An Analysis of the Olympic Sponsorship Effect on Consumer Brand Choice in the Carbonated Soft Drink Market Using Household Scanner Data

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Abstract

Diverse notions on the effectiveness of sport sponsorship have been discussed to some degree in literature on consumer psychology and shareholder wealth. However, there is little investigation on a micro-level that provides empirical evidence for financial returns resulting from sponsorship. In fact, few studies have explored issues related to the evaluation of sponsorship return on investment (ROI), particularly regarding the scope of measurement. This study investigates the effects of a major Olympic sponsorship on consumers’ actual soft drink choices. It analyzes Nielsen Homescan purchase data for over 10,000 American households for a 3-year period spanning Coca-Cola’s sponsorship of the 2006 Olympic Winter Games and the 2008 Summer Games. Our analysis indicates that Olympic sponsorship may have generated significantly greater consumer choices for Coke over Pepsi during the Games. The effectiveness of sponsorship is statistically supported, even after controlling for sales increases attributed to traditional media advertising. It demonstrates that evaluation of sponsorship ROI is empirically achievable.

Keywords: sponsorship, brand choice, return on investment, household scanner data
Introduction

Sponsorship as a form of commercial activity is clearly differentiated from philanthropic sponsorship (Meenaghan, 1991). First, a sponsorship program requires the sponsor to deliver a contribution, in cash or in kind, to the sport organization. Second, the sponsored activity is not a part of the sponsoring company’s own commercial functions. Finally, the sponsor expects a commercial return for its investments. Based on these elements, Meenaghan (1991) defined commercial sponsorship as “an investment, in cash or in kind, in an activity, in return for access to the exploitable commercial potential associated with that activity.” (p.36)

Basically, this perspective accentuates the mechanism of sponsorship as a process of value transaction, such as product and service bartering, direct financial support, or indirect investment for some marketing initiatives. That is, unlike philanthropic donations, strategic commercial sponsorship of athletic events seeks to fulfill marketing objectives in exchange for giving cash or non-cash resources to sporting events. To be specific, sponsors cite various commercial reasons for sponsorship: increased brand awareness (Javalgi, Taylor, Gross, & Lampman, 1994), stronger brand identification (Chebat & Daoud, 2003), image transfer from sporting events to corporate sponsors (Deane, Smith, & Adam, 2003; Gwinner & Eaton, 1999), building positive attitudes (Dees, Bennett, & Ferreira, 2010; Lee & Cho, 2009; Roy & Graeff, 2003), and increased sales (Cornwell, Pruitts, & Clark, 2005).

In recent years, the worldwide sponsorship market has maintained its rapid and consistent growth as the number of transactions and the value of sponsorship have significantly increased. According to Cameron (2009), the worldwide sponsorship market in 2007 is estimated to be over $37.7 billion. Among all the sponsorship categories, including arts and other types of events, sport sponsorship is the leading category, accounting for 84% of worldwide sponsorship expenditure in 2007 (Fenton, 2009). Sport sponsorship has grown exponentially because of its unique attractiveness to marketers (Aaker, 1996) and due to historical events such as the Public Health Smoking Act, which made it illegal to advertise tobacco products in traditional mass media (Kropp, Lavack, Holden, & Dalakas, 1999). Today, sport sponsorship has become a dominant industry as a fair number of major sporting events heavily rely on revenues from sponsorship agreements. In particular, the Olympic Games are one of the most popular event types in the industry. According to the International Olympic Committee (IOC), 34% of its total revenues for the 2001–2004 period came from its flagship corporate sponsorship agreements (i.e., The Olympic Partner program; Papadimitriou & Apostolopoulou, 2009). Many multinational corporations pursue Olympic sponsorship in consideration of various marketing benefits, such as widespread media coverage and exclusivity (Papadimitriou & Apostolopoulou, 2009) and brand image leveraging (Deane et al., 2003; Grohs & Reisinger, 2005; Gwinner & Eaton, 1999; Kropp et al., 1999).

Given the commercial interest and sizable investment associated with sponsorship, sponsors demand more tangible evidence of benefits (i.e., financial returns attributable to sponsorship; D’Esopo & Almquist, 2007; Lough, Irwin, & Short, 2000). For years, various marketing and financial approaches have been devised and implemented in the evaluation of sponsorship (Meenaghan, 1991; Thwaites, Manjarrez, & Kidd, 1998). In spite of these many pioneering efforts, sponsorship evaluation remains a
An Analysis of the Olympic Sponsorship Effect on Consumer Brand Choice

daunting challenge due to several inherent problems (Crosby, 2009; Howard & Crompton, 2004). Primarily, there has been no comprehensive and widely accepted framework outlining how to make a sponsorship program commercially accountable (Harvey, 2001). It is also difficult to isolate the pure effect of sponsorship from other marketing efforts (Brooks, 1994; Thomas, 1996). In addition, limited access to actual market data has made it difficult to directly examine the commercial value of sponsorship. According to Crompton (2004), the ideal measure by which to evaluate sponsorships is sales—traffic, leads, or sales figures—followed by intent to purchase, and finally media equivalency and awareness or recall studies. In addition, a majority of the literature in sponsorship research has primarily employed consumer-behavioral approaches—for example, media exposure time (Abratt & Grobler, 1989), awareness, attitude, image association (Deane et al., 2003; Gwinner & Eaton, 1999; Javalgi et al., 1994; Kinney & McDaniel, 1996; Kropp et al., 1999; Lee & Cho, 2009), purchasing intent, and brand consideration (Harvey, Gray, & Despain, 2006). Although these consumer-oriented inquiries established valuable theoretical notions and frameworks, they only suggest proxy values for a sponsorship effect; brand perception, for example, may not precisely translate to the commercial or financial value of sponsorship.

Meanwhile, a small number of studies have attempted to assess the economic value of sponsorships in an indirect way: the Event Study Analysis that examines the stock prices of sponsoring companies before and after an initial sponsorship announcement. Using Event Study Analysis, Mishra and colleagues (1997) found a positive impact of 76 sponsorship announcements, including sport (i.e., in-arena promotion and Olympics) and miscellaneous events (i.e., exhibits, charities, and concerts). Farrell and Frame (1997) and Miyazaki and Morgan (2001) examined sponsorship announcements associated with the 1996 Summer Olympics and their impact on shareholders’ wealth. Cornwell and colleagues (2005) conducted a similar study that investigated official sponsorship of major professional sport leagues in the United States. Although some of these studies found a positive sponsorship effect on stock price and overall shareholder wealth, the implemented methodology (Event Study Analysis) was limited in that the direct impact on the market itself, such as consumers’ brand choice and sales, remains speculative.

In measuring the effects of sponsorship, scholars have paid relatively little attention to separating the effects of traditional advertising conduct from sponsorship. For instance, in Harvey (2001), Next Century Media reported that the click-through rate of sponsored information on the internet was almost double that of the average advertising application in an e-Voice interactive audio medium. Although the study indicated higher efficacy of sponsorship as a marketing communication vehicle when compared with traditional advertising alone, the author did not examine whether consumers’ perception of a specific sponsor was indeed connected to their actual brand-choice behavior. Similarly, the commercial accountability of sponsorship as a marketing vehicle has not been thoroughly studied for various methodological and conceptual challenges (Howard & Crompton, 2004).

Despite the methodological and conceptual problems, the current corporate culture under the economic recession demands an interdisciplinary effort to develop a comprehensive sponsorship evaluation framework based on financial concepts, such as Return on Investment (ROI) (Kitchen, 2010). Although ROI is a financial term, it has been intro-
Cho, Lee, Yoon, Rhodes

duced to the field of marketing as one measure of the financial accountability of sponsorship campaigns. Recently, marketing ROI has become a significant interdisciplinary subject and a bridge between finance and marketing (Harden & Heyman, 2011; Moeller & Landry, 2009). ROI can be defined simply as a ratio between the cost of production of goods or services and the revenue from their sales. However, a direct application of this definition is somewhat problematic when used for discovering the commercial value of sponsorship because a large amount of revenue does not necessarily warrant a profitable business (Moeller & Landry, 2009). As a result, Moeller and Landry (2009) expounded a marketing ROI formula that reflects the profitability of a particular event:

\[
ROI = \frac{(VCM \times \text{Incremental Volume}) - \text{Total Cost}}{\text{Total Cost}}
\]

where \(VCM\) (variable contribution margin) stands for the variable profit per volume unit (i.e., earned profit per product or service unit sold). This ROI element can be calculated by subtracting the unit COGS (component cost of goods) and other costs from the unit price of products or services. Incremental Volume in the equation refers to the number of units sold in excess of normal sales volume. The formula suggests how the ROI from a particular sponsorship program can be estimated to proxy for actual financial returns. After all, the incremental volume, the number of units sold that can be attributed to the event, and total cost of the event would be critical determinants of sponsorship ROI.

Arguably, one of the most controversial issues in calculating sponsorship ROI would be how to define the scope of measurement (Harden & Heyman, 2011). Given the vague boundaries among different marketing initiatives and programs, it is crucial to determine the extent to which this ROI can be estimated. There are two different but somewhat related issues involved: the types of marketing initiatives subject to ROI metrics and the timeline of the analysis. One ROI-metric question is whether a macro-level branding cost, such as a sponsorship right fee, must be included in the ROI metrics. Scholars and practitioners have designed a hierarchical diagram, the so-called “funnel-shape” ROI approach, to address this type of issue (Harden & Heyman, 2011; Lenskold, 2002; Paterson, 2007). The funnel-shape diagram first lays out all levels of marketing practices—from marketing programs primarily aimed at capturing intangible proxy benefits, such as brand awareness, to other programs that eventually elicit brand choice and sales, such as an on-site promotion. The funnel then indicates from which point the ROI metrics would allow the evaluation of a particular investment. In practice, where to begin the evaluation may significantly affect the outcome of analysis. Marketers are generally reluctant to take proxy branding costs into the equation, while financial professionals would more likely want to expand the scope of the analysis (Harden & Heyman, 2011; McCafferty, 2007).

For instance, Coca-Cola’s marketing department may prefer to conduct an ROI analysis of the company’s Olympic sponsorship program, limiting its scope to on-site promotions, because this approach would likely present a better ROI than an all-inclusive analysis that counts the sponsorship right fee. Marketing practitioners frequently argue that the financial accountability of proxy branding cost, such as a sponsorship fee, might not be empirically sustainable (Harden & Heyman, 2011). Yet, no study has investigated whether an empirical approximation of sponsorship ROI is plausible.
The second issue related to the scope of ROI measurement is whether the evaluation should focus on short-term or long-term effects. Studies have consistently found that promotional events, such as price discounts or couponing, are likely to have a short-term effect on sales, while macro-level brand advertisement would more likely have a lasting effect (Baghestani, 1991; Chudy, 2008; Mela, Gupta, & Lehmann, 1997). This proposition suggests that sponsorship might need to be evaluated in terms of its long-term effect because it can be characterized as a proxy branding cost aimed at intangible benefits. Nevertheless, no empirical study has scrutinized whether sponsorship would have measurable long-term effects that can be separated from short-term effects.

In summary, the evaluation of sponsorship ROI raises two concerns related to the scope of measurement: whether a sponsorship effect might be empirically tested at a micro-level and whether sponsorship can be separately evaluated in terms of short- and long-term effects. These concerns call for an attempt to measure the impact of sponsorship on consumers’ actual brand choice behavior in response to a particular sponsorship program and after controlling for other marketing variables, such as price, discount, and traditional media advertising. This attempt would suggest a plausible scope of measurement for the evaluation of sponsorship ROI. Given the absence of empirical evidence that may directly address these problems, this study aims to examine (a) whether consumers purchase more of a brand that actively sponsors a major sporting event, (b) if so, whether the impact of sponsorship upon consumers’ brand choice is statistically significant even after the model controls for other marketing variables, and (c) whether sponsorship has a long-term and/or short-term effect on consumers’ brand choice. Our results may ultimately speak to the threshold question for sponsorship ROI evaluation—that is, whether the ROI metrics may plausibly be applied to sponsorship evaluation rather than just proxying for marketing cost, as has been the rule in the field of marketing. To achieve these inquiries, this study uses a panel dataset that spans two Olympic Games—the 2006 Torino Winter and 2008 Beijing Summer Olympics—during which Coca-Cola, a major sponsor of the Olympic Games, engaged in aggressive marketing campaigns. This study also focuses on changes in consumers’ brand choice within the top name-brand colas, Coke and Pepsi.

Methodology

Data Management

The original scanner data are from 14,065 households that recorded their soft drink purchases on a daily basis for about 3 years from February 2006 to December 2008. The first step of data management was to extract the data from data on the whole soft drink market. Because this study exclusively focused on the cola market, we extracted a subsample of 11,887 households across 15 designated marketing areas (DMA) that had actually purchased cola at least once during the 3-year period. The second step was to establish continuity of the data for the purpose of analysis. A problem with the original scanner data was that most households would not purchase cola on a daily basis, and as a result, there could be a significant number of zero values in the data entries. Such infrequent purchasing made it difficult to locate the exact moment when the change of brand choice actually happened, if it does. Therefore, it is necessary to use a more continuous dataset to track consumers’ brand choice, particularly during
the Olympic Games. Therefore, the household data were collapsed to the DMA level and aggregated from daily to weekly data: The 11,887 households collapsed into 15 DMAs and, therefore, 2,280 observations for the period (15 DMAs × 152 weeks).

We match weekly television advertising expenditure data for each DMA with the purchasing data above. Television advertising data are constructed by summing expenditures of local advertising, network advertising, and syndication advertising.4

Explanation of Variables
The name-brand cola market is dominated by only two companies, Coca-Cola and Pepsi. Assuming that the utility a consumer perceives from a cola product is identical regardless of brand, it is reasonable to infer that determinants of consumer brand choice result mainly from other intangible marketing factors and not from the functional attributes of the product per se. This study assumes that a brand choice is determined by three types of factors: (a) promotional efforts by each company, for example pricing, advertising, and sponsorship; (b) intra-brand substitution within Coke or Pepsi (i.e., a substitution effect between new and classic products); and (c) heterogeneity of each DMA in terms of demographics (e.g., average income and racial composition).

Based on these three assumptions about the determinants of brand choice, this study introduces the brand-choice ratio between Coke and Pepsi as the dependent variable. By using the ratios instead of absolute quantities, we excluded cumbersome factors that might have affected the consumption of the product. For instance, if the consumption of Coke peaks during the summer, estimated sponsorship effects might be somewhat less reliable because summer Olympic Games are held between July and October. That is, it might not be conclusive whether the increase in cola consumption can be attributed to the company’s marketing efforts (i.e., sponsorship) or merely a seasonal fluctuation. Although such a seasonal effect might be handled using statistical methods such as introducing dummies, subtle effects still might not be captured. Another example of an external factor that can be controlled using the ratio between Coke and Pepsi would be the current economic recession. Although it would definitely affect the market, filtering out its effects would be very difficult because we are not

<table>
<thead>
<tr>
<th>Name brand</th>
<th>Consumer expenditure ($)</th>
<th>Market ratio (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Regular Coke</td>
<td>42,526,882</td>
<td>10.2</td>
</tr>
<tr>
<td>Diet Coke</td>
<td>41,388,538</td>
<td>9.9</td>
</tr>
<tr>
<td>Regular Pepsi</td>
<td>34,776,880</td>
<td>8.3</td>
</tr>
<tr>
<td>Diet Pepsi</td>
<td>27,253,624</td>
<td>6.5</td>
</tr>
<tr>
<td>Caffeine Free Diet Coke</td>
<td>14,944,160</td>
<td>3.6</td>
</tr>
<tr>
<td>Regular Dr Pepper</td>
<td>11,303,720</td>
<td>2.7</td>
</tr>
<tr>
<td>Caffeine Free Diet Pepsi</td>
<td>10,524,412</td>
<td>2.5</td>
</tr>
<tr>
<td>Regular Sprite</td>
<td>9,786,360</td>
<td>2.3</td>
</tr>
<tr>
<td>Regular Mountain Dew</td>
<td>9,663,018</td>
<td>2.3</td>
</tr>
<tr>
<td>Diet Dr Pepper</td>
<td>8,590,807</td>
<td>2.1</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td><strong>419,012,932</strong></td>
<td><strong>100.0</strong></td>
</tr>
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sure exactly when it began. In addition to brand choice, price and advertising expenditures are also introduced in the form of ratios. The employment of these ratio terms is also supported by the notion of a “choice of map” (Elrod, 1988)—rather than a birds-eye view of a broadly defined product market, this focuses on a submarket where closely competing brands have saturated a market.

This study focuses on leading classic brands from each company—Regular Coke, Diet Coke, Regular Pepsi, and Diet Pepsi—which indeed represent their respective companies as flagship brands. These four brands account for 34.8% and 69.7% of consumer purchases of the whole carbonated soft drink and the whole cola soft drink markets, respectively (See Table 1 and Table 2). To enable analytical tractability, the study focused on these four brands.

In order to deal with the substitution effect between the four leading brands of Coke and Pepsi, and other new brands excluded from the analysis, new cola brands emphasizing dietary-health concerns were also considered in the study. For instance, two new Coke brands—Caffeine Free Diet Coca-Cola and Diet Coca-Cola Zero—supposedly substitute for existing classic Coke brands in the market (i.e., Regular and Diet Coke), specifically for more health-conscious consumer groups. Given that a substitution effect is highly probable, the study includes the prices of four new products in the analysis. First of all, we assumed that consumers might directly associate these new brands with the classic products rather than perceive them as distinctively independent items. As a result, we introduced the price differences between the classic and new brands of both companies instead of using the absolute prices of the new products in the model. For instance, the weighted-average price of two new Coke brands—Caffeine Free Diet Coca-Cola and Diet Coca-Cola Zero—represents the price of the new products. Then, the difference between this average price and the weighted-average prices of two classic brands (i.e., Regular Coke and Diet Coke) denotes the relative price of new brands introduced in the model, which can then be used to evaluate the existence of a substitution effect of new brands. Likewise, Caffeine Free Diet Pepsi and Caffeine Free Pepsi are constructed in the same way.

In addition, various promotional pricing strategies, such as coupons, shopper cards, and buy-one-get-one-free programs, would presumably influence consumers’ brand choice. This study attempted to control for these effects by using the prices actually

| Table 2. Consumer Expenditures by Top Name Brands in the Cola Market |
|------------------|------------------|------------------|------------------|------------------|
| Name brand       | Consumer         | Market           | Name brand       | Consumer         | Market           |
|                  | expenditure ($)  | ratio (%)        |                  | expenditure ($)  | ratio (%)        |
| Regular Coke     | 42,526,882       | 20.3             | Regular Pepsi    | 34,776,880       | 16.6             |
| Diet Coke        | 41,388,538       | 19.8             | Diet Pepsi       | 27,253,624       | 13.0             |
| Caffeine Free Diet Coca-Cola | 14,944,160 | 7.1   | Caffeine Free Diet Pepsi | 10,524,412 | 5.0 |
| Diet Coca-Cola Zero | 6,224,377 | 3.0   | Caffeine Free Regular Pepsi | 5,078,599 | 2.4 |
| Regular Coca-Cola Cherry | 2,925,017 | 1.4   | Diet Wild Cherry Pepsi | 3,042,300 | 1.5 |
| Coca-Cola (total)| 117,261,294      | 56.0             | Pepsi Cola (total)| 92,224,253      | 44.0             |
Cho, Lee, Yoon, Rhodes

paid by consumers at the point of sales after accounting for all promotional discounts. For instance, assuming that the retail unit price for a 2-liter bottle of Coke Classic is $2.00, if there is a buy-one-get-one-free promotion, the unit price applied to the model becomes $1.00 per bottle, which is the amount the consumer actually paid. It is also true that demographic features of each DMA—such as household income, education level of female head, employment of male head, and household composition—might create a different pattern of product consumption in each DMA. For instance, the Houston DMA and the Boston DMA show a substantial difference (more than 2.5 times) in their brand choice, which is measured by the purchase ratio, and notwithstanding their equivalent pricing strategies and similar advertising expenditures. Unfortunately, it is hardly possible to consider all these potential demographic variables altogether. This study seeks to address this possible heterogeneity problem by introducing DMA dummies that proxy for the combined demographic variable set.

Coke, but not Pepsi, is one of the major official sponsors of the Olympic Games, and the data period encompasses two Olympic Games: Torino and Beijing. Sponsorship effects are examined by tracking the change in consumers’ brand choice ratios before, during, and after the Olympic Games. As mentioned before, there is still not agreement about where to separate short-term effects of sponsorship from long-term ones. For our analysis, the short-term effect was defined as an increased brand-choice ratio during the Olympic Games after controlling for other factors. On the other hand, the long-term effect, if one exists, would maintain a higher brand-choice ratio after the Games are over, just as traditional advertising may have a lasting effect. Here we defined a long-term effect as an increased brand-choice ratio after the Olympic Games after controlling for other factors. Dummy variables, designating the time periods during and after the Olympic Games, were employed to estimate each of these effects.

**Panel Model**

The data for our analysis were repeated observations across the same DMAs for about 3 years (i.e., panel data). For concreteness, the time period is per week, from February 2006 to December 2008 (\( T = 152 \)), and there was an \( i \) for each of 15 DMAs (\( N = 15 \)). So, this study applied models for long panel data with several time periods over relatively few DMAs. Whereas short panel models focus on unobserved heterogeneity, long panel models are concerned with the temporal element of the error process (\( u_{it} \)) to explore more efficient generalized least-squares (GLS) estimation. Consider a general long panel model below:

\[
y_{it} = X'_{it} \beta + u_{it}, \quad t = 1, ..., N, \quad i = 1, ..., T
\]

where \( y_{it} \) is a dependent variable, \( X_{it} \) is a vector of explanatory variables, \( \beta \) represents a vector for coefficients to be estimated, and \( u_{it} \) is an error term. Because \( T \) is large relative to \( N \) it is necessary to specify a model that can correct for any serial correlation in the error term. This study assumed AR(1) serial correlation with a constant correlation coefficient; that is, \( \rho_i = \rho \) for all \( i \) in (3). In addition, given the small \( N \), it was tractable to relax the assumption that \( u_{it} \) is independent over \( i \). A general form for the error term can be expressed in (3):

\[
u_{it} = \rho u_{i,t-1} + \varepsilon_{it}
\]
where $\rho$ is a coefficient that allows for AR(1) serial correlation, and $\varepsilon_{it}$ is serially uncorrelated but can be correlated over $i$ with $\text{Corr}(\varepsilon_{it}, \varepsilon_{is}) = \sigma_{ij}$. Accordingly, for long panel data, the feasible GLS model can be considered under different assumptions on the error process. It is generally possible to consider three different assumptions about the error process: (a) contemporaneous correlations allow correlation over DMAs $E(u_{it}u_{jt}) = \sigma_{ij}$; (b) serial allow for an AR(1) error process ($\rho \neq 0$); and (c) heteroskedasticity that allows different variance across DMAs $E(u_{it}^2) = \sigma_i^2$. This study tested these three assumptions, and then, on the basis of test results, suggested the richest feasible GLS model in terms of the assumed error process.

On the other hand, the GLS models give the best linear unbiased estimators if the error process is correctly specified. If misspecified, these estimators are generally inconsistent. In this case, the ordinary least-squares (OLS) model with panel-corrected standard errors gave consistent estimators in spite of its efficiency loss. This study also estimated the OLS model with panel-corrected standard errors and compared the estimation results from both models to check the robustness of our results.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
<th>Average (SD)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$P_Ratio$</td>
<td>the relative price of Coca-Cola : calculated as the ratio of the price of Coca-Cola to Pepsi</td>
<td>1.10 (0.14)</td>
</tr>
<tr>
<td>$PD_Coke$</td>
<td>the price of new Coca-Cola brands : calculated as the price difference between classic Coca-Cola brands and new Coca-Cola brands</td>
<td>0.17 (0.09)</td>
</tr>
<tr>
<td>$PD_Pepsi$</td>
<td>the price of new Pepsi brands : calculated as the price difference between classic Pepsi brands and new Pepsi brands</td>
<td>0.04 (0.10)</td>
</tr>
<tr>
<td>$In_AD_Ratio$</td>
<td>the relative advertising expenditure of Coca-Cola : natural logarithm of the ratio of Coca-Cola advertising expenditures to Pepsi advertising expenditures</td>
<td>1.42 (2.51)</td>
</tr>
<tr>
<td>$Oly_Short$</td>
<td>the short-term effect of Olympic sponsorship : = 1 if the Olympic Games held during that week ; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$Oly_Long$</td>
<td>the long-term effect of Olympic sponsorship : = 1 after the Beijing Summer Olympic Games; 0 otherwise</td>
<td></td>
</tr>
<tr>
<td>$Oly_AD$</td>
<td>the interactive term : multiplication of $\beta$ by</td>
<td></td>
</tr>
</tbody>
</table>
Results and Conclusion

Descriptive Analysis

Table 1 shows that the top four brands among 905 brands in the sample dominated the carbonated soft drink market during the 3-year period, occupying a total of 34.8% of the market. Also, in the cola market, the four leading products aggregatedly maintained a dominant position, with 69.7% of market share among 39 cola brands (see Table 2). The brand-choice ratio, representing brand choice of Coke relative to Pepsi, was calculated as the ratio of the purchased quantities of the Coke and Pepsi brands (i.e., Regular Coke, Diet Coke, Regular Pepsi, and Diet Pepsi). In general, consumers in the sample preferred Coke brands to Pepsi brands, yielding a brand-choice ratio of 1.35 over the total market sampled. Still, the ratio varied by period and DMA, with a low of 0.30 for the second week of June 2006 in the Detroit DMA and with a high of 9.66 for the last week of December 2007 in the Atlanta DMA (SD = 1.02).

Table 3 describes the primary explanatory variables which were expected to determine the brand choice, along with respective averages and standard deviations. In accordance with the brand-choice ratio, price and advertising expenditures were also analyzed in terms of ratios. For instance, 1.10, the average value of the relative price of Coke ($P_{Ratio}$), indicated that consumers in the sample on average paid 1.10 times more for Coke than Pepsi. Coke spent a total of $114 million on advertising for its two leading brands in 15 DMA regions during the 3-year period. Hence, compared with the $44 million that Pepsi spent for its two leading brands, Coke expended over 2.5 times more on advertising. The study introduced this ratio of advertising expenditures ($In_{AD}_{Ratio}$) in natural logarithm form to transform the distribution of the raw ratios into a normal distribution.

The graphs in Figure 1 depict scattered data and the locally weighted scatterplot smoothing estimators (LOWESS) for two primary determinants—price and advertis-

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*For readability, both graphs are truncated at a brand-choice ratio of 6. Both LOWESS estimators in this figure are depicted with bandwidth 0.5.

Figure 1. The Relationship between Brand-Choice Ratio and Price Ratio, and Between Brand-Choice Ratio and the Log of Advertising Expenditure Ratio*
ing—in relation to brand-choice ratios. The negatively sloped price ratio in the first graph is reasonable because consumers chose Coke more frequently as the relative price of the product decreased. The LOWESS estimator in the second graph shows positive curvature. That is, as Coke spent more on advertising relative to Pepsi, consumers purchased more Coke brands—that is, there was a greater frequency of brand choice. Meanwhile, the slope of the second LOWESS graph shows an abrupt upturn at one point. This may indicate that the advertising effect on the brand-choice increases when the gap between the advertising expenditures of Coke and Pepsi exceeds some threshold point. Alternatively, assuming a linear relationship between brand-choice ratios and the log of the advertising expenditure ratios, the upturn in the LOWESS slope in the second graph would indicate that some unaccounted factors must be coming into play. These unknown factors are probably interrelated with the advertising expenditures but manifest only when Coke spends significantly more on advertising than Pepsi does. Figure 2 indicates that such large gaps between the advertising expenditures of Coke and Pepsi indeed existed during both Olympic periods. Actually, the In_AD_Ratio was estimated to jump on average from 1.32 to 3.52 during the Olympic Games, and the brand-choice ratio also increased from 1.55 to 2.00. As a result, one could presume that, in addition to the advertising effects, Olympic sponsorship effects might be lifting the second LOWESS estimator in Figure 1.

Following the four leading brands in Table 2 are Caffeine Free Diet Coca-Cola, Caffeine Free Diet Pepsi, Diet Coca-Cola Zero, and Caffeine Free Regular Pepsi. These new products are expected to substitute for the four leading brands of both companies. Therefore, the pricing strategies of these new products might have a direct impact on the brand-choice ratio of the four leading brands. While Pepsi did not significantly differentiate the pricing strategies for its new products, Coke set relatively higher prices on its new products (see Table 3). Consequently, it is expected that Pepsi’s new products might have more substitution impact on its leading classic brands than new Coke products might have on its classic brands.

Lastly, two dummy variables were included in the model to analyze the short-term (Oly.Short) and long-term (Oly.Long) effect of Olympic sponsorship. Another
dummy interacted the short-term effect and the natural logarithm of the advertising expenditure ratio (\(\text{In}_{-} \text{AD}_{-} \text{Ratio}\)). Figure 2 also demonstrates that the advertising expenditure of Coke greatly increased during the Olympic Games, but its effects on brand choice, both short-term and long-term, are not explicitly supported.\(^{13}\)

**Test Results and Model Specification**

To explore the feasible GLS model with the best fitted error process for the data, this study implemented three tests for three assumptions: (a) contemporaneous correlation, (b) serial correlation, and (c) heteroskedasticity.\(^{14}\) Table 4 names and summarizes results for tests of these three assumptions. The null hypotheses for the first and third assumptions—that is, there is no contemporaneous correlation and there is homoskedasticity—were rejected at the 1% significance level, while the null hypothesis for the second assumption was not rejected. Given the result, this study estimated the feasible GLS model with an error process that assumes contemporaneous correlation, heteroskedasticity, and no serial correlation.

In addition, an OLS model with panel-corrected standard errors, which also allow contemporaneous correlation and heteroskedasticity across DMAs, was estimated together with the feasible GLS model. If there is a considerable difference between the estimates from these two models, the reliability of the feasible GLS model might come into question.

**Estimation Results**

Table 5 summarizes the estimates of the coefficients, standard errors, and z-statistics for the two models mentioned above: (a) the feasible GLS model that assumes contemporaneous correlation and heteroskedasticity and (b) the OLS model with panel-corrected standard errors. For ease of presentation, the estimation results for the DMA dummies are not provided in Table 5.\(^{15}\) The estimates from both models were fairly similar, with the feasible GLS generally showing smaller standard errors.

The signs on the \(P\_\text{Ratio}\) were both negative, as expected, and statistically significant at the 5% level. The marginal effect of the relative price of Coke (or the price-ratio) was -1.56 in the GLS model and -1.93 in the OLS model. Brand loyalty based on par-

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Table 4. The Results of Tests on the Error Process

<table>
<thead>
<tr>
<th>Error process</th>
<th>Contemporaneous correlation</th>
<th>Serial correlation</th>
<th>Heteroskedasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test name</td>
<td>Breusch-Pagan LM Test*</td>
<td>Wooldridge Test**</td>
<td>Modified Wald Test***</td>
</tr>
<tr>
<td>Null hypothesis ((H_0))</td>
<td>(E(u_{it}u_{jt}) = 0)</td>
<td>(\rho = 0)</td>
<td>(E(u^2_{it}) = \sigma^2)</td>
</tr>
<tr>
<td>Test statistic</td>
<td>chi2(105) = 158.040</td>
<td>F(1, 14) = 0.074</td>
<td>chi2 (15) = 2897.48</td>
</tr>
<tr>
<td></td>
<td>(Pr. &gt; chi2 = 0.0006)</td>
<td>(Pr. &gt; F = 0.7889)</td>
<td>(Pr. &gt; chi2 = 0.0000)</td>
</tr>
</tbody>
</table>

Note. *see Breusch and Pagan (1980); **see Greene (2000, p. 598); ***see Wooldridge (2002, pp. 274-276).
Table 5. Estimation Results of the Feasible GLS Model and the OLS Model

<table>
<thead>
<tr>
<th></th>
<th>Feasible GLS</th>
<th></th>
<th></th>
<th>OLS</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coefficient</td>
<td>Standard</td>
<td>Coefficient</td>
<td>Standard</td>
<td>Coefficient</td>
<td>Standard</td>
</tr>
<tr>
<td></td>
<td>error</td>
<td>z-statistic</td>
<td>error</td>
<td>z-statistic</td>
<td>error</td>
<td>z-statistic</td>
</tr>
<tr>
<td>P_Ratio</td>
<td>-1.55691</td>
<td>0.091</td>
<td>-17.18**</td>
<td>-1.92906</td>
<td>0.136</td>
<td>-14.19**</td>
</tr>
<tr>
<td>In_AD_Ratio</td>
<td>0.01787</td>
<td>0.004</td>
<td>4.24**</td>
<td>0.01716</td>
<td>0.007</td>
<td>2.34**</td>
</tr>
<tr>
<td>PD_Coke</td>
<td>0.67863</td>
<td>0.156</td>
<td>4.34**</td>
<td>0.89011</td>
<td>0.232</td>
<td>3.79**</td>
</tr>
<tr>
<td>PD_Pepsi</td>
<td>-0.11654</td>
<td>0.109</td>
<td>-1.07</td>
<td>-0.11610</td>
<td>0.166</td>
<td>-0.70</td>
</tr>
<tr>
<td>Oly_Short</td>
<td>0.31936</td>
<td>0.084</td>
<td>3.78**</td>
<td>0.23177</td>
<td>0.141</td>
<td>1.65*</td>
</tr>
<tr>
<td>Oly_Long</td>
<td>0.01757</td>
<td>0.031</td>
<td>0.56</td>
<td>0.04096</td>
<td>0.053</td>
<td>0.77</td>
</tr>
<tr>
<td>In_AD_Only</td>
<td>0.02228</td>
<td>0.021</td>
<td>1.02</td>
<td>0.04940</td>
<td>0.036</td>
<td>1.36</td>
</tr>
</tbody>
</table>

Note. *the estimate is statistically significant at the 10% level; **the estimate is statistically significant at the 5% level.

Table 6. Calculation of the Short-Term Sponsorship Effect

<table>
<thead>
<tr>
<th></th>
<th>Estimates</th>
<th>Average of In_AD_Ratio</th>
<th>Marginal Effect of In_AD_Ratio</th>
<th>Sponsorship effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>Not during</td>
<td>0.0179</td>
<td>1.318</td>
<td>0.0179 × 1.318 = 0.024</td>
<td>0.319 (Oly_Short) + (0.143-0.024)</td>
</tr>
<tr>
<td>(In_AD_Ratio)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>During the Olympics</td>
<td>0.0179 + 0.023</td>
<td>3.519</td>
<td>0.041 × 3.519 = 0.143</td>
<td>0.438</td>
</tr>
<tr>
<td>(In_AD_Ratio + Oly_AD)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Particular product characteristics would constrain these coefficients at absolute levels less than -1.00, reflecting that the change in relative quantity would be less than the change in relative price. Compared with this standard, these numbers seem to be relatively large. This result may support a fundamental assumption of this study: Substantive differences in functional attributes do not drive brand choice to a greater degree than marketing variables. At the least, it suggests that product attributes, such as taste or composition of ingredients, might not be the primary factors eliciting brand choice. Therefore, intangible properties associated with the product that are not based on experience with the product—but are based on perceptions influenced by marketing factors, such as advertising or sponsorship—may be determinative.

The estimated coefficients for the prices of new cola brands presented signs that might suggest a substitution effect. For example, the estimate 0.67863 means that, if the price of new Coke products increased by 10% relative to that of Regular Coke and Diet Coke, consumers’ brand choice of classic products also would increase by approximately 6.8%, in terms of the brand-choice ratio. The relatively higher prices of new brands may deter consumers from the consumption of the new products relative to the
classic products. Meanwhile, the price difference between new and classic Coke brands was statistically significant at the 5% level; the same does not hold for the price difference between Pepsi brands.

Next, this study investigated the estimation results for the four pivotal variables that provide information about the relationship between advertising/sponsorship and brand choice. First, the signs of three estimates—\( In\_AD\_Ratio \), \( Oly\_Short \), and \( Oly\_Long \)—showed positive effects of advertising and sponsorship on consumers’ brand choice. But the long-term effect of sponsorship (\( Oly\_Long \)) was not statistically significant in either model. An interesting result came from the positive sign on the interactive term, \( In\_AD\_Oly \), which presumably suggests some synergistic effect arising from advertising and sponsorship. The advertising effect increased during the Olympic period; thus, this additional effect, represented by \( In\_AD\_Oly \) could be interpreted as a kind of sponsorship effect. Therefore, the short-term sponsorship effect could be calculated as the sum of the pure effect from the estimates of \( Oly\_Short \) and the synergistic effect from increased advertising effects. The short-term sponsorship effect can be measured on the basis of the estimation results of the GLS model, as in Table 6. The synergistic effect was computed by comparing the two marginal effects of \( In\_AD\_Ratio \), one estimated during the Olympic period and one outside of the Olympic period. In the GLS model, Coke’s Olympic sponsorship increased the brand-choice ratio (Coke:Pepsi) of the product by 0.438 during the Olympic period. This figure represents the short-term sponsorship effect on the brand-choice ratio, consisting of the pure effect from the estimate of \( Oly\_Short \) (0.319) and the synergistic effect from increased advertising effects (0.119)—that is, the advertising effect during the Olympics (0.143) minus the effect outside the Olympics (0.024). The interactive term, \( In\_AD\_Oly \), was not statistically significant at the 10% level in either model.

In sum, the estimation results from the GLS and OLS models show that: (a) consumer’s brand choice between Coke and Pepsi largely depends on the firm’s promotional strategies, such as pricing, advertising, and sponsorship, and may not depend on functional attributes such as taste; (b) an interactive effect of advertising and sponsorship was observed but was not supported as statistically significant by the models; and (c) after controlling for advertising effects, there was still a short-term sponsorship effect on consumer brand choice, but a long-term effect was not statistically supported in either of the models, despite the expected positive signs.

It is noteworthy that our results only support existence of a short-term effect. Indeed, it has been found that a long-term effect for advertising might not easily be captured econometrically, even if it may exist. While some scholars claim that a proxy branding effort such as sponsorship presumably has a long-term effect on sales (Baghestani, 1991; Cain, 2010; Chudy, 2008; Mela, Gupta, & Lehmann, 1997), studies have questioned the measurability of any long-term advertising effect (Dekimpe & Hanssens, 1999; Clarke, 1976). Givon and Horsky (1990) found that advertising’s carryover effect is not greater than the purchase reinforcement effect in the evolution of market share. Clarke (1976) surveyed the literature that examined lasting effects of advertising on sales and concluded that the cumulative advertising effect on sales would likely last only several months rather than years. Even though a long-term effect from sponsorship as advertising has been widely maintained, it might not be empirically captured unless a more comprehensive macro-level analysis is employed.
An Analysis of the Olympic Sponsorship Effect on Consumer Brand Choice

Alternatively, this absence of a long-term effect might be due to the short span of the panel data. Because the household panel data began from the Torino Winter Games period, it is impossible to extrapolate the long-term effect of sponsorship with respect to the whole 3-year span. Therefore, the 5-month span before and after the Beijing Summer Games was used to analyze the long-term effect. This may not be long enough to manifest a long-term effect, if one exists.

In general, the results support that an evaluation of ROI for Coca-Cola’s Olympic Games sponsorship is empirically attainable, even though only a short-term effect has been evidenced. Because Coca-Cola’s Olympic Games sponsorship had a statistically significant effect on consumer brand choice during the event period, one could calculate the variable Incremental Volume in ROI equation (1) by converting the short-term effect—presented as a brand-choice ratio term in Table 6—into a sales volume term, using information about the entire market for Coca-Cola and Pepsi, if available. In addition, information about total advertising expenditures by Coca-Cola and Pepsi during the Olympic periods and Coca-Cola’s Olympic sponsorship fee would make it possible to derive the Total Cost term in ROI equation (1). Then, adding net unit profit information from Coca-Cola would define the VCM variable in equation (1). Thus, with all of the elements, evaluation of ROI for Coca-Cola’s Olympic sponsorship is a matter of simple calculation.

Conclusion

This study sought evidence for sponsorship effects on consumer brand choice to determine whether sponsorship ROI can be empirically achievable. By focusing on a vigorous Olympic sponsorship program, and utilizing long panel household scanner data, we examined the actual market responses to the efforts of sponsorship engagement—that is, consumer brand choice during and after Olympic Games periods. By introducing dummies during the Olympic Games for the short-term and after the Olympic Games for the long-term, Olympic sponsorship effects were extracted. In developing the long panel model, we used various ways to separate the sponsorship effect from other factors expected to impact consumer brand choice: using the ratio terms; introducing other promotional variables, such as price and advertising, as explanatory variables; and considering heterogeneity of DMAs and any substitution effects from new brands. In addition, for the feasible GLS model, this study tested three assumptions on the error process. Then, the GLS model—with contemporaneous correlation and heteroskedasticity, chosen based on test results—was run, along with an OLS model with panel-corrected errors to check for robustness of estimation results.

Results from the models show that, advertising effects apart, a sponsorship effect on consumer purchasing behavior actually exists, although it seems limited to a short-term effect—that is, limited to the duration of the sponsored event itself. Moreover, this short-term effect may be decomposed into a pure effect from sponsorship, after other marketing variables are controlled, as consumers purchase more sponsored products during a sports event than they otherwise would. It also captured an indirect effect from sponsorship, as sponsorship increases the effectiveness of a sponsor’s traditional advertising efforts during the sponsored event.

Identifying a sponsorship effect has implications for event organizers and potential sponsors. Organizers seeking sponsorship fees may be asked to submit empirical evi-
dence of a positive sponsorship effect. Potential sponsors may also turn to empirical evidence of a positive effect before deciding to sponsor an event. A positive sponsorship effect means that strategic action has the intended effect on sales volume of sponsored products. This implies a financial return attributable to sponsorship. This investigation demonstrated that sponsorship effect can be empirically captured by using panel data. Its results show that the elements necessary for ROI calculations can be practically produced. That is, for sport sponsorship for the major soft drink brand, using this study’s results along with full market information would enable sponsorship ROI calculations to be conducted. Thus, an analyst could use ROI to conclude whether the event sponsorship yields net financial gains.

Although only a short-term effect was statistically significant, our empirical result at least established a baseline foundation that could be used for ROI calculation in sponsorship. It is still possible that evaluation of a firm’s sponsorship based solely on the short-term effect could be flawed—whereas if a long-term effect exists, this could tip the balance to a positive ROI. The timeline within which ROI is calculated, remains at the discretion of the analyst and available dataset. Further breakthroughs in modeling and econometric identification of a long-term sponsorship effect could lead to more complete ROI evaluation for sponsors.

This investigation has several limitations. For tractability we primarily examined only four leading brands of two dominant companies in the market, since both Pepsi and Coca-Cola have been diversifying their soda brands remarkably in recent years. Focusing on the small number of leading brands this study may not explicate the complicated multivariate dynamics present in the market. Most of all, it only investigated the sponsorship dynamics in the cola market with its very unique characteristics. Consumption of cola is presumed to be more dependent on marketing factors rather than the functional values associated with the product, such as taste. Our analysis of sponsorship effects heavily depended on the particular characteristics of the cola market and the functional substitutability of the products. The implications may not be generalizable to other products that are more likely associated with functional values. The 15 DMAs from which the data were originally extracted may not represent the entire U.S. cola market. In addition, the aggregation of the individual household data to establish the DMA clusters makes it impossible to consider heterogeneity across households. Finally, the models may fail to explore the long-term effect because of the limited span of the dataset. This result could be different if the same analyses were done with longer panel data.

References

An Analysis of the Olympic Sponsorship Effect on Consumer Brand Choice


Cameron, A. C., & Trivedi, P. K. (2009). *Microeconometrics using stata*. College Station, TX: Stata Press.


**Endnotes**

1Our thanks go to the Food Marketing Policy Center at the University of Connecticut for Nielsen Homescan Data and corresponding advertising data.

2Households in the sample might not be representative of the U.S. population as a whole and might not record their purchases accurately. However, Einav, Leibtag, and Nevo (2008) recently submitted a report on the credibility of the Nielsen Homescan data with the conclusive com-
An Analysis of the Olympic Sponsorship Effect on Consumer Brand Choice

The overall accuracy of self-reported data by Homescan panelists seems to be in line with other commonly used (government-collected) economic datasets” (p. 3).

A DMA is a group of counties that form an exclusive geographic area for which the local market television stations hold a dominance of total hours viewed. In total, there are 207 DMAs for the entire U.S. and the data for our analysis cover 15 of the largest DMAs (i.e., Atlanta, Boston, Baltimore, Chicago, Detroit, Hartford-Springfield, Houston, Kansas City, Los Angeles, Miami, New York, Philadelphia, San Francisco, Seattle, and Washington D.C.), accounting for around 38% of total DMA markets by population (Trade Dimension, 2009). For a detailed description of how Nielsen collects Homescan Data, refer to Nielsen (2009, pp. 5-9).

In order to investigate advertising effects on viewers’ behavioral response, many of the studies apply audience measurement systems, called Nielsen ratings, from a Nielsen advertising dataset (e.g., Kanazawa & Funk, 2001; Szczypka et al., 2003). However, the level of our analysis is no longer each viewer (i.e., at the household-level) is now at the DMA-level. Thus, this study directly employs advertising expenditures, rather than Nielsen ratings, to fit the aggregated DMA-level dataset.

Although the price ratio and the advertising expenditure ratio of these DMAs are 1.05 versus 1.08 and 37.7 versus 35.8, the brand-choice ratio is 1.39 versus 3.27.

Cameron and Trivedi (2009) suggest that individual effects from heterogeneity may be incorporated into explanatory variables as dummy-variable regressors when there are relatively few individuals relative to the number of time periods in long panel datasets.

As explained before, this unobserved heterogeneity is no longer an issue in a long panel model because that can be largely handled by including dummy variables.

For panel data, it is often the case that the error correlation declines as the time difference increases. The assumption of AR(1) makes it possible to consider this dampening in the error process (Cameron & Trivedi, 2009, p. 249). That is, in the error form in (3), AR(1) implies that $\rho_{ts} = \rho^{ts}$, where $t$ and $s$ are different time periods.

The feasible GLS estimation replaces the error variance matrix assumed in the GLS estimation by the estimated error variance. For a detailed discussion, see Cameron and Trivedi (2005).

Advertising expenditures for both Coca-Cola and Pepsi have about 1.7 times greater standard deviations than their mean values—a large degree of variation, as shown in Figure 2. The ratio constructed with these expenditures has, as a result, a significantly skewed distribution. After taking a logarithm, skewness and kurtosis dropped from 8.47 to 0.15 and from 107.7 to 2.6.

The LOWESS, as a variation of the local linear estimator, is generally used as an alternative curve-fitting approach that uses nonparametric methods to fit a local relationship between a $y$ variable and an $x$ variable. For details, refer to Cameron and Trivedi (2009, pp. 65-67).

In Figure 2, outside of the Olympic period, Coca-Cola’s advertising expenditure jumped in the last week of January in 2007 and 2008 due to promotional activities around the Super Bowl. However, Pepsi’s advertising expenditure also increased remarkably in these weeks.

We chose these tests for their robustness among a class of tests for each assumption. For example, while the Baltagi-Wu test is also widely accepted as a test for serial correlation because of its optimality, it is known that the Wooldridge test is more robust because it is based on fewer assumptions. The Modified Wald test is also free of the normality assumption.

In both models, almost all of the 14 dummies show statistically significant estimates at the 5% level. That means that heterogeneity clearly exists across DMAs.