5-2011

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Recommended Citation

Karniouchina, Ekaterina V., Can Uslay, and Grigori Erenburg. "Do marketing media have life cycles? The case of product placement in movies." *Journal of Marketing* 75.3 (2011): 27-48.
DOI:10.1509/jmkg.75.3.27

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Do Marketing Media Have Life Cycles? The Case of Product Placement in Movies

This article examines the economic worth of product placement in movies over a time span of 40 years (1968–2007). The authors find an inverted U-shaped relationship between the year of the movie release and the returns associated with product placements. In addition, a similar inverted U-shaped relationship characterizes the economic worth of tie-in campaigns associated with product placements. These findings are consistent with the habituation–tedium theory used to explain the inverted U-shaped pattern in response to novel advertisements and suggest that the same mechanism could be influencing the response to an entire marketing medium. Overall, the results reinforce the notion that marketers find it increasingly difficult to get their message across using traditional media and underscore the need for the marketing industry to reinvent itself when new tactics lose their luster. The authors conclude with a discussion of additional empirical regularities.

Keywords: product placement, marketing media life cycles, movies, habituation–tedium theory, event study, cumulative abnormal returns, hierarchical linear modeling

For better (e.g., the Nokia 7110 in *The Matrix* [1999]) or worse (e.g., more than four dozen brands in *The Departed* [2006]), product placement in the movies has become a part of the contemporary marketing arsenal, lending its power to offerings ranging from pregnancy tests to luxury cars (Grover 2009). Gupta and Gould (1997, p. 37) define product placement as a marketing strategy that "involves incorporating brands in movies in return for money or for some promotional or other consideration." Industry sources boast that it can do wonders and significantly boost sales of featured brands. For example, Ray-Ban considered the lifespan of its Wayfarer model sunglasses to be almost over when it placed them in *Risky Business* (1983). Before the release of the movie, the declining sales were at approximately 18,000 units a year; following the movie release, the annual sales of the revived product jumped to 360,000 units. By 1989, following a number of successive placements (e.g., *Top Gun* [1986]), sales reached 4 million units (Sengrave 2004). Despite the abundance of such success stories, the evidence for the tangible benefits of product placement is mostly anecdotal, and studies that empirically demonstrate its economic worth are scant at best. Nevertheless, firms can take extreme measures to establish strategic dominance in branded entertainment. At the peak of the "cola wars" in the early 1980s, Coca-Cola went as far as purchasing Columbia Pictures to control the entertainment arena (Sengrave 2004).

Product placement originally fell under the umbrella of covert marketing because viewers were often unaware of the commercial persuasion effort. Many early marketing research efforts concentrated on the subliminal and covert nature of this marketing medium (Nebenzahl and Secunda 1993). However, as consumers have become more marketing savvy and the technique more prominent, it has shifted closer to the realm of conventional marketing. At present, the question remains whether this tactic is still as effective as it was in the past; it is commonly believed that when advertisers cross the line and overwhelm the audience with blatant product placements, their efforts will backfire (Mandese 2006; Wei, Fischer, and Main 2008).

In this article, we adopt a longitudinal perspective and examine the evolution of the effectiveness of product placement in the movies over a 40-year time frame. First, we provide a literature review that focuses on the history and the suggested efficacy of this marketing medium. Second, we introduce our conceptual framework and present our hypotheses. Third, we discuss the data and methodologies (event study and hierarchical linear modeling [HLM]). Fourth, we present and discuss our findings. We conclude

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ISSN: 0022-2429 (print), 1547-7185 (electronic)

with managerial implications, future research directions, and limitations.

An Historical Perspective on Product Placement

Although many researchers believe that product placement was born when a little boy made an extraterrestrial friend by laying a trail of Reese's Pieces in *E.T.* (1982) (Newell, Salmon, and Chang 2006), other sources are starkly divided on its true origins. For example, Karrh, McKee, and Pardun (2003) argue that product placement originated in the 1940s, while others suggest that this marketing medium can be traced back to the end of nineteenth century, when Lever Brothers' Sunlight soap was placed in several films (Newell, Salmon, and Chang 2006). However, most sources agree that the practice emerged as a legitimate marketing instrument in the mid-1970s and has been rapidly expanding since that time. The biggest surge has arguably been during first decade of the twenty-first century (La Ferle and Edwards 2006). Product placement spending in the United States grew at an annual rate of almost 34% to $2.9 billion in 2007 and was projected to reach $5.6 billion in 2010 (PQ Media 2008).

In the early stages of its development, product placement was governed by ad hoc decisions and intuition (Steortz 1987). Branded placement was a casual process, in which branded items were donated, loaned, or purchased at a discount for particular scenes (DeLorme and Reid 1999). However, in the new millennium, the process of placing branded consumer products in feature films has gained mass appeal, becoming orderly and institutional, with clearly defined roles involving multiple parties and intermediaries (Karrh, McKee, and Pardun 2003). For example, NextMedium has propelled itself as a leader in the product placement arena by automating the process of product placement in the movies, television shows, and video games and even allowing product placement needs to be filled using an auction-based platform (Schonfeld and Borzo 2006). With more than 80% of national marketers using branded placement (Johannes 2006), the practice is certainly a part of today's mainstream marketing arsenal.

Because of the proliferation of this marketing medium, consumers are becoming aware of product placement tactics and have started to show evidence of resistance to persuasion (Wei, Fischer, and Main 2008). In addition, in an ironic twist, product placements have now created a cluttered environment, which marketers initially designed the tactic to avoid. Furthermore, consumers and industry participants are beginning to question whether the overabundance of placements detracts from the viewing experience and interferes with filmmakers' creative vision (e.g., Writers Guild of America West 2005). Numerous Internet blogs are devoted to dissecting and mocking placement-heavy films (e.g., http://www.brandspotters.com). Multiple consumer advocacy groups are calling on the Federal Trade Commission and other government agencies to curb and/or regulate product placement practices (e.g., Commercial Alert 2003). This study provides an empirical examination of the effectiveness of product placements. Thus, we forgo a detailed examination of related public policy issues, many of which are covered elsewhere (see the special section on covert marketing in the Spring 2008 issue of *Journal of Public Policy & Marketing*).

Product Placement Efficacy

Researchers have traditionally attributed the efficacy of product placement as a marketing medium to its ability to cut through advertising clutter by relying on transference mechanisms. Instead of competing against a plethora of competitive advertisements in more traditional advertising channels, product placement acts in a more unobtrusive way by evoking the positive associations, aspirations, and symbolic meanings connected with the underlying movie content (Russell 1998). Excitation transfer theory (Zillmann 1996) also suggests that the excitement associated with film sequences can be transferred to other subsequently presented objects, including embedded products. Labeled by the industry as "the anti-TiVo," product placements are also believed to be more effective in reaching the target audience than traditional advertising spots because they are immune to ad skipping (Schonfeld and Borzo 2006). Finally, product placements might circumvent consumer resentment by blurring the lines between commercial content and entertainment, thereby providing "advertainment" (Kretchmer 2004).

Academic studies on the efficacy of product placement to date have dealt with its economic value (Wiles and Danielova 2009), the effects of execution-related factors (e.g., Gupta and Lord 1998; Russell 2002), cross-cultural differences in audience response (e.g., Gould, Gupta, and Grabner-Kräuter 2000; Karrh, Frith, and Callison 2001; Nebenzahl and Secunda 1993), and ethical concerns related to its use (e.g., d'Astous and Seguin 1999; Gupta and Gould 1997; Nebenzahl and Secunda 1993; Wenner 2004). Table 1 summarizes the relevant literature on the efficacy of product placements (also see DeLorme and Reid 1999). In this study, we largely limit our inquiry to the first area—namely, the economic worth of placements.

As listed in Table 1, there is an abundance of survey-based and experimental studies devoted to product placement. However, empirical work that has investigated the impact of this marketing strategy on firm value is almost nonexistent. In their conceptual framework, Balasubramanian, Karrh, and Patwardhan (2006) propose three conative outcomes of product placement (i.e., purchase intentions, brand choice, and brand usage behavior). However, to measure the true efficacy of this marketing medium, we must ensure that these factors ultimately translate into firm value.

At present, the consensus is that, despite the large spectrum of research on product placement, the economic value of a placement remains a pressing research question (Balasubramanian, Karrh, and Patwardhan 2006). We are aware of only one study that has attempted to evaluate the effect of product placement in movies on firm value: In a cross-sectional study, Wiles and Danielova (2009) investigate price reactions for stocks of publicly traded companies that placed their brands in the 24 most popular movies of 2002. Their daily event study indicates that product place-

TABLE 1
Overview of Select Literature on Product Placement Efficacy

Study	Dependent Variable	Method	Sample	Findings
Wiles and Danielova (2009)	Stock price	Event analysis	24 most popular films, single year, 126 placements total	.89% abnormal return over the (–2, 0) event window.
Cowley and Barron (2008)	Brand recall	Survey	3532 French DVD viewers	Brand recall is enhanced when the respondents like the director or the movie.
Wei, Fischer, and Main (2008)	Evaluations of embedded brands	Experiment	Three experiments with 81, 108, and 209 college students	Activation negatively affects evaluations of brands embedded in radio shows. Perceived appropriateness and brand familiarity diminishes this negative effect, and activation with high brand familiarity can even reverse it.
De Gregorio, Sung, and Jung (2007)	Attitude toward placements	Survey	3340 consumers	Most consumers are still positively disposed toward product placement, do not see a need for regulation, and have a tendency toward neutrality regarding certain elements associated with the practice.
Lee and Faber (2007)	Brand recall	Experiment	155 college students	Brand recall is enhanced when the placement in computer games is incongruent with the brand.
Balasubramanian, Karrh, and Patwardhan (2006)	N.A.	Conceptual	N.A.	Conative responses to product placements include purchase intention, brand choice, and brand usage behavior.
Karrh, McKee, and Pardun (2003)	Practitioners' beliefs regarding placements	Survey	28 ERMA members	Practitioners believe that the number of placements will grow, leading to trade-offs between creative and financial concerns. They also strongly believe that product placements increase product sales.
Russell (2002)	Brand recall and attitude toward brand	Experiment	5 × 30 college students	Memory improves when modality and plot connection are incongruent, but persuasion is enhanced by congruency.
Gupta and Gould (1997)	Attitude toward brand placement	Survey	1012 college students	A generally positive attitude exists toward brand placement. The authors find that certain categories (e.g., tobacco, guns) are less acceptable.
Gupta and Lord (1998)	Recall of placed brands	Experiment	274 college students	Prominent product placements lead to greater recall. Conventional advertising is a better strategy if prominent placement is unattainable or cost prohibitive.
Babin and Carder (1996a)	Brand recognition	Experiment	98 college students	Subjects correctly identified brands that were present in or absent from the movie.
Babin and Carder (1996b)	Brand salience	Experiment	108 college students	Salience is greater for placed brands but only for approximately one quarter of the product placements.
Baker and Crawford (1996)	Attitude toward brand placement	Survey	43 postgraduate students	Most respondents had a neutral attitude toward brand placement.
DeLorme, Reid, and Zimmer (1994)	Attitude toward brand placement	Focus group	29 college students	Generally positive attitude toward placements. Negative attitude toward overexposed brands.
Karrh (1994)	Recall of placed brands	Experiment	76 college students	Prominent product placements lead to greater recall and recognition. The results are inconsistent across movies and brands.
Ong and Meri (1994)	Recall of placed brands, purchase intentions for placed brands	Experiment	75 moviegoers	Generally positive attitude toward product placements but poor unaided recall. No link between recall of placement in movies and increased purchase intentions.
Vollmers and Mizerski (1994)	Recall of placed brands	Experiment	71 college students	96% of participants were aware of a brand placement, and 93% of participants correctly identified brands that had appeared in movies they had viewed.

Notes: N.A. = not applicable.

ment in these movies resulted in .89% positive abnormal return over the (–2, 0) movie release event window.[1] Surprisingly, the cumulative abnormal return (CAR) over the (–2, 1) time window was not significant, indicating a possible price reversal that takes place immediately after the movies' release. Therefore, additional research on the efficacy of such a heavily used marketing medium is warranted. In this study, we examine both blockbuster and nonblockbuster movies and extend this emerging research stream with a longitudinal examination of the value of product placements and related tie-in campaigns (i.e., concurrent advertisement campaigns marketers use to accentuate the effect of placements).

Conceptual Framework

A possible explanation why so little research has been done to estimate the financial worth of product placements is the complex lagged effects of product placement on firms' cash flows. Moreover, other concurrent activities affect cash flows and revenues, making it difficult to tease out the value product placement adds specifically. We attempt to overcome this problem by analyzing stock market reaction to product placement.

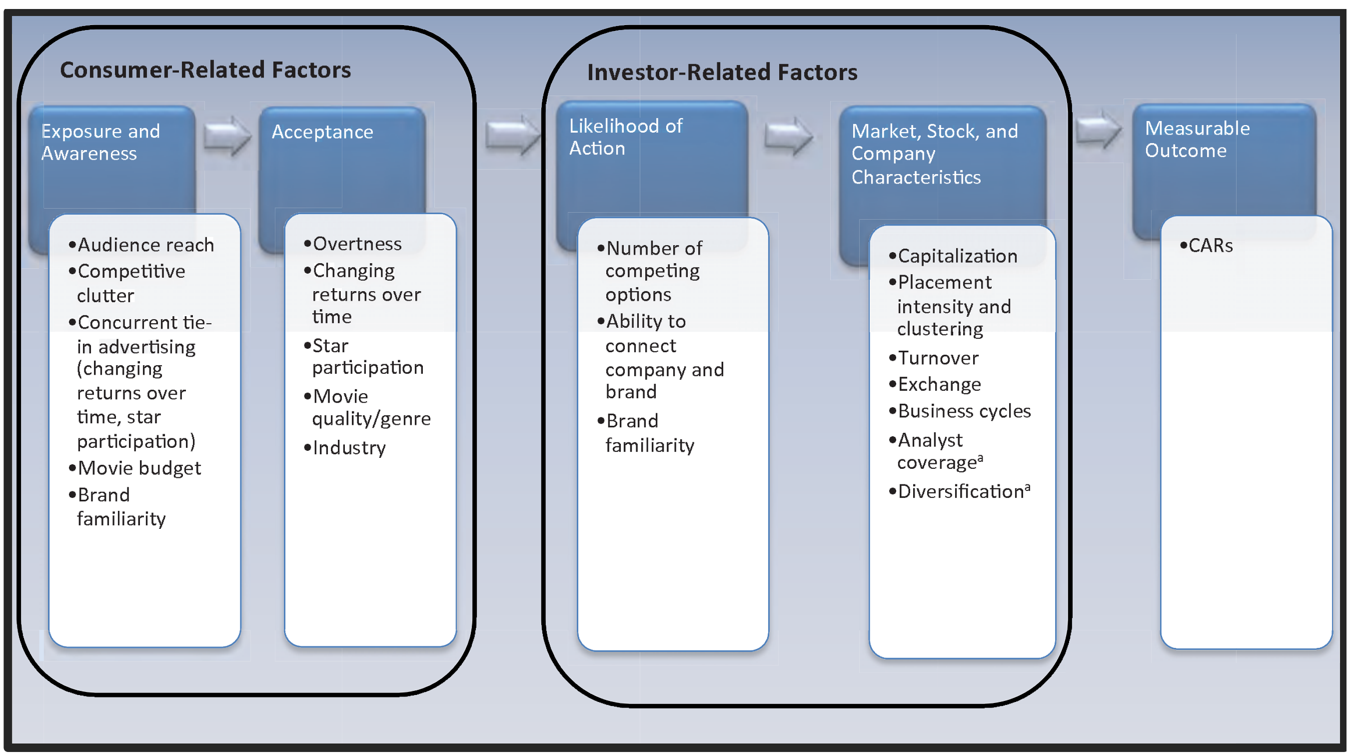
[1]In event studies, the defined event (in this case, the release of the movie with a given placement) takes place at Time 0. Therefore, (–2, 0) event window represents the time from two trading days before the release date through the release date.

The efficient market theory (EMT) stipulates that stock prices reflect available information regarding a firm's future cash flows (Fama 1970). According to this theory, once information about the product placement is available to investors, the resulting change in stock price should reflect investors' expectations of the total change in future cash flows due to the product placement. Our conceptual framework builds on the EMT, which posits that investors' responses to product placements are contingent on their expectations regarding customer behavior (see Figure 1). By measuring stock price reaction to the release of the movie in which the company's brand is featured, we estimate the incremental value that the investors place on that product placement. We introduce several factors related to the placements' ability to resonate with moviegoers, and produce the desired effect. In addition, we introduce information-processing effects and market-related controls because they can influence investors' willingness and ability to invest in brands that are placed in feature films and our ability to detect abnormal returns. Next, we discuss the conceptual framework and its key factors in more detail.

Exposure and Awareness

For the markets to register a response to product placements, consumers first must become aware of or at least exposed to the placement. (Exposure would be sufficient if we posit that placements act on a subliminal level.) Therefore, our framework accounts for audience reach. In addition, it considers the possible effects of competitive clutter

FIGURE 1
Conceptual Framework



[a]Factors that may offer alternative explanations for time-related effects. See the "Robustness Checks" section for details.

within the same movie because excessive product placements can create consumer information overload (Malhotra, Jain, and Lagakos 1982) and decrease the attention given to each placement.

Srinivasan and Hanssens (2009) note that product innovation has a greater impact on firm value when coupled with greater advertising support. It is possible that product placements that are tied to concurrent traditional advertising/sales promotion campaigns also generate higher returns because they can create more traction with consumers. To control for this, we incorporate promotional tie-in campaigns into the framework. The framework also recognizes that the effectiveness of the tie-in campaigns can follow a certain trajectory over time (e.g., an inverted U-shaped trajectory suggested by the habituation–tedium theory that we discuss subsequently) and be affected by additional drivers such as A-list celebrity participation.

To account for the awareness of the movie before its release, we incorporate adjusted production budget, which research has found to be highly correlated with advertising spending (Ravid and Basuroy 2004) because advertising data are not available for the majority of time frame covered by our study. Moreover, the framework includes brand familiarity because it can influence the awareness and acceptance of the placement effort.

Acceptance

In addition to exposure, consumers should also be receptive to buying the products placed in the movies. More prominent placements could be more memorable; at the same time, consumers can show resistance to over-the-top marketing efforts and exhibit general anticonsumption tendencies in various settings (Cherrier 2009; Close and Zinkhan 2009). Some placements can be so overt (e.g., repeated placements of the same brand within the film) that the centrality of the brand/product to the plot can alert the viewers to the placement effort and even cause resentment. Therefore, we incorporate overtness of the placement in our framework.

Meanwhile, growing resentment of product placements could give rise to negative time effects, and familiarity with the medium and increased product placement expertise of marketers could give rise to positive time effects. We also include the actors' star power in the framework because it can influence the acceptance level of the placed brands if the stars are perceived as endorsers. The degree of annoyance might be greater when placements are embedded in poor-quality films. In addition, we anticipate that certain movies and movie genres are less suitable for product placement. Consequently, our framework includes control variables related to observed and unobserved movie heterogeneity. In addition, we include industry classification because product placement activities might be more (less) successful in generating value according to industry membership of the firms making the placements. Mundane, industrial products might be less memorable, while consumer goods might generate more buzz and excitement through placement.

Likelihood of Investor Action

It is understood that enhancing brand equity enhances the firm's market valuation (Srinivasan and Hanssens 2009). However, the ability to connect the brand to its parent company is critical because failure to do so can restrict the flow of funds to the firm. Finance literature has demonstrated that there is significant confusion on the part of "noise traders" (i.e., investors whose decisions to buy, sell, or hold are not based on company's fundamentals [Black 1985]) when it comes to the ticker symbol–company connection. For example, Rashes (2001) reports on the comovement of stocks with similar ticker symbols. There is significant correlation between returns, volume, and volatility of these ticker pairs at short frequencies. Furthermore, the impact of product placement on a company's stock price is likely to be quicker and less noisy when there is a clear and straightforward connection between the featured brand and the parent company. Therefore, we distinguish between the companies whose name and ticker symbols are closely tied to a focal brand and the companies for which the immediate connection between the brand and corresponding security is more difficult to establish.

Our framework also incorporates other competing options (i.e., other placements in the movie) because they have the potential to decrease the resource flows to the focal security and create additional clutter (as we described previously in the "Exposure and Awareness" section). In addition, brand familiarity (relevant to consumer response) can also be relevant when it comes to investor action; for example, the marketing literature has indicated that brands that are less familiar to investors (and analysts) might be systematically undervalued (Srinivasan and Hanssens 2009).

Market- and Stock-Related Characteristics

The framework incorporates traditional factors related to market quality (e.g., market structure, liquidity, analyst coverage). In addition, we control for variables that might affect our ability to detect abnormal returns. A marketing action's impact is often difficult to measure because there are many marketing activities that take place concurrently. In the case of diversified companies, it is even more difficult because multiple brands in multiple industries are marketed using different strategies, and multiple contaminating events come into play, creating measurement noise. Therefore, we control for the firms' degree of diversification because the increase in firms' diversification over time (as Rumelt [1974] notes) could influence our findings with respect to time effects. Finally, market conditions might moderate the strength of market response to product placements; therefore, we consider business-cycle effects an alternative explanation for time-related effects.

Hypotheses

There are several product placement intermediaries/marketing research firms that use proprietary models to value branded entertainment (e.g., Brand Advisors, Delivery Agent, IEG, Image Impact, Intermedia Advertising Group, iTVX, Joyce Julius & Associates, Millward Brown, NextMedium [Embed], Nielsen IAG [Place*Values], Propaganda Entertainment Marketing). However, because the models and methods that these companies employ are proprietary, they are typically not available for examination. In light of the limited evidence from academic studies (Wiles and Danielova 2009) and limited industry information, there is a need to examine the overall economic worth of the product placement strategy using a large sample. We begin by examining the general connection between product placement and firm value.

H_1: Product placements (in the movies) increase firm value.

In the case of product placement, initial stock price reaction to product placement may be affected by noise trading; naive investors are known to buy stocks that have appeared in the news (Barber and Odean 2008), have been advertised in periodicals (Jain and Wu 2000), and have even been mentioned in spam e-mails (Frieder and Zittrain 2007). However, noise trading is not based on fundamental information regarding company's value, so it does not have a permanent effect on the market prices. If price run-ups associated with product placements were a result of noise trading, the resulting gains would be unsustainable, and stock prices would quickly return to their original state. We address this possibility in our second hypothesis:

H_2: The increase in firm value in response to product placement is persistent.

Because currently, there are few studies exploring specific theoretical underpinnings of product placement marketing medium, we rely on theories relevant to the advertising domain to develop the next set of hypotheses. We acknowledge that not all product placements are paid for and/or have identifiable sponsors, which might exclude them from the traditional advertising domain. However, advertising literature seems relevant because most placements tend to be paid for in some form (Balasubramanian, Karrh, and Patwardhan 2006), and more important, these theories have proved to be relevant in settings beyond traditional advertising (e.g., Karniouchina, Moore, and Cooney 2009).

Habituation–tedium theory (Sawyer 1981; Tellis 2004), which is based on Berlyne's (1970) two-factor model, suggests a two-stage process that governs response to repeated messages. The first stage (wear-in) is related to habituation, and the second stage (wear-out) is connected to tedium. When consumers are first exposed to novel advertising stimuli, they experience tension. Repeated exposure reduces the apprehension through habituation, which initially leads to more positive response. However, as the number of exposures exceeds a certain level, boredom and resentment set in, and attitude toward the ad as well as response diminish; the two forces lead to an inverted U-shaped relationship between the number of exposures and ad response.

Numerous studies have explored the effects of repeat exposure to advertising on consumer attitudes and purchase intentions. Vakratsas and Ambler (1999) review the advertising literature regarding repeat exposure and find diminishing returns in short-term advertising effectiveness.[2] That is, after a certain point, additional advertising impressions become ineffective. While there is some disagreement regarding the intensity of consumer response to consecutive advertising exposures (e.g., Little 1979; Simon and Arndt 1980; Tellis 2004), the majority opinion seems to lie with the inverted U-shaped relationship between the number of exposures and attitude formation, indicating wear-in and wear-out effects consistent with habituation–tedium theory (also see Appel 1971; Blair 2000).

What distinguishes our study from the aforementioned work is that we extend the examination of the wear-in and wear-out effects associated with repeat placements for individual brands by considering the wear-in/out effects associated with the product placement marketing medium in general and the tie-in campaigns used to enhance its effectiveness. In addition to the underlying habituation–tedium dynamics appearing on the consumer end, it is also possible that marketers initially gained benefits from learning to place products more effectively and run and optimize the tie-in campaigns. Industry sources suggest that Madison Avenue is constantly "learning more about what not to do with product placement than what … works best, especially when it comes to research and testing on consumer reactions to branded-entertainment deals" (Mandese 2006, p. 2). Therefore, a combination of consumer habituation, industry learning, and diminishing returns effects would suggest a curvilinear relationship between product placement effectiveness, concurrent tie-in campaigns, and time:

H_3: The longitudinal effect of product placement on firm value follows an inverted U-shaped relationship.

H_4: The longitudinal effect of tie-in campaigns on firm value follows an inverted U-shaped relationship.

We are aware of only one other study that examines the habituation–tedium dynamics when it comes to a novel advertising form: Edwards and Gangadharbatla (2001) examine the success of three-dimensional online product presentations in an experimental setting. They find that for study participants with limited prior exposure to this advertising medium, the novelty of the advertisement interfered with information processing and thus adversely affected purchase intentions. This is consistent with the habituation notion of the previously described two-step process; however, because of the novelty of the examined medium, the aforementioned study was not able to examine the effect of tedium (Schumann and Thorson 2007). The advantage of analyzing the product placement medium is that we can analyze this form of advertisement from the early stage in its development through the point at which the tedium dynamics have been established (Wei, Fischer, and Main 2008).

[2]The law of diminishing returns is an empirical regularity found in many economic relationships. It stipulates that after a certain point, with all other inputs held constant, the marginal benefit from adding one more unit of input drops as that input increases (Samuelson and Nordhaus 2001). This law has been applied in several advertising contexts (Picard 1989). For example, Horsky and Simon (1983) build a successful diffusion model that relies on two fundamental properties of advertising: lagged effects and diminishing returns.

Data and Methods

In this study, we employ the Brand Hype Movie Mapper data set. Brand Hype (University of Concordia) is an educational resource that includes a searchable movie/brand placement data set starting with 1968. Our investigation is based on the 1968–2007 time frame and uses 928 product placement observations (linked to 159 films) that have sufficient financial data for our analysis (for a list of the firms making the product placements, see Table 2). The average opening box office revenue in our sample is \$18.3 million, which is significantly lower than the \$44.8 million average Wiles and Danielova (2009) report. Therefore, the sample used in this study represents a broader cross-section of small and blockbuster films.

The Brand Hype data set was originally conceived as a collaborative data set (as was IMDb at its early stage of development). However, to date, the vast majority of data collection effort has been carried out by a graduate research assistant assigned to this project at the University of Concordia. We excluded the few wiki-like entries (related to foreign films, which the data set creators identified to us) from our analysis. For financial information on companies and their stock prices, we accessed the Center for Research in Security Prices (CRSP) database for stock-related data, the COMPUSTAT segments database for data needed to compute diversification measures, and the I/B/E/S database for data related to analyst coverage.

Event Study Model

Event studies that examine the impact of marketing actions on firm value are becoming popular in marketing research (e.g., Sood and Tellis 2004; Wiles and Danielova 2009). We contribute to this emerging research tradition and employ an event study methodology to detect market reaction to product placements. We assume that the event (or movie release) takes place at t = 0, and we use the estimation window preceding the event to estimate the normal or expected return. To predict normal performance, we use the traditional market model and the four-factor model that augments the market model by adding several well-documented market abnormalities (Carhart 1997; Fama and French 1996):

$$(1)\qquad R_{it} = \alpha_i + \beta_i R_{mt} + s_i SMB_t + h_i HML_t + u_i UMD_t + \varepsilon_{it},$$

where

- R_{it} = the return of stock i at time t,
- R_{mt} = the monthly return on the CRSP equally weighted index,
- β_i = a measure of stock i's sensitivity to market changes,
- ε_{it} = generalized autoregressive conditional heteroskedasticity (GARCH) error term,
- SMB_i = average return on small minus average return on large stock portfolios,
- HML_t = average return on high minus average return on low book-to-market stock portfolios, and
- UMD_t = average return on high minus average return on low performing stock portfolios.

Using the four-factor model, we define abnormal returns as follows:

$$(2)\qquad AR_{it} = R_{it} - (\hat{\alpha}_i + \hat{\beta}_i R_{mt} + \hat{s}_i SMB_t + \hat{h}_i HML_t + \hat{u}_i UMD_t),$$

where $\hat{\alpha}_i$, $\hat{\beta}_i$, $\hat{s}_i$, $\hat{h}_i$, and $\hat{u}_i$ are GARCH (1, 1) estimates of α_i, β_i, s_i, h_i, and u_i.

We used the GARCH (1, 1) estimation method (as Bollerslev [1986] suggests) because it allows the conditional variance to change as a function of both previously realized residuals and past variances. Boehmer, Musumeci, and Poulsen (1991) and Corhay and Rad (1996) provide evidence that event-study regression models that account for time-varying conditional variance properties and stochastic parameters lead to more efficient estimators of parameters and thus promote more robust conclusions than traditional event-study methodologies.

Identifying the appropriate data interval to estimate advertising effects is one of the most challenging questions in marketing research (Tellis and Franses 2006). The task becomes even more complicated when the objective is to isolate the impact of product placement on the market value of the firm. It is possible that information regarding product placements affects the market before the movie release (e.g., due to information leaked by industry insiders). Therefore, we began by estimating abnormal returns 30 trading days (six weeks) before the release date. Next, we extended this window because most movies collect the vast majority of their revenues over a ten-week period (there are sharp drop-off rates associated with this product category). The resulting broad time window is (–30, 50). Our choice of the time window that is broader than a few days around the event date is consistent with the common practice adopted in finance (e.g., MacKinlay 1997). Next, we adjusted this window according to the empirical results. The majority of the reaction takes place within a (–10, 16) event window (see Figure 2); thus, we focused the rest of our analysis on this time window, which roughly corresponds to two business weeks before and three business weeks after the movie release. We further verify the appropriateness of the event window by examining pre– and post–event window returns. Cumulative abnormal returns for various pre– and post–event window time frames, such as (–30, –11), (–20, –11), (17, 20), (17, 30), and (17, 50), are not significant.

We empirically control for event clustering and use statistical tests that account for autocorrelation and event-induced volatility; that is, we use a standardized cross-sectional test that is better suited than the conventional standard deviation test to deal with autocorrelation and event-induced volatility. It is more powerful than the Brown–Warner test (Brown and Warner 1985) but is equally well specified (Boehmer, Musumeci, and Poulsen 1991).

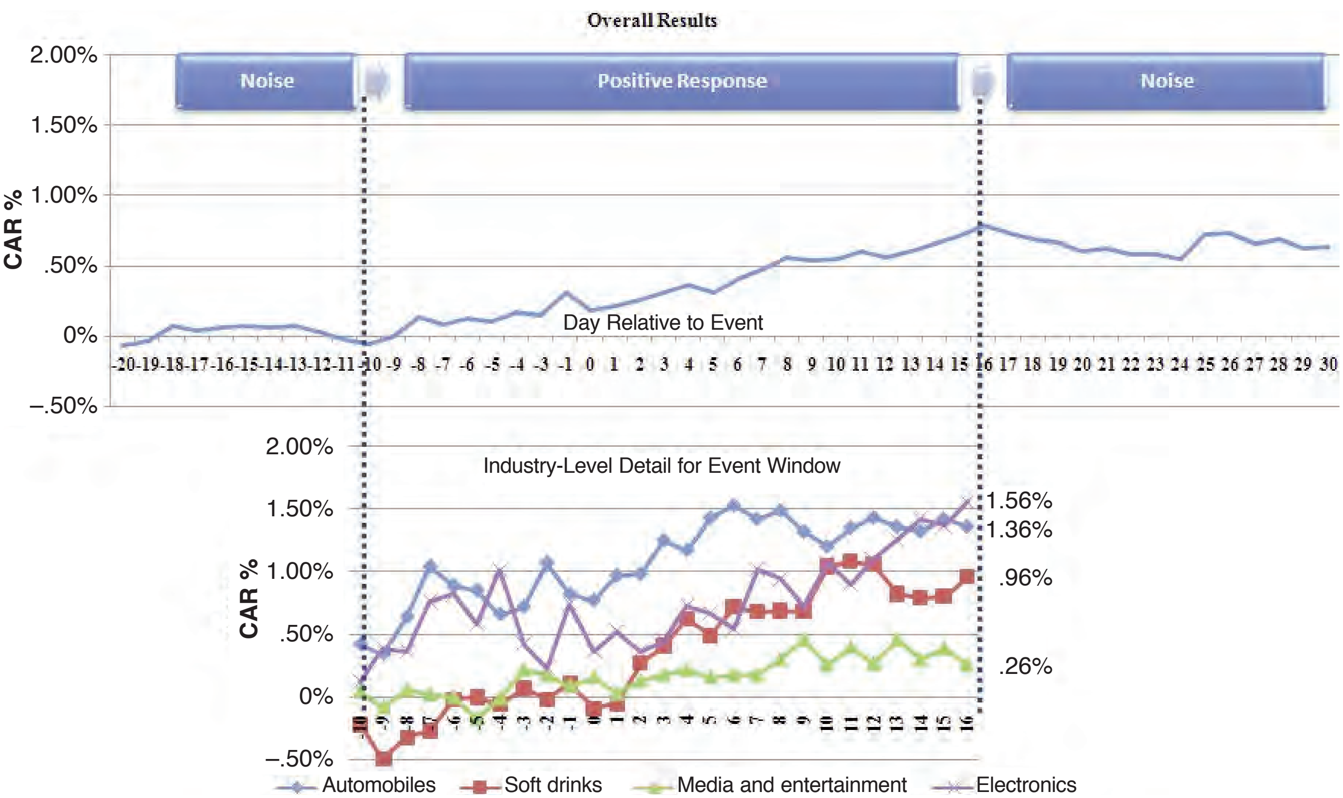
Multilevel Mixed Coefficient Model (Hierarchical Linear Modeling)

The drivers in our conceptual model relate to either a particular placement or a particular motion picture in which the placement was embedded (Figure 1). In addition, the brand placements we analyze in this study belong to different industries. Multilevel models focus on the analysis of data with such complex patterns of variance (i.e., nested structures; Luke 2004). Marketing researchers have been using multilevel models increasingly because they can model

TABLE 2
Firms with Product Placement in the Sample

Company	Frequency	Company	Frequency	Company	Frequency
Coca-Cola Co.	75	ConAgra Foods Inc.	3	Del Monte Foods Co.	1
PepsiCo Inc	61	Costco Wholesale Corp.	3	Domino’s Pizza Inc.	1
General Motors Corp.	45	Dr Pepper Snapple Group	3	Donna Karan International Inc.	1
Anheuser-Busch Cos. Inc	34	Gannett Co. Inc.	3	Dow Jones & Co. Inc.	1
Procter & Gamble Co.	32	The Hershey Co.	3	Dunkin Donuts	1
Apple Computer Inc.	29	Intercontinental Hotels	3	DynCorp International Inc.	1
Daimlerchrysler AG	28	Molson Coors Brewing Co.	3	eBay Inc.	1
Sony Corp.	27	Philip Morris International Inc.	3	Energizer Holdings Inc.	1
Time Warner Inc	27	Polo Ralph Lauren Corp.	3	Ericsson L M Telephone Co.	1
Diageo plc	18	Reynolds American Inc.	3	Foot Locker Inc.	1
NIKE Inc.	18	Sears Holdings Corp.	3	GlaxoSmithKline PLC	1
The Walt Disney Co.	16	Wyeth	3	Groupe Danone	1
News Corp.	15	YUM! Brands Inc.	3	Gulf Oil Limited Partnership	1
McDonald’s Corp.	13	Bank of America Corp.	2	Halliburton Company	1
Unilever NV	13	Bristol-Myers Squibb Co.	2	H.J. Heinz Co.	1
Cadbury Schweppes GmbH	12	The British Petroleum Co. PLC	2	Holiday Cos.	1
General Mills Inc.	12	Cendant Corp.	2	Home Depot Inc.	1
Altria Group Inc	11	Chevron Corp.	2	Hanes Brands Inc.	1
Microsoft Corp.	11	Clorox Co.	2	Intel Corp.	1
FedEx Corp.	10	Compaq Computer Corp.	2	Estee Lauder Inc.	1
Kraft foods inc	10	Deere & Co.	2	Liz Claiborne Inc.	1
Matsushita Electric Industrial Ltd.	10	The Dow Chemical Co.	2	Luxottica Group S.p.A.	1
Motorola Solutions Inc.	10	Federated Department Stores Inc.	2	Marriott International Inc.	1
The New York Times Co.	10	Fortune Brands Inc.	2	Marvel Entertainment LLC.	1
Eastman Kodak Co.	9	Fuji Photo Film	2	The McClatchy Co.	1
Toyota Motor Corp.	9	Harrah’s Entertainment Inc.	2	Meredith Corp.	1
Viacom Inc.	9	Hewlett-Packard Co.	2	NTL Inc.	1
AOL Inc.	8	JPMorgan Chase & Co.	2	Palm Inc.	1
Nokia Corp.	8	Jones Apparel Group Inc.	2	Payless Shoesource Inc.	1
Starbucks Corp.	8	Krispy Kreme Doughnuts Inc.	2	Pearson PLC	1
Washington Post Co.	8	Eli Lilly & Co.	2	Red Hat Inc.	1
Campbell Soup Co.	7	Limited Brands Inc.	2	Reed Elsevier Group PLC	1
Adolph Coors Co.	7	Martha Stewart Living Omnimedia Inc.	2	Reuters Group PLC	1
Dell Inc.	7	Morgan Stanley Dean Witter & Co.	2	Revlon Inc.	1
General Electric Co.	7	Phillips-Van Heusen Corp.	2	Riviera Holdings Corp.	1
Google Inc.	7	Prentiss Properties Trust	2	Sara Lee Corp.	1
Johnson & Johnson	7	Prudential Financial Inc.	2	Sea Containers Ltd.	1
Pfizer Inc.	7	Sanyo Electric Co. Ltd.	2	Skechers U.S.A. Inc.	1
AMR Corp.	6	Schering Plough Products Corp.	2	Smith & Wesson Holding Corp.	1
Hasbro Inc.	6	Starwood Hotels & Resorts Worldwide Inc.	2	Sprint Nextel Corp.	1
Koninklijke Philips Electronics NV	6	Target Corp.	2	Staples Inc.	1
Mattel Inc.	6	VF Corp.	2	Sunoco Inc.	1
William Wrigley Jr. Co.	6	Wal-Mart Stores Inc.	2	The TJX Companies Inc.	1
AT&T Inc.	5	3M Co.	1	Talbots Inc.	1
Brown-Forman Corp.	5	Air France KLM	1	Telecom Italia S.p.A.	1
Church & Dwight Co. Inc.	5	Alcoa Inc.	1	Tiffany & Co.	1
Ford Motor Co.	5	Allied Domecq PLC	1	Tootsie Roll Industries Inc.	1
The Gap Inc.	5	Amazon.com Inc.	1	Toys “R” Us Inc.	1
International Business Machines Corp.	5	Applebee’s International Inc	1	Tricon Global Restaurants Inc.	1
Tribune Company	5	BP PLC	1	UAL Corp.	1
Verizon Communications Inc.	5	Berkshire Hathaway Inc.	1	USA Network	1
American Express Co.	4	Borders Group Inc.	1	United Parcel Service Inc.	1
Goodyear Tire & Rubber Co.	4	Boyd Gaming Corp.	1	Vodafode Group PLC	1
Honda Motor Co. Ltd.	4	British American Tobacco	1	Warner Communications Inc.	1
Kellogg Co.	4	CBS Corp.	1	Warner-Lambert Co.	1
Kimberly-Clark Corp.	4	Canon Inc.	1	Whirlpool Corp.	1
Playboy Enterprises Inc.	4	Capital One Financial Corp.	1	Yahoo! Inc.	1
TDK Corp.	4	Cisco Systems Inc.	1		
Colgate Palmolive Co.	3	CNH Global NV	1	Total	928

FIGURE 2
CARs to Product Placements (with Detail by Industry)



various multilevel market phenomena (e.g., Inman, Winer, and Ferraro 2009).

Additional levels render the model more general and often more useful because when a hierarchy exists, an analysis of data aggregated from different levels may produce inaccurate and unreliable results (Kreft and De Leeuw 2002). For example, with nested structures, the assumption of independent errors is violated (observations belonging to the same higher-level unit tend to covary), rendering the traditional regression approaches that rely on this assumption inadequate. In the context of this study, hierarchical linear modeling (HLM) enables us to consider several levels of analysis (i.e., the movie, industry, and placement levels) to capture unobserved movie- and industry-level heterogeneity and analyze cross-level interactions when it comes to time-related effects. After aggregating abnormal returns and assessing the significance of CARs across different periods, we estimate an HLM that links the CARs to variables reflected in our conceptual framework. We confine the drivers to their respective levels (see Figure 3).

In the HLM model, the dependent variable is CAR over the (–10, 16) time window. We modeled CAR as a function of brand placement–related (Level 1), movie-related (Level 2), and industry-related (Level 2) factors. We cross-classified the model because at each level, one unit is simultaneously classified by two higher-level effects (i.e., movie and industry).

Tables 3 and 4 present the variables used and their sources. Table 5 presents descriptive statistics for the variables used in estimation.

The Level 1 Model:

$$
\begin{aligned}
(3)\ \text{CAR}_{ijk} = {} & \pi_{0jk} + \pi_{1jk}(\text{BRAND–TICKER MATCH})_{ijk} \\
& + \pi_{2jk}(\text{TIE-IN CAMPAIGN})_{ijk} \\
& + \pi_{3jk}(\text{NUMBER OF OTHER BRANDS FROM SAME FIRM})_{ijk} \\
& + \pi_{4jk}(\text{NUMBER OF APPEARANCES WITH MAIN CHARACTER})_{ijk} + \pi_{5jk}(\text{TURNOVER})_{ijk} \\
& + \pi_{6jk}(\text{NYSE})_{ijk} + \pi_{7jk}(\text{NASDAQ})_{ijk} \\
& + \pi_{8jk}\ \ln(\text{ADJUSTED MARKET CAPITALIZATION})_{ijk} \\
& + \pi_{9jk}\ (\text{BRAND CLUSTERING})_{ijk} \\
& + \pi_{10jk}(\text{OVERALL CLUSTERING})_{ijk} \\
& + \pi_{11jk}(\text{BRAND FAMILIARITY})_{ijk} \\
& + \pi_{12jk}(\text{PLACEMENT INTENSITY})_{ijk} + \varepsilon_{ijk},
\end{aligned}
$$

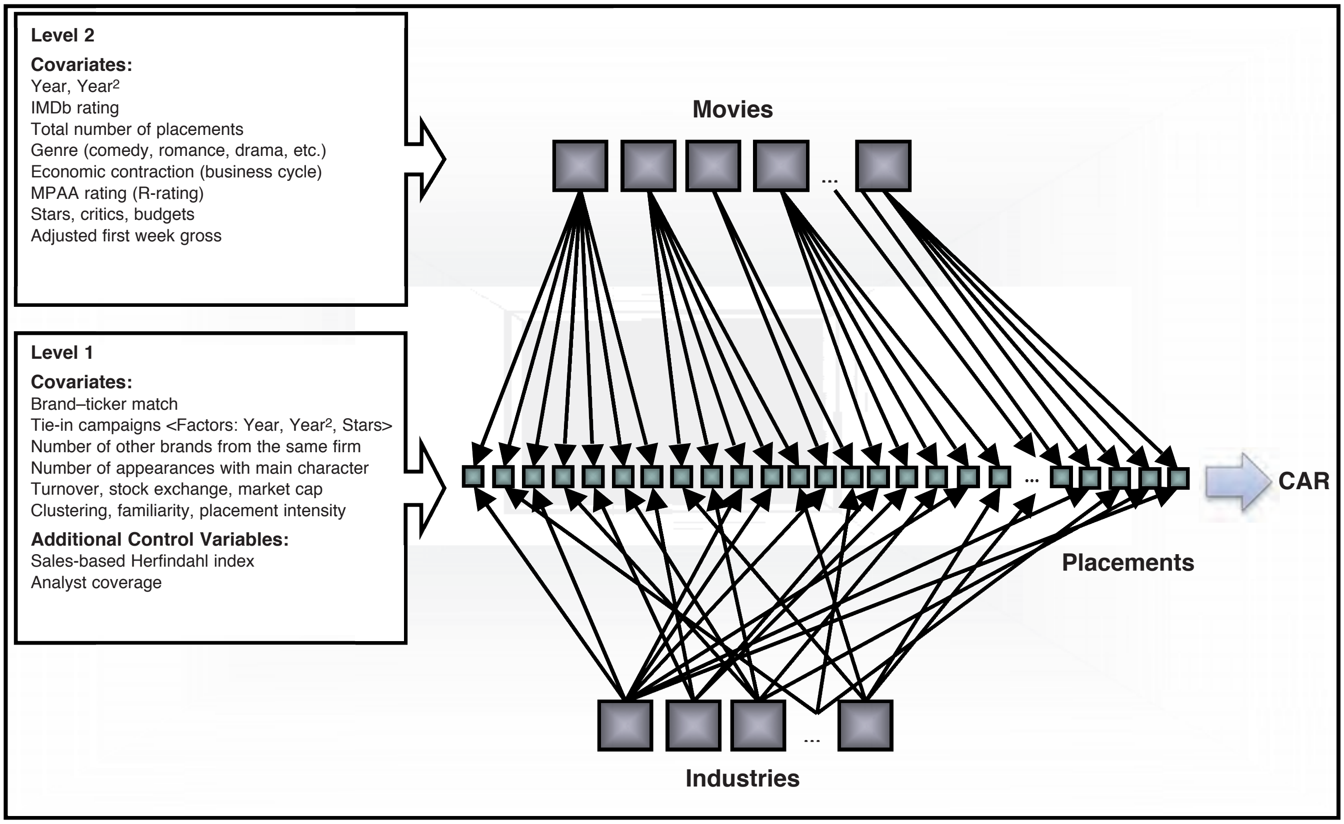
where

CAR_{ijk} = the cumulative abnormal return over the (–10, 16) event window that pertains to placement i in movie j in industry k,

π_{0jk} = the intercept or average CAR for a product placement in movie j industry k,

$\varepsilon_{ijk} \sim N(0, \sigma^2)$ = Level 1 within-the-cell random effect measured by the deviation of CAR asso-

FIGURE 3
HLM Modeling Approach



ciated with placement i in movie j industry k from the predicted outcome based on the Level 1 descriptors.

The Level 2 model has two levels because it estimates the impact of the characteristics of movie j and industry k on the size of the CAR. The model incorporates an unobserved movie- and industry-level heterogeneity, which we model with random effects, and the observed movie heterogeneity, which we model with several fixed movie-level variables. We incorporated potential curvilinear effects central to our hypotheses by introducing YEAR and YEAR² variables.

The Level 2 Model:

$$
\begin{aligned}
(4)\quad \pi_{0jk} = {} & \theta_0 + \gamma_{01}(\text{YEAR})_j + \gamma_{02}(\text{YEAR}^2)_j \\
& + \gamma_{03}(\text{IMDB USER RATING})_j \\
& + \gamma_{04}(\text{TOTAL PLACEMENTS})_j + \gamma_{05}(\text{COMEDY})_j \\
& + \gamma_{06}(\text{CRIME})_j + \gamma_{07}(\text{ROMANCE})_j + \gamma_{08}(\text{DRAMA})_j \\
& + \gamma_{09}(\text{ACTION})_j + \gamma_{010}(\text{HORROR})_j + \gamma_{011}(\text{SCIFI})_j \\
& + \gamma_{012}(\text{THRILLER})_j + \gamma_{013}(\text{R-RATING})_j \\
& + \gamma_{014}(\text{ECONOMIC CONTRACTION})_j \\
& + \gamma_{015}(\text{STAR\_NEXT})_j + \gamma_{016}(\text{CRITICS})_j \\
& + \gamma_{017}\ln(\text{ADJUSTED BUDGET})_j \\
& + \gamma_{018}\ln(\text{ADJUSTED FIRST-WEEK GROSS})_j \\
& + b_{00j} + c_{00k},
\end{aligned}
$$

where

θ_0 = the model intercept or $E[\pi_{0jk}]$ when all the nondummy explanatory variables are set to the mean and all the dummy variables are set to 0;

b_{00j} = the residual random effect associated with movie j, $\sim N(0, \tau_{b00})$; and

c_{00k} = residual random effect associated with industry k, $\sim N(0, \tau_{c00})$.

Finally, we assume most Level 1 coefficients to be fixed. However, we model the effectiveness of tie-in campaigns and the time-related dynamics describing their effectiveness by introducing cross-level interactions. The Level 1 coefficients are as follows:

$$
\begin{aligned}
\pi_{1jk} &= \theta_1, \\
\pi_{2jk} &= \theta_2 + \gamma_{21}\text{YEAR} + \gamma_{22}\text{YEAR}^2 + \gamma_{23}\text{STAR\_NEXT}, \\
\pi_{3jk} &= \theta_3, \\
&\vdots \\
\pi_{12jk} &= \theta_{12}.
\end{aligned}
$$

TABLE 3
Level 1 Variables

Variable	Description	Rationale for Inclusion	Source	Relationship to Conceptual Framework
CAR_{ijk}	CAR for firm that owns brand i (in industry k) that appeared in movie j over a (–10, 16) event window.	Dependent variable, widely accepted measure of economic worth.	EVENTUS	Measureable outcome
BRAND–TICKER MATCH $_{ijk}$	Dummy variable that takes a value of 1 if a brand can be easily mapped to its owner (i.e., brand name search on Yahoo! Finance produces the ticker of the parent company).	Noise traders have been shown to be confused by stock tickers. The variable also indirectly controls for company diversification.	Yahoo! Finance	Likelihood of action: ability to connect company and brand
TIE-IN CAMPAIGN $_{ijk}$	Dummy variable that takes a value of 1 for placements with concurrent tie-in campaigns Based on detailed review of news archives (±one month of the movie release date).	Measuring impact of tie-ins and existence of time-related effects after additional time-related variables are added (H_4).	LexisNexis search for brand and movie title.	Exposure and awareness
NUMBER OF OTHER BRANDS FROM SAME FIRM$_{ijk}$	Total number of brands belonging to the same company i in movie j. Mean centered.	Competitive clutter; competing investment options.	Brand Hype	Exposure and awareness/likelihood of action
NUMBER OF APPEARANCES WITH MAIN CHARACTER$_{ijk}$	Number of times the brand appeared with the main character throughout the film. Mean centered.	Proxy for placement overtness.	Brand Hype	Acceptance
TURNOVER $_{ijk}$	Daily share trading volume of company's stock divided by the number of shares outstanding (averaged over 30 days before event window).	Control variable, captures trading intensity and liquidity.	CRSP	Market, stock, and company characteristics
$NYSE_{ijk}$	Dummy variable that takes a value of 1 if the stock is traded on the New York Stock Exchange. AMEX serves as a base category.	Control variable for stock exchange.	CRSP	Market, stock, and company characteristics
$NASDAQ_{ijk}$	Dummy variable that takes a value of 1 if the stock is traded on the NASDAQ. AMEX serves as a base category.	Control variable for stock exchange.	CRSP	Market, stock, and company characteristics
ADJUSTED MARKET CAPITALIZATION$_{ijk}$	Regressions included a customary ln transformation of this variable instead of its raw value. Mean centered.	Control variable for company characteristics.	CRSP	Market, stock, and company characteristics
BRAND CLUSTERING$_{ijk}$	Number of product placements of the same company within two weeks before and two weeks after the focal movie release.	Control variable for placement intensity and measurement noise.	Brand Hype	Market, stock, and company characteristics
OVERALL CLUSTERING$_{ijk}$	Number of all product placements within two weeks before and two weeks after the focal movie release.	Control variable for number of competing options.	Brand Hype	Likelihood of action/market, stock, and company characteristics
BRAND FAMILIARITY$_{ijk}$	Number of *Wall Street Journal* mentions during the year preceding the release of the film. Mean centered.	Control variable for brand familiarity; affects exposure, awareness, and persuasiveness of brand communication.	*Wall Street Journal*	Exposure and awareness/likelihood of action
PLACEMENT INTENSITY$_{ijk}$	Number of previous placements divided by time from the first placement. Mean centered.	Control variable; measures overall intensity of placements for focal brand.	Brand Hype	Exposure and awareness/market, stock, and company characteristics
DIVERSIFICATION$_{ijk}$	Sales-based Herfindahl index. Control variable, not in final model.	Alternate explanation for change in effectiveness over time.	COMPUSTAT	Market, stock, and company characteristics
ANALYST COVERAGE$_{ijk}$	Number of analysts covering stock in a given year. Not in final model.	Alternate explanation for change in effectiveness over time.	I/B/E/S	Market, stock, and company characteristics

TABLE 4
Level 2 Variables

Variable	Description	Rationale for Inclusion	Source	Relationship to Conceptual Framework
$YEAR_{j}$, $YEAR\ SQUARED_{j}$	Year of release for movie j. Mean centered.	Habituation–tedium dynamics, testing H_3 and H_4.	IMDb	Acceptance
$IMDB\ RATING_{j}$	IMDb user rating for movie j. Mean centered.	Captures movie quality and likability.	IMDb	Acceptance
$TOTAL\ PLACEMENTS_{j}$	Total number of brand placements in movie j (Brand Hype data set). Mean centered.	Competitive clutter. Number of competing investment options.	Brand Hype	Exposure and awareness/likelihood of action
$COMEDY_{j}$	Dummy variable taking a value of 1 if movie j is a comedy.	Some genres could be more/less suitable to serve as a backdrop for placements.	IMDb	Acceptance
$CRIME_{j}$	Dummy variable taking a value of 1 if movie j falls under the crime category.	See preceding item.	IMDb	Acceptance
$ROMANCE_{j}$	Dummy variable taking a value of 1 if movie j falls under the romance category.	See preceding item.	IMDb	Acceptance
$DRAMA_{j}$	Dummy variable taking a value of 1 if movie j is a drama.	See preceding item.	IMDb	Acceptance
$ACTION_{j}$	Dummy variable taking a value of 1 if movie j falls under the action category.	See preceding item.	IMDb	Acceptance
$HORROR_{j}$	Dummy variable taking a value of 1 if movie j falls under the horror category.	See preceding item.	IMDb	Acceptance
$SCIFI_{j}$	Dummy variable taking a value of 1 if movie j falls under the science fiction category.	See preceding item.	IMDb	Acceptance
$THRILLER_{j}$	Dummy variable taking a value of 1 if movie j falls under the thriller category.	See preceding item.	IMDb	Acceptance
$R\text{-}RATING_{j}$	Dummy variable taking a value of 1 if the movie j received an R rating from the MPAA.	Violence, bad language, and so on could interfere with information processing (Wiles and Danielova 2009).	IMDb	Acceptance
$ECONOMIC\ CONTRACTION_{j}$	Dummy variable taking a value of 1 when economy is in recession.	Business cycles influence consumer response to advertisements and consequently investors' desire to invest.	NBER	Market, stock, and company characteristics
$STAR\ NEXT_{j}$	Dummy variable taking a value of 1 if a major star involved in the film had a blockbuster within three years before movie's release	Star power can make placements more visible and memorable.	IMDb	Acceptance
$CRITICS_{j}$	Composite score on 1–100 scale.	Movie's critical acclaim is known to be negatively associated with placement effectiveness (Wiles and Danielova 2009).	Meta-Critic, Rotten Tomatoes	Acceptance
$ADJUSTED\ BUDGET_{j}$	Production budget adjusted for inflation using historical movie ticket prices. Natural log-transformed, mean centered.	Captures movie's pre-release visibility.	IMDb, industry sources, MPAA	Exposure and awareness
$ADJUSTED\ FIRST\text{-}WEEK\ GROSS_{j}$	Opening week numbers from Internet Movie Database (imdb.com), adjusted for inflation using historical movie ticket prices. Natural log-transformed, mean centered.	Captures audience reach.	IMDb, MPAA	Exposure and awareness

Notes: Genre variables are not mutually exclusive. Non-R-rated movies serve as the base category. MPAA = Motion Picture Association of America, and NBER = National Bureau of Economic Research.

TABLE 5
Descriptive Statistics

	N	M	SD	Minimum	Maximum
Level 1 Variable					
CAR	928	.75	9.48	–45.75	46.16
BRAND–TICKER MATCH	928	.55	.50	.00	1.00
TIE–IN CAMPAIGN	928	.02	.13	.00	1.00
NUMBER OF BRANDS FROM THE SAME COMPANY	928	1.36	.67	1.00	5.00
NUMBER OF APPEARANCES WITH MAIN CHARACTER	928	1.35	2.07	.00	42.00
TURNOVER	928	.01	.01	.00	.24
NYSE	928	.89	.32	.00	1.00
NASDAQ	928	.11	.31	.00	1.00
LN (ADJUSTED MARKET CAP)	928	23.51	1.80	14.37	26.92
BRAND CLUSTERING	928	1.53	.91	1.00	6.00
OVERALL CLUSTERING	928	18.20	14.29	1.00	62.00
BRAND FAMILIARITY	928	1.77	.85	.00	4.54
PLACEMENT INTENSITY	928	.00	.00	.00	.06
Level 2 Variable					
YEAR	159	2001.52	7.29	1968.00	2007.00
$YEAR^2$	159	4,006,143.00	29,034.10	3,873,024.00	4,028,049.00
IMDB USER RATING	159	7.02	.98	2.40	8.80
TOTAL PLACEMENTS IN FILM	159	5.84	5.08	1.00	41.00
COMEDY	159	.30	.46	.00	1.00
CRIME	159	.16	.37	.00	1.00
ROMANCE	159	.13	.34	.00	1.00
DRAMA	159	.54	.50	.00	1.00
ACTION	159	.19	.40	.00	1.00
HORROR	159	.05	.22	.00	1.00
SCIFI	159	.09	.28	.00	1.00
THRILLER	159	.22	.42	.00	1.00
R-RATING	159	.47	.50	.00	1.00
ECONOMIC CONTRACTION	159	.06	.24	.00	1.00
STAR NEXT	159	.47	.50	.00	1.00
CRITICS	159	67.74	18.57	17.00	98.00
LN (ADJUSTED BUDGET)	159	15.40	1.12	11.07	17.29
LN (ADJUSTED FIRST-WEEK GROSS)	159	15.49	2.20	8.54	18.63

All nondummy variables are mean centered. We used a full maximum likelihood approach (as Raudenbush 1993 outlines) to estimate the mixed model that combines both levels with the specified cross-level interactions (see the Appendix).

Discussion of Findings

Event Study Results

Figure 2 presents the CAR results. They reveal a gradual stock price buildup that begins approximately ten days before the movie release and continues for approximately three business weeks (i.e., 16 days) after the release date, followed by price stabilization. Over the price buildup period (i.e., the [–10, 16] event window), the stocks gain .75% on average (see Table 6). The returns to product placements in the movies are positive and significant. Therefore, H_1 is supported.

In addition to CARs, Figure 2 presents event window results for the top four industries represented in our sample. Although there is some noise due to reduced sample size, there is a clear pattern of positive abnormal returns in our event window. There is variation in the magnitude of CARs across industries (from .26% for media and entertainment to 1.56% for electronics); however, the overall pattern of CARs is consistent: All four industries experience positive abnormal returns during the event window.

In line with recent marketing research, the documented price pattern (Figure 2) suggests that investors' new information processing takes time; delayed stock market response to marketing-related information may be a more common phenomenon than previously believed (Kimbrough and McAlister 2009; Srinivasan and Hanssens 2009). For example, Pauwels et al. (2004) find that it takes six weeks in the automobile sector to absorb new product introductions. This finding is also consistent with traditional finance literature that notes that it takes time for the information to be fully reflected in stock prices (Kyle 1985).

Although stock prices can be driven by informed trading, they can also be affected by uninformed noise trading. If the latter is the case, stock price reaction would only be temporary, and the change in stock prices would not be a good measure of the value of product placement. Figure 2 indicates that when prices peak three business weeks after the event date, they stay on a new level for at least three more weeks. We also note the potential presence of noise trading, which results in a minor price adjustment in the

TABLE 6
CARs and Significance Tests for Fama–French-Momentum Time-Series Model, Equally Weighted Index, GARCH (1, 1) Estimation

Days	N	Mean CAR	Positive: Negative	Portfolio CDA t	Cross-Sectional Error t	Generalized Sign Z
(–2, 0)	928	.04%	452:476	.266	.325	–.006
(–10, +16)	928	.75%	498:430**	1.867*	2.404**	3.015**
(+17, +30)	928	–.29%	439:489	–1.369	–1.628	–.860

*$p < .05$.
**$p < .01$.
Notes: CDA = crude dependence adjustment.

post event window. However, when we examine (17, 30) event window, the CARs are not significant, indicating that there is no noticeable price drift in the longer run. This supports H_2 and our position that the observed price changes indicate the informed nature of the revised estimates of a company's value around the event.

Multilevel Mixed Coefficient Model Results

The HLM results indicate significant differences in CARs for brands placed in different films. The variance component associated with the random film effect is significant ($p <$ .01). The fixed effects component of the model produces a significant, positive coefficient for the YEAR and a significant, negative coefficient for the $YEAR^2$ variable. This longitudinal pattern of abnormal returns provides support for H_3, indicating a curvilinear, inverted U-shaped relationship between time and CAR. We estimate that the effectiveness of product placement peaked in the late 1980s (i.e., 1988) and has been declining since then.[3] Additional analysis reveals that the mean market response to placements from the 2005–2007 time frame is actually negative (i.e., –.014%) and significantly different ($p = .01$) from the 1.4% response associated with the rest of the sample. These results indicate that product placement may now be overstaying its welcome. The medium that was once considered new, fresh, and capable of sliding under the radar of the average consumer at present may create "a healthy dose of resentment … for its commercial intrusion into entertainment that [the consumer] has already paid for" (Yglesias 2009). Alternatively, or in conjunction, the decline in return over time during the later time periods could also be potentially explained by the soaring costs of placements.[4] Detailed examination of the efficacy of recent product placements seems warranted to justify continued adoption of this marketing practice.

We find a similar return trajectory for tie-in campaigns. The economic worth of those campaigns seems to have peaked in 2000, suggesting that this relatively new tactic may also have gone through the prime of its economic worth. Even though the coefficient associated with tie-in campaigns (intercept) is negative ($p < .05$), we must also consider the time-related interactions related to tie-ins. The model coefficient for YEAR interaction is positive and significant, and the coefficient for $YEAR^2$ is negative and significant. The combination of these coefficients results in an inverted U-shaped relationship. Therefore, H_4 is also supported.

Other Significant Findings

The variable (NUMBER OF APPEARANCES WITH MAIN CHARACTER) has a significant negative coefficient. (An alternative measure of overtness using time on screen with the main character generated qualitatively the same results.) There is anecdotal evidence suggesting that blatant product placements can be detrimental. For example, FedEx drew criticism for the relentless abundance of FedEx references in the movie *Cast Away* (2000) (Friedman 2004). Our result is consistent with the literature that suggests that "in your face," overt placements may not be as effective as their more subtle counterparts.

Table 7 presents the complete results for the mixed-coefficient model. The coefficient of the BRAND TICKER MATCH variable is marginally significant and positive, which implies that part of the stock price movement may be attributable to the involvement of naïve individual traders.[5] This finding does not persist during the validation check on a subsample of the data corresponding to the later time period (for a detailed discussion, see the "Robustness Tests" section), indicating that that naive traders may have gotten better at identifying parent companies over time. This is plausible because finance portals are making increasingly sophisticated search tools available to individual investors. Even if naive investors drive some of the response, their involvement does not undermine the support found for H_2. Moreover, the presence of uninformed trading may actually

[3]We mean-centered time-related variables. The coefficients for YEAR and $YEAR^2$ are 56.81 and –.0143, respectively. Therefore, the following function needs to be maximized: $56.81 \times (X - \overline{X}) \times -.0143 \times (X^2 - \overline{X^2})$. First-order conditions indicate that the function is maximized when X = 1987.82, or roughly in 1988.

[4]The investors may also have gotten better at anticipating the impact of product placements, and their expectations may already be priced in the stock valuations during later periods. A simple check conducted by splitting the sample into time-related categories and extending the event window revealed that this is not likely to be the case. Similarly, Wiles and Danielova (2009) find no evidence that preannounced placements generated lower returns than regular placements. Indeed, preannounced placements were associated with higher returns in their sample.

[5]Conceivably, the stock prices of diversified conglomerates are not affected as much as the stock prices of smaller companies (whose brand ticker matches tend to be greater). However, the first explanation seems more plausible because controlling for diversification does not change this finding.

TABLE 7
HLM Results for Fixed Effects and Cross-Level Interactions

Fixed Effect	Coefficient	Estimates	SE	T-statistic	*p*-Value
INTERCEPT	θ_0	–2.678	5.046	–.531	.595
BRAND–TICKER MATCH	θ_1	**1.1770**	**.696**	**1.691**	**.091**
TIE-IN CAMPAIGN	θ_2	**–14.60705**	**6.579**	**–2.220**	**.027**
NUMBER OF BRANDS FROM SAME COMPANY	θ_3	–.31327	.512	–.611	.541
NUMBER OF APPEARENCES WITH MAIN CHARACTER	θ_4	**–.42066**	**.172**	**–2.441**	**.015**
TURNOVER	θ_5	.245953	.333	.738	.461
NYSE	θ_6	3.82948	3.835	.999	.319
NASDAQ	θ_7	3.94559	3.991	.989	.324
LN (ADJUSTED MARKET CAP)	θ_8	.09953	.157	.633	.527
BRAND CLUSTERING	θ_9	–.3989	.370	–1.076	.283
OVERALL CLUSTERING	θ_{10}	.0320	.042	.758	.449
BRAND FAMILIARITY	θ_{11}	–31.808	81.358	–.391	.696
BRAND PLACEMENT INTENSITY	θ_{12}	3.8295	3.835	.999	.319
YEAR	γ_{01}	**56.812**	**23.604**	**2.407**	**.016**
YEAR SQUARED	γ_{02}	**–.0143**	**.006**	**–2.410**	**.016**
IMDB USER RATING	γ_{03}	.4813	.685	.703	.482
TOTAL PLACEMENTS IN FILM	γ_{04}	.0279	.073	.380	.704
COMEDY	γ_{05}	.0137	1.100	.012	.990
CRIME	γ_{06}	.4279	1.041	.411	.681
ROMANCE	γ_{07}	**–3.7764**	**1.174**	**–3.217**	**.002**
DRAMA	γ_{08}	**–1.6223**	**.873**	**–1.858**	**.063**
ACTION	γ_{09}	.5220	1.300	.402	.687
HORROR	γ_{010}	–3.2309	2.436	–1.326	.185
SCIFI	γ_{011}	–1.1287	1.593	–.709	.479
THRILLER	γ_{012}	–1.8059	1.155	–1.564	.118
R-RATING	γ_{013}	.7506	.921	.815	.415
ECONOMIC CONTRACTION	γ_{014}	–.9145	1.672	–.547	.584
STAR NEXT	γ_{015}	–.1709	.853	–.200	.842
CRITICS	γ_{016}	**–.0583**	**.033**	**–1.762**	**.078**
LN (ADJUSTED BUDGET)	γ_{017}	–.2212	.489	–.452	.651
LN (ADJUSTED FIRST-WEEK GROSS)	γ_{018}	.0149	.222	.067	.947
(YEAR) × (TIE-IN CAMPAIGN) $_{ij}$	γ_{21}	**1754.614**	**671.336**	**2.614**	**.009**
(YEAR^2) $_j$ × (TIE-IN CAMPAIGN) $_{ij}$	γ_{22}	**–.438623**	**.168**	**–2.614**	**.009**
(STAR_NEXT) $_j$(TIE-IN CAMPAIGN) $_{ij}$	γ_{23}	7.355332	6.530	1.126	.261

Random Effect	Coefficient	SD	Variance Component	χ^2	*p*-Value
Movie	b_{00}	1.71	2.94	190.44	.003
Industry	c_{00}	.69	.48	31.52	.000

Notes: Results significant at 90% level and higher are in bold.

attract informed traders (Kyle 1985). In turn, informed trading facilitates permanent market price adjustment to the new information, which we observe in our sample (i.e., prices do not retreat to preplacement levels).

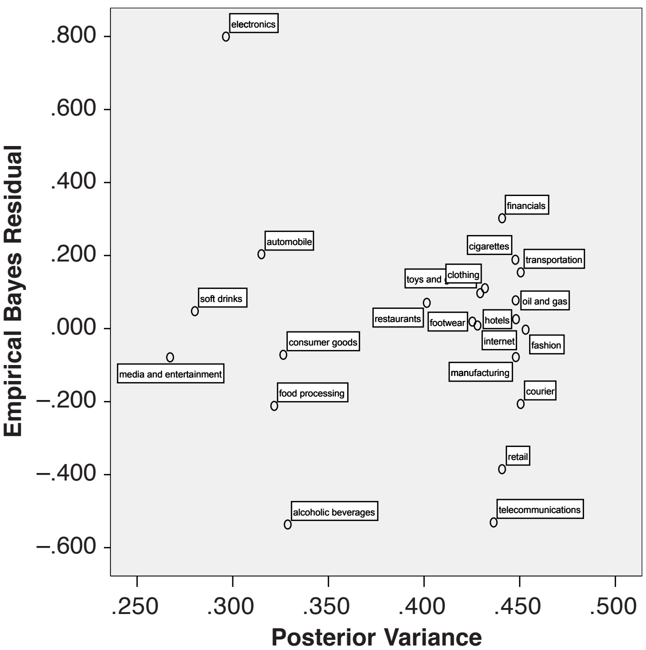
Differences Across Movies and Industries

The results indicate that our sample has significant movie and industry specific heterogeneity ($p < .01$). The implication is that picking appropriate films for placement is a relevant managerial concern. Further examination of the industry-related random effects revealed additional dynamics associated with industry differences.[6] We analyzed empirical Bayes (EB) residuals associated with random industry coefficients in our mixed effects model, which are indicative of the size of the random effects associated with individual industries (Raudenbush and Bryk 2002). Figure 4 presents the sizes of EB residuals compared with posterior variance of the estimates.

Two industries are characterized by large positive residuals and low posterior variance: electronics and automotive placements enjoy .8% and .2% higher returns, respectively, when compared with other placements. At the same time, other popular placements, such as those for soft and alcoholic drinks, media and entertainment, and food processing, do not enjoy similar advantages. Alcoholic beverages lag almost half a percentage point behind average placements. Although it is possible that some of the alcohol-related placements do not present the product in a positive light, the examination of our sample offers another explanation. The vast majority of placements are for inexpensive domestic

[6]In addition to examining random industry effects, we incorporated various industry classification schemes into our analysis. For example, we examined delineation of products along the consumer–industrial goods continuum and introduced fixed effects for convenience, shopping, specialty, and unsought product categories. These additional analyses did not produce any significant findings.

FIGURE 4
Empirical Bayes Residuals by Industry



beer, a relatively mundane product category. We also note that, across the board, the "unexciting" product categories (e.g., food processing; telecom; retail, which captures retail "super-chains" and large box stores) have lower returns.

Our results also indicate that placements in movies with higher critical scores may be associated with lower CARs. In addition, drama placements are associated with marginally lower abnormal returns, while romance placements are associated with significantly lower CARs. These findings suggest that movies that require deep emotional involvement on the viewer's part and/or heavily rely on story lines and convincing character portrayal may not be good candidates for product placements. In such environments, placements could be viewed as disruptive or risky or may be simply overlooked because of their incongruence with the films.

Resonance between advertisement-induced emotions and consumers' incidental emotions facilitates message processing (Petty and Wegener 1998). Drama and romance movies may provoke emotional states that are incongruent with emotional states provoked by placements for cars, soft drinks, and other commonly placed categories. Another explanation for the lack of success for placements in these genres is emotional and cognitive overload. Dramas are usually more cognitively demanding, and romance films tend to send the viewers on an emotional roller coaster, leaving little room for processing secondary information. Furthermore, overload of negative emotions may drive people to shut down and avoid processing the message (Agrawal, Menon, and Aaker 2007).

Robustness Checks

We performed numerous robustness checks to reinforce the validity of our findings. First, we alternated the model specification used to estimate the dependent variable for our mixed-coefficient model. We used market and three- and four-factor market models and alternative estimation procedures (GARCH and ordinary least squares) to compute CARs in our event study. All the models and estimation procedures produced similar results.

We also examined the robustness of our HLM model. First, we employed the jackknifing procedure and made predictions for every observation while leaving that observation out of the estimation procedure. Next, we observed the correlation of these predictions and actual CARs, the correlation of .35 was significant ($p < .001$). We also followed Cooil, Winer, and Rados (1987) and calculated the cross-validatory (or predictive) R-square for the model, which is equal to .12. These estimates suggest modest predictive power but compare favorably against extant stock market return-based marketing studies (e.g., Sood and Tellis 2009; Sorescu, Shankar, and Kushwah 2007).

Next, we examined CARs in different industries and within individual brands to determine whether our generalizations regarding the curvilinear trends hold in individual brands and product categories. Specifically, we observed the top four product categories and the three most frequently placed brands (in categories in which we had enough data to examine trends). We found evidence of an inverted U-shaped relationship between CARs and time for each of the three most frequently placed brands (Coca-Cola, PepsiCo, and General Motors). In all three cases, the quadratic trend line produced the best fit with the quadratic terms that have a negative coefficient (R-square ranged from .03 to .19). We also examined individual industries with the largest number of placements and again found evidence of an inverted U-shaped relationship (see Table 8).

We also used our conceptual framework to consider alternative explanations for the existence of time-related effects. In particular, we considered degree of company diversification (for estimation details, see Comment and Jarrell 1995) and intensity of analyst coverage, measured by the average number of analysts covering a particular stock in a given calendar year. The resulting model (unreported) revealed insignificant coefficients for these control variables.

We also examined market response to three movie groups (small, average, and blockbuster films) by conducting separate event studies for three tertiles based on adjusted opening week movie revenue. (Tertiles based on total gross revenue results provided qualitatively the same

TABLE 8
Trends Within Individual Brands and Industries

Industry	N	R^2 Linear Trend	R^2 Quadratic Trend (Sign of Squared Coefficient)	Approximate Peak
Media and entertainment	144	.000	.04 (–)	1995
Soft drinks	124	.000	.05 (–)	1992
Electronics	109	.000	.04 (–)	1993
Automobiles	91	.001	.01 (–)	1995

results.) We used case ranking procedure to divide the data set into the three groups (i.e., low, average, and high tertiles). The average opening week figures (expressed in 2006 dollars) for the three groups were $2.6 million, $15.6 million, and $44.3 million, respectively. Our top tertile is similar to the sample of Wiles and Danilova (2009), who report average opening revenue of $44.8 million for their entire sample (see Table 9).

Figure 5 presents the dynamics of the prices around the movie release date separately for the three groups of movies. The significant price increases for the high-grossing films start 30 trading days before the release of the film, with most of the CARs taking place before Day 4; then, a period of insignificant price movements are followed by the downward adjustment. The price reaction for the movies with lower box office revenues starts later (right after the release date) but takes less time to complete. Prices stabilize on the new level within two weeks. The price pattern for the blockbuster films suggest that, while the investors' reaction to the placements in such movies reaches a higher magnitude than the reaction to the lower-grossing films, some of the initial reaction may be driven by uninformed trading and, to that degree, is not indicative of the potential increase in companies' future revenues. The earlier prerelease price run-up for high-grossing movies is consistent with this explanation because hype among the noise traders could be driven by the intense prerelease advertising campaigns associated with these high-grossing/high-budget films. Nevertheless, the permanent price impact of the placement in high-grossing movies does not seem to be different from that in low-grossing movies.

The combined results from this study and that of Wiles and Danielova (2009) indicate that blockbuster films may be associated with higher initial CARs to product placements in films but also with a strong downward adjustment that takes place when the movie opens. Blockbuster films may generate more hype, encouraging noise trading. However, this increased hype does not lead to an additional sustainable increase in the firm's economic value.

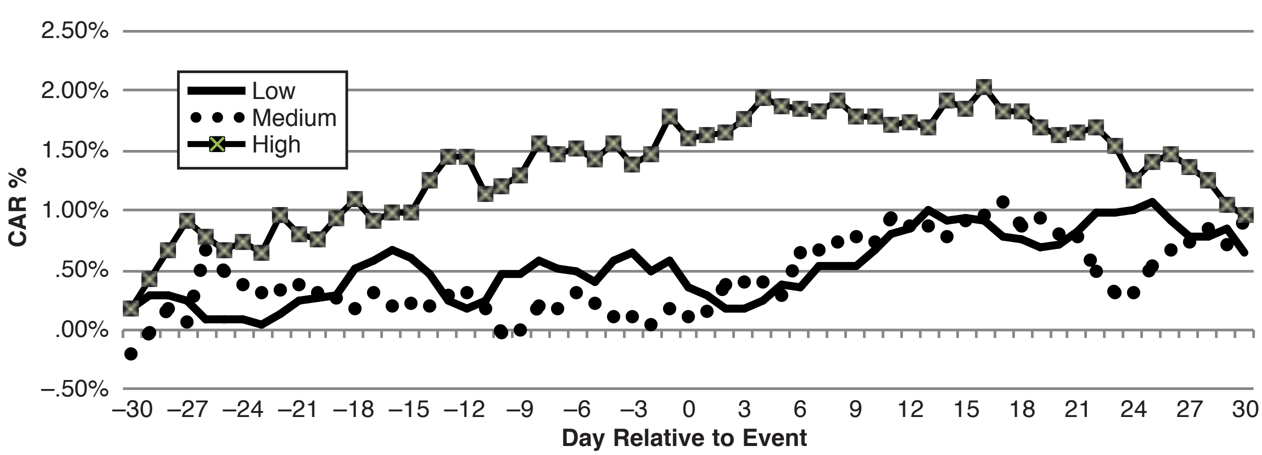
Finally, we considered the possibility that longitudinal changes in advertising spending at both film and brand level could influence the relationship between time and placement effectiveness. We performed this robustness check with the 1994–2007 subsample by including advertising expenditure across all media for brands and total advertising budget for films. (Our source, ACNielsen, began collecting both types of data in 1994.) The quadratic curve produced similar estimates to the linear trend (also similar to results for the full sample).[7] The only difference was that CARs fell more slowly than predicted by the original model.

[7]Because the peak in the effectiveness of placements was approximately 1988 (using the full sample), 1994–2007 corresponds to the later part of the life cycle. There is a high degree of collinearity between YEAR and YEAR^2 variables during this time period where there is an approximately linear negative relationship between time and CARs. (We found a virtually identical negative trend in the CARs during the same period when advertising variables are excluded, so this is not related to their inclusion). Thus, we estimated additional regressions that include only one of the time variables. The results for the remaining variables were qualitatively identical for each specification.

TABLE 9
Opening Weekend Gross Tertiles (Based on Rank Order of Cases)

			95% Confidence Interval	
Tertile	**M**	**SE**	**Lower Bound**	**Upper Bound**
Low (small)	$2,572,293.41	$846,038.98	$911,914.92	$4,232,671.90
Medium (average)	$15,597,485.26	$837,942.73	$13,952,995.92	$17,241,974.59
High (blockbuster)	$44,282,374.72	$852,968.16	$42,608,397.48	$45,956,351.95

FIGURE 5
CARs for Three Opening-Week Gross Revenue Tertiles



We also examined the curvilinear trend associated with the effectiveness of tie-in campaigns for the subsample that includes the data on advertising spending. The effectiveness of tie-in campaigns peaked in 2000, so the 1994–2007 subsample period captures both pre- and post-peak data for tie-in campaigns. Consequently, we were able include both YEAR and YEAR^2 variables as predictors of tie-in effectiveness (without collinearity issues), and we observed a curvilinear effect even during this relatively short period of time.

Including both advertising related variables (i.e., movie and brand related advertising spending) did not affect the inverted U-shaped trend or the timing of the peak in the effectiveness of the tie-in campaigns. First-order conditions indicated that the peak in effectiveness of the tie-in campaigns took place in 2000 (as we found in the full data set results). Although inclusion of advertising-related variables did not affect the underlying time related trends, it enriches our understanding of tie-in effectiveness. For example, negative and significant interaction between the tie-ins and brand-level advertising spending suggest that tie-ins are more effective for brands with lower advertising intensity.

In summary, including both movie- and brand-level advertising variables did not seem to affect the declining trend in the CARs attributable to placements. As a side note, previously significant DRAMA and marginally significant (i.e., $p < .10$) BRAND TICKER MATCH variables lost their significance during the subsample time period. This finding is not related to advertising spending information; these variables were not significant regardless of whether the advertising spending data are included in the subsample.

Implications for Managers

Our findings suggest that, just as products go through a life cycle, so too do the instruments used to market them. When a new technique shows promise, innovators and early adopters expand its use and start perfecting its application, which lead to growth and increased effectiveness. In the case of product placement in the movies, it seems this happened before the 1990s. However, as a new marketing technique gains wider acceptance, lack of novelty may diminish its effectiveness and consumers may start showing resistance to persuasion. They turn to consumer advocacy groups (e.g., Media Awareness Network, Commercial Alert) and technologies that enable them to avoid exposure to advertising (e.g., DVR) and even lobby for blanket legislation (e.g., do-not-call lists). Even in the absence of regulatory action, consumers seem to learn to tune out the messages, or they become savvy and impervious to the new type of marketing media. It is also possible that the costs of effective forms of marketing media increase, rendering them less profitable. Regardless of the exact mechanism, our findings indicate the presence of inverted U-shaped relationship over time in the returns for a new marketing practice and reinforce the need for the marketing industry to reinvent itself as new tactics lose their luster. The inverted U-shaped relationship holds true not only for product placements themselves but also for promotional tie-in campaigns used to support them.

DeLorme, Reid, and Zimmer (1994) report negative attitudes toward placements involving overexposed brands. Our results suggest that overexposing the brand within the same film (as measured by the number of appearances with the main character) can be detrimental. Furthermore, we find that tie-in campaigns are less effective for brands with larger advertising budgets. Counterintuitively, lower-intensity, fleeting placements can be more profitable than repetitive and potentially more expensive marquee placements with main characters. This finding is consistent with previous literature that suggests that "visual-only placements, typically the lower-priced placements, are processed by viewers at a low level of cognition and therefore may lead to stronger emotional and purchase intent effects than more elaborate placements that mention the product by name or show the product in use" (Petty and Andrews 2008, p. 15; see also Balasubramanian, Karrh, and Patwardhan 2006). Moreover, romance movies in particular seem to be less suitable for placements. This finding suggests that movies that require deep emotional involvement do not necessarily make the best platforms for placements, because they could be perceived as disruptive.

Previous literature has suggested that too many brand placements can result in less attention devoted to each individual placement (Burke and Srull 1988; Kent and Allen 1993; Webb and Ray 1979) due to clutter (Webb and Ray 1979) and information overload (Malhotra, Jain, and Lagakos 1982). Surprisingly, it seems that this insight from traditional advertising research does not transfer to the product placement arena. We do not find the overall number of placements to be significant in explaining CARs. Perhaps movies that are more suitable for placements attract more placements, potentially masking the underlying relationship. We considered other functional forms representing various types of curvilinear relationships but failed to detect any significant empirical regularity. Therefore, more product placement in a movie does not necessarily affect the value of a given placement in a negative way. Marketers may actually benefit from aligning themselves with a movie with other placements: Given the confirmed importance of selecting the movie for placement, existing placement agreements can signal suitability and serve as qualifiers.

Future Research Directions and Limitations

It is an ongoing challenge for marketers to constantly develop, identify, experiment with, and adopt novel media and techniques to reach and persuade their audiences. Meanwhile, marketers must gauge, decrease, and abandon less effective media activity just to remain competitive. Is it inevitable that all marketing media ultimately succumb to a life cycle (introduction, growth, maturity, and decline), just as products do? To our knowledge, this study represents a first attempt to investigate the longitudinal effectiveness of a successful marketing medium through its life cycle and could be viewed as a building block toward a theory of marketing medium life cycle. We advocate the longitudinal examination of the economic worth of both traditional and emerging media.

Extant literature has primarily concentrated on product placements in the movies consistent with Gupta and Gould's (1997) definition. However, product placements have found several additional outlets, such as traditional television shows, reality shows, newscasts, video games, music videos, lyrics, catalogs, comic strips, novels, live broadcasts, Internet casting, and even magazine editorials. There is a need to develop an integrated definition that incorporates the variety of current and emerging product placement domains and forms. It would be of interest to examine the extent to which such alternative placement media registers abnormal returns and whether they are also subject to a curvilinear relationship (i.e., life cycle). If so, what would be the expected trajectory of their effectiveness over time? Future studies would also benefit from incorporating various placement-related factors that have been shown to have an impact on advertising effectiveness, such as brand/plot/genre congruity, execution-related factors, and attitude toward sponsor, which we did not explore in this study. These factors may explain how some companies manage to achieve success through placements despite life-cycle considerations.

Although the data set we used in this study represents a great resource for product placement researchers, it is not without limitations. For example, because the data collection was led by film scholars, critically acclaimed and mature content movies were overrepresented in the data set.[8] Although most differences are relatively mild, the high critical acclaim of the movies included in the Brand Hype data set may have led to more conservative estimates of the economic worth of product placements because Wiles and Danielova's (2009) and our findings suggest that the placements in such films are associated with lower CARs.

Despite the tremendous growth and volume of product placements in recent years, Balasubramanian, Karrh, and Patwardhan (2006) note that only 29% of these placements are paid. It seems to be important to examine the antecedents and consequences of barter, gratis, and hybrid forms of product placements to improve the return on investment of this marketing medium and to determine best practices. An interesting caveat is that the Federal Communication Commission currently requires the disclosure of paid product placements but does not penalize the omission of such disclosures unless there is a deliberate nonobjective claim or deception related to the product (Petty and Andrews 2008). This means creative room for the interpretation of regulation regarding barter and gratis placements. It is likely that nonpaid product placements (which do not have to be disclosed) not only offer greater return on investment but also can be more effective. Still, nonpaid placements can come at a cost: It is not uncommon for a marketer to pay six-figure fees to product placement agencies for annual service contracts (Wasko 2003). It would be worthwhile to distinguish between paid and nonpaid forms of product placements in further research.

Our focus in this study was on assessing the effect of product placement in the movies on the value of the companies that owned the advertised brands. An interesting research question is the flip side of this issue: What is the impact of product placements on the movie's success? In the context of print advertising, it has been shown that too much advertising relative to editorial content can be detrimental to consumers' perceptions of editorial quality and can have a negative impact on circulation (Ha and Litman 1997). Mandese (2006, p. 3) cites industry sources who argue that in the television context, "when consumers grow wary of product placement … they may not simply react negatively about the brands involved but may actually turn the shows off." Consistent with the literature on distrust, Wei, Fischer, and Main (2008) find that audience members who recognized a paid placement not only lowered their evaluations of the placed brand but also lowered their evaluations of the hosts, show, and radio station. We did not find any evidence of such a relationship in our sample.[9] Organically integrated brands in a movie may actually enhance a film's artistic qualities by creating a more realistic setting and providing a connection between the story and the "real world" (DeLorme and Reid 1999; Hirschman and Thompson 1997; Spillman 1989). A more detailed investigation that considers endogeneity between movie quality, placement volume, and placement quality is warranted.

This article draws generalizations regarding the effectiveness of product placements over time. However, other areas of longitudinal exploration remain to be addressed. For example, is there a value in lasting relationships between movie stars and brands? For example, Will Smith

[8]More than 16% of the movies received a lead actor/actress nomination, and roughly 17% had won at least one Oscar. Approximately one quarter of the movies in our sample had a star or a director who won at least one Academy Award in previous years, compared with just less than 15% reported in the sample Basuroy, Chatterjee, and Ravid (2003) use. Similarly, our sample contains movies with relatively high critical scores (65.7). In comparison, the average critics' rating for Wiles and Danielova (2009) was 55.9 on a 100-point scale. Approximately one half of the movies in the sample are rated R, which is consistent with the sample De Vany and Walls (2002) examine; however, it includes more PG-13-rated movies (44% compared with 25% industry average) and fewer PG-rated movies (8% versus 20%). The sample does not include any G-rated movies, which traditionally comprise about 3% of all films (De Vany and Walls 2002). Therefore, our sample contains a lower proportion of films geared toward families and children and relatively more movies with mature content. We also note that the average production budget of the movies in our sample is roughly $45 million (expressed in 2007 dollars), whereas the average budgets in other studies are somewhat lower (e.g., $36.9 million; Elberse and Eliashberg 2003).

[9]We explored whether the number of placements influences the drop-off rates for individual films. To this end, we fitted an exponential decay function to movies' weekly revenue streams. The function was specified as follows: $\text{Revenue}(t) = \text{Revenue}_{open}\, e^{kt}$, where the negative k coefficient signifies the speed of revenue decay. The higher (less negative) the coefficient, the slower is the decay. Correlation analysis indicates that although the staying power is significantly positively related to IMDb user rating, critical scores, and the number of weeks the movie stayed in the theaters (correlation coefficients of .46, .48, and .58, respectively, $p <$ .01), there is no relationship between the number of placements in the film and any of the variables indicative of films' success.

seems to have a long-standing relationship with Ray-Ban (e.g., *Men in Black* [1997]; *Men in Black II* [2002]; *Bad Boys II* [2003]; *Hancock* [2008]). Do these continuous relationships benefit advertisers by allowing the brand to adhere to the star's persona and capitalize on celebrity appeal, thereby enhancing the realism of the placement? Similar questions could be asked about the enduring relationships between the brands and movie franchises. For example, the James Bond franchise has had a long engagement with the Rolex brand since the 1960s; however, starting with *Golden Eye* (1995), the franchise switched to Omega. Whether the effective formation and management of such relationships can result in tangible benefits to firms' bottom lines remains to be explored.

Appendix
Mixed Model

$$
\begin{aligned}
\text{CAR}_{ijk} = {} & \theta_0 + \theta_1(\text{BRAND–TICKER MATCH})_{ijk} \\
& + \theta_2(\text{TIE-IN CAMPAIGN})_{ijk} \\
& + \theta_3(\text{NUMBER OF OTHER BRANDS FROM} \\
& \quad \text{THE SAME FIRM})_{ijk} \\
& + \theta_4(\text{NUMBER OF APPEARANCES WITH MAIN} \\
& \quad \text{CHARACTER})_{ijk} + \theta_5(\text{TURNOVER})_{ijk} \\
& + \theta_6(\text{NYSE})_{ijk} + \theta_7(\text{NASDAQ})_{ijk} \\
& + \theta_8\ln(\text{MARKET CAPITALIZATION})_{ijk} \\
& + \theta_9(\text{BRAND CLUSTERING})_{ijk} \\
& + \theta_{10}(\text{OVERALL CLUSTERING})_{ijk} \\
& + \theta_{11}(\text{BRAND FAMILIARITY})_{ijk} \\
& + \theta_{12}(\text{PLACEMENT INTENSITY})_{ijk} \\
& + \gamma_{01}(\text{YEAR})_j + \gamma_{02}(\text{YEAR}^2)_j \\
& + \gamma_{03}(\text{IMDB USER RATING})_j \\
& + \gamma_{04}(\text{TOTAL PLACEMENTS})_j + \gamma_{05}(\text{COMEDY})_j \\
& + \gamma_{06}(\text{CRIME})_j + \gamma_{07}(\text{ROMANCE})_j + \gamma_{08}(\text{DRAMA})_j \\
& + \gamma_{09}(\text{ACTION})_j + \gamma_{010}(\text{HORROR})_j + \gamma_{011}(\text{SCIFI})_j \\
& + \gamma_{012}(\text{THRILLER})_j + \gamma_{013}(\text{R-RATING})_j \\
& + \gamma_{014}(\text{ECONOMIC CONTRACTION})_j \\
& + \gamma_{015}(\text{STAR\_NEXT})_j + \gamma_{016}(\text{CRITICS})_j \\
& + \gamma_{017}\ln(\text{ADJUSTED BUDGET})_j \\
& + \gamma_{018}\ln(\text{ADJUSTED FIRST-WEEK GROSS})_j \\
& + \gamma_{21}(\text{YEAR})_j(\text{TIE-IN CAMPAIGN})_{ij} \\
& + \gamma_{22}(\text{YEAR}^2)_j(\text{TIE-IN CAMPAIGN})_{ij} \\
& + \gamma_{23}(\text{STAR\_NEXT})_j(\text{TIE-IN CAMPAIGN})_{ij} \\
& + b_{00j} + c_{00k} + \varepsilon_{ij}.
\end{aligned}
$$

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