Measuring the effect of promotion in non-controlled settings: a decompositional approach

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This paper provides a market based method that allows firms to obtain an accurate measure of the effects of promotion in non-controlled settings. Determining the effect of promotion is often confounded by differences in price between promoted and non-promoted sales as well as heterogeneity among consumers who buy promoted and non-promoted products. This paper provides a market based method that overcomes both these obstacles. We begin first by providing a brief graphical analysis outlining the problems associated with accurately measuring the effects of promotion. We address the particular issue of price and how to decompose the effects of price from promotion. Next, we address the issue of heterogeneity of consumers, allowing those who buy on promotion to differ from those who buy off promotion. Finally we introduce a formal methodology to isolate the effects of promotion.

Keywords: promotion effects; return on investment (ROI); decomposition

Introduction

Estimating the return on investment (ROI) from promotion is a critical part of effective marketing. An accurate measure of ROI from promotion is essential not only to decide whether or not to promote but also to the decisions of how much to promote, when to promote and what type of promotion should be undertaken. Ideally, a ROI for promotion captures the pure effect of promotion absent any other influences. Unfortunately, the reality of measuring the effects of promotion is less than ideal. For example, one issue confounding the effect of promotion is the fact that a price change often is made in conjunction with a promotional effort. As a result, it becomes difficult to disentangle any increase in unit sales due to the promotion from increases in sales due to, for example, a lower unit price. Another obstacle to obtaining an accurate measure of ROI of promotion is the assumption that those who buy on sale/promotion are identical to those who buy off sale/promotion. If there is heterogeneity between these two groups, then the estimated lift from advertising and promotion may be inaccurate.

The purpose of this article is to provide a market based method that allows firms to obtain an accurate measure of the effects of promotion in non-controlled settings. We begin first by providing a brief graphical analysis of the problems confounding an accurate measurement of the effects of promotion. We address the particular issue of price and how to decompose the effects of price from promotion. Next, we address the issue of heterogeneity of...
consumers, allowing those who buy on promotion to differ from those who buy off promotion. Finally we introduce a formal methodology to isolate the effects of promotion.

**Theory**

The use of experimental design methods to evaluate the effect of promotion on sales has been well established. Ideally a control group (unit sales in the absence of promotion) would be compared to a treatment group (unit sales in the presence of promotion) and the difference in unit sales between the two groups would be examined for statistical significance. Ensuring that the two groups are identical in all aspects, except for the treatment eliminates the potential for bias. In a purely time series approach, unit sales to a specific group are compared before and after a promotional campaign. In cross-sectional analyses, unit sales in one market where the promotion occurred are compared with unit sales in another market where no promotion occurred. Analysis of panel data is perhaps most desirable, since it combines both methods. Underlying all three methods, however, is the *ceteris paribus* assumption that control and treatment groups are similar in all aspects except for the exposure to the promotion. If the *ceteris paribus* conditions hold, then estimates of the lift in sales from promotion are relatively straightforward.

Diagrammatically, we can show the effect of promotion on unit sales as a simple shift in the demand curve. For example, Figure 1 shows two standard downward sloping demand curves illustrating the inverse relation between unit price and quantity sold. If we assume, for simplicity, that the goal of a promotion is to increase unit sales of the product, then we can represent this as a simple parallel shift in a demand curve such as that shown in Figure 1. Furthermore, if we assume that the consumers represented by the two demand curves are identical except for exposure to the advertisement or promotion, then the horizontal distance between the two demand curves provides an accurate measure of the increase in sales due to advertising or promotion. This is represented by $\Delta Q = Q_1 - Q_0$.

Consider now, however, a situation in which the promotional campaign is combined with a price change. Figure 2 shows an effective promotional campaign combined with a price reduction, with non-promoted price shown as $P_0$ and promoted price as $P_1$, where $P_0 > P_1$.

![Diagram showing demand curves](image-url)

Figure 1. Measuring promotion with homogeneous consumers.
Because the promotion and price reduction occur simultaneously, the total increase in sales \((\Delta Q = Q_1 - Q_0)\) includes any effect due to promotion as well as the effect due to the price reduction. Attributing the total effect \(\Delta Q\) to promotional efforts will overestimate the effect of promotion on unit sales. To accurately measure the effect of promotion on unit sales, the effect of price \((\Delta Q_0 = Q_2 - Q_0)\) must be decomposed from the effect due to advertising or promotion \((\Delta Q_1 = Q_1 - Q_2)\).

Another complication arises if we allow heterogeneity between the promoted and non-promoted demand curves. This would occur if, for example, promotion induces consumers to behave differently than when the product is not on promotion. Additionally, consumers who purchase on promotion may differ from those who purchase off promotion. If either or both situations exist, then the two demand curves are not parallel, and the effect of promotion will vary at different prices. An example of this is shown in Figure 3, where the price responsiveness of consumers on the promoted demand curve is greater at any point than the price elasticity of demand of consumers on the non-promoted demand curve. As a result, the effect of promotion at lower prices is greater than the effect of promotion at higher prices. In this instance, if the effect of promotion is measured at the means, then the resulting estimate will be biased downward and underestimate the true effect of promotion at prices below the mean, and biased upward and overestimate the true effect of promotion at prices above the mean.

Ideally, properly controlled settings are designed to eliminate differences in price and consumer heterogeneity in obtaining the lift in sales due to promotion. However, even when these experiments are undertaken, they are expensive and may not effectively eliminate any differences between the two settings. In this paper we propose a methodology that overcomes both obstacles, decomposing the effect of price from promotion and accounting for differing effects of promotion by price.

**Methodology**

The decompositional method we apply, first proposed by Oaxaca (1973), is econometrically based and relies on estimates of the promoted and non-promoted
demand functions for the good in question. Consider the linear demand functions represented by Equations 1 and 2:

$$Q_{Promoted} = \beta_0^P + \beta_1^P \text{Price}^P + \beta_X^P + u$$  \hspace{1cm} (1)

$$Q_{Non-Promoted}^{Promoted} = \beta_0^N + \beta_1^N \text{Price}^N + \beta_X^N + u.$$  \hspace{1cm} (2)

Where:

- $\beta_0$ is a constant,
- $\beta_1$ is the partial effect of price on quantity demanded. Assume $\beta_1 < 0$,
- Price is the own price of the good,
- B is a vector of coefficients,
- X is a vector of variables that affect demand for the good such as income, the price of a competing good, region and season.

The total increase in unit sales is represented by the difference:

$$Q_{Promoted} - Q_{Non-Promoted}^{Promoted}.$$  \hspace{1cm} (3)

Substituting Equations 1 and 2 into Equation 3 results in:

$$(\beta_0^P + \beta_1^P \text{Price}^P + \beta_X^P + u) - (\beta_0^N + \beta_1^N \text{Price}^N + \beta_X^N + u).$$  \hspace{1cm} (4)

Adding and subtracting $\text{Price}^P \beta_N^P$ and evaluating the vector X at mean values produces the following:

$$(\beta_0^P - \beta_0^N) + (\beta_X^P - \beta_X^N) + \text{Price}^P (\beta_1^P - \beta_1^N) + \beta_1^N (\text{Price}^P - \text{Price}^N)$$  \hspace{1cm} (5)

where the sum of the first three terms in brackets represents the effect of promotion on unit sales and the final bracketed term represents the effect of price on unit sales. Equation 5 illustrates two main points. First, note that the effect of promotion will depend on price. More
precisely, as long as the marginal effects of price on unit sales differ between the promoted and non-promoted demand functions (i.e. $\beta_P^1 & \beta_N^1$), the effect of promotion on unit sales will differ at different prices. Second, if the price between promoted and non-promoted unit sales is the same, the last term goes to zero. If, however, the price between promoted and non-promoted sales differs, then the price effect will bias the promotion effect.

Data
To illustrate the decomposition, we examine retail scan data on wine. The wine industry provides an ideal example of a differentiated product market characterized by a high degree of competition along a variety of dimensions including price and promotion. Scan data, provided by proprietors such as Information Resources Incorporate and the Nielson Company, are increasingly becoming the primary source of data for analytics in the consumer packaged goods industry. This ubiquity is due to the ready availability of data at the item level on price, quantity and promotional activities of sales.

We utilize a pooled cross-section of Nielsen Scantrack data for the years 2004–2007, which measures point of sale purchases of wines from major US retail chains. The data consist of national sales of all wines, foreign and domestic, purchased from major retail chain stores, defined as those with over 2 million dollars in sales, across the USA. The data are aggregated for all markets and include the price paid, quantity sold, store keeping unit (SKU) and promotional activity of each purchase. Promotion in the dataset is defined as one of four types: (1) features, which includes such things as mailers and newspaper advertisements (Feature); (2) in store displays (Display); (3) a combination of features and displays (Feature & Display); (4) temporary price reductions of 5% or more (Temporary Price Reduction). For uniformity, we concentrate on wine purchases of standard 750 ml glass bottles (approximately 84% of all purchases) and exclude boxed wine or larger 1.5 liter bottles.

The benefit of scan data is that they represent actual purchases of wine by consumers and are reflective of the consumer demand for wine. The drawback of scan data is that they only record purchases in major US retail chains and do not represent wine sold on premise at wineries, purchases through wine clubs or purchases at restaurants. However, while these limitations may be relevant for wines sold directly to consumers, through restaurants or through small wine shops, scan data work well for wines sold mainly through retail chains.

Summary statistics
Table 1 shows mean price in dollars per 750 ml glass bottle and mean four-week ending unit sales in cases for the sample of approximately 600,000 observations. From Table 1 it is clear that the mean non-promoted price is greater than the mean promoted price; the non-promoted price is over 15% more than the promoted price on average. While

<table>
<thead>
<tr>
<th></th>
<th>Unit price</th>
<th>Four-week sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-promoted</td>
<td>$13.40</td>
<td>254</td>
</tr>
<tr>
<td>Promoted</td>
<td>$11.61</td>
<td>346</td>
</tr>
<tr>
<td>Feature</td>
<td>$9.82</td>
<td>147</td>
</tr>
<tr>
<td>Display</td>
<td>$10.49</td>
<td>147</td>
</tr>
<tr>
<td>Feature &amp; Display</td>
<td>$8.35</td>
<td>127</td>
</tr>
<tr>
<td>Temporary Price Reduction</td>
<td>$11.76</td>
<td>188</td>
</tr>
</tbody>
</table>
promoted prices are lower than non-promoted prices across all types of promotional activity, wines on Feature & Display have the lowest average price while those on Temporary Price Reduction have the highest average promoted price. Likewise, promoted unit sales are greater than non-promoted sales.

The summary statistics provided in Table 1 support what Figure 2 shows graphically, namely that to accurately measure the effect of promotion on unit sales, the effect of price must be disentangled from the effect of promotion. To control for the many complex factors that may affect unit sales such as varietal and price point, we provide a specific example, using an anonymous high volume California Cabernet Sauvignon in the $7–$10 price point. The mean price and mean weekly sales (in cases) are provided in Table 2. The same relationship between price and promotion is observed for the anonymous Cabernet Sauvignon as in the summary statistics for the full sample shown in Table 1. Specifically, the mean promoted price is more than 10% lower than the mean non-promoted price, while mean unit sales on promotion are greater than mean unit sales off promotion. A simple comparison indicates that promoted sales are 50% greater than non-promoted sales. However, attributing the 50% increase in sales to promotion ignores the effect of the difference in price.

**Demand estimation**

We begin by estimating simple linear demand functions for promoted and non-promoted case volume, the results of which are shown in Table 3. While these simple demand functions are somewhat limited for practical purposes, they are useful for illustrating the decomposition. Despite their simplicity, the demand functions do conform to theoretical expectations in that price is negative and statistically significant at the 1% level. Note also that the coefficient of price differs between the two estimated demand curves, with the estimated price coefficient on the promoted demand nearly twice as large as the estimated price coefficient on the non-promoted demand.

Figure 4 provides a graphical representation of the demand functions and clearly shows that, for this particular wine, the estimated demand for promoted wine is different than the estimated demand for non-promoted wine and, as Table 3 indicates, that the prices associated with the promoted and non-promoted wine sales are different. Using the mean promoted and non-promoted values for price and quantity given in Table 2, we estimate non-promoted elasticity at approximately 6.66 with the promoted elasticity estimated at 6.99. While these elasticities are statistically different from each other, they do not seem significant for practical purposes. These results appear consistent with Guadagni and Little (1983) who find that promoted and non-promoted elasticities are similar. However, recall that these elasticities are calculated at the means and that the mean prices and quantities of promoted and non-promoted wines are significantly different. If we evaluate the price

<table>
<thead>
<tr>
<th>Unit price</th>
<th>Weekly sales</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-promoted</td>
<td>$9.75</td>
</tr>
<tr>
<td>Promoted</td>
<td>$8.68</td>
</tr>
<tr>
<td>Feature</td>
<td>$8.18</td>
</tr>
<tr>
<td>Display</td>
<td>$9.04</td>
</tr>
<tr>
<td>Feature &amp; Display</td>
<td>$8.18</td>
</tr>
<tr>
<td>Temporary Price Reduction</td>
<td>$8.87</td>
</tr>
</tbody>
</table>
elasticity of demand between promoted and non-promoted wines at a specific price we find that they do differ. For example at price of $9 per bottle, the price elasticity of demand for non-promoted wine is approximately 4.07, while price elasticity of demand for promoted wine is more than twice as elastic at 9.83. These results are consistent with the findings of Blattberg and Wisniewski (1989), Lattin and Bucklin (1989) and Mulhern and Leone (1991) who find that promoted elasticities are greater than non-promoted elasticities.

Decomposition

We can decompose the effect of price from promotion by first considering a situation where non-promoted sales occur at a price of $9 and promoted sales occur at a price of $8. Using the estimated demand functions, unit sales would be 2159 and 3315 at the non-promoted and promoted prices respectively, resulting in an increase in sales of 1156 units. The uncorrected effect of promotion on unit sales is 53.53%.

Table 4 shows the decomposition based on Equation 5. Decomposing the effect of price from promotion we find that 84% of the increase in sales is due to the price reduction and only 16% is due to promotion. Thus the true promotional lift is approximately 8%.

Table 3. Estimated demand functions.

<table>
<thead>
<tr>
<th></th>
<th>Non-promoted weekly cases</th>
<th>Promoted weekly cases</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price</td>
<td>−976.417</td>
<td>−1730.44</td>
</tr>
<tr>
<td></td>
<td>(6.82)**</td>
<td>(7.42)**</td>
</tr>
<tr>
<td>Constant</td>
<td>10,947.06</td>
<td>17,158.83</td>
</tr>
<tr>
<td></td>
<td>(7.84)**</td>
<td>(8.48)**</td>
</tr>
<tr>
<td>Observations</td>
<td>156</td>
<td>156</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.23</td>
<td>0.26</td>
</tr>
</tbody>
</table>

Note: Absolute value of t-statistics in parentheses. *Significant at 5% level; **significant at 1% level.

![Figure 4. Estimated demand functions.](image-url)
In addition to providing a method to obtain an accurate measure of promotional lift, the decomposition allows examination of the interaction between price and promotion. Recall that the effect of promotion may differ at different prices. To examine this we now consider a situation in which the price of non-promoted and promoted wines is $8 and $7 respectively. The decomposition, shown in Table 5, indicates that, in this case, the uncorrected effect of promotion increases to 61%. However, approximately half of that increase, 31%, is due to price and 30% is due to promotion. Thus the promotional lift goes from 8% to 30% as price falls from $8 to $7 per bottle promoted price.

If we examine the price elasticities of demand at these points, we find that at a price of $8 per bottle, the price elasticity of non-promoted demand is 2.49 while the price elasticity of promoted demand is 4.18. Comparing these values with the price elasticities obtained above at $9, we find the familiar result that consumers are less price responsive at lower prices than at higher prices for both promoted and non-promoted demand. Understanding the interaction between price and promotion allows firms to find the price and promotion combination that optimizes revenue.

Additionally, while this simple example illustrates the basic decomposition process, the methodology is easily extended. Recall that the vector X in Equation 5 includes any factors such as region, channel, retailer and temporal variables, across which promotional effects may differ. Thus, strategically choosing different price and promotion combinations across these dimensions allows firms to maximize promotional impact. For example, Cuellar and Karnowsky (2008) show that promotional effects differ significantly throughout the year and that, for the data they examine, promotional effects are greatest in the off season months. Thus, not only can firms optimize the timing of promotional activity, but they can also use promotion as a counter-cyclical tool.

### Summary

Ideally estimates of promotional lift should be obtained using a controlled experimental design methodology. Unfortunately, this is often impractical and expensive. As a result, firms rely on inaccurate baseline or average effects. Inaccurate measures of promotional...
lift will lead to an incorrect allocation of resources toward promotional activity at both the extensive margin, whether or not to promote, and the intensive margin, how much promotional activity should be undertaken. In addition, since price is not explicitly accounted for, the optimal price–promotion combination is not considered. This paper provides a new method to evaluate the effect of advertising and promotion on sales using non-controlled market based data. By decomposing the effect of price from the effect of promotion, our method produces a more accurate measure of promotional lift. Furthermore, by explicitly accounting for the interaction between price and promotion, our method allows firms to examine how the effects of promotion differ at different prices. For instance, in the example provided, we showed that promotion at lower prices had a larger effect on unit sales than promotion at higher prices. For other products, however, it may be that promotion has a larger effect at higher prices. Irrespective, the methodology proposed is perfectly general and allows firms across product categories to find the price–promotion combination that produces the greatest increase in promotional lift or revenue.

The implications of this research are several. First, the methodology developed in this paper allows firms to more accurately measure the effects of promotion on sales and revenue. Second, with a more accurate measure of promotion, firms can efficiently allocate scarce promotional dollars to achieve the greatest return on investment from promotion. Third, the methodology allows firms to find the optimal price–promotion combination that will maximize revenue from promotional activities. Finally, the methodology is general enough to allow firms to exploit differences in promotional lift over time, due to for example seasonality, over space, due to for example regional differences, or over any other dimension where promotions may have varying effects.

Notes
1. For simplicity we refer only to promotion but the methodology is perfectly applicable to advertising also.
2. We ignore for the moment issues related to estimating demand functions such as endogeniety, which is covered more thoroughly in, for example, Cuellar and Huffman (2008).

References