Returns to Mushroom Council Promotion

Timothy J. Richards, Ph.D. *Arizona State University*

Mushroom demand in the U.S. has increased significantly over the 2011 - 2015 study period. While lower retail prices have played a role, promotion activity by the Mushroom Council has been equally as important. In this report, we summarize our findings from the econometric analysis of Council promotion activities.

Executive Summary

- The objective of this study is to determine the return on investment to grower funds invested in Mushroom Council marketing activities. The relevant markets for US mushrooms are defined as the retail market for mushrooms of all varieties (whites, portabellas, shiitakes, etc) and types (organic or conventional) and the foodservice market, or mushrooms that are sold to restaurants, cafeterias and institutional food delivery services such as schools and hospitals. For both purposes, US mushrooms are defined to include mushrooms imported from abroad by US entities.

- Returns to Council marketing activities are calculated using an equilibrium model of mushroom supply and demand. Econometric models are used to estimate the demand impact of Council activities. Two models are created for this purpose: a retail model and a foodservice model.

- All models are estimated with data made available from Council records and include retail scanner data from IRI and Council shipment data on a monthly basis over the study period. Council records provide monthly data on impressions in four categories of activity: retail, consumer and nutrition, foodservice, and digital. Budget amounts for each of these four activity categories are also taken from Council records and used to measure the amount of investment on a monthly basis.

- For both the retail and foodservice model, we estimate short- and long-run elasticity values for six different demand drivers: (1) price, (2) price-promotion, (3) retail marketing, (4) consumer and nutrition marketing, (5) foodservice marketing, and (6) digital outreach activities. Elasticity is defined as the ratio of the percentage change in demand to the percentage change in the variable of interest. Elasticities are important as they are unit-free measures of the responsiveness of demand to each variable.

- The short-run retail price elasticity of demand is -1.354 on average over all mushroom types and varieties. In other words, if the retail price rises by 10 percent, demand is expected to fall by 13.54 percent. Our estimate is larger than recent estimates from other studies because we explicitly differentiate among varieties. Unlike other studies, our estimated elasticity value is highly statistically significant. The short-run elasticity of retail marketing impressions is 0.036, while it is 0.049 for consumer and nutrition marketing, 0.056 for foodservice activities, and 0.032 for digital impressions in the retail market. Long-run marketing elasticities are: 0.098 for retail activities, 0.136 for consumer and nutrition activities, 0.127 for foodservice messages, and 0.122 for digital.

- Return on investment is measured using two, equivalent metrics: (1) the benefit:cost ratio (BCR), and (2) return on investment (ROI). BCR is calculated as the present value of grower profit divided by the amount of investment, while ROI is the same calculation expressed as a percentage of the initial investment. In this summary, we report only BCR values as the two measures are equivalent.
- Retail Model Results: We calculate BCR values for each type of marketing activity in the retail market. For retail marketing, the estimated short-run BCR is 1.014 (1.014 dollars in profit for each 1.00 dollar invested) and 2.608 in the long run. The BCR for consumer and nutrition marketing is 2.631 in the short-run and 7.186 in the long-run. Foodservice marketing provides a short-run BCR of 0.479 and a long-run BCR of 1.279. Digital activities generate a short-run BCR of 0.547 and long-run returns of 1.457. All forms of communication are profitable in the long run, but some generate negative returns (do not cover their cost) in the short run.
- The volume of mushrooms in foodservice was calculated as the difference between total shipments (from Council data) and IRI retail movement. Foodservice demand was estimated as a function of lagged demand, prices, price promotion, marketing impressions (retail, consumer and nutrition, foodservice, and digital impressions, as in the retail model) and yearly dummies. Unlike the retail model, we did not estimate the demand for each type of mushroom. The average price elasticity of demand in the foodservice market was -0.889 in the short run and -1.667 in the long run. All estimated parameters were highly statistically significant. The elasticity with respect to retail marketing is 0.022 in the short run and 0.041 in the long run. Consumer and nutrition impressions also had a significant, positive effect on demand with a 0.039 elasticity in the short run and 0.075 elasticity in the long run. Aggregate mushroom demand elasticity with respect to foodservice marketing activity is 0.046 in the short run and 0.086 in the long run. The elasticity with respect to digital impressions is 0.017 in the short run and 0.032 in the long run.
- Foodservice Model Results: BCRs were also calculated for the foodservice market. Retail marketing in the foodservice market has a BCR of 2.274 in the short run, and a BCR of 2.874 in the long run. Consumer and nutrition marketing has a BCR of 0.828 in the short run, and 1.047 in the long run, while foodservice marketing has a BCR of 1.211 in the short run and 1.531 in the long run and digital activity has a short-run BCR of 1.955 and a long-run BCR of 2.471. As in the retail market, all marketing activities have BCRs greater than 1.0, and three are profitable in the long run as they provide returns greater than Council members likely opportunity cost of capital (approximately 5.0 percent). Consumer and nutrition impressions, however, return slightly below this benchmark.

Introduction

In 2016, US consumers purchased 3.01 lbs per capita of fresh and processed mushrooms, up from some 2.65 lbs per capita a decade earlier (USDA-ERS 2016). With stagnant income growth over the intervening 10 years, and an increasingly competitive array of food products available to consumers, any growth in demand would suggest that retail prices had fallen. However, over the same period, grower prices rose from 1.13 dollars per lb to 1.25 dollars per lb (USDA-ERS 2016). Rising demand amid with rising prices suggests that other factors must have been at work. Although summary evidence is not conclusive, from a high-level view, it appears as though Mushroom Council marketing activities have been effective in increasing demand.

Econometric analysis is required to determine where mushroom consumption would be in the absence of any Council marketing activities. Because the food market is a crowded place, and growing demand is difficult, we need to control for all possible factors that may have influenced mushroom consumption and prices in order to disentangle the unique effect of the Mushoom Council's work. The difference between what we observe in sales reports and what might have been constitutes a return on investment. In this study, we quantify that return and determine what works for marketing fresh mushrooms in the long and short run using econometric models of mushroom demand.

What is an econometric model, and why are they useful? Econometric models are statistical methods that are able to identify the true causes of observed changes in demand when many things are changing at the same time: prices, incomes, tastes, demographics and, most important for the purposes of this study, marketing investment. Econometric models answer the question: if everything else is held constant, what is the independent effect of changes in advertising or promotion? For immediate purposes, econometric models are useful because the 2002 Farm Security and Rural Investment Act (FSRIA) requires econometric analyses of federally-sanctioned marketing organizations every five years. More fundamentally, however, investment and allocation decisions are better informed when the stakeholders know what works and what doesnt, or what deserves more investment and what less. The models used here are designed with this purpose in mind.

We also recognize that many investments made by the Council are long term in nature. Whether it is communicating nutritional messages, spreading the word about new menu items, or even building a strong web-presence, marketing investments are intended to build the brand as a long-term proposition. In this study, we estimate both the short- and long-term effects on demand of Council activities, and define member returns to include both immediate impacts and those that may not be felt until several quarters in the future.

Objectives

The primary objective of this research is to estimate the long-run return on growers investment in each marketing activity during the period 2011 - 2015. To this end, our research encompasses a number of intermediate objectives. They are:

- To estimate the long-run impact of Council retail marketing, consumer and nutrition research, foodservice and digital marketing activities on the retail and foodservice demand for all major mushroom varieties using a variety of econometric modeling techniques applied to scanner and shipment data.

Table 1: *Impressions and Budget Data: 2013 - 2015*

	Retail	Consumer	Foodservice	Digital
Imp.	0.26	114.47	0.24	10.31
Bud.	30.04	150.75	117.31	43.47

- To determine the long-run impact of Council retail marketing, consumer and nutrition research, foodservice, and digital activities on retail and grower prices by developing models of each supply chain.

- To use the estimated demand effects at the grower level to calculate an expected annual increment to grower profit, the net present value of all future profit (net of program costs) and, ultimately, the return on investment (defined as the benefit:cost ratio, or BCR) due specifically to Council marketing and research activities.

To achieve these objectives, retail sales data is essential in order to accurately measure the movement of mushrooms contemporaneous to any marketing activity. However, because the Council changed data vendors between 2012 and 2013, retail sales data were only available from 2013 - 2015. Therefore, due to limited data availability, we focus our analysis on investments made from 2013 through 2015, which should represent a conservative estimate given the expansion of demand prior to the 2013 marketing year. In addition, the study uses a combination of grower price data made available by the Mushroom Council, as well as several sources of demand data, also collected by the Council, including monthly shipments and marketing intensity measures (impressions). We also use other relevant data on input prices and aggregate demand factors, all of which are taken from public data sources (USDA-ERS). All data analysis methods are well understood and accepted in the marketing-evaluation field and have been used extensively by the researchers.

In the next section, we describe the specific research methods used in each model and explain the economic logic behind our approach. Table 1 summarizes the impressions data used in the analysis (Note: Impressions are in millions per month and budget is in thousands of dollars per month).

Demand Models

Overview

Marketing activities benefit grower-shippers by increasing demand, thereby raising surplus, or profit, on all mushrooms sold. Therefore, modeling demand is at the core of any econometric analysis of the returns to commodity marketing. In this section, we describe in detail two demand models estimated in order to achieve the goals described above: (1) a variety-specific retail demand model, and (2) a food-service demand model. In the following section, we describe how elasticity estimates from these demand models are used to calculate incremental profit, and return on investment.

Retail Demand for Mushrooms

The first model estimates the demand for each variety of mushroom (including organic and conventional variants) in each of 9 IRI regions in the US, on a monthly basis, from 2013 through 2015 (8 regions plus the total U.S.). In this model, the share of each type of mushroom is assumed to be driven by its own price, the price of other mushrooms, price-promotion activity, seasonality, a trend variable, and each of the 4 classes of marketing activity defined above. In each case, the level of marketing activity is measured by the number of impressions purchased by Council marketing staff. The specific form of the model (a random-parameters logit (RPL) model) is well-accepted in the quantitative marketing literature, and regarded as state-of-the-art for demand analysis.

Our choice of these variables is guided by best-practices from the promotion-evaluation literature. As such, there are a number of fundamental principles that must be captured by the econometric specification. First, advertising is expected to have a long-lasting effect on demand. Therefore, we differentiate between the short-run and long-run effects of both price and advertising as investments in "brand equity" are assumed to accumulate slowly over time. Second, advertising is subject to the principle of diminishing marginal returns. That is, the more a particular medium is used, the less the incremental gain from an additional dollar spent on that medium so we assume marketing activities have a non-linear effect on demand. Third, advertising expenditure is generally a poor measure of effort, so we use impressions as a physical measure of the intensity of each type of marketing activity. Fourth, marketing expenditures are generally targeted to many different media, markets or purposes so we allow for random marginal effects for each type of marketing investment.

Marketing programs are an investment and not an expenditure, so are expected to have a lasting effect on consumers perception of the product, and their likelihood of purchase. Whether this is through brand loyalty for a consumer good, goodwill toward a commodity, or simply by contributing to consumers stock of knowledge regarding the nutritional and taste attributes of a product, the effect of marketing activities both builds over time with additional expenditure, and decays as older campaigns are forgotten or abandoned. Being able to model the lagged-effects of advertising carefully is important as these competing effects likely differ in strength as time passes. For example, publishing the effects of new nutritional research results may result in an increase in demand only after a considerable amount of time has passed before consumers learn or truly understand the effect, while older research results may be forgotten or superseded by new results. To capture the complexity of the dynamics involved in this process, we model each measure of marketing intensity using a polynomial inverse lag (PIL) process (Mitchell and Speaker, 1986). Simply put, a PIL process is a flexible and parsimonious way to capture both long-term and short-term advertising impacts in an econometric model. We develop the PIL model more formally in the appendix.

Measures of the stock of advertising capital, or A_{ij} in the econometric model, typically comprise expenditure values for each media type. Doing so is convenient because the estimated parameter provides a direct measure of the marginal or incremental effect of one more dollar of expenditure. However, expenditure is a poor measure of advertising intensity because consumers do not see dollars of advertising, but rather ads, stories, promotions or media impressions. For current purposes, however, the Council has collected impressions data for each of a number of different categories (retail, consumer and nutrition, food service, and digital) as well as by media type. Therefore, we estimate the econometric model using impressions as the variable definition and not simple dollar expenditure. This provides an estimate of the incremental volume per impression in category of outreach. We then measure the effectiveness of each type of message by calculating the marginal effect on sales volume per dollar spent in each area through the advertising elasticity metric. Our method is thus more direct than using dollar expenditure directly as a measure of marketing intensity.

Price promotion is also likely to have a significant effect on demand. The retail data included a measure of the number of pounds sold on promotion, so we created a promotion proxy by calculating the proportion of volume in a given month sold on promotion, relative to total pounds. We expect to find a positive relationship between this variable, and the amount of monthly volume movement.

Casual inspection of retail mushroom sales data shows that they are subject to extreme seasonality. Reaching a peak around December - January and a trough in August - September, this pattern is repeated reliably from one year to the next. Therefore, the econometric model is designed to represent this seasonality in a parsimonious and useful way. Specifically, we capture seasonality by including monthly fixed-effects, or simple binary indicators that allow the demand curve to shift each month, in the model.

Foodservice Demand

We estimated a second model of demand focusing on the foodservice market. Although foodservice, comprising not only restaurants, but schools, hospitals, prisons and other institutions, is an important market for fresh mushrooms, very little detailed data exists regarding the demand for mushrooms in this channel. Firms such as Technomic and NPD track restaurant meals, but their data provides information only on whole-meal choices and total-bill prices. Consequently, we developed a proxy measure for the total amount of mushrooms flowing into the foodservice market by subtracting what we know moves into retail from the IRI data from Council measures of total mushroom shipments. The result is a reasonably accurate measure of what is purchased by foodservice managers.

Foodservice purchases are what is known as a derived demand, meaning that mushrooms are not purchased by the ultimate consumer, but by the restaurant or other organization that serves them. Therefore, the relevant price paid is the wholesale price, which we approximate by using the grower price recorded by Council staff. Because there are many varieties of mushrooms purchased for foodservice uses, we construct a value-weighted index by dividing the total dollars spent by the volume purchased. This "unit value index" represents a reasonable proxy for the average price paid for foodservice mushrooms.

In addition to the monthly price of wholesale mushrooms, the foodservice demand model includes yearly indicator variables and marketing capital. We account for the long-run effect of marketing investments in a method similar to that described above, but allow for each impression to have an lasting effect through a geometric lag process. Essentially, a geometric lag simply means that the impression has its largest effect in the first month, and then declines geometrically for every month after that. In terms of the econometric model, a geometric lag is specified simply by including a one-period lagged value of the dependent variable (lagged quantity). We also account for the diminishing marginal returns to marketing investments by taking the log of each type of impression. We again use retail marketing, consumer and nutrition, foodservice, and digital impression types because foodservice consumers are likely to see each one (or so we would hope) at some point prior to ordering a dish that includes mushrooms.

Algebraically, the foodservice model is relatively simple. Unlike the retail model (random-parameters logit form), we regress the log of quantity on the logs of all the explanatory variables described above. This log-log, or Cobb-Douglas, demand model has the advantage that each of the estimated parameters is the relevant elasticity measure. Elasticities of demand, in addition to the elasticities of supply and price transmission, are all that is needed to calculate the returns to mushroom marketing.

As with the retail model above, we estimate the foodservice demand model using instrumental variables methods to account for the fact that prices are likely to be endogenous, or determined simultaneously with the quantity demanded. Instruments for prices in both models are formed from a set of input prices (chemicals, fertilizer, energy and various grains that are used for mushroom substrate) as well as other variables that are determined outside of the demand model, such variations in the U.S. population, interest rates and lagged consumption values. These instruments explain much of the variation in prices and are independent of the equation errors *a priori*.

Calculating Return

With the demand effects estimated above, we then calculate the return to each type of marketing investment. We use two, equivalent measures of return: (1) the benefit:cost ratio (BCR) and (2) the return on investment (ROI). BCR is calculated as the ratio of the present value of grower profit to the amount of investment. ROI is calculated as the ratio of the present value of the incremental gain in profit (producer surplus) generated by each program in the most recent fiscal year to the total amount of capital invested, or the cost of each type of marketing activity. Although the mathematical details of how incremental profit is calculated are in the appendix below, the intuition is straightforward. Incremental profit is the present value of the difference between higher revenue generated from the increase in demand and higher production costs. BCR is expressed on a per-dollar-of-investment basis as it communicates how much profit each invested dollar is expected to generate. ROI is expressed on an annualized, rate of return basis in order to remain as comparable as possible to returns growers can expect on other investments, such as capital invested in their farms or in external capital markets. Because we estimate both short- and long-run demand elasticities, we estimate both short- and long-run changes in profit. In the long-run calculation, however, we also allow for the fact that growers are likely to increase the supply of mushrooms in response to higher returns so we account for the feedback effects that are expected to result from a successful marketing program. Further, because the BCR / ROI estimate depends on the parameters of the producer surplus model (the elasticity of supply), we calculate BCR / ROI using a value for the supply elasticity taken from the literature on mushroom supply (Molina and Richards 2014).

Results and Discussion

Demand Models

Retail demand was estimated using the econometric model described above. Based on the estimates from this model, we calculated response elasticities with respect to the retail price, and all four marketing activities, and summarize these elasticity estimates, both short-run and long-run, in table 2. Most importantly, the short-run price elasticity is approximately -1.35, which is a bit higher than in previous studies (Sexton and Saitone, 2009). Our elasticity estimate is relatively high because we account for differentiation among mushroom varieties, and elasticity estimates averaged over very specific product variants are, logically, much higher than when estimated for undifferentiated aggregates. In particular, studies that do not distinguish between varietal demand are likely to miss the fact that consumers tend to substitute among varieties, so ignore an important source of demand variation. A price elasticity of -1.35 means that if price were to rise by 10 percent, the retail quantity demanded would fall by 13.5 percent, all else equal.

All of the marketing-mix elasticities were found to be statistically significant, and positive, which means that each activity – independent of the others – had a positive effect on demand. In terms of the individual types of activity, we found a short-run elasticity with respect to retail marketing of 0.036, and a long-run elasticity of 0.098. These estimates mean that a 10 percent increase in retail marketing can be expected to lead to a 0.36 percent increase in retail mushroom volume in the short run and a 0.98 percent increase in the long run. For consumer and nutrition messages, we found a short-run elasticity of 0.049, and a long-run elasticity of 0.136. Given that consumer and nutrition messaging is the most important activity, both by number of impressions and budget (table 1), finding a positive response is both important, and surprising, given the diminishing marginal returns to any type of promotional activity. Foodservice marketing produced similar elasticity estimates, ranging from 0.056 in the short-run to 0.127 in the long-run. Because retail demand is not the primary focus of foodservice messaging, finding a positive result for this activity class suggests that there is an important element of "trickle down" from investments in one channel, to buyers in another. Finally, the elasticity with respect to digital impressions was 0.032 in the short-run, and 0.122 in the long-run. Because the Council is relatively new to digital marketing, or at least in measuring its effectiveness, finding a significant, positive response is indicative of both a relatively un-tapped medium, and effective choice of online and digital media.

Table 2: *Retail Demand Model Estimates*

	Short-Run	Long-Run
Price	-1.3541	-1.5232
Retail	0.0357	0.0976
Consumer	0.0496	0.1358
Foodservice	0.0562	0.1272
Digital	0.0318	0.1217

Unlike retail mushroom demand, foodservice demand was found to be inelastic with respect to mushroom prices (table 3). The short run price elasticity of demand is -0.889 and the long run price elasticity is -1.666. Finding a long run elasticity that is substantially larger than the short run elasticity is due to the fact that the rate of adjustment over time is relatively small, which means that quantity demanded adjusts to its long run equilibrium value only slowly over time. For marketing purposes, however, it is the short run price elasticity that matters as markets are always in a state of fluctuation and price changes in

Table 3: *Foodservice Demand Model Estimates*

	Short-Run	Long-Run
Price	-0.8894	-1.6662
Retail	0.0219	0.0410
Consumer	0.0399	0.0747
Foodservice	0.0456	0.0855
Digital	0.0169	0.0316

Table 4: *Retail Model BCR Estimates*

	Short-Run	Long-Run
Retail	1.0139	2.6082
Consumer	2.6305	7.1860
Foodservice	0.4788	1.2792
Digital	0.5470	1.4573

one month are nearly always superseded by changes in the following month.

With respect to the marketing activity variables, we find a short run elasticity with respect to retail marketing of 0.022 and a long-run elasticity of 0.0410. Consumer and nutrition marketing, on other hand, has a considerably larger impact on foodservice demand as the short run elasticity is 0.040 and the long run elasticity 0.0747. Including both retail and consumer / nutrition marketing in the foodservice model is necessary because foodservice consumers likely see messages targeted to retail stores, or hear nutrition messages on the value of mushrooms. Because foodservice consumers see these messages, buyers for institutional foodservice providers are compelled to respond and meet consumers demands. For impressions targeted specifically to the foodservice market, we find a short run elasticity of 0.046 and a long run elasticity of 0.086. The fact that both measures are higher than their retail and consumer / nutrition counterparts is due to the fact that foodservice messages are targeted more directly to this market. With respect to digital impressions, we find a short-run elasticity of 0.017, and a long-run elasticity of 0.032. Consumers' response to digital marketing may be smaller than the other channels due to is relatively new-ness or the noisiness of the online market. Although these elasticities are of value independent of any other purpose, our primary interest in estimating them is to use them as inputs to the returns-calculation model.

Returns to Marketing Investments

In this section, we present and explain the returns to each type of marketing investment, in both the retail and foodservice channels. Further, due to the long-term nature of marketing investments, we calculate present value of incremental profit over the sample period for both the BCR and ROI measures. Taking into account the entire future stream of profit due to an investment in each period is important because any marketing investment is expected to have long-term demand effects. Our calculations provide estimates of the marginal return, as opposed to the average, as growers and shippers are interested in the return on the next dollar invested when making budget allocation decisions. In this study, we calculate BCRs and ROIs for each type of marketing activity in the retail market over a range of possible supply elasticities, from 0.25 to 1.5 with the most-likely value 1.0, and report the most-likely BCR values in table 4 below. The ROI values show a similar pattern, so are not included in the table. In general, returns fall as the elasticity of supply rises (price effects are muted with more elastic supply) and, given that empirical estimates of most commodity-supply elasticities are substantially lower than 1.0, our estimates are relatively conservative.

From the results reported in table 4, we see that all activities generate positive returns in the long-run as all BCR values are above 1.0. A BCR greater than 1.0 means that an activity generates more dollars in incremental value (present value of future profit) than the investment cost. With respect to individual activities, the estimates in table 4 show that activities targeted toward retail sales generate a BCR of 1.014 (ROI = 1.4 percent) in the short-run, and 2.608 (ROI = 160.8 percent) in the long-run. In other words, funds invested in retail activites generate only 1.014 dollars of incremental profit for every dollar invested in the short-run, but 2.608 dollars in the long-run. Equivalently, the ROI estimates imply that the same investment would not be viable with a hurdle rate of return of 5 percent (1.4 ¡ 5.0) in the short-run, but would easily exceed this threshold in the long-run. Because most producers are presumably invested for the long-run, for practical purposes the long-run estimate is more meaningful, and suggests that investments in retail marketing are highly profitable.

Returns to each of the other activities show a similar pattern, albeit to differing degrees. Consumer and nutrition marketing is the one exception that provides a relatively high short-run BCR (2.631, ROI = 163.1 percent) and an exceptionally high long-run

Table 5: *Foodservice Model BCR Estimates*

	Short-Run	Long-Run
Retail	2.2742	2.8742
Consumer	0.8281	1.0466
Foodservice	1.2114	1.5310
Digital	1.9551	2.4709

BCR (7.186, ROI = 618.6 percent). This result is significant, given the relative importance of consumer and nutrition messaging among all Council activities. Foodservice messages are not profitable in the short-run (BCR = 0.479, ROI = -52.1 percent), but is highly profitable in the long-run (BCR = 1.279, ROI = 27.9 percent) as markets adjust to reflect the full effect of marketing activities. Similarly, digital efforts are also not profitable in the short-run (BCR = 0.547, ROI = -45.3 percent), but are very profitable in the long-run (BCR = 1.457, ROI = 45.7 percent). To put these returns in context, the opportunity cost of capital for most growers is likely in the 5 - 7 percent range, so any investment yielding over 45 percent generates considerable excess profit.

In the foodservice channel, marketing communications, or impressions in our data, are expected to have their greatest impact when targeted to restaurant and institutional food buyers. However, the estimates in table 5 suggest that foodservice marketing has an expected BCR of 1.211 (ROI = 121.1 percent) in the short-run and a BCR of 1.531 in the long-run (ROI = 53.1 percent), while retail impressions have a BCR of 2.274 (ROI = 127.4 percent) in the short-run and a BCR of 2.874 in the long-run (ROI = 187.4 percent). Therefore, retail marketing generates a higher return in the foodservice market, but both activities have substantial, positive returns. Consumer and nutrition marketing, however, does not cover its investment in the short-run (BCR = 0.828, ROI = -17.2 percent) although it is more profitable in the long-run (BCR = 1.047, ROI = 4.7 percent). Consumer marketing is the only activity that does not reach a hurdle rate of return of 5 percent, even in the long run. Digital marketing, on the other hand, is easily profitable in both the short- and long-runs (short-run BCR = 1.955, ROI = 95.5 percent, long-run BCR = 2.471, ROI = 47.1 percent). Consequently, all activities but consumer and nutrition marketing can be described as profitable.

In summary, we find that many mushroom marketing activities are profitable in the short run (BCR ¿ 1.0), while all are profitable in the long run. Because we measure return on investment in terms of the profit expected on the last dollar spent, our results suggest that mushroom production and marketing would be significantly more profitable if more dollars were allocated to each activity. If marketing budgets are fixed, then our findings suggest re-allocating funds toward consumer and nutrition messaging in the retail channel, and retail marketing in the foodservice channel.

Conclusions and Recommendations

Both prices and shipments have been rising steadily over the study period (2011 - 2015). This study uses data from 2013 - 2015 to investigate the return on investment for grower-shipper dollars invested in all Council marketing activities: retail marketing, consumer and nutrition research, foodservice, and digital marketing. Because many factors other than marketing activities can explain changes in demand over time, the specific role of the Mushroom Council in helping maintain consumer demand is an important, and empirical question.

We find that all Council activities were effective in raising demand when controlling for the effect of prices, seasonality, changes in production conditions and other factors relevant to the demand for mushrooms. Among the four types of activity defined by Council staff, we find that consumer marketing was particularly profitable in the retail market, but not profitable in the foodservice market. On the other hand, retail marketing is significantly more profitable than either consumer and nutrition research, foodservice marketing, or digital messages in the foodservice market. In general, however, nearly all activities are highly profitable in the long-run, which should be the focus of all marketing activities.

In arriving at these conclusions, we recognize that the quality of our findings are inevitably limited by the quality of the data. While the IRI data describing retail sales of mushrooms are widely regarded as accurate and useful for this purpose, there is less certainty regarding the value of the data used for the foodservice market. Moreover, limitations in the IRI data prevented us from estimating returns over the entire 5-year period. Future evaluations of this type would benefit greatly from direct measures of consumption and prices for mushrooms sold into the foodservice market. This recommendation is particularly relevant given the importance of the foodservice market both in terms of the overall dollar sales level and at the margin, or the changes in shipments from month to month that have a magnified effect on prices.

Appendices

Appendix 1. Retail Demand Model

This appendix describes in more detail the specific econometric models that are used in estimating the impact of MC retail, consumer and nutrition, foodservice, and digital marketing activities on the demand for various mushroom varieties in the domestic retail and foodservice markets. For this analysis, it is assumed that the market segments are independent so we estimate separate models for each.

In this appendix, we use the retail market model (estimated using IRI data) as an example. Implicitly, by using this model we assume retail mushrooms are differentiated by variety and type (conventional or organic). As such, an individual consumer is assumed to choose only one product (ie., conventionally grown white mushrooms) from all other substitutable products available to them on that particular trip to the store. Consequently, we represent the demand for retail mushrooms with a discrete choice model of differentiated product demand (Berry 1994; Berry, Levinsohn and Pakes 1995; Nevo 2000). We begin by defining a random utility representation of individual household demand, and then aggregate over the distribution of consumer heterogeneity to arrive at a consistent aggregate demand for mushrooms in the market as a whole. We write the utility for household h as:

$$u_{hj} = v_{hj} + \epsilon_{hj} = \beta_{0j} + \sum_k \beta_{1k} x_{jk} + \sum_l \gamma_l f(A_1) - \alpha p_j + \xi_j + \epsilon_{hj}.$$

where β_{0j} is the maximum willingness to pay for mushrooms of type or variety j, p_j is the retail price of product j, x_j is a set of other explanatory variables, including personal income, a time trend or qualitative indicators to account for other non-quantifiable factors that may affect mushroom sales, $f(A_1)$ is the stock of marketing capital created by investments in marketing activity l by the MC, ξ_j is an unobservable (to the econometrician) error term and ϵ_{hj} is a random error, assumed to be iid extreme value distributed. Household h will choose the product of type j if the utility from this choice is greater than the utility from all other alternatives. In other words, the probability that household h chooses j over all others is governed by the distribution of ϵ_{hj} because:

$$\begin{aligned} Pr(j = 1) &= Pr(v_{hj} + \epsilon_{hj} > v_{hi} + \epsilon_{hi}) \\ &= Pr(v_{hj} - v_{hi} + \epsilon_{hj} > \epsilon_{hi}). \end{aligned}$$

As is well understood, if ϵ_{hj} is distributed extreme value, the random utility model in this equation implies share functions for each product of type $j = 1, 2, ..., J$ of:

$$S_j = \frac{\exp(v_{hj})}{1 + \sum_{i=1}^{I} \exp(v_{hi})}$$

where S_j is the market share of product type j. This expression yields the multinomial logit (MNL) model of discrete choice used by Berry (1994), Nevo (2001) and many others to study the structure of demand for differentiated products. Although the simple MNL model in this equation suffers from the proportionate draw problem (also called the independence of irrelevant alternatives, or IIA problem), meaning that the cross-elasticities for all alternatives are equal, the IIA problem is of little consequence in this application. Promotion effectiveness depends on the own-price and marketing-elasticity and, to a much lesser extent, on the cross-price elasticity. Consequently, the degree of error caused by the IIA simplification is likely to be very low.

Our primary interest in estimating these equations lies in obtaining price and marketing elasticities. Elasticities are derived from the MNL model by finding the derivative of the share function in price (marketing) and multiplying by the ratio of price (marketing capital) to the mean share. The resulting expressions are given by:

$$\epsilon_{p_j} = (\partial S_j / \partial p_j)(p_j / S_j) = \alpha \bar{p_j}(1 - \bar{S}_j),$$

in price, and:

$$\epsilon_{A_{jl}} = (\partial S_j / \partial A_l)(\bar{A}_l / \bar{S}_j) = \gamma_l \bar{A}_l (1 - \bar{S}_j)$$

in marketing capital. Evaluating each elasticity specific to each product type provides valuable information on the differential effect of price changes and marketing investments on sales of each type of mushroom product. These response parameters form the key input to the profit calculation model described below.

The stock of marketing capital in the RPL demand model is estimated using a polynomial inverse lag (PIL) process. Formally, a PIL process for an advertising variable A_{jt} of type j in time period t is given by:

$$\sum_{i=1}^{\infty} w_{ji} A_{jt-i},$$

where i is the number of lag periods (time periods in the past that may have an impact on current demand and w_{ji} are lag-weights, or the relative importance of advertising on demand at each lag. The lag-weights are defined as:

$$w_{ji} \;=\; \sum_{k=2}^{n} \frac{\phi_{jk}}{(i \;+\; 1)^k}`, \;\; i \;=\; 0, 1, 2, ...\infty,$$

where k is the order of the polynomial in the lagged-effects, or the degree to which advertising has a humped relative to a constant-decline effect over time, and ϕ_{jk} are parameters to be estimated. Substituting the expression for the lag-weights into the previous expression provides a new variable that can be easily calculated for each polynomial order k:

$$Z_{jkt} \;=\; \sum_{i=0}^{t-1} \frac{A_{jt-i}}{(i \;+\; 1)^k}`, \;\; j \;=\; 2, 3, ...n,$$

plus a remainder term that can be ignored for lag-lengths greater than 8. As a result, the final model of demand can be estimated as:

$$q_t \;=\; \sum_{l`=`1}^{L} \beta_l X_{lt} \;+\; \sum_{j=1}^{J} \sum_{k=2}^{n} \phi_{jk} Z_{jkt} \;+\; \mu_t,$$

where X_{lt} is a set of l other variables that are thought to be important to mushroom demand such as prices, seasonal effects, price promotions, yearly-effects or choice-specific preferences. The model is easily estimated by estimating different versions for each polynomial order and choosing the one that provides the best fit. Using the parameters estimated above, we calculate the implied advertising effect over time. That is, because an investment in some form of advertising has an impact both in the current year and in all future years, we calculate the impact in each year using the PIL model. Short term demand effects are thus defined as occurring within the first 1 - 3 months, while long-term effects last for up to 40 months.

Appendix 2. Returns Calculation

This appendix describes the way in which we will calculate the increment to total grower profit given the impact parameters estimated according to the procedure described above. This model is similar to one used in Richards and Patterson (2000) and was originally developed by Kinnucan et al. (2000). To calculate profit, the analysis takes into account: (1) the activity impact on demand quantity (retail or foodservice), (2) the impact on price, (3) the feedback effect of higher prices on market supply, and (4) the transmission of retail prices to the grower level. Although the final solution consists of a single equation, the model requires separate components for each element (1) to (4). Again in mathematical terms, this model, written in terms of the change in the log of each variable value, appears as:

$$\begin{aligned} d\ln \mathbf{Q_r} &= \mathbf{N_r} d\ln \mathbf{P} + \mathbf{G} d\ln \mathbf{Z_r} + \sum \mathbf{B_j} d\ln \mathbf{A_j} \\ d\ln \mathbf{X} &= \mathbf{E_s} d\ln \mathbf{W} \\ d\ln \mathbf{W} &= \mathbf{T} d\ln \mathbf{P} \\ w_r d\ln \mathbf{Q_r} &= d\ln \mathbf{X}, \end{aligned}$$

where the first equation represents the effect of marketing investments on demand, the second is the effect on output supply, the third measures the rate of price-transmission from retail to the farm-gate, and the fourth is the market equilibrium identity. Each equation is then substituted into market equilibrium to solve for the resulting price impact of the marketing program:

$$d\ln \mathbf{P} = \mathbf{M}^{-1} \mathbf{G} d\ln \mathbf{Z_r} + \sum \mathbf{M}^{-1} \mathbf{B_j} d\ln \mathbf{A_j},$$

Given this change in prices, the addition to profit is then calculated as:

$$d\pi \;=\; \sum_i S_i^f P_i Q_i d\ln W_i (1 \;+\; 0.5 d\ln X_i),$$

where the subscript indicating activity 1 has been suppressed for clarity. Each of the variables and parameter values are defined as follows: $\mathbf{W}$ = variables representing FOB (grower) prices for each product, $\mathbf{X}$ = variables representing supplies of each product, $\mathbf{P}$ = variables representing market prices, $\mathbf{Q_r}$ = variables representing retail and food service quantities, w_r = share of market in retail or food service, S_{if} = growers share of the retail dollar for the i^{th} product type, $\mathbf{Z_r}$ and $\mathbf{Z_x}$ = factors affecting demand in retail and food service markets, $\mathbf{A_j}$ = variable representing marketing activity j, $\mathbf{N_r}$ and $\mathbf{N_x}$ = groups of retail and import demand price-response terms, $\mathbf{B_j}$ = response measures for the k^{th} type of activity, $\mathbf{T}$ = price-transmission elasticities (percent of price going to grower), $\mathbf{G}$ = demand elasticities with respect to exogenous retail factors, E_s = supply response elasticities, $\mathbf{M} \;=\; \mathbf{E_s}\mathbf{T} - w_r \mathbf{N_r}$ = solution for the change in price variable. While values for most of these variables are estimated in the relevant demand model, the supply-response elasticities, price-transmission elasticities and growers share of the retail dollar are not. First, reliable estimates of the elasticity of supply are difficult to come by and are not estimable with the data at hand. Therefore, we calculate the return to each marketing activity under a range of supply elasticities from 0.25 to 1.5. Based on previous research for other commodities, however, it is determined that a supply elasticity of 1.0 in the long run is the most likely. This means that a 10 percent increase in the grower price is likely to lead to a long run increase in the supply of mushrooms of 10 percent. Second, the price-transmission elasticity is calculated using the formula in Gardner (1975) as:

$$\mathbf{T} = \frac{\mathbf{E_b}}{S_f \mathbf{E_b} + (1 - S_f)\mathbf{E_s}},$$

where E_b is the elasticity of supply of non-farm inputs, which is assumed to equal 1.5. Third, ERS-USDA reports the farm share of the retail dollar for all vegetables as 0.255, so we adopt this value as an approximation to the share earned by mushroom growers. This model, while appearing quite complicated, is easily implemented with any spread sheet or data base software. Based on the incremental profit calculated in the model above, the net present value of investment in activity l is calculated as:

$$NPV_l = \sum_{t=1}^{40} \exp(-rt) d\pi_l - c_l,$$

where $\exp(-rt)$ is the present value factor that is used to calculate the present value of incremental operating in month t at time 0 at a discount rate r, c_l is the amount of expenditure on activity l and summing over a forty month period reflects the assumed long-range planning horizon of the Council. If NPV_l is greater than zero at an interest rate that reflects MC members opportunity cost of capital, then investments in activity l are economically viable.

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