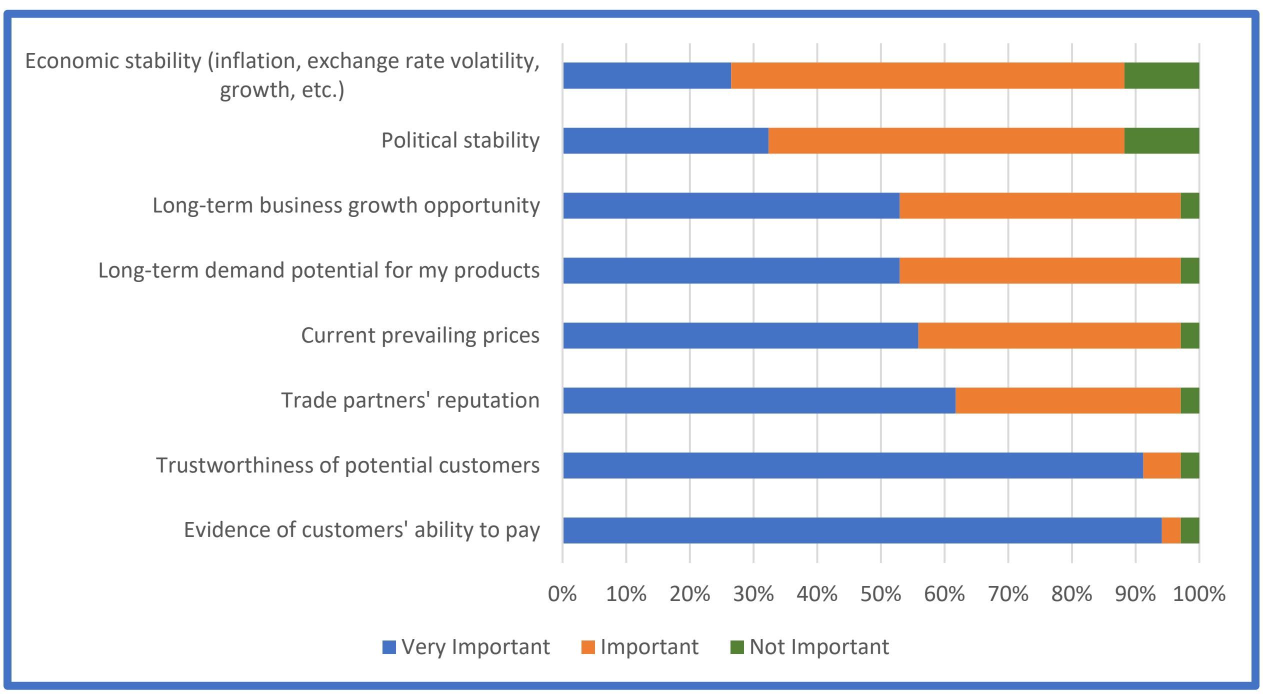
About 37.5% of the conversation participants involved with exporting had an annual turnover of \$500 million or more, compared to 6.3% with an annual turnover of less than \$10 million. While 9.4% of them had annual turnover of between \$10 million and \$50 million, the annual turnover of 12.5% was between \$50 million and \$100 million. The average proportion of total revenue emanating from exports was 17.6%, with a median of 10.5%. For participants for whom exports accounted for up to 10% of total revenue, the average contribution of exports to total revenue was 5%, with a standard deviation of 3.6% and a median of 4%. For those with export contributions above 10% but less than 20%, the average contribution was 17%, with a standard deviation of 3.5% and a median of 18%. Finally, for those for who exports continued 20% or more of their total revenue, the average contribution was 45% with a standard deviation of nearly 20% and a median of 38.5%. Exhibit 2 shows that contributions from exports for participants whose annual turnover was less than \$10 million was up to 10%. Exports accounted for more than 10% for three-quarters of participants whose firms had annual turnovers of between \$250 and \$500 million. Overall, exports accounted for up to 10% of the annual turnover of nearly 47% of exporters participating in the conversations. Those indicting exports accounted for 20% or more of their annual turnover were only a quarter of all participants.

Exhibit 2: Distribution of Company Size by Contribution of Exports to Total Revenue



Participants were asked to rank as very important, important, or not important eight factors developed from the literature and from conversation with exporters as influencing their choice of export destinations. Evidence of customers' ability to pay and their trustworthiness were two factors scored as very important by more than 90% of participants. Exhibit 3 shows that current prevailing prices are very important only about half of the participants, while the macroeconomic and political environment are very important only 26.5% and 32.3% of the time.

Exhibit 3: Distribution of Respondents by Consumer-Oriented Product



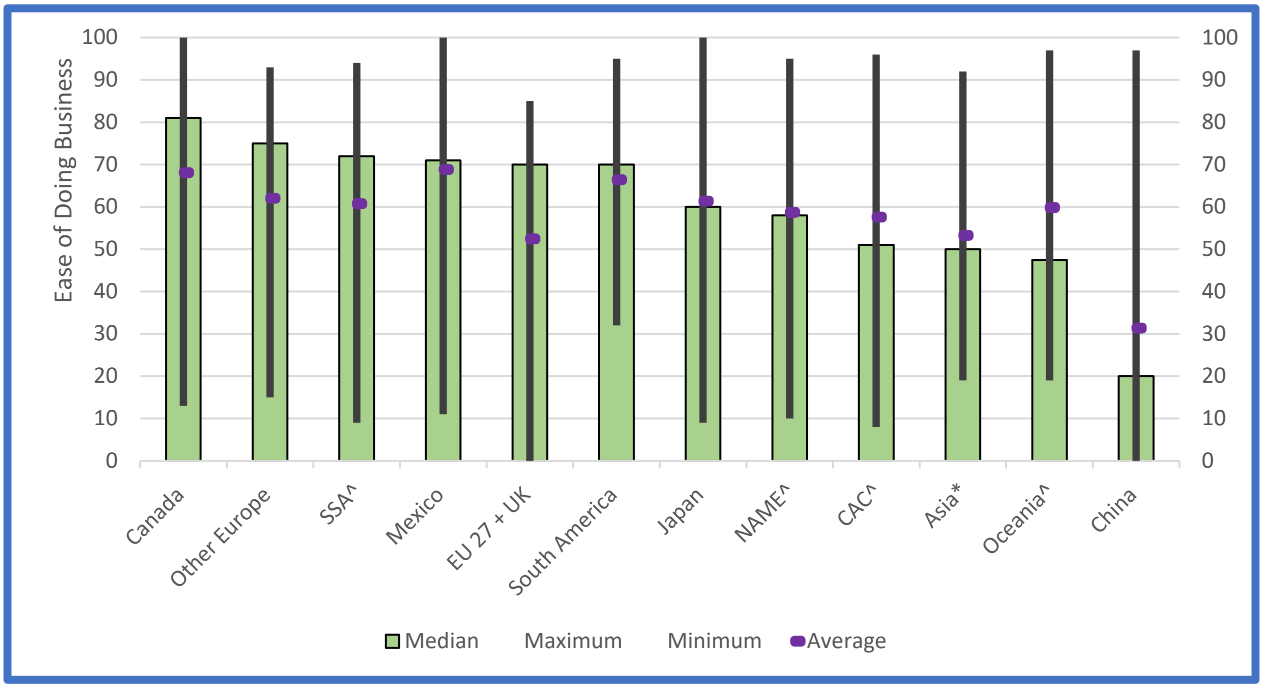
Conversation participants had a minimum of two years' exporting experience, with nearly 92% of them reporting more than 5 years. The majority of them (65%) sell directly to a foreign buyer and about 18% of them indicated using independent representatives in the destination country to sell their products. About 9% of them have their own sales office in the destination country and the remainder use all the listed channels, i.e., directly to foreign buyers, independent representatives and use their own sales office.

Most participants ship to Mexico, Canada, Central America and the Caribbean, Asia (excluding China and Japan), the EU+UK, Japan, and China. Participants selected only 13 of the 194 countries as potential future export destinations. Interestingly, these were countries to which the US was already exporting, suggesting that exporters use the proven selection criteria in their assessment of future export destinations.

Not all export destinations are created equal: It is a lot easier to do business in certain places than others. Among the 12 regions considered, participants identified Mexico and Canada as the easiest regions in which to do business (Exhibit 4). This is not a surprise since they are the closest neighbors and partners in the USMCA (formerly known as NAFTA) free trade agreement. There was no statistical difference between the mean ease of doing business score in Mexico (68.8) and Canada (68.1), but they were statistically different from China's mean score of 31.4 at the 1% level.

Exhibit 3 contextualizes the observed wide variation in the means across regions and countries by also reporting the median scores. It shows that the ease of doing business in China for half of the participants was 20 points or less. The median score for ease of doing business in Sub-Saharan Africa was 72, which was higher those for all other regions/countries except Other European countries (75) and Canada (81). Participants' median scores for the ease of doing business South America are higher than those of Central American and the Caribbean, Asia (including Japan and China), Oceania, and North Africa and the Middle East.

Exhibit 4: Summary Statistics for Participants' Scores for the Ease of Doing Business in Different Regions and Countries

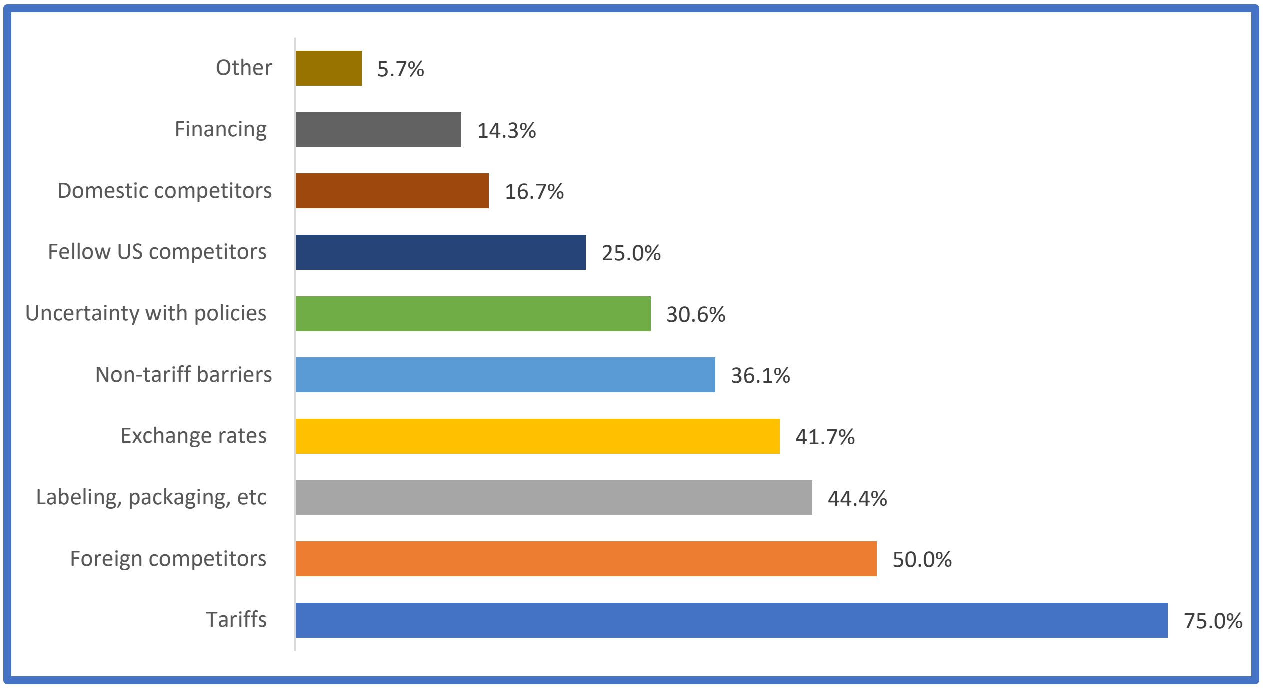


* Asia excluding China and Japan; ^ CAC (Central America and the Caribbean); NAME (North Africa and the Middle East; Oceania (Australia, New Zealand, and Pacific Island); and SSA (Sub-Saharan Africa)

Exhibit 5 presents the proportion of participants in conversations selecting an issue as a challenge to their exporting activities. Tariffs are the biggest challenge to exports, according to the participants, selected by three-quarters of participants. Foreign competitors, selected by 50% of participants, was a distant second. The remaining issues were selected by less than 40% of participants in the conversations except for labelling ad packaging (44%), and exchange rates (42%). Distribution challenges, brand recognition, and institutional corruption in export countries were among the "other" factors not specifically identified as presenting challenges to US agri-food exporters.

The correlations between exchange rates on the one hand, and tariffs and non-tariff barriers on the other, were 0.36 and 0.20, respectively, and statistically significant at the 5% level. Similarly, the correlation between non-tariff barriers and policy uncertainty was 0.38 and statistically significant at the 5% level. However, the correlation between Fellow US competitors and labelling and packaging regulations in export countries was -0.39 and statistically significant at the 5% level. All other pairwise correlations were not statistically significant at 5% or less level.

Exhibit 5: Proportion of Participants in Conversation Identifying Selected Issues as Challenges to Their Exports



The majority of participants in the conversations indicated that short-term prices do not influence their export decisions. This was true across all markets. It was also true for both price increases and decreases and for the different types of exported products, i.e., bulk, intermediate, and consumer-oriented product. That bulk exporters indicated not responding to short-term price changes was a little surprising given the "commodity" nature of such products. However, for strategic exporters who see exports as long-term relationships, short-term price changes may be ignored for long-term strategic objectives. In other words, the price elasticity of exports is infinitely inelastic over a foreseeable duration. A comment shared in follow-up interviews with some of the participants about their price responses may be paraphrased thus:

> "When you initiate an export program, you follow the program. You make a commitment over months, sometimes years. Therefore, short-term price changes do not affect the program. You stick to the program when price falls. It allows customers to stick to the program too when price increases. That is what trust and commitment is all about."

Appendix 2: Equations, Annotations, Documentation, and Notes for System Dynamics Model for US Exports of Distilled Spirits to Morocco

Top-Level Model:
"First-Time_Buyers"(t) = "First-Time_Buyers"(t - dt) + (adopting - repeat_buying) * dt {NON-NEGATIVE}
INIT "First-Time_Buyers" = 0
UNITS: persons
DOCUMENT: First time buyers are not considered customers because they may try it out of curiosity and never purchase again.
Potential_Customers(t) = Potential_Customers(t - dt) + (becoming_potentials - adopting) * dt {NON-NEGATIVE}
INIT Potential_Customers = 0
UNITS: persons
DOCUMENT: Number of potential customers in the new market. We define this as households with the characteristics indicating they are capable of purchasing the product
Repeat_Customers(t) = Repeat_Customers(t - dt) + (repeat_buying) * dt {NON-NEGATIVE}
INIT Repeat_Customers = 0
UNITS: persons
DOCUMENT: Repeat customers continue to purchase the product after first trying it as first-time buyers. It is assumed that they do not defect after first purchasing the product and will remain customer over the duration of the simulation. However, the entry of competitors into the market with similar value products with lower prices or higher value products at the same prices might engender defection.
Sales(t) = Sales(t - dt) + (generating_sales) * dt {NON-NEGATIVE}
INIT Sales = 0
UNITS: Liters
DOCUMENT: Volume of product sold
Sales_Revenue(t) = Sales_Revenue(t - dt) + (generating_revenue) * dt {NON-NEGATIVE}
INIT Sales_Revenue = 0
UNITS: USD
DOCUMENT: Total accumulated revenue over the plan/forecast period.
adopting = adoption_from_advertising + WOM_adopters {UNIFLOW}
UNITS: person/year
DOCUMENT: Potential customers adopting the product. They are influenced by advertising and word of mouth.
becoming_potentials = market_gap * potential_fraction {UNIFLOW}
UNITS: person/year
DOCUMENT: Developing potential customers.
generating_revenue = pricing * Sales {UNIFLOW}
UNITS: US Dollars Per Year
generating_sales = market_size * per_capita_consumption * purchase_frequency {UNIFLOW}
UNITS: Liters/Year
pricing = INIT(entry_price) *(1 -price_growth * (TIME-2013)^market_pressure) {UNIFLOW}
UNITS: USD
DOCUMENT: Price is sticky upwards. So, prices are adjusted downwards over time to meet changing customer preferences and competitor behavior (entry with superior product, etc.)
repeat_buying = "First-Time_Buyers" * (retention_adjustment) {UNIFLOW}

UNITS: person/year
DOCUMENT: Proportion of first-time buyers who repeat their purchases.
adoption_from_advertising = advertising_effectiveness * Potential_Customers
UNITS: persons
DOCUMENT: Number of customers adopting as a result of advertising campaign. This is the coefficient of innovation (p) in the Bass Diffusion Model.
adults = population * (1 - children)
UNITS: persons
DOCUMENT: Adults are those over 14 years of age.
Advertising_allocation = pricing*advertising_multiplier*Potential_Customers
advertising_effectiveness = 0.2
UNITS: Dimensionless
DOCUMENT: Effectiveness of the advertising campaign. It is measured by the number of customers converted per dollar of advertising.
advertising_multiplier = .1
UNITS: Dimensionless
ambassadors = champions * Repeat_Customers
UNITS: persons
DOCUMENT: Number of repeat customers actively promoting the product to current potential buyers. They define the ambassadors for the product available to tell their contacts about the product.
champions = 0.1
UNITS: Dimensionless
DOCUMENT: Proportion of repeat customers who champion the product in their social network.
children = 0.2704
UNITS: Dimensionless
DOCUMENT: Proportion of children in the population. Children are defined as those under 15 years of age.
contact_with_potentials = Potential_Customers*probability_of_contact
UNITS: persons
DOCUMENT: Number of potential customers coming in contact with repeat customers.
drinkers = 1 - "non-drinkers"
UNITS: Dimensionless
eligible_customers = "top-10" * potential_drinkers * market_share
UNITS: persons
DOCUMENT: Market to go after.
entry_price = 18
UNITS: USD/liter
DOCUMENT: The export market entry price for the product.
The product of interest here is liqueur, with an average entry price of $18/liter.
GDP = 114700000000
UNITS: USD
DOCUMENT: Gross domestic product (GDP).
income_level_check = GDP * "top-10"/(population_percent * population)
UNITS: $/person
DOCUMENT: The income per capita for the top-10 population.
market_gap = eligible_customers-total_market

UNITS: persons
DOCUMENT: Eligible customers who have not become potential customers yet.
market_pressure = 1.25
UNITS: Dimensionless
market_share = .15
UNITS: Dimensionless
DOCUMENT: Desired or target share of market aimed for by company strategy
market_size = "First-Time_Buyers" + Repeat_Customers {SUMMING CONVERTER}
UNITS: persons
DOCUMENT: First-time buyers plus repeat buyers
"non-drinkers" = 0.974
UNITS: Dimensionless
DOCUMENT: Proportion of people identified as non-drinkers in the populations. These people are not included in the market. Source is WHO. Reference: https://www.who.int/publications/i/item/9789241565639
per_capita_consumption = 24.5
UNITS: Liters/person
DOCUMENT: Per capita consumption of alcohol per year. (liters/year). Total consumption in 2017 was 120 million liters, of which 17% is liquor, 43% is beer and 40% is wine. Only 2.6% of the adult population (over 14 years) drink. This leads to a per capita consumption of about 30.3 liters per year. Assume that the elite status of the eligible customers causes them to drink a little less than the average population, about 20% less. Hence, the average per capita consumption used in the model is 24.5 liters per capita per year. Source: Morocco World New (https://www.moroccoworldnews.com/2017/04/213152/alcohol-consumption-rise-morocco/)
population = 35561654
UNITS: persons
DOCUMENT: Total national population
population_percent = 0.1
UNITS: Dimensionless
DOCUMENT: Percent of population under consideration . In this case, it is top 10%.
potential_drinkers = adults * drinkers
UNITS: persons
DOCUMENT: Population of drinkers (market base)
potential_fraction = 0.0135
UNITS: Dimensionless
DOCUMENT: Direct engagement with eligible customers who have not become potential customers yet at time (t). This is the proportion of unexposed eligible customers who become potential customers.
price_change = ((INIT(pricing) - pricing)/INIT(pricing))
UNITS: Dimensionless
price_growth = 0.002
UNITS: Dimensionless
probability_of_contact = 0.01
UNITS: Dimensionless
DOCUMENT: Probability of potential buyers coming in contact with repeat customers.
purchase_frequency = 1
UNITS: Dimensionless

DOCUMENT: Purchase frequency of the product per year. This is necessary if per capita consumption is not on an annual basis.
retention_adjustment = retentions * (1 + DELAY1(price_change, 3))
UNITS: Dimensionless
DOCUMENT: It is hypothesized that decreasing price increases first buyer retention.
retentions = 0.9
UNITS: Dimensionless
DOCUMENT: The proportion of first-buyers who go on to become repeat buyers, and hence, customers.
"top-10" = 0.332
UNITS: Dimensionless
DOCUMENT: Proportion of GDP controlled by top 10% of population
total_market = Potential_Customers + Repeat_Customers {SUMMING CONVERTER}
UNITS: persons
DOCUMENT: Potential customers and repeat customers.
WOM_adopters = contact_with_potentials *ambassadors*WOM_adoption_fraction
UNITS: persons
DOCUMENT: Number of potential customers becoming first time buyers because of word-of-mouth contact with repeat customers.
WOM_adoption_fraction = 0.2
UNITS: Dimensionless
DOCUMENT: The proportion of people coming in contact with repeat buyers who purchase the product.
The model has 45 (45) variables (array expansion in parens). Stocks (5); Flows (6); Converters (34); Constants (19) ;Equations (21); and Graphicals (0). There are also 6 expanded macro variables.