Returns to Mushroom Council Promotion: 2016 - 2020

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This analysis covers the period 2016 - 2020. The Council is charged by United States Department of Agriculture with conducting a mandated 5-year evaluation of its research and marketing programs to evaluate its effectiveness in the promotion of fresh mushrooms. Mushroom shipments in the U.S. fell slightly over the 2016 - 2020 study period, with shipment volumes some 0.41% lower in 2020 than in 2016. However, prices rose by some 10.12% over the same period, so grower revenue rose substantially. Stable volume and higher prices suggest that active marketing by the Mushroom Council may have played an important role in increasing the total returns to fresh-mushroom growers. However, there are many factors that may explain changes in demand, and pricing, over time so an in-depth, fact-based analysis is necessary to determine the role of Council activities in influencing mushroom-grower returns. In this report, we summarize our findings from the econometric analysis of Council promotion activities.

Executive Summary

- Objective: 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), types (organic or conventional), and preparations (sliced and whole) 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.

- Econometric Modeling: 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.

- Data: All models are estimated with data made available from Council records and include retail scanner data from Fusion Marketing (sourced from IRI retail scanner data) and Council shipment data on a monthly basis over the study period. Council records provide monthly data on impressions in four types of media: Online, print, broadcast, and syndicated advertisements. We also have date on impressions allocated to three thematic-areas: Consumer and nutrition, retail, and foodservice. Budget amounts for each of these four media categories and thematic areas are also taken from Council records and used to measure the amount of investment on a monthly basis.

- Elasticities: For both the retail and foodservice model, we estimate short- and long-run elasticity values for six different demand drivers: (1) price, (2) price-based promotion strategies, (3) online impressions, (4) print media, (5) broadcast messaging, and (6) syndicated promotional activities. We also estimate elasticities, in a separate model for: (1) consumer and nutrition ads, (2) retail-focused ads, and (3) foodservice ads. [1]

- Retail Elasticities: The short-run retail price elasticity of demand in the base, media-focused model is -1.157 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 11.57 percent. Our estimate is slightly smaller (closer to -1.0) than in our previous evaluation report, likely due to higher incomes and stronger economic activity more generally. The short-run elasticity of print impressions is 0.040, while it is 0.065 for online ads, 0.012 for broadcast activities, and 0.001 for syndicated marketing opportunities. Long-run marketing elasticities are: 0.133 for print, 0.215 for online, 0.041 for broadcast impressions, and 0.004 for digital.

- Retail "Channel" Elasticities: When we categorize impressions by channel (consumer and nutrition, retail, and foodservice), we find a short-run retail price elasticity of -1.097, and a long-run retail price elasticity of -3.429.[2] The short-run retail elasticity with respect to consumer and nutrition impressions is 0.026, while it is 0.004 with respect to retail advertising, and 0.001 for foodservice advertising. In the long run, the advertising-elasticity estimates are 0.081 for consumer and nutrition advertising, 0.013 for retail advertising, and 0.003 with respect to foodservice advertising.

- ROI: Return on investment (ROI) is measured using two, equivalent metrics: (1) the benefit:cost ratio (BCR), and (2) return on investment. 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 Media ROIs: We calculate BCR values for each type of marketing media in the retail market. For print advertising, the estimated short-run BCR is 8.541 (8.541 dollars in profit for each 1.00 dollar invested) and 11.673 in the long run. The BCR for online marketing activities is 13.787 in the short-run and 18.843 in the long-run. Broadcast advertising provides a short-run BCR of 2.653 and a long-run BCR of 3.626. Syndicated activities generate a short-run BCR of 0.253 and long-run returns of 0.345. All forms of communication provide positive returns (BCR greater than 1.0), except for syndicated messaging which does not cover its cost in either the short or long-term scenarios.

- Retail Channel ROIs: We also calculate BCR values for each type of marketing-channel in the retail model. In the case of consumer and nutrition messaging, the short-run BCR is 5.755, and the long-run return is 7.881. The BCR for retail advertising is 0.950 in the short run, and 1.302 in the long run, while the BCR for foodservice advertising is 0.234 in the short run and 0.320 in the long run. We find that consumer and nutrition investments provide a positive return in both the short and long runs, while retail marketing is only profitable in the long run, and foodservice advertising is profitable in neither. This is perhaps not surprising as the foodservice demand-enhancement mechanism in the retail market is only indirect, and can only operate through consumers' experiences in restaurants, as mediated by chefs and restaurant purchasers.

[1] 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.

[2] These elasticities differ slightly from the base model as the advertising variables in the model also differ. Changing the model specification can be expected to lead to minor differences in all parameter estimates.

- Foodservice Models: 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, media impressions (online, print, broadcast, and syndicated, in one model, and consumer / nutrition, retail, and foodservice channels, as in the retail model) and yearly dummies. We did not estimate the demand for mushroom types in the foodservice model, due to a lack of data.

- Foodservice Media Elasticities: The average price elasticity of demand in the foodservice market was -0.828 in the short run and -1.113 in the long run. All estimated parameters were highly statistically significant. The elasticity with respect to print impressions is 0.070 in the short run and 0.094 in the long run; online impressions 0.016 in the short run and 0.021 in the long run; broadcast impressions 0.009 in the short run and 0.012 in the long run; and syndicated impressions 0.005 in the short run and 0.007 in the long run.

- Foodservice Channel Elasticities: In the foodservice channel model, we estimated the short-run price elasticity of demand as -0.734, and the long-run price elasticity as -1.039, both of which are very close to the media-based model. The short-run elasticity of demand with respect to consumer and nutrition impressions was estimated to be 0.027 in the short run, and 0.038 in the long run; retail impressions 0.012 in the short run and 0.018 in the long run; and foodservice impressions 0.030 in the short run and 0.043 in the long run.

- Foodservice Media BCRs: BCRs were also calculated for the foodservice market. Print impressions in the foodservice market have a BCR of 5.262 in the short run and 5.974 in the long run; online impressions 1.173 in the short run and 1.332 in the long run; broadcast impressions 0.679 in the short run and 0.771 in the long run; and syndicated impressions 0.379 in the short run and 0.430 in the long run. While print and online impressions appear to add incremental value to Council members, broadcast and syndicated impressions have returns substantially below 0.

- Foodservice Channel BCRs: Using the foodservice channel model, we estimated the BCRs with respect to consumer and nutrition impressions as 2.147 in the short run and 2.512 in the long run; retail impressions 0.983 in the short run and 1.150 in the long run; and for foodservice impressions 2.420 in the short run and 2.832 in the long run. As expected, foodservice impressions have the greatest return in the foodservice channel, but consumer and nutrition impressions remain strongly profitable.

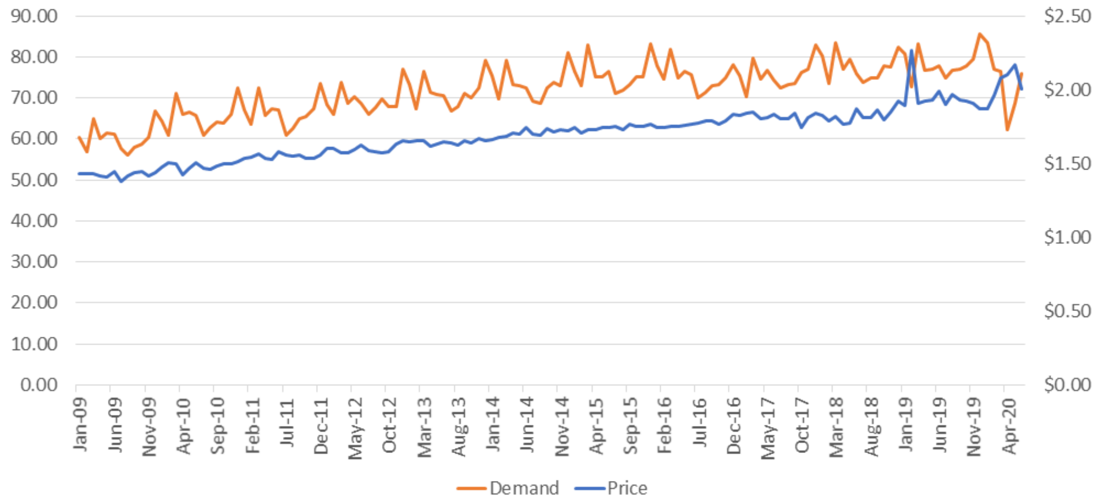
Introduction

Demand, measured as the total volume movement of US mushrooms over the 2016 - 2020 sample period, appears to have been relatively stable (see figure 1). Total US mushroom volume, aggregated over the retail and foodservice channels, rose 4.1% between 2016 and the end of 2019 (the latest full year of data), which is roughly in line with the rate of population growth during the same time period. However, the total value of mushrooms sold increased by 15.5%, due to a 10.1% increase in average prices. Maintaining sales volumes while supporting higher prices suggests that Mushroom Council marketing activities have been successful in a very broad sense of the term.

That said, higher volumes and prices may be due to many other factors that can move commodity markets. Econometric analysis is required to determine where the demand for mushrooms, and their prices, would be without Council marketing activities. In order to estimate the independent effect of Council programs, it is necessary to control for as many other economic variables that change over time as possible. In this report, we explain how we disentangle the effect of Council activities from these other factors, and how we calculate the return on investment implied by our econometric estimates.

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 market-

Figure 1. US Mushroom Demand and Prices
Source: Mushroom Council (million lbs.)



ing organizations every five years. More fundamentally, however, investment and allocation decisions are better informed when the stakeholders know what works and what does not, 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' marketing investments during the period 2016 - 2020. To this end, our research encompasses a number of intermediate objectives. They are:

- To estimate the long-run impact of Council print, online, broadcast, and syndicated marketing activities on the retail and foodservice demand for US mushrooms using econometric modeling techniques applied to scanner and shipment data.
- To determine the long-run impact of Council print, online, broadcast, and syndicated messages, and consumer / nutrition, retail, and foodservice-focused messages, 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.

Our analysis is data-driven, and powered by data from several different sources. Completing the econometric analysis required three different types of primary data: (1) scanner data, in order to measure mushroom sales, by variety, through the retail sales channel, (2) shipment data, from which we subtract retail sales in order to arrive at an estimate of foodservice sales, and (3) impressions, which serve as measures of "marketing intensity," or the relative level of investment in different types of media, or methods of marketing communications. We rely on data from IRI Marketing (via Fusion Marketing) for our scanner data, while we derive shipments and impressions data from Mushroom Council sources. [3] Table 1 below summarizes the impressions data used in the analysis, and demonstrates the extent to which the Mushroom Council focuses on online advertising, relative to other media types. Further, the data in this table also show that Council activities tend to focus on consumer markets, generally with nutrition-based messaging, and much less on either retail or foodservice markets.[4]

In the next section, we describe the specific research methods used in each model and explain the economic logic behind our approach.

Demand Models

Overview

Marketing activities benefit Council members by increasing demand, raising prices, and thereby generating incremental profit on all mushrooms that are sold. Therefore, econometric models of demand lie at the core of any quantitative 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 foodservice 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 Mushroom Demand

The first model provides estimates of 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 2016 through 2020 (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 (merchandising, features, and temporary price discounts), monthly changes in demand, a trend variable, a variable to account for the Covid-19 impact on retail markets in 2020, 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 generated by the marketing materials created by the Council's marketing agency. 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 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.

The dynamic nature of marketing-impacts are important, so we need to be particularly clear how we account for the long-run effects of marketing investments. That is, 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.

Modeling the lagged effects of advertising in a rigorous way 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,

[3] Although we have retail scanner data from January 1, 2015, the Mushroom Council changed marketing agencies in 2016, so we only have comparable impressions data from January 2016 through December 2020.

[4] Note that impressions are in millions per month.

Table 1: *Summary of Impression Data, by Type*

Media Type	Mean	Std. Dev.	Minimum	Maximum
General Print	57.811	27.996	4.205	117.393
General Online	89.370	216.459	0.900	137.614
General Broadcast	21.429	21.435	0.119	96.741
General Syndicated	1.421	10.024	0.000	88.709
Consumer and Nutrition	216.384	235.639	73.419	1,490.313
Retail	0.181	0.165	0.000	0.782
Foodservice	0.152	0.182	0.000	1.043

Note: Values in millions. Source: Mushroom Council records.

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 communication channels (print, online, broadcast, and syndicated).

In the previous analysis, we focused on different message-types (retail, consumer and nutrition, food service, and digital), so we also conducted the analysis with a similar breakout for comparison purposes, although digital impressions were not available as a separate category. Therefore, we estimate the econometric model using impressions as the variable definition and not simple dollar expenditure. Impressions data 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, the amount sold on feature, and the amount sold with any merchandising, so we created promotion proxy variables by calculating the proportion of volume in a given month sold on each type of promotion, relative to total pounds. We expect to find a positive relationship between these variables, and the amount of monthly volume movement.

Retail mushroom demand also differs by geography. Our retail scanner data are broken out by IRI market-region, so we include binary indicators for each. Although we do not have regional measures for each type of marketing impression, accounting for fixed geographical effects allows us to estimate national average marketing elasticities that are not biased by different consumption levels in each region.

The year 2020 was clearly an outlier in terms of the relative proportions of retail and foodservice demand. As figure 1 above shows, and in spite of the importance of the pizza industry to mushroom demand, foodservice mushroom sales collapsed to about 40% of their previous level. By the same token, retail demand for mushrooms exploded as home-bound consumers experimented with many new dishes that included mushrooms. Therefore, we control for the impact of Covid-19 on retail mushroom sales by including a fixed-effect, or binary indicator, for April - June of 2020 to ensure the model does not confuse the spike in retail mushroom sales as an artifact of Mushroom Council promotion activities.

Foodservice Demand

We estimated a second demand model that focused specifically 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, as in the 2016 study, we developed a proxy measure for the total amount of mushrooms flowing into the foodservice market by subtracting out retail sales (from the IRI scanner data) from Council measures of total mushroom shipments. The result is a reasonably accurate measure of what is purchased by foodservice managers. Even if the level of this measure is not perfectly accurate, its variation from month to month should approximate actual foodservice demand very closely.[5]

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, a monthly trend variable, and the measures of marketing activity defined above. As in the retail model, we estimate the returns to media-type and channel-based impression disaggregations. 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 print, online, broadcast, and syndicated impressions as our measures of marketing activity because foodservice buyers may have seen one of each type 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.

The mathematical details of how incremental profit is calculated are provided in the appendix below, but 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 pro-

[5] Econometric estimates depend on variation over time, and not the levels of each variable in the model.

gram. 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 for the base model (media impressions) 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. We summarize these elasticity estimates, both short-run and long-run, in table 2. Most importantly, the short-run price elasticity is approximately -1.16, which is slightly smaller than our previous study, but consistent with others in the literature (Sexton and Saitone, 2009). Our elasticity estimate differs from Sexton and Saitone (2009) 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 -1.16 means that if price were to rise by 10%, the retail quantity demanded would fall by 11.6%, all else equal.

Table 2: *Retail Media Demand Estimates*

	Short-Run	Long-Run
Price	-1.157	-3.844
Print	0.040	0.133
Online	0.065	0.215
Broadcast	0.012	0.041
Syndicated	0.001	0.004

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 print impressions of 0.040, and a long-run elasticity of 0.133. These estimates mean that a 10% increase in print impressions can be expected to lead to a 0.40% increase in retail mushroom volume in the short run and a 1.33% increase in the long run. For online impressions, we found a short-run elasticity of 0.065, and a long-run elasticity of 0.215. Because online impressions represent the largest category of marketing activity (see table 1), the fact that online messaging provides the largest demand response is important. Broadcast impressions generate a substantially smaller demand response, estimated as 0.012 in the short run, and 0.041 in the long run. While we cannot account for the specific nature of each broadcast impression, it is likely that this effect reflects the long-term decline of the importance of broadcast media more generally. Finally, we estimate the retail demand response to syndicated messaging as 0.001 in the short run, and 0.004 in the long run. Relative to the other media, syndicated messages produce a very small retail demand response.

We also use our model to estimate the shock to demand due to Covid, both the positive shock to retail demand, and the negative shock to foodservice demand. We expect this estimate to be substantial, as restaurants were nearly completely shut down for a period of time in April 2020. Although home-delivered pizza likely prevented foodservice demand from going to zero, and overall foodservice sales rebounded relatively quickly (see figure 2). With our retail model, we estimate the shock due to Covid as roughly 8.1% per month for 3 months, or a 24.3% gain over the April - June 2020 time period.

We also estimated a version of the retail model in which we categorized impressions by channel: Consumer and nutrition, retail, or foodservice. These estimates are summarized in table 3 below. As in the media-type model, all marketing elasticities were found to be positive, and statistically significant. The short-run elasticity with respect to consumer and nutrition messages was estimated to be 0.026, while the long-run elasticity was 0.081. These estimates are substantially higher than the retail and foodservice elasticities as the short-run estimates for these were 0.004 and 0.13, respectively, in the short run, and 0.001 and 0.003 in the long run. Given the large disparity in size-differences between these programs (table 1), we suspect that there may be important "threshold effects" in play here. That is, given the inherent difficulty in establishing a presence in a crowded commercial advertising world, scale is important, and reaching a minimum level of impressions may be necessary to actually move the demand needle.

Similar to the 2016 study, the foodservice demand for mushrooms was found to be considerably less elastic (closer to 0) than the retail demand (table 4).

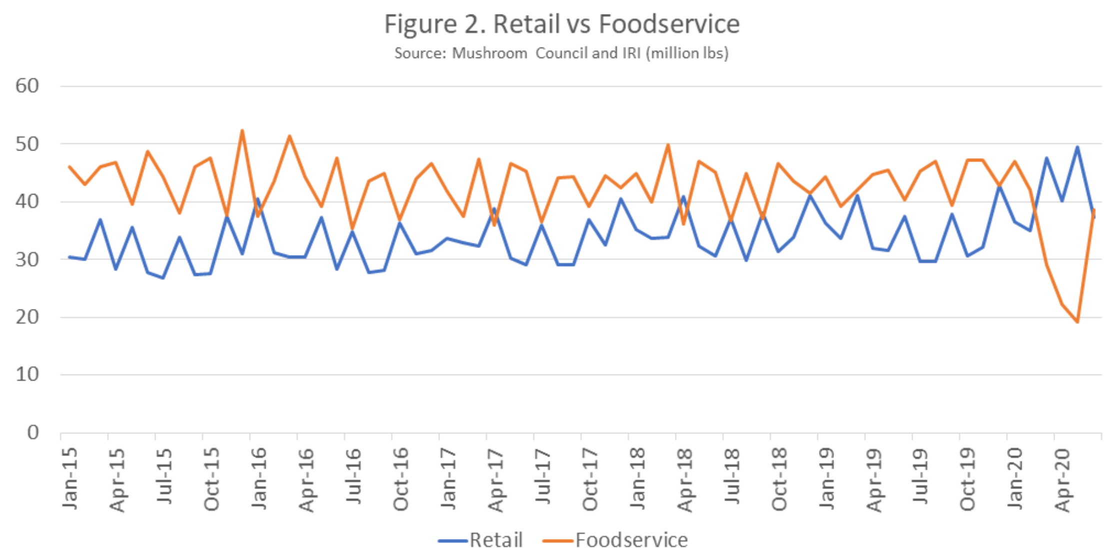


Table 3: *Retail Channel Demand Estimates*

	Short-Run	Long-Run
Price	-1.097	-3.429
Consumer/Nutrition	0.026	0.081
Retail	0.004	0.013
Foodservice	0.001	0.003

Table 4: *Foodservice Demand Estimates*

	Short Run	Long Run
Price	-0.828	-1.113
Print	0.070	0.094
Online	0.016	0.021
Broadcast	0.009	0.012
Syndicated	0.005	0.007

Specifically, the short run price elasticity of demand is -0.828 and the long run price elasticity is -1.113. It is not surprising that the long-run elasticity is substantially larger than the short run elasticity, because the rate of adjustment over time is relatively slow, 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 flux and price changes in one month are nearly always superseded by changes in the following month.

With respect to the marketing activity variables, we found a short run elasticity with respect to print impressions of 0.070 and a long-run elasticity of 0.094. In the foodservice market, print impressions had the strongest effect, even larger than the online efforts that were very effective in the retail market. We estimated the elasticities of foodservice demand with respect to online impressions as 0.016 and 0.021 in the short- and long-runs, respectively. Clearly, foodservice purchasers are more likely to be influenced by print ads than online, broadcast, or any other media. As in the retail model, the demand response with respect to both broadcast and syndicated impressions was very small. In the case of broadcast, the short-run elasticity was 0.009, and was estimated as 0.012 in the long run. For syndicated impressions, the short run elasticity was estimated as 0.005, and was 0.007 in the long run. As in the retail model, we account for diminishing marginal returns in the foodservice model, so it may be the case that the larger commitment to online impressions exceeds the point of diminishing marginal returns in the foodservice market, but does not do so in the larger (by volume) retail market.

Our estimate of the loss in foodservice demand due to Covid is a mirror-image of the retail gain. That is, we estimate that foodservice sellers lost some 27.1% of the market during the April - June 2020 time period, but recouped these losses by early July. Although this estimate appears slightly smaller than the observed losses documented in figure 2, it is important to remember that our model controls for all other factors, and the generally-higher prices during this time period could also explain some of the lost volume.

As with the retail model, we also estimated a version of the foodservice model with impressions disaggregated by channel, rather than by media type. These estimates are shown in table 5 below. In contrast to the retail model, consumer and nutrition messages are no longer the most important channel-focus for advertising, as the short-run elasticity with respect to foodservice messaging is slightly larger (0.030 versus 0.027). This finding is both to be expected, given that the foodservice market is likely to respond directly to messages targeted directly at foodservice buyers, and also validation of the econometric model. If the foodservice elasticities had shown an opposite pattern, then it would suggest the model is not differentiating between different marketing channels. In both the short- and long-runs, retail advertising has the weakest effect, with estimated elasticities of 0.012 and 0.018, respectively.

Table 5: *Foodservice Channel Estimates*

	Short Run	Long Run
Price	-0.734	-1.039
Consumer and Nutrition	0.027	0.038
Retail	0.012	0.018
Foodservice	0.030	0.043

Although each of these elasticity estimates are likely to be important for media-allocation and channel-focusing purposes, regardless of their implied return-on-investment value, our primary interest in these estimates is how they affect overall program returns, which we describe next.

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.

It is important to note that 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 6 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.

Table 6: *Retail Model BCR Estimates*

	Short Run	Long Run
Print	8.541	11.673
Online	13.787	18.843
Broadcast	2.653	3.626
Syndicated	0.253	0.345

From the results reported in table 6, we see that all activities generate positive returns in the long-run, except for syndicated impressions, as all the other 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 print impressions generate a BCR of 8.541 (ROI = 754.1%) in the short-run, and 11.673 (ROI = 1,067.3%) in the long-run. In other words, investments in print impressions generate \$8.54 of incremental profit for every dollar invested in the short-run, but \$11.67 in the long-run. Equivalently, the ROI estimates imply that the same investment would be viable with any reasonable hurdle rate of return in both the short- and long-runs. 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 print ads are highly profitable.

Returns to each of the other activities show a similar pattern, albeit to differing degrees. The return to online ads is notable, as they are some of the highest returns that we have ever seen in a commodity-marketing context. Namely, the short-run BCR for online impressions is 13.79, and 18.84 in the long run, which implies that the next dollar invested in online messaging is likely to return $18.84 in incremental profit. Recall that this estimate is particularly notable, given that online impressions represent the largest category, and presumably an area of focus for the Mushroom Commission.

Returns to the other categories are lower, yet broadcast impressions are likely still profitable. Specifically, we find a short-run BCR for broadcast impressions of 2.653 (ROI = 165.3%) and a relatively-high long-run BCR of 3.626 (ROI = 262.6%). However, in the case of syndicated impressions, the short-run BCR is substantially below the 1.0 threshold (BCR = 0.253, ROI = -74.6%) and remains below zero in the long run (BCR = 0.345, ROI = -65.5%). If these results are suggestive of potential budget-reallocations, our findings imply that industry revenues would be higher by moving budget dollars from syndicated services to online and print ads.

We also calculate BCRs with impressions defined by channel, rather than by media type. The BCR estimates for the retail-channel model are in table 7 below. Consistent with the pattern of channel-based elasticities, we find that investments in consumer and nutrition messaging are strongly profitable in both the short (BCR = 5.755, ROI = 475.5%) and long runs (BCR = 7.881, ROI = 688.1%). However, impressions targeting the retail market are only profitable (BCR ¿ 1.0) in the long run (BCR = 1.302, ROI = 30.2%), while foodservice messages are profitable in neither. The foodservice result is not surprising as the positive profitability of foodservice messaging in the foodservice market (documented in table 8 below) make up for the lack of profitability in the retail market.

Table 7: *Retail Channel Model BCRs*

	Short Run	Long Run
Consumer/Nutrition	5.755	7.881
Retail	0.950	1.302
Foodservice	0.234	0.320

We find a similar pattern of media-based returns in the foodservice channel to those found in the retail media model. These BCR estimates are shown in table 8. Namely, print and online impressions appear to be solidly profitable, while broadcast and syndicated impressions do not cover their investments. Specifically, in the foodservice model we find a short-run BCR for print impressions of 5.262 (ROI = 426.2%) and a long-run BCR of 5.974 (ROI = 497.4%). While online investments were more profitable than any other type in the retail channel, they are less profitable than print impressions in foodservice as the short-run BCR is 1.173 (ROI = 17.3%) and the long-run BCR is 1.332 (ROI = 33.2%). Nonetheless, both print and online activities appear to be value-creating. On the other hand, the short-run BCR for broadcast media is 0.679 (ROI = -32.1%) and the long-run return is 0.771 (ROI = 22.9%). Similarly, we find low returns to syndicated impressions in the foodservice channel as the short- and long-run BCRs to syndicated impressions are 0.379 (ROI = -62.1%) and 0.430 (ROI = -57.0%), respectively. Again, these findings suggest a reallocation of budget space from syndicated and broadcast media to print and online.

Table 8: *Foodservice Model BCR Estimates*

	Short Run	Long Run
Print	5.262	5.974
Online	1.173	1.332
Broadcast	0.679	0.771
Syndicated	0.379	0.430

Returns to foodservice advertising in the channel-based model reflect the relative size of the elasticities described above (table 9). Namely, we find positive returns to both consumer / nutrition and foodservice messaging in the short (BCR = 2.147, ROI = 114.7% and BCR = 2.420, ROI = 183.2%, respectively) and long runs (BCR = 2.512, ROI = 151.2% and BCR = 2.832, ROI = 183.2%, respectively). Further, retail messaging is only profitable in the long run (BCR = 1.150, ROI = 15.0%). While foodservice impressions are slightly more profitable than consumer and nutrition impressions in the foodservice market, it is important to keep in mind the relative scale of these targeting efforts (table 1) as consumer and nutrition efforts are likely well into the region of diminishing marginal returns and foodservice-targeted programs appear to be just ramping up toward their threshold-level of profitability.

In summary, we find that many mushroom marketing activities are profitable in both short- and long-run scenarios, while others are neither. Because we measure return on investment in terms of the profit expected on the last dollar spent, our results suggest

Table 9: *Foodservice Channel Model BCRs*

	Short Run	Long Run
Consumer/Nutrition	2.147	2.512
Retail	0.983	1.150
Foodservice	2.420	2.832

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 online and print media, for both the retail and foodservice channels, and toward broadcast media for the retail channel. In terms of target-channels, we find that consumer and nutrition messaging still provides the greatest return in the retail market, while more investment in foodservice-targeted messaging is likely a sound decision.

Conclusions and Recommendations

Mushroom demand, and prices, were relatively strong over the 2016 - 2020 examination period. However, it is not clear whether these favorable market conditions were due to structural factors in the mushroom market (i.e. population and income growth), or Mushroom Council marketing activities. In this study, we use data from 2016 - 2020 to investigate the return on investment for grower-shipper dollars invested in all Council marketing activities: Placing ads in print, online, broadcast, and syndicated media, and crafting either consumer / nutrition, retail, or foodservice messages. 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 not all Council activities were effective in raising demand when controlling for the effect of prices, monthly variation, changes in production conditions and other factors relevant to the demand for mushrooms. Among the four types of activity defined by the available marketing data, we find that online impressions were particularly profitable in the retail market, whereas print media were much more profitable for foodservice operators. In general, the returns to print and online investments in the retail market were very high – some of the highest we have seen. These findings suggest that Council activities are finding substantial traction in the retail channel, in spite of higher prices.

In terms of thematic-focus, we find solid returns to consumer and nutrition messaging in both the retail and foodservice markets. However, we note that these findings should be interpreted with some caution as the size of the consumer and nutrition focus-area is an order-of-magnitude greater than the other two programs. While we suspect consumer and nutrition messaging may be subject to diminishing marginal returns, the other two are likely not even near their threshold levels, beyond which returns may increase.

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 agency-provided impressions data prevented us from estimating returns over an expanded 6-year analysis period. As in previous evaluations of the Mushroom Council marketing programs, we believe that data more specific to foodservice movements would be very useful. In general, this type of data would be useful not only for evaluation purposes, but for making fact-based managerial decisions on how and where to allocate scarce marketing dollars.

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 print, online, broadcast, and syndicated 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; 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:

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

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:

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

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:

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

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, monthly 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} = grower's 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, $\mathbf{M} = \mathbf{E_s T} - w_r \mathbf{N_r}$ = 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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