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A Marketing Model Using Enhancement Variables

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This paper provides an applied case study to motivate the identification of enhancement variables in the two-variable, multiple-regression case for teaching and learning purposes. It is well known that enhancement variables have a synergistic effect on the coefficient of multiple determination. However, it is not well known that there are alternative technical approaches for the investigation of this condition, and there has been a lack of real examples that discuss and demonstrate the presence of enhancement variables. This study uses prior research in the areas of suppression and synergy to identify enhancement variables in a marketing model that uses promotional activity to explain sales.

Keywords: *Regression Methods, Case Studies, Enhancement, Suppression, Second Course*

1. Introduction

While suppression has been discussed in the psychological literature (Darlington, 1968; Conger, 1974; Tzelgov and Henik, 1991), the definition of suppression and enhancement continues to take on multiple definitions across functional areas. In addition, although the presence of suppressor variables has been discussed in the development of applied multivariate models (Glorfeld and Fowler, 1988), the identification of enhancement variables has not been widely discussed in the educational literature. Finally, a notable absence of real enhancement or synergy examples amplifies the difficulty of implementation of recent progress in this important area of research. Thus our main objectives here are 1) to clarify recent research and definitions of suppression and enhancement; and 2) to provide a real example that includes enhancement variables that can be used in an advanced regression or marketing research course.

Recent research on suppression and synergy has discussed a variety of approaches for identification. Sharpe and Roberts (1997) presented a necessary and sufficient condition for the situation of suppression and enhancement and presented a streamlined graphical approach for identification. Shieh (2001) built upon this graphical approach and called the same condition "enhancement-synergism" and Lynn (2003) expanded the application of this condition to logistic regression using public health data. Most recently, Friedman and Wall (2005) extended the graphical representation of these earlier works to distinguish among suppression, redundancy, and enhancement. Here, we apply conditions for enhancement to a marketing data set, both to test its reliability, as well as its applicability.

The lack of discussion of enhancement variables in the classroom is due to the paucity of real-world examples. In this case study, we provide a real example using a real marketing dataset obtained for educational purposes. It is worth noting that the lack of analysis of enhancement, or synergy, in marketing has been attributed to the lack of a consistent definition in the marketing literature (Wind & Robertson, 1983). In fact, synergy is defined in marketing as the "result achieved when the combination of elements in a marketing communications program provide greater impact than the sum total of each individual element of the program, i.e., the whole is greater than the sum of its parts" (Govoni, 2004). For example, advertising, sales promotion, product placements and other activities used simultaneously can deliver a better value to marketers than the sum of each activity used alone. The concept of synergy in marketing is similar to what we understand as the positive interaction effect in a regression model. Hence, synergy in marketing is the effect of the predictor variables on the mean level of the response or the value of the dependent variable, whereas enhancement or suppression affects the partial sum of squares of a regression model and explains more of the variability of the dependent variable.

This paper identifies an enhancement effect among marketing mix variables using data that are readily accessible for students in a second course on regression. Current textbooks do not emphasize the concept of enhancement – largely due to a lack of real examples. Since it is well known that student motivation, comprehension, and retention of statistical concepts is enhanced by the use of real data (see, for example, Bradstreet, 1996; Cobb, 1992), if students are to be aware of the condition of synergy, the concept should be emphasized with recent examples. Here we provide an accessible and widely applicable example for the purpose of motivating student learning.

2. Theoretical Background

In a linear regression model with two independent variables denoted as X_1 and X_2 the regression sum of squares is computed as

$$SSR(X_1,X_2) = SSR(X_1) + SSR(X_2 | X_1), \tag{1}$$

where it is arbitrarily assumed that X_1 is the variable entered first and $SSR(X_2 | X_1)$, is the extra sum of squares obtained after entering X_2. The presence of a suppressor variable can be identified by the following relationship

$$SSR(X_2 | X_1) > SSR(X_2). \tag{2}$$

Horst (1941) first used the term "suppressor variable" as a variable in multiple linear regression that has a negligible correlation with the dependent variable Y, but due to its correlation with the part of X_1 that is orthogonal to Y, suppresses some of the variance in X_1, thereby increasing the value of the multiple correlation coefficient when included in the model. This definition corresponds to the condition $R^2 > r^2_{y1} + r^2_{y2}$ in Hamilton (1987), where r_{y1} denotes the correlation between Y and X_1 and r_{y2} denotes the correlation between Y and X_2. In fact, Hamilton showed that a necessary and sufficient condition for this definition of suppression is dependent on the correlation between X_1 and X_2 (r_{12}):

$$r_{12}\left(r_{12} - \frac{2r_{y1}r_{y2}}{r_{y1}^2 + r_{y2}^2}\right) > 0. \tag{3}$$

This definition of suppression agreed with the definition given by Velicer (1978), as well as with the definition for enhancement given by Currie and Korabinski (1984). Schey (1993) also used this definition of suppression when he focused on the geometric interpretation of the correlation coefficients and expressed the condition for suppression in terms of the cosine and sine of the angles between the two vectors derived from the variables (Schey, 1993).

Sharpe and Roberts (1997) referred to the classical definition of suppression noted above in (2) as both suppression and enhancement and presented an alternative form for the necessary and sufficient condition for suppression to facilitate their graphical analysis:

$$r_{12} > \frac{2\gamma}{1+\gamma^2} \quad \text{if} \quad r_{12} > 0 \tag{4}$$

$$r_{12} < \frac{2\gamma}{1+\gamma^2} \quad \text{if} \quad r_{12} < 0, \tag{5}$$

where $\gamma = r_{y1}/r_{y2}$ and $r_{y1} > r_{y2}$. When $r_{12} = 0$ synergy cannot occur, because in this case the two sums of squares in Equation (2) are equivalent.

A similar ratio of these two correlations had been used in Mitra (1988) and in Tselgov and Henik (1991). Shieh (2001) used the traditional definition for suppression denoted in equation (2) – where the coefficient of determination is greater than the sum of the two squared simple correlations – and referred to the same shaded areas in the Sharpe and Roberts graphs as regions of "enhancement-synergism." Lynn (2003) extended the Sharpe and Roberts analysis by separating the shaded regions of their graphic into areas of classical suppression (i.e., γ =0) and cooperative suppression, which both satisfy equation (2), and also extended the condition of suppression to logistic regression using the log-odds ratios.

Most recently, Friedman and Wall (2005) distinguished among enhancement, redundancy, and suppression in terms of the beta weight in the standardized regression model (β) and R^2. They defined enhancement when $|\hat{\beta}_1| > |r_{y1}|$ and $R^2 > r^2_{y1} + r^2_{y2}$; suppression when $|\hat{\beta}_1| > |r_{y1}|$ but $R^2 \leq r^2_{y1} + r^2_{y2}$; and redundancy when both $|\hat{\beta}_1| \leq |r_{y1}|$ and $R^2 \leq r^2_{y1} + r^2_{y2}$ (see Table 1). Please note that Friedman and Wall's definition of suppression has now become a sub-category of what most think of as the "macro" or "classical" notion of "suppression."[1] The presence of a "suppressor" variable in a regression model does not increase the variance explained ($R^2 \leq r^2_{y1} + r^2_{y2}$), whereas the "classical" notion of suppression would be similar to what Friedman and Wall define as "enhancement" variable whose presence in the regression model increases the variance explained ($R^2 > r^2_{y1} + r^2_{y2}$). Friedman and Wall's (2005) analysis produced an equivalent set of necessary and sufficient conditions for enhancement as Sharpe and Roberts (1997), although the latter publication referred to this situation as part of suppression, which did not rely on a definition of γ:

$$\frac{2r_{y1}r_{y2}}{r^2_{y1}+r^2_{y2}} < r_{y1}r_{y2} + \sqrt{(1-r^2_{y1})(1-r^2_{y2})}. \tag{6}$$

They also note that enhancement is not possible when $r_{y1} = r_{y2}$.

Table 1. Identification of Enhancement, Suppression, and Redundancy

	$R^2 > r^2_{y1} + r^2_{y2}$	$R^2 \leq r^2_{y1} + r^2_{y2}$
$\lvert\hat{\beta}_1\rvert > \lvert r_{y1}\rvert$	Enhancement	Suppression
$\lvert\hat{\beta}_1\rvert \leq \lvert r_{y1}\rvert$	-------	Redundancy

Clearly, the presence of enhancement variables can be counterintuitive and the identification may be complicated, because it may occur when the relationship between the independent variables is significant, a situation typically associated with collinearity. In two-dimensions, however, if r_{12} is significant and has an opposite sign from the ratio of the two pairwise correlations (r_{y1}/r_{y2}), then enhancement exists (assuming the correlation matrix is positive-definite). In addition, there are also circumstances of enhancement when r_{12} is extremely large (and positive) and the ratio (r_{y1}/r_{y2}) is also large and positive, although these are less likely.

[1] We thank one reviewer for pointing out the need to clarify the concept of suppression from both the current and past research perspective.

3. Results For Marketing Case Study

The data set for the estimation of the model was developed by A.C. Nielsen for a frozen food product. This scanner database contains extensive marketing data for this product in several metropolitan markets measured weekly over a period of three years, although we will use the data for only one metropolitan area in this case study. The weekly sales volume (in pounds) of a specific brand of this frozen food product will be used as the dependent variable and independent variables include promotional data, such as All Commodity Volume (ACV) of stores (in %) having a feature, display, both a display and feature, or a temporary price reduction (see Table 2 for variable definitions). Promotional discounts are measured as a percent of price in combination with other promotions, a feature, a display, or with no other promotions. Variety of the product is measured as the average number of items (SKUs) per store (within the same brand).

Table 2. Variable Definitions

Variable	Variable Description
WEEK	Weekly period for that data
VOLUME	Total volume (in pounds)
PRICE	Average retail price
ACV.ANY*	% ACV with any promotion
ACV.FEA	% ACV with feature
ACV.DIS	% ACV with display
ACV.D/F	% ACV with display & feature
ACV.TPR	% ACV with price reduction
DSC.ANY	Amount of price discount (%) with any promotion
DSC.FEA	Amount of price discount (%) with feature
DSC.DIS	Amount of price discount (%) with display
DSC.D/F	Amount of price discount (%) with display & feature
DSC.TPR	Amount of price discount (%) with no other promotion
SKU.IPS	Average # items carried per store (product variety)

*ACV – All commodity volume refers to the total annual dollar volume in a given geography (or, retail channel) expressed as a percentage of the total market for that commodity, for example, frozen pizza. More specifically, in this case ACV.FEA refers to the percentage of ACV dollar sales accounted for by stores carrying a feature for this brand of frozen pizza.

4. Model Identification and Multicollinearity

One objective of this analysis was to develop a parsimonious marketing mix model for sales volume. The variables in the data set with the greatest correlation with sales volume were ACV.D/F (0.45), ACV.FEA (0.43), DSC.ANY (0.34), and SKU.IPS (0.31), although the correlation with volume was significant for all the variables in the data set ($p < 0.05$), except DSC.DIS. We used the best subset procedure as an initial analysis tool for the multi-variable combinations. This procedure produced the five best variable combinations at each level (as measured by R^2). Since the largest gains in R^2 were realized in the two- and three-variable models, these variable combinations were selected for more detailed analysis. For these two- and three-variable models, model diagnostics were performed to ensure validity of regression assumptions. (We discuss the issue of seasonality below.) The two-variable models with the greatest R^2 exhibited enhancement between an All Commodity Volume (ACV) variable and the number of SKUs of this brand per store (SKU.IPS). Producing the greatest amount of enhancement was the ACV variable representing the percent of sales volume accounted for by stores who ran a display and feature on the brand (ACV.D/F) in combination with the number of SKUs; these variables generated an additional 10% in R^2 beyond the sum of their individual contributions ($r_{y1}^2 + r_{y2}^2 = 0.45^2 + 0.31^2$) for a total R^2 of 40%. In addition, the SKU variable in combination with the ACV variable for stores who ran just a feature on the brand (ACV.FEA) displayed synergistic effects and generated an additional 8% in R^2 (total $R^2 = 36\% > 0.43^2 + 0.31^2$). Table 3 displays the results for the two-variable models.

Table 3. Model Results for Two-Variable Case

Variables in Model	r_{12}	$r_{y1}^2 + r_{y2}^2$	R^2	Add. R^2
ACV.D/F and SKU.IPS	-0.26	20.2 + 9.6 = 29.8	40.0	10.2
ACV.FEA and SKU.IPS	-0.22	18.5 + 9.6 = 28.1	35.6	7.5
ACV.DIS and SKU.IPS	-0.24	2.9 + 9.6 = 12.7	16.1	3.4
DSC.D/F and SKU.IPS	-0.14	7.7 + 9.6 = 17.3	20.1	2.8

In addition to enhancement in the two-variable case, increases in R^2 were also found, in the three-variable case. For three-variable combinations including both the SKU.IPS and the ACV.D/F variable, the additional R^2 (beyond $r_{y1}^2 + r_{y2}^2 + r_{y3}^2$) ranged from as high as 12% to as low as 0% (no enhancement). While it is difficult to extract enhancement effects in higher order models, because of confounding variables, enhancement remained in the four-variable case and the gain in additional R^2 ranged as high as 10%.

First, it is interesting to note, that the highest level of enhancement was attained in the two-variable combination of the All Commodity Volume variable representing breadth of promotion using displays and features (ACV.D/F) and the variable representing breadth of choice offered the consumer (SKU.IPS). Second, the presence of enhancement is useful in this case, because it exists in the models identified using traditional model building tools. It is important, however, that as part of our model selection process, we also examined the models beyond fit and parsimony, and looked for enhancement among the variables.

It is important to note that multicollinearity plays a role in enhancement, since it is the correlation between X_2 and the part of X_1 that is orthogonal to Y, that enables the variance in X_1 to be suppressed, thereby increasing the value of the multiple correlation coefficient when both X_1 and X_2 are included in the model. While multicollinearity can cause interpretation issues, it is also dangerous to assume that this relationship makes these two variables redundant (Hamilton, 1987), and thereby miss the opportunity to identify suppressor, or enahancement, variables. Furthermore, Friedman and Wall (2005) show that given 1) the increased power in computation and 2) the importance of the relationship of *all three* correlations in a two-predictor model (r_{12}, r_{y1}, *and* r_{y2}), in evaluating instability in the beta coefficients (not just r_{12}), the presence of multicolinearity itself may not be a great concern.

Our time series is considered stationary, since the trend component is insignificant, thus no trend was removed. However, we did remove seasonality, which we found to be a significant source of variation in the sales volume of this particular product. The models were then redeveloped on the deseasonalized data and the existence of suppression among the same set of variables (All Commodity Volume, Discounts, and Number of SKUs) was reexamined. First, we found that enhancement among the same variables (ACV.D/F and ACV.FEA with SKU.IPS) still exists, even when the seasonal effect is removed. Second, as expected, the additional R^2, beyond the sum of the pairwise correlations, for these two variables in combination with SKU is less (now only 6.3% and 3.8%, respectively). Third, and perhaps most importantly, the strength of the relationships with sales volume is reversed; the Number of SKUs now has the strongest relationship with deseasonalized sales volume ($r = 0.33$), where in the original time series, the ACV variables had the stronger correlation with sales. In fact, of all the promotional variables in the database, the SKU.IPS variable is the single greatest predictor of the deseasonalized sales volume. The strength in the predictive ability of each of the All Commodity Volume and the Discount (DSC) variables decreased. Thus these promotional activities appear to be more related to the seasonal variation in sales volume than the variety offered to the consumer.

We chose to model the original time series data (as opposed to the deseasonalized data), since the seasonal variation in sales volume appears to be related to the marketing mix variables. This may be a function of decisions made by the retail managers, which would indicate that prior experience is influencing the level of promotional variables. In addition, since enhancement exists in the presence of the variety variable (Number of SKUs), and since this SKU.IPS variable is the least sensitive to seasonal variation, we investigated the presence of enhancement in other promotional variables in combination with this variable.

5. Enhancement Variable Identification

This discovery of enhancement in the ordinary course of identification of a parsimonious sales volume model caused us to question the presence of synergistic variables among the remaining promotional variables in our database. The procedure of creating all possible two-variable combination models to compare the coefficient of multiple determination to the individual pairwise correlations (i.e., to examine the relationship $R^2 > r^2_{y1} + r^2_{y2}$) was cumbersome and time consuming. Therefore, the identification of enhancement for other marketing mix variables in the Nielsen database for this particular product and market was based on the condition presented in Sharpe and Roberts (1997). One advantage of the Sharpe and Roberts condition is that identification of enhancement variables can occur directly from the correlation matrix.

First, we obtained the correlations r_{y1}, r_{y2}, *and* r_{12} from the correlation matrix for each variable in the database. Then we calculated the value of the ratio of the correlations (γ) for each combination of variables with the variety variable (SKU.IPS) to evaluate the condition stated in Equations (4) and (5) above. For positive values of r_{12}, if this point falls above the value of the synergy function in Equations (4) and (5), then enhancement exists; for negative values of r_{12}, if this point falls below the function, then enhancement exists. Table 4 contains each of the ACV and DSC marketing variables with their respective values for r_{12}, γ, and the Sharpe and Roberts (S&R) condition.

The technical benefit of this analysis is that enhancement variables can be investigated directly from correlations in the standard correlation matrix with minor computations and is easily implemented using modern software packages.

Table 4. Identification of enhancement for each of the two-variable models in decreasing magnitude of r_{12}, assuming that SKU.IPS is the second variable.

Variable*	r_{12}	$\gamma = r_{y1} / r_{y2}$†	S&R Condition	Enhancement‡
ACV.D/F	-0.26	1.45	0.93	Yes
ACV.DIS	-0.24	1.81	0.85	Yes
ACV.FEA	-0.22	1.39	0.95	Yes
DSC.D/F	-0.14	1.11	0.99	Yes
ACV.TPR	0.13	-8.38	-0.23	Yes
DSC.FEA	-0.09	1.16	0.99	Yes
DSC.DIS	-0.06	3.30	0.55	Yes
ACV.ANY	-0.02	1.35	0.96	Yes
DSC.ANY	0.02	1.08	1.00	No
DSC.TPR	0.01	2.14	0.77	No

*Each of the ACV and DSC variables are measured in the presence of any promotion (ANY), displays and features (D/F), displays only (DIS), features only (FEA), and a temporary price reduction (TPR).

†To compute the ratio r_{y1} / r_{y2}, it is assumed that $r_{y1} > r_{y2}$.

‡Enhancement exists when r_{12} > S&R Condition in Equations 4 and 5. (Inequality is reversed for $r_{12} < 0$.)

The practical benefit of this identification approach for students is that it can be easily used in any context that includes continuous variables, without the creation of the separate models and without the computation of the partial sums of squares. Furthermore, this approach is accessible to students, who have a fundamental understanding of multiple regression.

6. Pedagogical Use Of Enhancement Example

During the past decade it has repeatedly been demonstrated that using real data promotes the learning of statistical concepts; students learn by doing and applying (Bradstreet, 1996; Cobb, 1992; Sharpe, 2000). Furthermore, in the marketing literature, Blattberg, et al. (1995) agree that few empirical results on the combined use of feature advertising, displays, and price discounts, have actually been published. Thus the lack of basic applications for suppression or enhancement in the literature has contributed to the scarcity of these concepts in textbooks in statistics – and more specifically in business statistics. As the technological capabilities, and therefore the efficiency, of model building grow, model builders should have the capacity and flexibility to expand their approaches. Considering evidence of suppression and enhancement should become part of the model selection process when developing models.

To aid in our teaching efforts of building models, we have used these data with students in an introductory joint segment of a course on statistics and marketing, as well as in an intermediate course that included more advanced modeling techniques. In general, statistics courses should: emphasize the need/importance of data; emphasize statistical concepts; incorporate more real data and technology; and foster active learning through exercises, laboratories, projects, presentations and demonstrations (Garfield et al., 2002). By using this dataset we found that the students appeared more motivated to learn and understand advanced modeling concepts.

More specifically, we required the students to work collaboratively in groups to develop alternative models for sales of this product and experiment with different model building procedures. Their analysis was summarized in a written report, which explained the objectives, process, statistical procedures used, and recommendations from their analysis. Following this stage of the student work, we then motivated a discussion of multiple two- and three-variable models. A comparison of resulting R^2 for these models resulted in questions leading to the introduction of the topic of enhancement variables. While it is true that students in these courses have already had one required course in statistics at our institution (i.e., they are expected to have a knowledge of regression), most of these students do not declare a major in statistics – and it is rare that we have students continue on to graduate school in statistics. (In a more advanced forecasting course, we have the students model the deseasonalized data, as well as the original data, and discuss the implication of seasonality, autocorrelation, and the application of distributed lag models.)

7. Implications for Future Research and Practice

This paper reviewed suppression and enhancement from a historical perspective and applied the condition presented in Sharpe and Roberts (1997) to a promotional marketing database. This concept of enhancement is of particular use in the area of marketing, because it indicates which combination of promotions can have a greater than expected explanatory power for a sales model. For example, in the area of demand forecasting, managers might be concerned with over- or under-stocking and therefore, would be benefited by understanding the impact of enhancement variables in explaining the fluctuation of demand. In particular, if variables are found to act together as enhancement variables, then managers can identify, anticipate, and/or control these variables to improve the management of demand and inventory.

The research findings here are based on a weekly time series data of a frozen food product for a specific metropolitan market. In addition to examining this one southern market, we replicated our analysis in four other metropolitan markets. It is interesting to note that in the two northern markets, enhancement was almost nonexistent (additional R^2 of less than 1%), while enhancement variables did exist in the mid-range market and the one other southern market. Not surprisingly, the impact of the seasonal variation on sales volume of this product was also greater in the northern markets. Since one of the variables identified as being an enhancement variable, SKU.IPS, was most strongly related to the deasonalized sales volume, this may explain the strength of the presence of enhancement in the southern markets; the market data that have the least amount of variation explained by seasonality may provide the greatest opportunity for synergy. The relationship between seasonality and strength of synergy requires further study.

In addition to seasonality, the timing of the promotional activities may also impact the presence and magnitude of enhancement. Note in Table 4, that in almost every case where enhancement is present in the two-variable case, the pair-wise correlation between the two promotional variables is negative. This negative relationship over time suggests that when one promotional activity is increased, the other activity is decreased. This may suggest that when promotional activities are alternated – or at least lagged – the end result may be an increase in efficiency – or cooperative enhancement. For example, managers might first ensure that retailers build up enough inventory (i.e., increase SKUs) before starting a heavy promotional campaign (i.e., using features, displays, and price cuts). To examine this lagged relationship in such promotional events requires store-level longitudinal data and suggests future research.

Finally, it is our hope that this example will provide an opportunity for instructors to introduce and discuss the concept of enhancement, or synergy, in the context of a regression or marketing research course. With increased computing capabilities and greater availability of data, we feel that students now have greater opportunities to be exposed to real problem solving situations and cases. Only with real data can students truly realize the importance of statistics.

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