Evaluation of Grower-Funded Activities by the Mushroom Council

Final Project Report Prepared for the

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by

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Executive Summary

- The U.S. mushroom market has been volatile over the past five years (CY 2006 - CY 2010). According to USDA data, the per capita consumption of mushrooms of all forms in the U.S. fell over most of this period, recovering slightly in 2010. Grower prices, on the other hand, rose significantly. While lower consumption may be due to higher prices, more careful analysis is required as there are many factors that influence both output and prices.

- In 2006, the Mushroom Council resumed marketing activities after a Supreme Court imposed hiatus of some five years. The Mushroom Council is actively involved in retail promotion activities, consumer and nutrition research and foodservice promotion.

- 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 for the period 9/2006 - 10/2010. Council records (prepared by Edelman) provide monthly data on impressions in three categories of activity: retail, consumer and nutrition and foodservice. Budget amounts for each of these three 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 values for four different demand drivers: (1) price, (2) retail marketing, (3) consumer and nutrition marketing, and (4) foodservice marketing. 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 -1.131 on average over all mushroom types and varieties. In other words, if the retail price rises by 10%, demand is expected to fall by 10.24%. Our estimate is higher 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 0.034, while it is 0.089 for consumer and nutrition marketing, and 0.008 for foodservice activities in the retail market. Long-run marketing elasticities are: 0.246 for retail activities, 0.676 for consumer and nutrition activities and 0.126 for foodservice messages.

- 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 2.517 ($2.517 in profit for each $1.00 invested) and 18.321 in the long run. The BCR for consumer and nutrition marketing is 0.658 in the short-run and 4.987 in the long-run. A BCR less than 1.0 implies a negative rate of return in the short run. Foodservice marketing provides a short-run BCR of 0.607 and a long-run BCR of 9.367. Clearly, all forms of communication are profitable in the long run.

- The volume of mushrooms in foodservice was calculated as the difference between total shipments (from Council data) and the IRI retail movement. Foodservice demand was estimated as a function of lagged demand, prices, marketing impressions (retail, consumer and nutrition and foodservice 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 -0.686 in the short run and -3.726 in the long run. All estimated parameters were statistically significant. The elasticity with respect to retail marketing is 0.035 in the short run and 0.199 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 0.212 elasticity in the long run. Aggregate mushroom demand elasticity with respect to foodservice marketing activity is 0.058 in the short run and 0.321 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 0.967 in the short run, and a BCR of 5.349 in the long run. Consumer and nutrition marketing has a BCR of 0.256 in the short run, and 1.414 in the long run, while foodservice marketing has a BCR of 0.530 in the short run and 2.934 in the long run. As in the retail market, all marketing activities are profitable in the long run as they provide returns greater than Council members' likely opportunity cost of capital (approximately 7.0%).

- Future evaluations would be improved by continuing and refining the process of data acquisition and recording. Investments in gathering market intelligence are inherently difficult to quantify, and yield returns only in the long run.

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Introduction

Despite a recent upturn in demand, mushroom consumption has been trending modestly downward over the five year period from 2005 - 2010 (figure 1). While this would seem to suggest that demand over this period has been stagnant or declining, upon closer inspection retail prices for mushrooms (agaricus) have risen sharply (figure 2). Consequently, it is not possible to assess whether the apparent decline in demand is due to higher prices, consumer preferences shifting away from mushrooms, or if mushroom marketing efforts simply have not been effective in recent years. The question this study seeks to answer is: "Where would mushroom consumption and prices be – both today and in the future – without the marketing activities of the Mushroom Council?" 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.

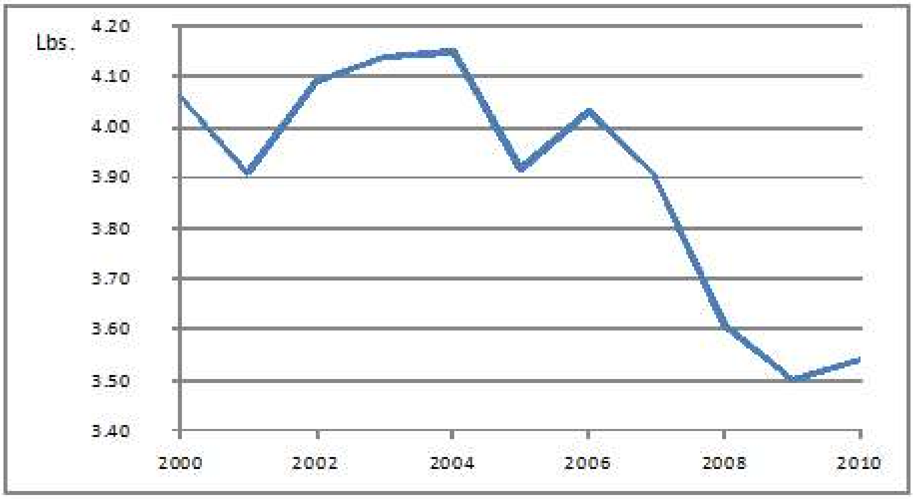

Figure 1 Mushroom Consumption, Lbs. per Capita, 2000 - 2010
Source: USDA, Economic Research Service. Note: 2010 estimated.

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 doesn't, 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.

Research Problem

In order to ensure that this analysis represents more than due diligence under the FSRIA, in this report we describe a set of models, datasets and empirical results that will help Council managers continue to make effective and efficient use of grower check-off funds. Specifically, we conduct an econometric evaluation of the return on investment to Council retail marketing, consumer and nutrition research, and foodservice activities and report our findings herein.[1]

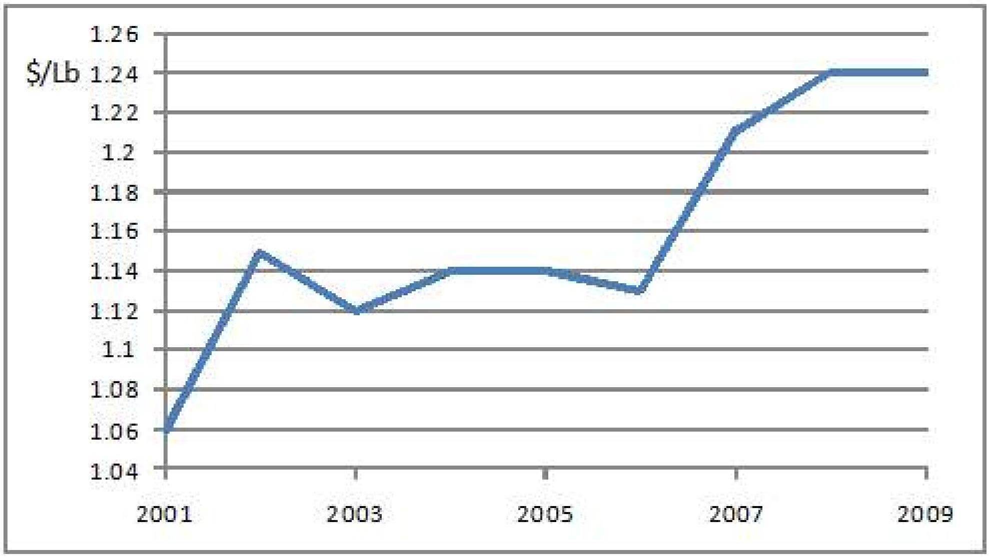

Figure 2 Mushroom Grower Prices: 2001 - 2009
Source: USDA, Economic Research Service

Objectives

The primary objective of this research is to estimate the long-run return on growers' investment in each marketing activity since the MC resumed operations in 2006. In achieving this objective, our research encompasses a number of intermediate objectives. They are:

• to estimate the long-run impact of Council retail marketing, consumer and nutrition research, and foodservice activities on the retail and foodservice demand for all major mushroom

[1] Throughout this proposal, the terms "marketing" and "research" activities are used to describe in general terms the entire set of MC activities, which are understood to be much broader in scope than traditional advertising and promotional efforts. Developing retail promotion programs, building public relations, industry outreach, internet and social network strategies and supporting product research and other activities are assumed to fall within these broad definitions.

varieties using a variety of econometric modeling techniques applied to scanner and shipment data;

• to determine the long-run impact of Council retail marketing, consumer and nutrition research, and foodservice 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, our study uses a combination of publicly available grower price data (USDA-NASS), as well as several sources of demand data collected by the Council: IRI supermarket scanner data, Mushroom Council shipment data, Edelman marketing intensity (impressions) data and other relevant data on input prices and aggregate demand factors from the 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 impression and budget data used in this analysis.

Table 1. Average Monthly Impressions / Budget, by Activity Category: 2006 - 2010

	Retail	**Consumer / Nutrition**	**Foodservice**
Impressions ('000)	241	59,133	609
Budget ($)	$8,753	$75,408	$36,344

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 three demand models estimated pursuant to the goals described above: (1) a variety-specific retail demand model, (2) an aggregate retail demand model, and (3) a foodservice demand model. In the following section, we describe how these demand estimates are used to calculate incremental profit, and return on investment.

Retail Demand for Mushrooms

The first model is a random-parameters logit (RPL) model defined over all different varieties and conventional / organic with three types of advertising impressions used as exogenous shifters. Random parameter, or mixed, logit models have become the standard method of analyzing the demand for differentiated products using highly detailed scanner data. These models recognize that the demand for individual products – whether they are brands, varieties or even different sizes of the same brand – cannot usefully be aggregated into a category total because the factors that drive product-specific demand are unique. RPL models are readily amenable to the analysis of advertising effects because the underlying assumption is that demand for differentiated products is driven by their attributes, and one key attribute is the amount of marketing expenditure used to support demand. In this model, the other attributes include price promotion (defined as the percentage reduction in price from one period to the next), seasonality (a set of 12 monthly dummy variables) and a trend variable designed to capture any variety-specific changes in demand. One of the most important advantages of a RPL model is the ability to estimate observation-specific demand elasticities. That is, traditional demand models provide only a single demand-elasticity estimate, but an RPL model is capable of generating variety-specific, market-specific, even week-specific elasticity estimates. This is valuable for marketing-planning on a micro-scale.

The variables included in this model are determined based on economic principles of consumer demand and include prices, advertising, promotion, seasonal effects and annual effects. There are many ways in which the effect of advertising can be modeled. There are, however, 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, it is not appropriate to simply model the contemporaneous effect of advertising on demand. 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. Third, advertising expenditure is generally a poor measure of effort. Expenditure values are generally used because researchers do not have access to a better measure of the intensity of marketing activity. Fourth, marketing expenditures are generally targeted to many different media, markets or purposes. For this study, we employ solutions that reflect each of these economic principles of advertising.

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_{jt} 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, and food service) 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. We modeled retail price discounts by including a binary variable that equals 1 when the price for a particular product falls by more than 10% from one month to the next, and rises back at least to its previous level the following month. This captures the "shift effect" of price promotions and is intended to capture trade promotion activities administered by mushroom suppliers. We also include an interaction effect between the binary promotion variable and the shelf price. This variable captures the expectation that promotion also "rotates" the demand curve, or makes it less elastic during promotion periods. However, neither of these variables proved to be statistically significant in the final model, so were excluded. Given that the IRI data are aggregated over stores, and over weeks (when promotion decisions are typically made) it is perhaps not surprising that the price promotion variable does not appear to be statistically significant. In more detailed data – weekly and at the store level – these variables are typically very significant.

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 include two variables: a monthly indicator variable (January = 1, February = 2, and so on) and its square. This allows for a polynomial, or cyclical, seasonal effect, which is appropriate given the pattern evident from the data.

Aggregate Retail Demand Model

The second model aggregates movement and sales from the IRI retail data over all mushroom varieties from 2006 - 2010. Because the Council is interested in the sales of all mushroom varieties, and not just whites, this model attempts to more nearly approximate Council objectives. However, standard models of demand perform poorly, that is, metrics of fit are not acceptable, price-parameters are of the wrong sign and none of the marketing activities appeared to have a significant effect on demand. Poor fit is due to the aggregation issues discussed above. Upon inspecting the price series, it is apparent that the problem derives from the fact that much of the variation in the aggregate price series comes from variation in composition by varieties. Aggregating across varieties, moreover, is not a viable solution as a pound of whites is an entirely different thing from a pound of shiitakes or portabellas. The dominance of whites in the fresh mushroom market is clear from the IRI data, as the share of whites in the aggregate mushroom market for each variety over the 2006 - 2010 analysis period is typically greater than 75%. Therefore, we re-estimated this model using whites only. Because the fit did not improve, we retain only the variety-level RPL model described above for estimating the impact of Council activities on retail sales.

Foodservice Demand

We estimated a third 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. 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 develop 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.[2] 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 rather 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 the Agricultural Marketing Service (AMS) of the USDA. Because there are many varieties of mushrooms purchased for foodservice uses, we construct a value-weighted index over the grower prices of all varieties to establish a benchmark wholesale price index 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

[2] Although the IRI data measures only retail sales from stores > $2.0 m in sales, and excludes stores that do not participate in either IRI or Nielsen data syndication efforts (CostCo, Wal*Mart and Target, most importantly) retail sales from IRI should correlate very highly with total retail movement.

for the diminishing marginal returns to marketing investments by taking the square root of each type of impression. We again use retail marketing, consumer and nutrition and foodservice marketing definitions for the 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 RPL model above, 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 return 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.[3] 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

[3] A present value is simply the amount that someone would pay today for the right to receive a stream of payments extending a number of years into the future. Because one dollar in the future is worth less than one dollar today (that dollar today can be invested to earn interest), the present value of a stream of profit is less than the sum over the whole time period.

"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 over a range of supply elasticities.

Results and Discussion

Demand Models

Retail demand was estimated using a RPL econometric model. We summarize the elasticity estimates in this section and provide the estimation details in table A1 in the appendix below. Because the aggregate model performed poorly in the IRI data, we report only the variety-specific results here. Among all the parameter estimates reported in table A1, those of primary interest are the price and marketing effects. The parameters of the RPL model, and particularly the PIL extension, cannot be interpreted directly as elasticities, so we calculate the elasticities before estimating the returns model. Most importantly, the price elasticity is approximately -1.13, 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. 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. With respect to each marketing capital measure, we find a short-run elasticity with respect to retail marketing of 0.034, and a long-run elasticity of 0.246. These estimates mean that a 10% increase in retail marketing can be expected to lead to a 0.34% increase in retail mushroom volume in the short run and a 2.46% increase in the long run.

While these elasticities may appear to be small, they are best put into context by examining their implications for the famous "Dorfman-Steiner" rule, which specifies the optimal advertising intensity ratio (advertising dollars as a percentage of sales) as a function of the advertising and demand elasticities. By the Dorfman-Steiner rule, an advertising elasticity of 0.246 implies that a firm should invest fully 21.7% of sales in marketing. This is considerably higher than is currently the case in the mushroom industry. Second, we find that the short run elasticity of consumer and nutrition marketing is 0.089 and the long run elasticity is 0.676. Clearly, both of these elasticities are higher than with respect to retail marketing and speak to the outsize impact of investments in this area. Third, the short run elasticity with respect to foodservice marketing, which can be interpreted as a "spillover effect" onto retail sales, is 0.008 in the short run and 0.126 in the long run. While smaller than either of the other two elasticities, these values are both positive, and statistically significant in our demand model.

On a more technical level, the results in table A1 show the superiority of the RPL model over other alternatives. Specifically, the fact that each of the "standard deviations of the random parameters" are statistically different from zero means that the consumer heterogeneity captured by the RPL model is important and cannot be ignored. Further, these parameters suggest that the RPL model is also preferred to either a simple logit model or a nested alternative. Finally, the fact that the aggregate model did not produced results that made sense shows that a more comprehensive modeling tool is necessary for this task.

Unlike retail mushroom demand, foodservice demand was found to be inelastic with respect to mushroom prices (table A2). The short run price elasticity of demand is -0.686 and the long run price elasticity is -3.726. Finding a long run elasticity that is many times larger than the short run elasticity is due to the fact that the rate of adjustment over time (one minus the coefficient on lagged quantity) is only 0.182, which means that quantity demanded adjusts to its long run equilibrium value only 18.2% per year. For marketing purposes, however, it is the short run elasticity that matters as markets are always in a state of fluctuation and price changes in one month are nearly always superceded 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 0.035 and a long run elasticity of 0.199. Consumer and nutrition marketing, on other hand, has a very similar impact on foodservice demand as the short run elasticity is 0.039 and the long run elasticity 0.212. 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 0.058 and a long run elasticity of 0.321. 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. 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 Calculation

As explained above, we calculate present values 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 impacts. 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. We report most-likely values in table 2 and leave the sensitivity analysis for other supply elasticities to tables in the appendix (tables A3 and A4). As is clear from the results shown in tables A3 and A4, returns fall as the elasticity of supply rises. This is because higher prices elicit more supply, which moderates the equilibrium price increase and, hence, incremental profit.

Table 2. Benefit:Cost Ratios (BCR) for Retail and Foodservice Markets

Short Run BCRs:	Retail	Consumer/Nutrition	Foodservice
Retail Market	2.517	0.658	0.607
Foodservice Market	0.967	0.256	0.530
Long Run BCRs:			
Retail Market	18.321	4.987	9.367
Foodservice Market	5.349	1.414	2.934

We first discuss the returns to Council marketing activities into the retail mushroom market. These results are summarized in table 1 below. Activities targeted toward retail sales generate a range of returns in the short run from a BCR of 6.977 (ROI = 597.7%) when the elasticity of supply is assumed to be 0.25 to 1.765 (ROI = 76.5%) when the elasticity of supply is 1.5. A BCR of 6.977 means that for the next dollar spent on retail marketing, the present value of the stream of incremental profit from doing so is $6.977. The most likely value, which is associated with a supply elasticity of 1.0, is 2.517 (ROI = 151.7%). Retail marketing is clearly highly profitable in this market, even in the short run. In the long run, the range of BCRs is from 50.689 (ROI = 4,968.9%) for an elasticity of supply of 0.25 to 12.850 (ROI = 1,185.0%) when the elasticity of supply is 1.50, with a most-likely value of 18.321 (1,732.1%). With respect to consumer and nutrition marketing, the expected BCR is 0.658 (-34.2%) in the short-run, with a range from 1.825 (ROI = 82.5%) when supply is inelastic to 0.462 (ROI = -53.8%) for elastic supply. In the long run, the most likely BCR is 4.987 (ROI = 398.7%), so although consumer and nutrition marketing does not appear to be profitable in the short run, it most certainly is in the long run. Because it is assumed that most growers are in the industry for the long term, it could be argued that this is the only relevant returns metric. With respect to the spillover effects from foodservice marketing into the retail market, we find a range of short run BCRs from 1.682 (ROI = 68.2%) for a low supply elasticity to 0.425 (ROI = -57.5%) when the elasticity of supply is relatively high, with a most likely value of 0.607 (ROI = -29.3%). In the long run, the range is from 25.943 (ROI = 2,494.3%) to 6.569 (ROI = 556.9%) with an expected value of 9.367 (ROI = 836.7%). Clearly, all forms of communication in the retail market are profitable in the long run.

In the foodservice market, marketing communications – impressions – are expected to have their greatest impact when targeted to restaurant and institutional food buyers. However, foodservice marketing has an expected BCR of 0.530 (ROI = -47.0%) in the short run (ranging from 1.575 to 0.368), while retail impressions have a BCR of 0.967 (ROI = -3.3%, ranging between 2.871 and 0.670) for a dollar invested in the short run. In the short run, therefore, retail marketing generates a higher return in the foodservice market, but both activities have significantly negative returns. In the long run, however, foodservice marketing generates a BCR of 2.934 (ROI = 193.4%) for a dollar invested (range of 8.695 to 2.035) while retailing marketing returns between 15.850 and 3.710 with a 5.349 (ROI = 434.9%) long run BCR. Consequently, both foodservice and retail marketing are again highly profitable in the long run. The same can be said of consumer and nutrition marketing. In the short run, the expected BCRs range from 0.759 to 0.177 with a most likely value of 0.256 (ROI = -74.4%). Over time, however, the BCR for consumer and nutrition marketing is expected to be 1.414 (ROI = 41.4%) for a dollar invested in the long run, ranging between 4.191 and 0.981. All categories of marketing investment, therefore, generate positive returns over the long run.

In summary, we find that most 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 retail marketing, consumer and nutrition programs, and foodservice promotion.

Conclusions and Implications

Following the Supreme Court imposed retreat from actively marketing mushrooms in the U.S., the Mushroom Council restarted its marketing programs in 2006. This study uses data from the 2006 - 2010 period to investigate the return on investment for grower-shipper dollars invested in all Council marketing activities: retail marketing, consumer and nutrition research and foodservice marketing. Although aggregate mushroom consumption fell slightly over this period, retail prices were also significantly higher. Therefore, the 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 three types of activities defined by Council staff, we find that retail marketing is significantly more profitable than either consumer and nutrition research or foodservice marketing. In retail markets, retail marketing generates a long run BCR of 18.320 and 5.350 in foodservice markets. In both markets, this is nearly twice as profitable as the next-closest alternative. In the long run, however, all activities are highly profitable.

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. 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. 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 and foodservice 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 (Anderson, dePalma and Thisse 1992; 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:

$$u_{hj} = v_{hj} + \varepsilon_{hj} = \beta_{0j} + \sum_k \beta_{1k} x_{jk} + \sum_l \gamma_l f(A_l) - \alpha p_j + \xi_j + \varepsilon_{hj}, \qquad \textbf{(1)}$$

where v_{hj} is the deterministic component of utility, β_{0j} is the maximum willingness to pay for mushrooms of type or variety *j*, p_j is the retail price of product *j*, $\mathbf{x}_j$ 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, $f(A_l)$ 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:

$$Pr(j = 1) = Pr(v_{hj} + \varepsilon_{hj} > v_{hi} + \varepsilon_{hi}) = Pr(v_{hj} - v_{hi} + \varepsilon_{hj} > \varepsilon_{hi}). \qquad \textbf{(2)}$$

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

$$S_j = \frac{\exp\left(\beta_{0j} + \sum_k \beta_k x_{kj} + \sum_l \gamma_l f(A_l) - \alpha p_j + \xi_j\right)}{1 + \sum_{i=1}^{J} \exp\left(\beta_{0i} + \sum_k \beta_k x_{ki} + \sum_l \gamma_l f(A_l) - \alpha p_i + \xi_i\right)}, \qquad \textbf{(3)}$$

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 (7) 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 (7) 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:

$$\varepsilon_{p_j} = (\partial S_j / \partial p_j)(p_j / S_j) = \alpha \bar{p}_j (1 - \bar{S}_j), \qquad \textbf{(4)}$$

in price, and:

$$\varepsilon_{A_{jl}} = (\partial S_j / \partial A_l)(\bar{A}_l / \bar{S}_j) = \gamma_l \bar{A}_l (1 - \bar{S}_j), \qquad \textbf{(5)}$$

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:

$$\sum_{i=1}^{\infty} w_{ji} A_{jt-i}, \qquad \textbf{(6)}$$

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, ii. The lag-weights are defined as:

$$w_{ji} = \sum_{k=2}^{n} \frac{\varphi_{jk}}{(i+1)^k}, \quad i = 0, 1, 2, \ldots \infty, \qquad \textbf{(7)}$$

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 in (7) into (6) provides a new variable that can be easily calculated for each polynomial order *k*:

$$Z_{jkt} = \sum_{i=0}^{t-1} \frac{A_{jt-i}}{(i + 1)^k}, \quad j = 2,3,\ldots n, \tag{8}$$

plus a remainder term that can be ignored for lag-lengths greater than 8.[4] As a result, the final model of demand can be estimated as:

$$q_t = \sum_{l=1}^{L} \beta_l X_{lt} + \sum_{j=1}^{J} \sum_{k=2}^{n} \varphi_{jk} Z_{jkt} + e_t, \tag{9}$$

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 (see figure 4). 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.

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[4] Mitchell and Speaker (1986) suggest removing the first eight observations from the calculation to avoid introducing bias should this remainder term not be small in fact.

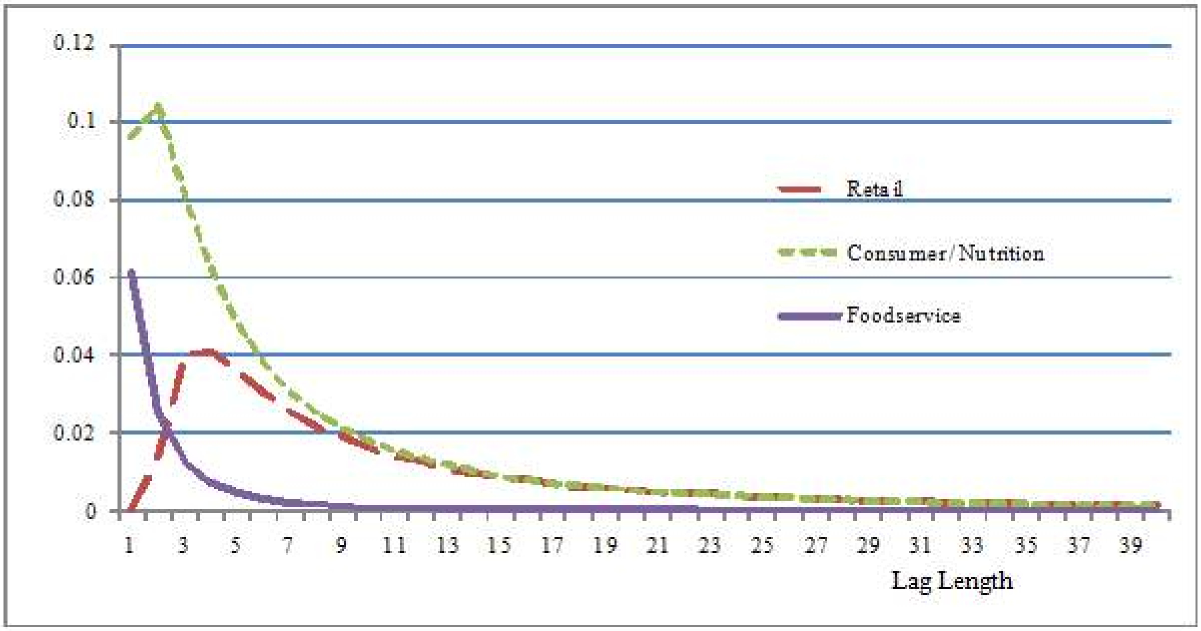

Figure 3 Lag Weights in PIL Model: Retail, Consumer / Nutrition and Foodservice Marketing Activities
Source: model estimates

Appendix 2. Returns Calculations

This appendix describes the way in which we will calculate the increment to total grower profit given the impact parameters estimated in equation (2) above. This model is similar to one used in Richards and Patterson and was originally developed by Kinnucan et al. To calculate profit, the analysis takes into account: (1) the activity impact on demand quantity (retail or food service), (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:

$$\begin{aligned} \text{Market Demand:} \quad & d\ln \boldsymbol{Q_r} = \boldsymbol{N_r} d\ln \boldsymbol{P} + \boldsymbol{G} d\ln \boldsymbol{Z_r} + \boldsymbol{B_1} d\ln \boldsymbol{A_1} + \boldsymbol{B_2} d\ln \boldsymbol{A_2}; \\ \text{Farm Supply:} \quad & d\ln \boldsymbol{X} = \boldsymbol{E_s} d\ln \boldsymbol{W}; \\ \text{Price Transmission:} \quad & d\ln \boldsymbol{W} = \boldsymbol{T} d\ln \boldsymbol{P}; \\ \text{Market Equilibrium:} \quad & \boldsymbol{w_r} d\ln \boldsymbol{Q_r} = d\ln \boldsymbol{X}. \end{aligned} \tag{10}$$

Each equation is then substituted into market equilibrium to solve for the resulting price impact of the marketing program:

$$d\ln \boldsymbol{P} = \boldsymbol{M}^{-1}\boldsymbol{G}\,d\ln \boldsymbol{Z_r} + \boldsymbol{M}^{-1}\boldsymbol{B_1}\,d\ln \boldsymbol{A_1} + \boldsymbol{M}^{-1}\boldsymbol{B_2}\,d\ln \boldsymbol{A_2}, \qquad \textbf{(11)}$$

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

$$d\pi = \sum_i S_i^f P_i Q_i\, d\ln W_i (1 + 0.5\, d\ln X_i). \qquad \textbf{(12)}$$

where the subscript indicating activity *l* has been suppressed for clarity. Each of the variables and parameter values are defined as follows:

$\boldsymbol{W}$ = variables representing FOB (grower) prices for each product;
$\boldsymbol{X}$ = variables representing supplies of each product;
$\boldsymbol{P}$ = variables representing market prices;
$\boldsymbol{Q_r}$ = variables representing retail and food service quantities;
$\boldsymbol{w_r}$ = share of market in retail or food service;
S_i^f = grower's share of the retail dollar for the i^{th} product type;
$\boldsymbol{Z_r}$ and $\boldsymbol{Z_x}$ = factors affecting demand in retail and food service markets,
$\boldsymbol{A_1}$ = indicator variable for marketing activity 1;
$\boldsymbol{A_2}$ = indicator variable for marketing or research activity 2;
$\boldsymbol{N_r}$ and $\boldsymbol{N_x}$ = groups of retail and import demand price-response terms;
$\boldsymbol{B_k}$ = response measures for the k^{th} type of activity;
$\boldsymbol{T}$ = price-transmission elasticities (% of price going to grower);
G = demand elasticities with respect to exogenous retail factors,
$\boldsymbol{E_s}$ = supply response elasticities;
$\boldsymbol{M} = \boldsymbol{E_s T} - \boldsymbol{w_r N_r} - \boldsymbol{w_x N_x}$ = 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% increase in the grower price is likely to lead to a long run increase in the supply of mushrooms of 10%. Second, the price-transmission elasticity is calculated using the formula in Gardner (1975) as:

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

where $\boldsymbol{E_b}$ 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 (12), the net present value of investment in activity *l* is calculated as:

$$NPV_l = \sum_{t=1}^{40} e^{-rt} d\pi_l - c_l, \qquad \textbf{(15)}$$

where e^{-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.

Table A1. Random Coefficient Logit Demand Model

Variable	Estimate	t-ratio	Means for Random Parameters		
Black Forest - Conv.	-13.310	-45.980	Retail Price	-0.086	-7.253
Chant - Conv.	-9.818	-43.963	Retail Mkt.	2.922	1.276
Cremini - Conv.	-3.240	-4.785	Retail Mkt.	-11.193	-1.498
Cremini - Org.	-7.416	-13.320	Retail Mkt.	8.415	1.572
Enoki - Conv.	-9.607	-24.256	Cons / Nut	0.028	1.980
Morel - Conv.	-10.450	-51.398	Cons / Nut	-0.069	-1.431
Other - Conv.	-6.768	-12.483	Cons / Nut	0.043	1.231
Other - Org.	-11.984	-49.986	Foodservice	-0.056	-0.054
Oyster - Conv.	-7.567	-14.415	Foodservice	-0.800	-0.220
Oyster - Org.	-13.827	-73.136	Foodservice	0.842	0.321
Porcini - Conv.	-6.733	-9.663	**Standard Deviations for Parameters**		
Portabella - Conv.	-3.933	-15.555	Price	0.011	6.476
Portabella - Org.	-6.163	-20.614	Retail Mkt.	0.239	3.823
Shiitake - Conv.	-5.757	-6.776	Retail Mkt.	0.117	1.727
Shiitake - Org.	-8.979	-23.220	Retail Mkt.	0.068	1.147
White - Conv.	-1.729	-2.513	Cons / Nut	0.001	3.118
White - Org.	-5.266	-8.195	Cons / Nut	0.146	0.071
Wood Ear - Conv.	-10.406	-23.949	Cons / Nut	0.002	5.242
Time Period	-0.098	-2.718	Foodservice	0.027	1.971
Time Period Squared	0.008	3.185	Foodservice	0.164	5.788
			Foodservice	0.044	2.323

Elasticity Estimates

Short Run		Long Run	
Price	-1.131	Price	-1.131
Retail Marketing	0.034	Retail Marketing	0.246
Consumer / Nutrition	0.089	Consumer / Nutrition	0.676
Foodservice Mktg.	0.008	Foodservice Mktg.	0.126

Goodness of Fit Measures

LLF	-338.180	σ	0.364	12.972

Table A2. Foodservice Demand Model: Dependent Variable = Quantity

Variable	Estimate	t-ratio
Constant	41.488*	2.622
Lagged Quantity	0.818*	8.991
Retail Marketing	4.631*	2.744
Consumer / Nutrition	0.269*	2.165
Foodservice	4.217*	2.759
Price	-9.349*	-2.234
R^2	0.205	

Elasticities	
Short Run	
Price	-0.686
Retail Marketing	0.035
Consumer / Nutrition	0.039
Foodservice	0.058
Long Run	
Price	-3.726
Retail Marketing	0.199
Consumer / Nutrition	0.212
Foodservice	0.321

Note: A single asterisk indicates significance at a 5.0% level.

Table A3. Benefit:Cost Ratios (BCR) for Retail Market

Short Run BCRs:		Retail	Consumer/Nutrition	Foodservice
	0.25	6.977	1.825	1.682
Elasticity	0.50	4.386	1.147	1.057
of	0.75	3.199	0.837	0.771
Supply	1.00	2.517	0.658	0.607
	1.25	2.075	0.543	0.500
	1.50	1.765	0.462	0.425

Long Run BCRs:		Retail	Consumer/Nutrition	Foodservice
	0.25	50.689	13.819	25.943
Elasticity	0.50	31.901	8.689	16.318
of	0.75	23.275	6.337	11.902
Supply	1.00	18.321	4.987	9.367
	1.25	15.105	4.111	7.722
	1.50	12.850	3.497	6.569

Table A4. Benefit:Cost Ratios (BCR) for Foodservice Mushroom Market

Short Run BCRs:		Retail	Consumer/Nutrition	Foodservice
	0.25	2.871	0.759	1.575
Elasticity	0.50	1.733	0.458	0.951
of	0.75	1.241	0.328	0.681
Supply	1.00	0.967	0.256	0.530
	1.25	0.792	0.209	0.434
	1.50	0.670	0.177	0.368

Long Run BCRs:		Retail	Consumer/Nutrition	Foodservice
	0.25	15.850	4.191	8.695
Elasticity	0.50	9.580	2.533	5.256
of	0.75	6.865	1.815	3.766
Supply	1.00	5.349	1.414	2.934
	1.25	4.381	1.158	2.403
	1.50	3.710	0.981	2.035