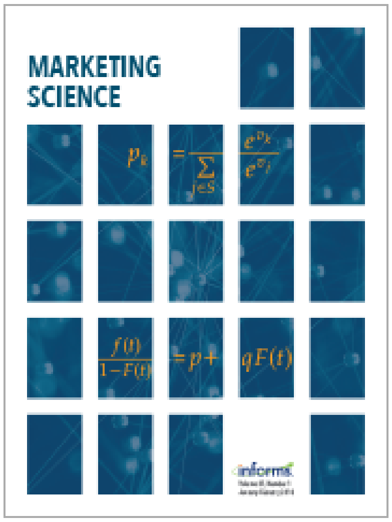

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Return on Roller Coasters: A Model to Guide Investments in Theme Park Attractions

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Despite the economic significance of the theme park industry and the huge investments needed to set up new attractions, no marketing models exist to guide these investment decisions. This study addresses this gap in the literature by estimating a response model for theme park attendance. The model not only determines the contribution of each attraction to attendance, but also how this contribution is distributed *within* and *across* years. The model accommodates saturation effects, which imply that the impact of a new attraction is smaller if similar attractions are already present. It also captures reinforcement effects, meaning that a new attraction may reinforce the drawing power of similar extant attractions, especially when these were introduced recently. The model is calibrated on 25 years of weekly attendance data from the Efteling, a leading European theme park. Our return on investment calculations show that it is more profitable to invest in multiple smaller attractions than in one big one. This finding is in remarkable contrast with the current "arms race" in the industry. Furthermore, even though thrill rides tend to be more effective than theme rides, there are conditions under which one should consider to switch to the latter.

Key words: entertainment industry; theme parks; return on investment; bundling
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1. Introduction

Over the last decade, the marketing literature has become increasingly interested in the entertainment industry. Although this interest has mostly centered on the motion picture industry (see, e.g., Eliashberg et al. 2006 for a comprehensive review), recent research has started to focus on the theme park industry (e.g., Milman 2001). Theme (or amusement) parks are generally outdoor venues with rides as the primary attraction. They require high capital investments and typically charge a single entry price. They often emphasize one dominant theme around which the landscaping, rides, shows, food, and personnel costumes are centered (Kemperman 2000). Well-known examples include Disney World, Disneyland, Universal Studios, and Six Flags in the United States, as well as Disneyland Paris and the Efteling (The Netherlands) in Europe.

The theme park industry is of high economic significance. Worldwide revenues in 2003 were \$19.78 billion, which were estimated to increase to \$24.71 billion by 2008 (PricewaterhouseCoopers 2004–2008). Revenues and visitor numbers have grown steadily in the United States in the past two decades according to the International Association of Amusement Parks and Attractions (IAAPA 2009). In 2006, total attendance at the world's top 25 parks amounted to 186.5 million visitors (Rubin 2007). Table 1 gives a more extensive overview.

The theme park industry requires considerable capital investments. First, huge outlays are needed to enter the market with a new park. Disneyland Paris, for example, cost almost \$4 billion to build (Spencer 1995). Once in business, considerable additional funds are needed to build new rides to attract visitors to the park. An often-heard industry rule is that one has to expand the theme park every year with one new attraction (Dietvorst 1995). On average, close to 20% of the turnover is spent on new and better rides (Kemperman 2000). Reasonable anecdotal evidence exists on the incremental drawing power of new attractions. In 1991, for example, Universal Studios reported a 52% attendance increase, which it

Table 1 **Key Players in the Amusement Park Industry**

	Europe		United States	
Rank	Park and location	2006 attendance (000)	Park and location	2006 attendance (000)
1	Disneyland Paris (France)	10,600	Magic Kingdom at Walt Disney World (FL)	16,640
2	Blackpool Pleasure Beach (UK)	6,000	Disneyland (CA)	14,730
3	Tivoli Gardens (Denmark)	4,396	Epcot at Walt Disney World (FL)	10,460
4	Europa Park (Germany)	3,950	MGM Studios at Walt Disney World (FL)	9,100
5	Port Aventura (Spain)	3,500	Disney's Animal Kingdom at Walt Disney World (FL)	8,910
6	Efteling (The Netherlands)	3,200	Universal Studios (FL)	6,000
7	Gardaland (Italy)	3,100	Disney's California Adventure (CA)	5,950
8	Liseberg (Sweden)	2,950	SeaWorld Florida (FL)	5,740
9	Bakken (Denmark)	2,700	Island of Adventure (FL)	5,300
10	Alton Towers (UK)	2,400	Universal Studios Hollywood (CA)	4,700

Source of data. TEA & Economics Research Associates (http://www.parkworld-online.com).

attributed to its new ride inspired by the popular movie *Back to the Future* (Formica and Olsen 1998).

The industry is increasingly concerned with the escalating scale of the investments required to add new rides. For example, Universal Studios' Adventures of Spider Man is estimated to have cost \$105 million, Disney World's Expedition Everest cost \$110 million, and the Test-Track ride in Epcot, Orlando, cost \$130 million (Hyman 2006). Not only are new rides becoming increasingly expensive, managers also fear they no longer give a similar boost to visitor numbers and start to question their return on investment (ROI) (Vugts and van Haver 2008).

At the same time, there is a growing recognition that marketing should demonstrate the financial returns of its investments (see, e.g., Ambler 2003), as also reflected in the recent research priorities of the Marketing Science Institute (2008). Despite the economic significance of the theme park industry and the exorbitant amounts spent on new attractions, there are no marketing models available to support the investment decisions.

The objective of this paper is to present a model to guide investments in theme park attractions. The model determines the return on investment of attractions based on a response model for their impact on theme park attendance. One core challenge for the response model is that the effect of a new theme park attraction over time may be complex. Attractions may have a drawing power that extends well *beyond* their year of introduction. Still, as the attraction grows older, its novelty is likely to gradually wear out. The drawing power of a given attraction may also vary *within* a given year, as visitor numbers are quite sensitive to seasonal fluctuations. Another challenge arises from the fact that theme park attractions are part of a larger bundle of interacting attractions. The direct impact of the new attraction may be smaller if similar attractions are already present, reflecting a *saturation* effect. Conversely, existing attractions may receive a boost from the new attraction, reflecting a *reinforcement* effect. For example, a new thrill ride may rejuvenate the drawing power of extant thrill rides. These potential saturation and reinforcement effects also require a formal modeling approach.

In §§2 and 3, we review the literature, develop the conceptual framework, and present the model. Next, we apply the model to a unique data set of 25 years of weekly visitor data from the Efteling, one of Europe's leading theme parks. We disentangle the relative contribution of each of its major attractions and derive the associated return on investment. We also show how our model can lead to different future investment decisions under various start configurations of the theme park. We finish with a discussion of managerial implications.

2. Literature Review

Our work can be situated in two literature streams. First, it adds to the growing literature on how marketing science can be applied to the entertainment industry. Although there are support systems for marketing decisions in the movie industry (see, e.g., Eliashberg et al. 2006), there are—to the best of our knowledge—no models that guide investment decisions in theme park attractions. This is surprising, as the industry has great economic importance and characteristics that differ considerably from the movie industry. Core quantitative marketing outlets such as *Marketing Science*, *Management Science*, the *Journal of Marketing*, and the *Journal of Marketing Research* have not published research on the theme park industry.[1] Within the leisure sciences, some studies have looked at the profitability of theme parks as a whole (e.g., Liu 2008, Roth 1994), but not at the impact of individual attractions. Other research has looked at how tourists

[1] We checked all issues since 1982. Some studies (often on the fate of Disneyland Paris) have appeared in other marketing outlets (see, e.g., Spencer 1995) but have been mostly descriptive in nature.

choose their theme park destination (e.g., Kemperman et al. 2000, Stemerding et al. 1999), how they choose among the different attractions (Darnell and Johnson 2001, Kemperman et al. 2002), and how theme parks can optimally manage visitor flows (Ahmadi 1997, Rajaram and Ahmadi 2003). None of these studies focused, however, on quantifying the effect of attractions on attendance and using this to guide investments in theme park attractions.

Second, theme parks are "bundles" consisting of multiple attractions. The practice of product bundling has received ample attention from both microeconomists (e.g., McAfee et al. 1989) and marketing researchers (e.g., Stremersch and Tellis 2002, Foubert and Gijsbrechts 2007). In the terminology of Adams and Yellen (1976), theme parks typically reflect pure bundling, as only the bundle (i.e., access to all attractions) can be bought, whereas the separate components of the bundle (i.e., access to only one of the attractions) cannot. However, prior empirical research has mostly considered bundles whose composition does not change over time and which consist of a limited (typically two) number of components (see, e.g., Harlam et al. 1995, Venkatesh and Mahajan 1997). Theme parks, in contrast, consist of multiple attractions and are regularly augmented with new attractions.

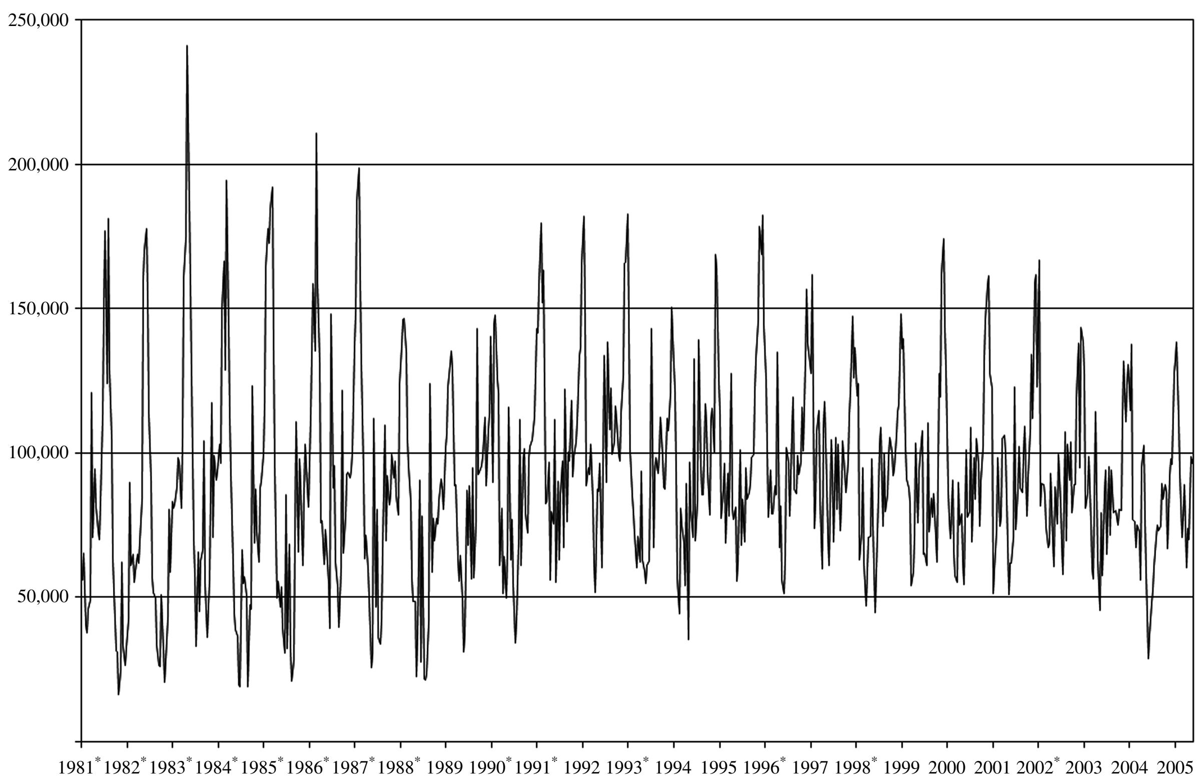
3. Model

3.1. Model Preliminaries

To guide investments in theme park attractions, we need a model for the impact of new attractions on theme park attendance. A key requirement is that the model should work with the available data (see Abraham and Lodish 1987, p. 103, for a similar premise). These are typically aggregate visitor numbers per time period (e.g., week). Because of their high costs, new attractions tend to be introduced quite infrequently (e.g., once per one or two years) and stay in the park for many years. Hence, to cover multiple attractions, a long time span is needed (multiple decades), especially to assess the long-term effects of attractions on attendance. Given this requirement, aggregate data are much more likely to be available than individual-level data.

Using aggregate data, our model derives the latent contributions of extant and new attractions to park attendance. We achieve this by imposing a certain structure on their contributions. To illustrate the problem at hand, we present in Figure 1 the focal theme park's attendance numbers, along with the introduction time of its main attractions. The key question is whether, and to what extent, each of these attractions contributes to the observed attendance fluctuations.

Figure 1 Weekly Attendance Numbers at the Efteling Theme Park



Note. Asterisks indicate years with new attractions.

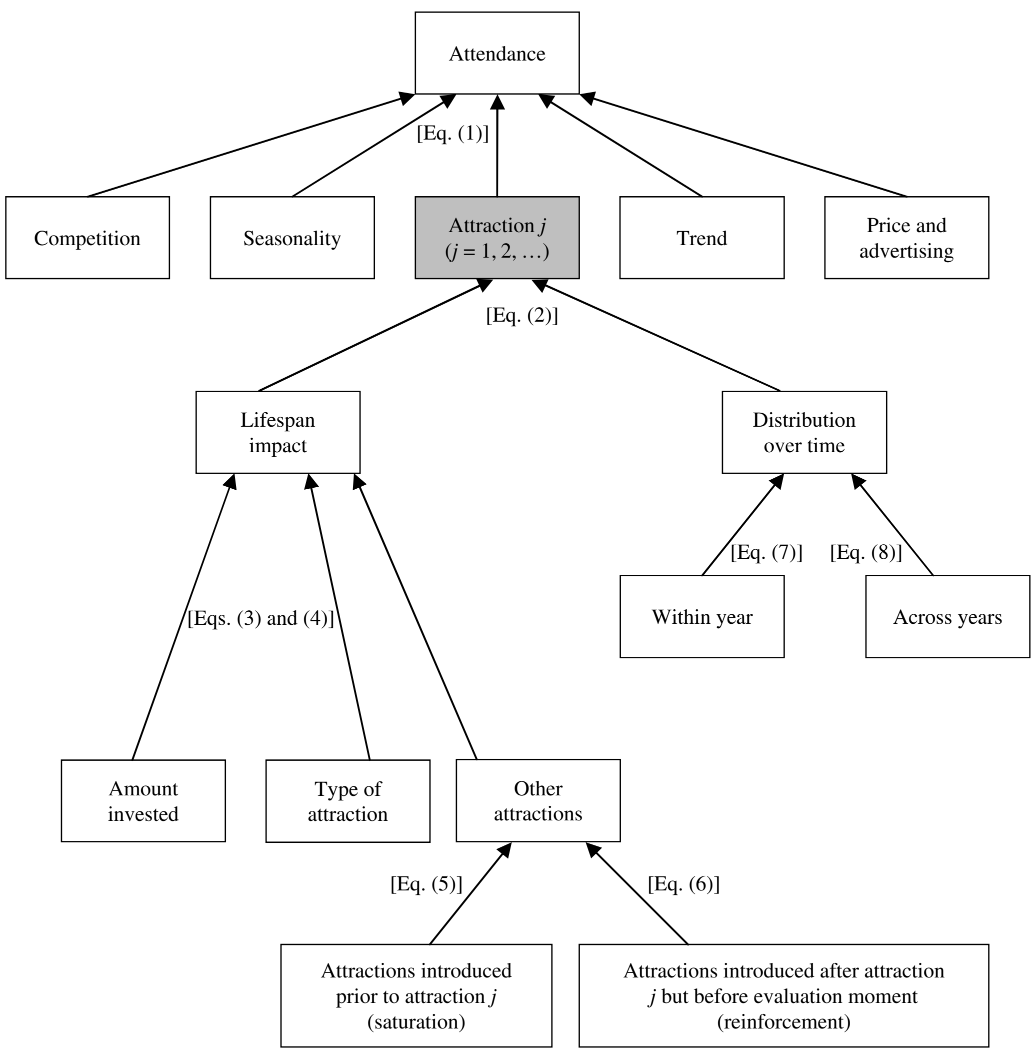
If so, the question arises whether this impact is restricted to the year of introduction or whether it lasts for multiple years. Similarly, is this impact uniform within each year, or is the impact highest shortly after the introduction, or rather is it in the middle of the year, corresponding to the high season? Our model accommodates each of these issues while controlling for other factors that could affect the number of visitors.

3.2. Conceptual Model

Our conceptual model is displayed in Figure 2. The equation numbers are included for later reference. In line with the tourism literature (see, e.g., Formica and Olsen 1998, Kemperman 2000, Milman 2001, PricewaterhouseCoopers 2004–2008), we postulate that the five main drivers of theme park attendance are (i) the park's attractions; (ii) competition; (iii) seasonality; (iv) price and advertising; and (v) overall trends in the economic, political, and sociodemographic environment. Our modeling focus is on capturing the effects of the attractions in the park, as these represent a park's core selling proposition. As a case in point, Kemperman (2000, p. 18) concludes that the rides and activities in the theme park "largely determine the tourist's motivation and choice for a park." Even though the other factors are not the focus of our model development, we control for their effects to have a stronger test of our focal constructs.

The total drawing power of the attractions consists of the combined impact of the different attractions in the park. In the spirit of the customer lifespan literature (Gupta and Lehmann 2005, pp. 177–178), we model the contribution of an attraction j as the product of two components: (i) the distribution of the attraction's impact over time, i.e., how much of the impact is realized in a given year and week; and (ii) the magnitude of its lifespan impact.

Figure 2 Conceptual Model for Drivers of Theme Park Attendance



3.2.1. Distribution of Impact of New Attractions. The impact of new attractions may vary both within and across years (Kemperman 2000). This distribution over time can take on many forms, as illustrated in Figure 3. *Within a year*, the impact could be most prominent in the first weeks of introduction (top left panel of Figure 3) as a result of the press coverage such a new attraction typically receives. On the other hand, theme park attendance tends to be highly seasonal, peaking in summer. Accordingly, the impact of new attractions on theme park attendance is also likely to be higher during this period (as shown in the top right panel of Figure 3) because there is a larger pool of potential visitors.

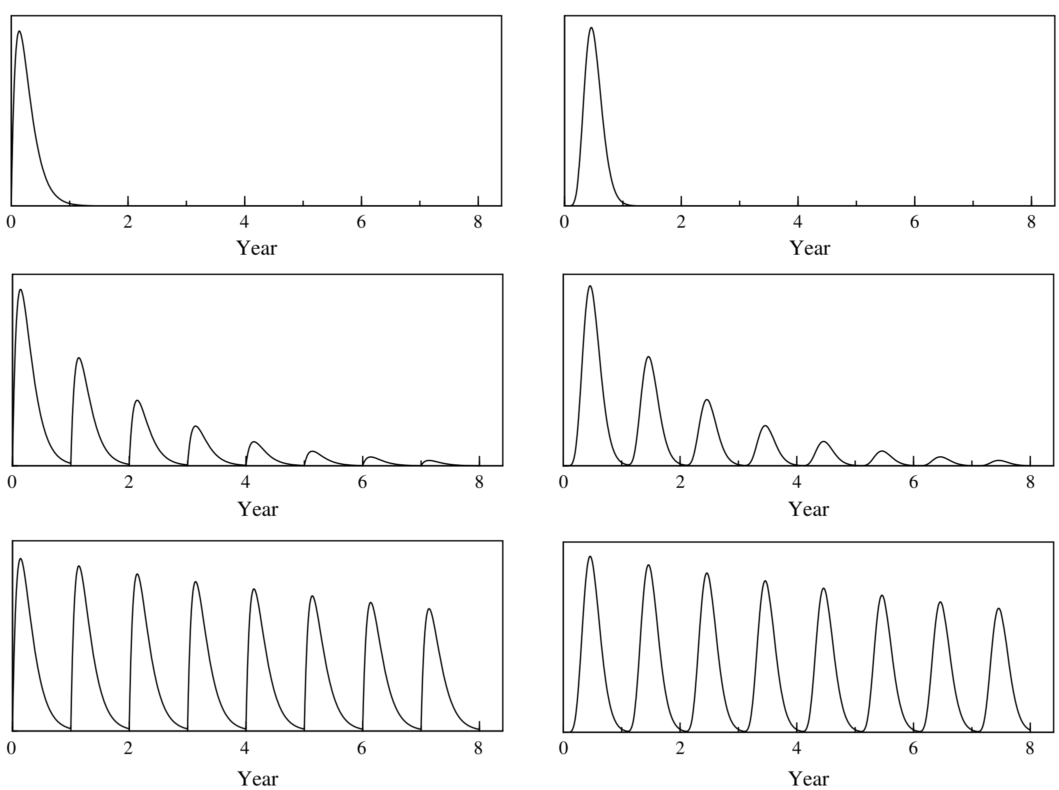
The impact may also vary *across years*. Indeed, the impact of a new attraction may not only manifest itself in the year directly following its opening (the top row of Figure 3) but may be spread over several years as the novelty wears out (Richins and Bloch 1986). Obviously, the speed of this wearout may be fast (row 2 of Figure 3) or gradual (row 3 of Figure 3).

3.2.2. Lifespan Impact of Attractions. Our conceptual model postulates that the total impact of a new attraction depends on the monetary investment (e.g., Cohen et al. 1997) and the type (e.g., thrill or theme) of the attraction (Formica and Olsen 1998). The latter distinction represents the multisegment strategy followed by many theme parks: they try to appeal not only to thrill-seeking youngsters, but also to more senior adults and families with small children.

Figure 2 shows that attractions may also interact with other attractions via saturation and reinforcement effects. Both of these effects are well grounded in the individual-choice literature. The *saturation* effect implies that the more attractions of a certain type (e.g., thrill rides) are available in the park, the less effective the next attraction of the same type will be. This is consistent with the assortment literature, which finds that adding items similar to existing ones does not necessarily improve consumer perceptions or sales (Broniarczyk et al. 1998). The saturation effect is also reflected in McAlister's (1979) model of attribute satiation, where the marginal utility of an attribute decreases in the attribute (see also Timmermans 1990).

The *reinforcement* effect implies that new attractions of a certain type may boost (reinforce) the effectiveness of extant attractions of the same type. As suggested by memory research (Solomon 2006, pp. 102–104), a new attraction of a certain type (e.g., a new thrill ride) may reactivate extant attractions of the same type (extant thrill rides) in consumers' memory. Moreover, studies on attribute alignability support the idea that attributes that are common across options are more salient to consumers, who subsequently base their preferences more on these common aspects (Van Ittersum et al. 2007, Zhang and Markman 2001). According to Brown and Krishna (2004), consumers

Figure 3 Potential Shapes of the Impact Over Time of an Attraction, Within and Across Years



search for alignable attributes in choice situations. This suggests that the new attraction may not only activate the memory of existing similar attractions but may also increase their appeal. Consequently, we need to model the impact of a new attraction of a certain type on the ability of extant attractions of that type to attract additional visitors to the park. We expect this effect to be positive, consistent with a reinforcement effect.

The interplay between the different factors is further illustrated in Figure 4. In the top panel, the black area shows the direct impact of attraction A, which clearly varies both within each year and across years. With a two-year lag, attraction B is introduced, which is of the same type and as expensive as A. A similar pattern over time is obtained (grey area in the middle panel). However, because of the saturation effect, the peaks for attraction B are lower than for A, even though the initial investment is the same. Moreover, the introduction of B gives a boost to (reinforces) the drawing power of A. This indirect effect is depicted in the top panel through the white areas (on top of the black areas). Combined across both attractions, the total impact for the theme park becomes the sum of three components (bottom panel): the direct impact of attraction A (black area), the direct impact of attraction B (grey area), and the indirect effect of B on A (white area). The last two only come into play once B is introduced.

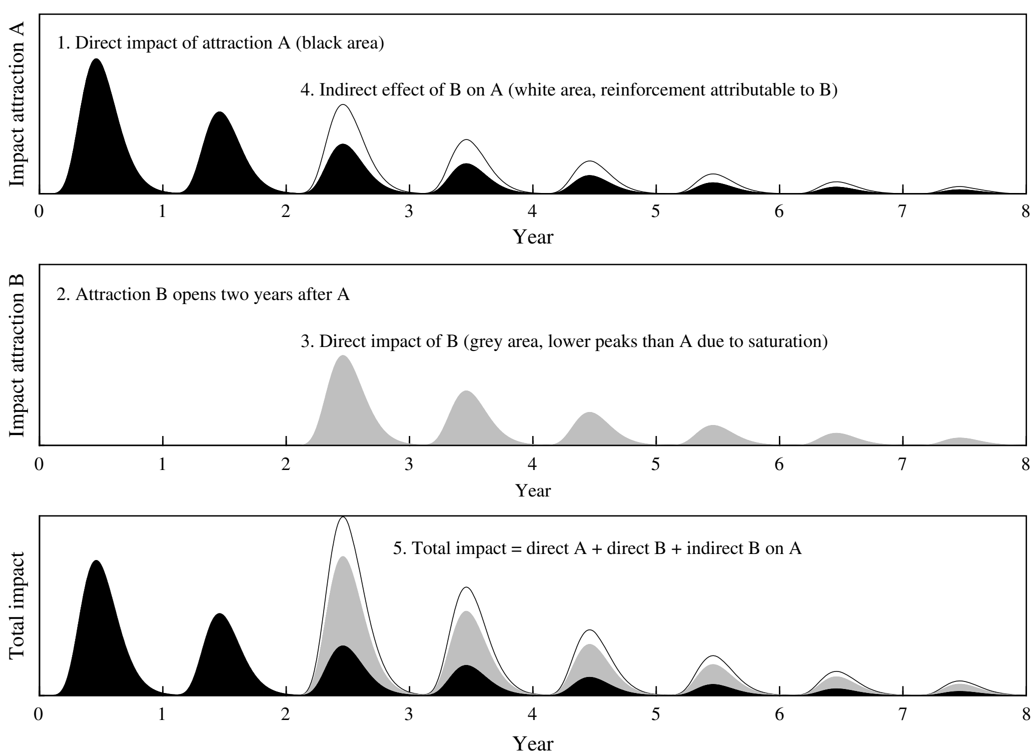
3.3. Model Equations

3.3.1. Attendance Equation. We now present the model specification consistent with our conceptual framework in Figure 2. We model weekly (rather than yearly) data to be able to capture within-year effects. In the tradition of many aggregate response models (see, e.g., Hanssens et al. 2001), our dependent variable is the logarithm of weekly attendance:

$$\ln(ATT_{s,t}) = \sum_{j=1}^{J} \theta_{j,s,t} I_{j,s,t} + X'_{s,t}\beta + u_{s,t}, \tag{1}$$

where the index s indicates the year (the period in which the theme park is open, e.g., from April until October), and the index t denotes the week within a specific year. $I_{j,s,t}$ is a step dummy variable for attraction j ($j = 1, \ldots, J$): 1 if it is present in year s, week t, and 0 otherwise. Prior to its opening, the attraction does not contribute to attendance, and after that its contribution is $\theta_{j,s,t}$ in year s and week t. $X'_{s,t}\beta$ captures the effect on attendance of variables other than attractions (see Figure 2): competition, seasonality, price and advertising, trends, and an intercept. The disturbance term $u_{s,t}$ captures autocorrelation between consecutive weeks within the same year: $u_{s,t} = \rho u_{s,t-1} + \varepsilon_{s,t}$, $\varepsilon_{s,t} \sim$ i.i.d. $N(0, \sigma_\varepsilon^2)$. A positive correlation could be due to, e.g., unmodelled weather dimensions such as wind or fog.

Figure 4 Saturation, Reinforcement, Direct and Indirect Effects



The contribution to attendance of attraction j in week (s, t), i.e., $\theta_{j,s,t}$, is operationalized as the product of (i) the attraction's impact *aggregated* over its lifespan, denoted $AttrContrLifespan_{j,s,t}$; and (ii) the share of this total impact materializing in year s and week t, denoted $Share_{j,s,t}$, yielding

$$\theta_{j,s,t} = AttrContrLifespan_{j,s,t} \cdot Share_{j,s,t}. \qquad (2)$$

3.3.2. Lifespan Impact. The attraction's lifespan contribution is linked to the size of its investment via a multiplicative specification (Cohen et al. 1997):

$$AttrContrLifespan_{j,s,t} = \lambda \cdot INVESTMENT_j^{\eta_{j,s,t}} \exp(\omega_{j,s,t}), \qquad (3)$$

where $INVESTMENT_j$ is the amount invested in attraction j, parameter λ is an intercept, and the error term $\omega_{j,s,t} \sim$ i.i.d. $N(0, \sigma_\omega^2)$ captures random effects for attraction j in year s and week t. Parameter $\eta_{j,s,t}$ is the elasticity of an attraction's contribution to its investment, and it may be driven by the type of the attraction, saturation, and reinforcement effects. We use a parameter process function (Foekens et al. 1999, Gatignon 1993), specified as

$$\eta_{j,s,t} = \exp\left(\alpha_1 + \sum_{i=1}^{M-1} \alpha_{2i} TYPE_{ij} + \alpha_3 SATURATION_j + \alpha_4 REINFORCEMENT_{j,s,t} + \xi_{j,s,t}\right), \qquad (4)$$

where the dummy variable $TYPE_{ij}$ equals 1 if attraction j is of type $i \in \{1, \ldots, M\}$. The saturation variable captures the saturation effect of all prior attractions of the same type as the focal attraction j and is defined as the sum of all previous investments in the same type:

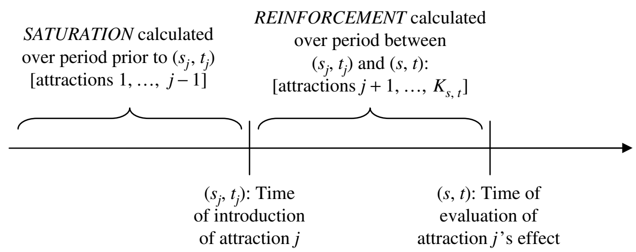
$$SATURATION_j = \sum_{k \in \{1,\ldots,j-1:\, TYPE_{ik}=1 \text{ if } TYPE_{ij}=1\}} INVESTMENT_k. \qquad (5)$$

Similarly, the reinforcement variable is the sum of all investments in subsequent attractions of the same type as attraction j up to year s and week t:

$$REINFORCEMENT_{j,s,t} = \sum_{k \in \{j+1,\ldots,K_{s,t}:\, TYPE_{ik}=1 \text{ if } TYPE_{ij}=1\}} INVESTMENT_k, \qquad (6)$$

where $K_{s,t}$ is the number of attractions in the park in year s and week t. Consistent with negative saturation effects and positive reinforcement effects, we expect $\alpha_3 < 0$ and $\alpha_4 > 0$. The error term $\xi_{j,s,t} \sim$ i.i.d. $N(0, \sigma_\xi^2)$ is a second random component for attraction j in year s and week t.

Figure 5 Saturation and Reinforcement Illustrated on a Timeline



Both *SATURATION* and *REINFORCEMENT* are predetermined exogenous variables at a given evaluation moment in year s, week t, as Figure 5 illustrates. When we conduct out-of-sample forecasting (see §5.3), we do so under the assumption of no further additions. When considering what-if scenarios (see §6) we derive the forecasts conditional on the investment amounts and the type of attractions introduced up to the future time of evaluation $(s^{\text{fut}}, t^{\text{fut}})$. As these attributes are known to the theme park's management (who can define future attractions in different what-if scenarios), we can compute the reinforcement variable over the period between (s_j, t_j) and $(s^{\text{fut}}, t^{\text{fut}})$. There are no additional unknowns involved in this calculation.

3.3.3. Distribution Over Time. To capture the within-year and across-year variation (see §3.2.1), we specify $Share_{j,s,t}$ in Equation (2) as

$$Share_{j,s,t} = \underbrace{\pi_{j,s}}_{\text{across-year share}} \cdot \underbrace{\frac{F(t;\gamma,\delta) - F(t-1;\gamma,\delta)}{F(T_s;\gamma,\delta)}}_{\text{within-year share}}, \qquad (7)$$

where F is the cumulative distribution function from a gamma distribution with shape parameter $\gamma > 0$ and scale parameter $\delta > 0$: $F(t;\gamma,\delta) = \int_0^t (\delta^\gamma \tau^{\gamma-1} \exp(-\delta\tau)/\Gamma(\gamma))\, d\tau$. The *within-year* share in week t is the gamma density mass falling inside week t, i.e., from time $t-1$ until time t. All within-year shares lie between zero and one, and they sum to one within each year s consisting of T_s weeks.[2] The gamma distribution is flexible and allows for nonmonotonic and asymmetric patterns (Law and Kelton 1991). The graphs in the top left (and right) panels of Figure 3, for example, correspond to values for γ and δ of 2 (11) and 0.25 (0.75), respectively.

We capture the *across-year* variation by

$$\pi_{j,s} = \begin{cases} \dfrac{\exp(\kappa(s - s_j))}{\sum_{\tilde{s}=s_j}^{\infty} \exp(\kappa(\tilde{s} - s_j))} & \text{if } s \geq s_j, \\ 0 & \text{if } s < s_j, \end{cases} \qquad (8)$$

[2] Summing over t yields as numerator $[F(1;\gamma,\delta) - F(0;\gamma,\delta)] + \cdots + [F(T_s;\gamma,\delta) - F(T_s - 1;\gamma,\delta)] = F(T_s;\gamma,\delta) - F(0;\gamma,\delta) = F(T_s;\gamma,\delta)$. As the denominator is $F(T_s;\gamma,\delta)$, the within-year shares sum to one.

where s_j is the year in which attraction j is introduced. The parameter κ determines how the impact of an attraction evolves over the years after introduction. We expect that $\kappa < 0$, i.e., that the impact decays over time because of the wear-out effects alluded to in §3.2.1. In rows 1, 2, and 3 of Figure 3, κ was set at -10, -0.50, and -0.05, respectively. If $\kappa > 0$, the impact increases over time. The shares $Share_{j,s,t}$ sum to one over all years s and all weeks t, as both the within-year and the across-year shares in (7) sum to one.

Equation (7) represents a *longitudinal mixture of shifted gamma distributions*, where each mixture component captures the within-year pattern in a different year.[3] The year of introduction of an attraction is covered by the first component, the first year after introduction is captured by the second component that has been shifted by one year, and so on. Working with *shifted* mixture components limits the number of parameters one has to estimate (as each component has the same shape and scale parameters). The electronic companion, available as part of the online version that can be found at http://mktsci.pubs.informs.org, outlines our model estimation with simulated maximum likelihood (Train 2003).

4. Data Description

4.1. Description of the Research Setting

We apply our model to data from the Efteling, a major theme park in the south of The Netherlands, currently attracting over three million visitors per year. In 1972, the Efteling received the Pomme d'Or (Golden Apple) for best European theme park, and in 1992 it collected the IAAPA Applause Award for the best theme park in the world. In 2005, the Efteling received the Themed Entertainment Association (THEA) Classic Award for its entire oeuvre. The Efteling not only attracts visitors from The Netherlands, but also from Belgium, Germany, and other countries. Almost all visitors stay in the park for only one day. The setup of the Efteling is similar to U.S. counterparts such as Disneyland and Universal Studios: an entrant pays one admission fee that allows him or her to visit all attractions as many times as he or she likes. The park is open from April until October.[4] Our data set covers the period 1981–2005, with a total of 732 weekly observations.

The original theme of the Efteling is based on fairy tales (van Assendelft de Coningh 1995). In 1952, the Efteling officially opened its fairy tales forest with three-dimensional and motioned characters of famous fairy tales. Only in the 1980s did the Efteling start investing in thrill attractions to also attract consumers outside its traditional target group of families with young children. The first in the series of thrill attractions was the Python, a roller coaster inaugurated in 1981 that was unrivalled in Europe at that time. Although the attraction did not fit the fairy tales character of the Efteling, the number of visitors increased by 30% in its opening year. In the subsequent 24 years, the Efteling has invested heavily in both types of attractions ("theme" and "thrill"), as shown in Table 2. Our categorization into thrill or theme has been closely coordinated with the park's management. We focus on the main attractions in the park and not on minor extensions (e.g., a new drink stand). The attractions do not replace existing ones, and no attractions have shut down during our observation period.

The $M = 2$ attraction types and the inflation-corrected investment amounts (expressed relative to the base year 2000) are used to operationalize the *TYPE* ($0 =$ thrill, $1 =$ theme) and *INVESTMENT* variables from Equations (3) and (4). For confidentiality reasons, we cannot reveal the exact investment of each individual attraction, but the amounts varied between 1 and 15 million euros, and include both design and construction costs. On average, attractions opened in the 1990s and the 2000s were more expensive than earlier introductions. The introduction frequency dropped from once a year before 1988 to once every two to four years after that.

4.2. Covariates

While estimating the effects of new attractions, we need to control for other factors (covariates) that may also affect theme park attendance, as shown in Figure 2 and Table 3. These covariates, together with an intercept, are captured by the vector $X_{s,t}$ in Equation (1). To capture competition, we include step dummies for the entry of three potential competitors within a radius of 500 kilometers: Disneyland Paris (France), Walibi World/Six Flags Holland (The Netherlands), and Warner Bros. Movie World (Germany). A step dummy specification implies that

[3] Our specification (7) has some similarities with functional data analysis (FDA). FDA approximates discrete-measured longitudinal data by smooth curves that are linear combinations of basis functions (Ramsay and Silverman 2006, p. 56). For example, Sood et al. (2009) start from multiple observed diffusion curves and use FDA as a data reduction technique to infer common patterns. Our approach resembles FDA in the sense that Equation (7) uses the product of share $\pi_{j,s}$ and a basis function (shifted gamma distribution). The extension we allow for is that in Equation (7) the weights $\pi_{j,s}$ of the basis functions are time varying (if $\kappa \neq 0$), as opposed to the time-invariant weights in earlier FDA applications such as Ramsay and Silverman (2006, p. 44) and Sood et al. (2009).

[4] Over the last few years, the Efteling is open a few weeks in the winter. We decided to omit the attendance data for these weeks from our model estimation because these observations are atypical in that only part of the park is open.

Table 2 Attractions Introduced in the Observation Period 1981–2005

Name	Year of introduction	Description	Type
Python	1981	Roller coaster with four loops (was the largest roller coaster in continental Europe)	Thrill
Half Moon Pirate Ship	1982	Swinging pirate ship (mentioned in the *Guinness Book of Records* as the largest in the world)	Thrill
Piraña	1983	White water rafting in a circular boat (first concept was Thunder River in Sixflags Astroworld in 1980; unique to Europe at the time of introduction)	Thrill
Carnival Festival	1984	Parade of figures that shows how people party in different countries (inspired by the It's a Small World attractions from Disney parks)	Theme
Bobsleigh Run	1985	Roller coaster shaped as a bobsleigh run (configuration was and is unique in Europe)	Thrill
Fata Morgana	1986	Boat ride through the fairy tales of *1,001 Arabian Nights* (second Arabic-themed dark ride in Europe; first was discontinued in 2001)	Theme
Pagoda	1987	Gently "flying temple" in Thai style	Theme
Monsieur Cannibale	1988	Quick merry-go-round with turning boiling pots	Thrill
Laaf People	1990	Ride on monorail to watch houses with dwarves	Theme
Pegasus	1991	Timber old-style roller coaster (first attraction of its type in The Netherlands, Belgium, Germany)	Thrill
Dream Flight	1993	Ride through fantasy world with elves and dwarves	Theme
Villa Volta	1996	Seemingly rotating house with bandit storyline (THEA Outstanding Achievement Award, first modern madhouse)	Theme
Bird Rok	1998	Indoor roller coaster with bird theme	Thrill
PandaVision	2002	4D movie with World Life Fund theme (fourth dimension for physical effects such as rain, wind, and vibration)	Theme

a certain percentage of attendance may be lost to competition. This assumption is consistent with the constant draw assumption made in multinomial logit models for theme park choice (e.g., Kemperman et al. 2000, Stemerding et al. 1999) and in a recent game-theoretic model of theme park competition (Yang et al. 2009).

For seasonality, we include dummies for low and high season (shoulder season is the base case), for school and national holidays, and several weather-related variables. In so doing, we control for various sources of seasonal variation mentioned in the tourism literature (Kemperman 2000). We use a flexible specification for the trend factors to capture the wide array of economical, political, and socio-economical trends (see, e.g., Formica and Olsen 1998, pp. 301–306; Milman 2001) that may influence the overall popularity of the theme park industry. In line with Jain and Vilcassim (1991) and van Everdingen et al. (2009), among others, we include a linear, quadratic, and logarithmic term to ensure sufficient flexibility.

We do not include direct measures of the ticket price and advertising support, nor do we include dummy variables for the years in which the Efteling received international awards. Ticket price went up almost linearly and hence was too collinear with the trend variable (correlation = 0.93).[5] Advertising information was only available from 1986 onwards (as opposed to 1981 for the other variables) and at an annual level of aggregation (whereas the attendance data are available at the weekly level). Moreover, these 20 observations were again very collinear with the trend terms (correlation = 0.92). Because we only want to control for the confounding effect of price and advertising to obtain more reliable estimates for our focal constructs (i.e., the impact of the attractions), we believe that this "control function" will be adequately captured through our flexible trend specification. Finally, preliminary testing revealed that the award dummies for the years 1992 and 2005 were both insignificant.

5. Results

We first present the parameter estimates. We use their values to estimate the additional numbers of visitors attributable to the park's attractions and the associated returns on investment. We also provide a comparison of our proposed model with several alternative specifications.

[5] Our data set includes posted ticket prices, which are the same for anyone between 4 and 60 years. In an unreported analysis, we added the price variable as a covariate to the model. It results in a positive yet insignificant price coefficient ($p = 0.22$), although all other effects are robust. Furthermore, ticket price is not significantly related to the introduction of new attractions: we regressed the annual growth in ticket price on an introduction dummy ($p = 0.22$) and in a separate regression on the investment amount ($p = 0.12$).

Table 3 Covariates in the Model to Explain Theme Park Attendance

Variable	Definition	Expected sign	Mean[a]	Std. dev.	Min	Max
Competition						
Disneyland	Dummy: One after opening of Disneyland Paris in 1992, zero otherwise.	−: The entry of a potential competitor in France may result in less visitors.	0.57	0.49	0.00	1.00
Walibi/Six Flags	Dummy: One after opening of Walibi/Six Flags in 1994, zero otherwise.	−: The entry of a potential competitor in The Netherlands may result in less visitors.	0.50	0.50	0.00	1.00
Warner Bros. Movie World	Dummy: One after opening of Warner Bros. Movie World in 1996, zero otherwise.	−: The entry of a potential competitor in Germany may result in less visitors.	0.41	0.49	0.00	1.00
Seasonality						
Low season	Dummy: One in weeks that the Efteling management categorizes as low season (April, September, October), zero otherwise.	−[Note that we omit from the model the dummy for the middle, or shoulder season (May, June, first half of July)]	0.39	0.49	0.00	1.00
High season	Dummy: One in weeks that the Efteling management categorizes as high season (second half of July, August), zero otherwise.	+[Note that we omit from the model the dummy for the middle, or shoulder season (May, June, first half of July)]	0.24	0.43	0.00	1.00
School holiday	Dummy: One in weeks coinciding with a school holiday outside the high season, zero otherwise.	+: School children (and their parents) are one of the primary target groups of the Efteling.	0.07	0.25	0.00	1.00
National holiday	Dummy: One in weeks containing a national holiday [Easter, Queen's Day, Ascension Day, Whit], zero otherwise.	+: A national holiday is often used for a one-day visit to a theme park.	0.20	0.40	0.00	1.00
Last week	Dummy: One in the last week of the season, zero otherwise.	+: Many theme park aficionados visit the theme park one more time before the park closes for winter.	0.03	0.18	0.00	1.00
Precipitation	Weekly millimeters of precipitation reported by the Royal Netherlands Meteorological Institute.	−: It becomes less appealing to be in a primarily outdoor theme park when it rains.	16.16	16.86	0.00	97.40
Temperature and Temperature^2	Temperature = Average weekly temperature (in centigrades) reported by the Royal Netherlands Meteorological Institute.	+: Main effect: warmer weather makes an outdoor theme park visit more enjoyable. −: Quadratic effect: it is less attractive to be outside when it is too warm.	18.81	4.40	7.00	31.70
Trend						
Trend, Trend^2, and ln Trend	Trend = Counter for the number of years since 1980.	We expect an upward trend in the number of visitors because of population growth and increasing wealth. We include *Trend*^{2} and ln *Trend* to allow for more flexibility than just linear trend patterns.	13.28	7.16	1.00	25.00

[a]The descriptives are based on the sample used for model estimation. This covers all weeks the theme park was open in the period 1981–2005. In total there are 732 weekly observations.

5.1. Parameter Estimates

The proposed model provides a good fit to the data, as the R^2 of the base Equation (1) for log attendance is 0.75. The parameter estimates are given in Table 4. Most coefficients of the covariates are significant at 1%, and they have the expected signs. The high season period ($\beta_6 = 0.375$) correlates with increased theme park attendance (+45% as $\exp(0.375) = 1.45$), as do holiday weeks ($\beta_7 = 0.314$; +37%), national holidays ($\beta_8 = 0.225$; +25%), and the season's last week ($\beta_9 = 0.169$; +18%). Temperature has an inverted U-shaped effect on attendance: linear term $\beta_{11} = 1.178$; quadratic term $\beta_{12} = -0.264$; and the optimal temperature is 22°C (72°F). Attendance is lower in rainy weather ($\beta_{10} = -0.032$, −3% for every centimeter of rainfall) and in the low season ($\beta_5 = -0.103$; −10%). For the three competing theme parks, only the closest park, the Walibi/Six Flags park, has a marginally significant negative effect on the Efteling ($\beta_3 = -0.097$; −9%). Finally, there is positive

Table 4 Parameter Estimates and Associated Standard Errors

Model component	Description	Symbol	Estimate	(Std. error)
Attendance equation [Equation (1)]	Intercept	β_1	−0.653**	(0.283)
	Disneyland Paris	β_2	0.089	(0.059)
	Walibi/Six Flags	β_3	−0.097*	(0.057)
	Movie World	β_4	−0.048	(0.054)
	Low season	β_5	−0.103***	(0.033)
	High season	β_6	0.375***	(0.037)
	School holiday	β_7	0.314***	(0.034)
	National holiday	β_8	0.225***	(0.026)
	Last week	β_9	0.169***	(0.048)
	Precipitation	β_{10}	−0.032***	(0.005)
	Temperature	β_{11}	1.178***	(0.135)
	Temperature^2	β_{12}	−0.264***	(0.035)
	Trend	β_{13}	1.662***	(0.334)
	Trend^2	β_{14}	−0.392***	(0.071)
	ln Trend	β_{15}	−0.261**	(0.118)
Attraction equation [Equations (3) and (4)]	Intercept	λ	3.776+	(1.500)
	Intercept of process function	α_1	0.311	(0.208)
	Type	α_2	−0.836***	(0.324)
	Saturation	α_3	−0.125***	(0.045)
	Reinforcement	α_4	0.028**	(0.013)
Decay pattern [Equations (7) and (8)]	Shape within	γ	7.639***	(1.296)
	Scale within	δ	0.488***	(0.084)
	Decay across	κ	−0.417***	(0.104)
	Std. deviation ε	σ_ε	0.209	
	Autocorrelation	ρ	0.293	
	Std. deviation ω	σ_ω	0.067	
	Std. deviation ξ	σ_ξ	0.023	
Model fit	R^2		0.75	
	Log likelihood		105.22	

*Significant at 10% (two-sided); **significant at 5% (two-sided); ***significant at 1% (two-sided); +significant based on BIC and AIC3 (Davies problem; see footnote 6).

first-order autocorrelation ($\rho = 0.293$). In an unreported analysis, we found that second-order correlation is much smaller (0.08) and insignificant at 5%.

The parameter λ is the intercept in the lifespan impact Equation (3). Because its estimate (3.776) is positive and significant, attractions have a positive effect on attendance.[6] We refrain from interpreting the exact value of λ and the other parameters from Equations (3), (4), (7), and (8), because visual summaries are more insightful (see Figures 7 and 8 later in this paper). The coefficient for type of attraction indicates that, all else equal, a thrill attraction is more effective in drawing additional visitors than an equally expensive themed attraction ($\alpha_2 = -0.836$ for the $TYPE = \text{theme}$ dummy). However, as we expected, the attraction's impact does not only depend on the type and the amount invested but also on its interaction with other attractions. The presence of extant attractions of the same type makes the new introduction less effective, as the saturation coefficient ($\alpha_3 = -0.125$) is negative and significant at 1%. On the other hand, a new attraction boosts the effectiveness of previous introductions of the same type: the reinforcement coefficient ($\alpha_4 = 0.028$) is positive and significant at the 5% level.

The decay pattern of the impact of new introductions is shown in Figure 6.[7] The within-year mode is week 14 (relative to the opening of the park season in April), implying that the impact on visitors peaks in the high summer season. More than 50% of the *within-year* effect is concentrated in eight weeks of the year, centered around that mode. This information should be highly relevant for staffing decisions, e.g., to hire temporary labor during those peak weeks (Aragon and Kleiner 2003). Second, the decay coefficient κ implies that on average 35% of the total *across-year* impact of a new attraction occurs in its first year, whereas 90% has materialized within the first five years after the introduction.[8] Hence, new attractions not only increase attendance in the year of introduction but also in subsequent years.

5.2. Impact of Individual Attractions on Theme Park Attendance

From the parameter estimates, we derive the number of additional park visitors for each attraction in the park accumulated from its introduction until 30 years later to capture the full reach of the attraction's impact. Essentially, we calculate the difference in expected attendance under two scenarios: including and excluding the focal attraction (more details in the electronic companion). Figure 7 shows the additional number of visitors for each attraction, both in terms of its direct effect (i.e., without reinforcement of extant attractions of the same type) and in terms of its indirect effect because of reinforcement.[9]

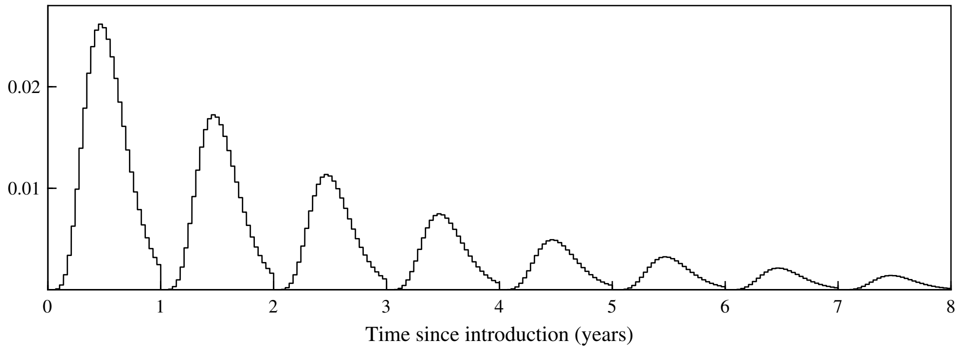
[6] The significance of $\boldsymbol{\lambda}$ cannot be tested via a regular z-test statistic because parameters related to attractions ($\boldsymbol{\alpha}_1$, $\boldsymbol{\alpha}_2$, $\boldsymbol{\alpha}_3$, $\boldsymbol{\alpha}_4$, $\boldsymbol{\gamma}$, $\boldsymbol{\delta}$, and $\boldsymbol{\kappa}$) disappear from the model under the null hypothesis $\boldsymbol{\lambda} = \mathbf{0}$ (Davies problem; Davies 1987). Instead, we use information criteria, which clearly favor the full model: BIC $= -32.35$ versus $+38.74$ for a model with $\lambda = 0$, and AIC3 $= -129.43$ versus -22.39 for a model with $\lambda = 0$.

[7] The "stepwise" nature of the graph is because we work with the discrete (weekly) difference $F(t) - F(t-1)$ in Equation (7) rather than with the underlying (continuous) density (used in Figures 3 and 4). Each mixture component is truncated at the end of the year, which has been accounted for by the denominator in Equation (7).

[8] Although some gaps between two new attractions are just one year, our model is able to disentangle the overlapping effects of different attractions well. This is evident from a simulation exercise (discussed in the electronic companion) showing that we can retrieve imposed model parameters well.

[9] As the model's parameter estimates are inherently uncertain, the implied estimates of extra attendance and ROI are also uncertain. To this end, we report in Figure 7 the means across a sample of 2,000 draws of the model parameters from their asymptotic multivariate normal distribution. To avoid clutter, the standard errors are not shown in Figure 6, but they are available from the authors on request. In the subsequent ROI analyses, we report standard errors.

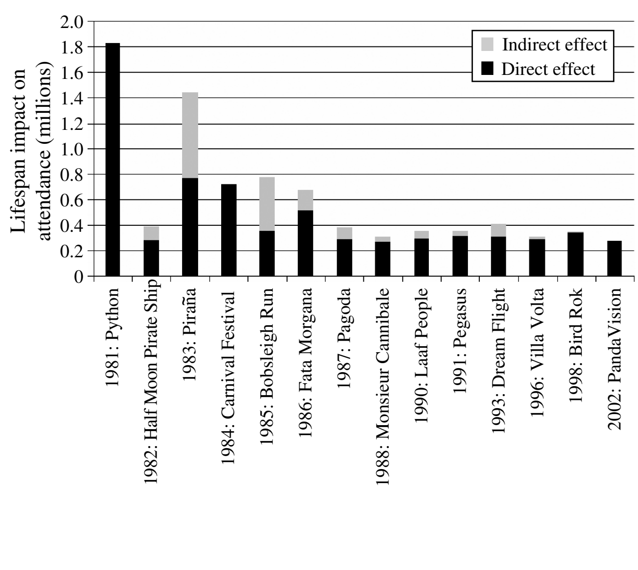
Figure 6 The Estimated Time-Varying Impact of a New Attraction on Theme Park Attendance



There are clear saturation effects: Although new attractions tend to be increasingly expensive, they become less effective over time. In some instances, strong reinforcement effects are present. For example, the direct impact of the Bobsleigh Run on park attendance is estimated at 356,000 visitors. This extra attendance is more than doubled to 776,000 visitors when accounting for the boost that the Bobsleigh Run provides to other, previously introduced, thrill rides. In the four years preceding the opening of the Bobsleigh Run, three thrill attractions had been added to the park, providing the Bobsleigh Run with ample opportunities to double its effectiveness. In contrast, the Pegasus (a timber roller coaster) and the PandaVision (a 4D movie theater) hardly generated any reinforcement effects. Their overall impact is almost completely determined by their direct effects: in the five-year periods preceding their introduction, no major attractions of the same type had been opened, resulting in few opportunities for reinforcement.

To evaluate attractions, we should not only consider the number of extra visitors but also the investment that was required. To that extent, we derive their ROI, i.e., the discounted revenue expressed as a percentage of the underlying investment. A value smaller than 100% implies a loss, whereas a number exceeding 100% means that the investment is profitable. We use an annual discount rate of 12% (Gupta et al. 2004) and assume that each visitor is worth the park entrance fee times a factor (100/60), reflecting an industry rule of thumb that 60% of the total revenues come from entrance fees and 40% from catering and merchandising (Kemperman 2000). This spending ratio has, according to the management of the Efteling, not changed substantially over time. For illustrative purposes, we focus on the same three attractions as before: the Bobsleigh Run, the Pegasus, and the PandaVision, for which the results are summarized in Table 5. The first two have very attractive ROIs of 236% and 237%, respectively. However, PandaVision does not recover its costs, as its ROI is 78%. Of the 14 attractions considered in our empirical analyses, 10 were successful in the sense that their ROI exceeded 100%. Across all attractions introduced in the observation period 1981–2005, the average ROI is 113% when only direct effects are considered and 142% when also the indirect effects as a result of reinforcement are included. This again underscores the importance of accounting for these indirect effects.

Figure 7 Lifespan Impact of the Attractions on Attendance



5.3. Robustness Checks

5.3.1. Decay Pattern. To test the decay pattern of the proposed model, we compare it with two alternatives. Alternative model 1 replaces the within-year gamma distributions in (7) by uniform distributions, implying a stepwise decay pattern without within-season variation. Alternative model 2 keeps the gamma specification for the within-year variation but captures the across-year variation by nonmonotonic decay patterns through yearly dummy variables up to a cutoff year after which the impact of the attraction is assumed to be zero. The cutoff year was varied from 1 to 15. A cutoff of three years provides the best Bayesian information criterion (BIC) (alternative model 2a), whereas a cutoff value of eight years

Table 5 Return on Investment of Attractions

	Bobsleigh Run	Pegasus	PandaVision	Overall
Year of introduction	1985	1991	2002	1981–2005
Type of attraction	Thrill	Thrill	Theme	Theme and thrill
ROI—Direct (%)	108	209	78	113
	(17)	(20)	(11)	(13)
ROI—Combined (%)	236	237	78	142
	(68)	(31)	(11)	(23)

Note. Standard errors are in parentheses.

gives the best Akaike information criterion with a penalty factor of 3 (AIC3) (alternative model 2b).

Table 6 contains the model comparison results. In-sample, we report the log-likelihood value and the BIC and AIC3 information criteria. For out-of-sample validation, we reestimated all models up to 1998, when the Bird Rok was introduced, and predict attendance levels in 2002, the year in which the last attraction (PandaVision) was added. We report the mean absolute error (MAE) and the root mean squared error (RMSE).

The proposed model performs better than the alternative models in terms of both in-sample information criteria and out-of-sample prediction. Hence, it is important to capture the within-year effect by a pulsing pattern (model 0) instead of by a constant within-year pattern (model 1). To capture the across-year effect there is no need for a nonmonotonic specification (models 2a and 2b); a more parsimonious monotonic decay as in focal model 0 (Equation (8)) suffices.

5.3.2. Saturation and Reinforcement. We have also tested whether there are not only saturation and reinforcement effects *within* types (theme or thrill) but also *across* types, but the likelihood ratio (LR) test ($LR = 0.71$, $df = 2$, $p = 0.70$) indicated this extension was not required. A second LR test shows that our operationalization of saturation and reinforcement variables (linearly aggregated investments) is not improved upon when working with geometrically aggregated investments, giving more weight to attractions that are introduced closer in time ($LR = 1.10$, $df = 2$, $p = 0.58$). For parsimony reasons, we opt to stay with the simpler linear specification.

5.3.3. Error Correlations. In our model specification, the disturbances $u_{s,t}$ (Equation (1)) are assumed to be independent of the attraction-specific random terms $\omega_{j,s,t}$ (Equation 3) and $\xi_{j,s,t}$ (Equation 4). To check this, we computed the correlations between their simulated values (a similar empirical assessment was used in Chandrashekaran and Sinha 1995, p. 446). We found these correlations to be very close to zero. In addition, $\omega_{j,s,t}$ and $\xi_{j,s,t}$ are assumed to be independent of each other. We tested a model in which (i) the $\omega_{j,s,t}$ are correlated across attractions j with correlation coefficient $\rho_{\omega,\omega}$, (ii) the $\xi_{j,s,t}$ are correlated with correlation coefficient $\rho_{\xi,\xi}$, and (iii) $\omega_{j,s,t}$ and $\xi_{j,s,t}$ are correlated with correlation coefficient $\rho_{\omega,\xi}$, without including autocorrelations in $\omega_{j,s,t}$ and $\xi_{j,s,t}$. The improvement in fit was not significant ($p = 0.14$). Next, we tested for first-order autocorrelation in $\omega_{j,s,t}$ and $\xi_{j,s,t}$. Again, the improvement in fit was not significant ($p = 0.36$). Finally, we estimated a model in which we added *time-invariant* random effects ω_j and ξ_j. The associated variances turned out to be extremely small, and much smaller than the variances of $\omega_{j,s,t}$ and $\xi_{j,s,t}$. We therefore retained Equations (3) and (4) as the focal model.

Table 6 Performance of Proposed Model and Alternative Decay Patterns

Model	Description	In-sample LL	In-sample BIC	In-sample AIC3	Out-of-sample MAE	Out-of-sample RMSE
0	Proposed model: monotonic pattern, varying within year	105.22	<u>−32.35</u>	<u>−129.43</u>	<u>1.482</u>	<u>2.068</u>
1	Monotonic pattern, constant within years	63.50	37.90	−51.99	1.611	2.221
2a	Nonmonotonic three-year pattern, varying within year	99.68	−14.68	−115.36	1.652	2.177
2b	Nonmonotonic eight-year pattern, varying within year	<u>107.84</u>	1.98	−116.68	1.516	2.122

Notes. The best value in each column is underlined. Within the class of nonmonotonic patterns, the three-year model provides the best BIC, whereas the eight-year model provides the best AIC3 value.

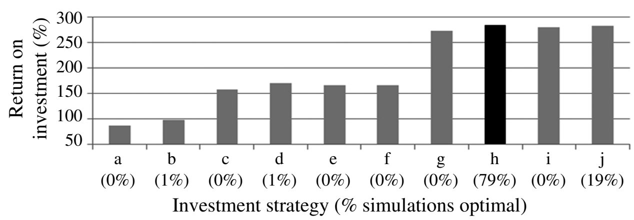
6. Using the Model to Evaluate New Attractions

Our model cannot only be used to evaluate *extant* attractions (see §5.2) but also hypothetical *new* attractions. We consider the following experiment in order to extract some general guidelines for profitable investments. We assume that the park has a budget of €12 million (M) for investments in a planning period of four years, labeled year 1 to year 4. To capture the full reach of the attractions, we consider a period of 30 years beyond year 4. The budget can be used in 10 different strategies ($a - j$) shown in Figure 8: one big attraction of €12 M, two medium-priced attractions of €6 M each, or four inexpensive attractions of €3 M each, where each attraction is either theme or thrill. As such, we also consider strategies that may involve multiple attractions in multiple years. To avoid too much extrapolation, we have kept these investment amounts within the range of €1 M to €15 M observed in the estimation sample. Each year that the theme park does not spend the available budget, it earns 12% over the remaining amount, consistent with the adopted discount rate.

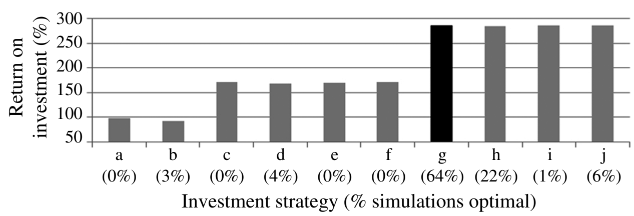
Figure 8 **Return on Investment (in Percent) for 10 Investment Strategies in Three Scenarios**

	Investment strategies									
	a	b	c	d	e	f	g	h	i	j
Year 1	12 M theme	12 M thrill	6 M theme	6 M thrill	6 M theme	6 M thrill	3 M theme	3 M thrill	3 M theme	3 M thrill
Year 2	—	—	6 M theme	6 M thrill	6 M thrill	6 M theme	3 M theme	3 M thrill	3 M theme	3 M thrill
Year 3	—	—	—	—	—	—	3 M theme	3 M thrill	3 M thrill	3 M theme
Year 4	—	—	—	—	—	—	3 M theme	3 M thrill	3 M thrill	3 M theme

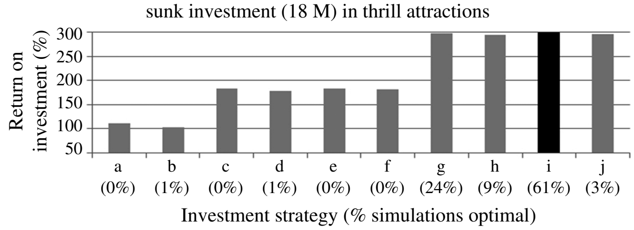
Scenario A: Sunk investments in theme (18 M) and thrill attractions (18 M)



Scenario B: Sunk investments in theme (12 M) and thrill attractions (24 M)



Scenario C: Sunk (6 M) and last-year (12 M) investments in theme attractions; sunk investment (18 M) in thrill attractions



Notes. For each strategy, a budget of €12 million (M) is available for investments in the four-year planning period; this budget can be spent on either one big €12 M attraction, two medium-sized €6 M attractions, or four consecutive small €3 M attractions of either type (theme or thrill). For each scenario, the strategy with the highest average ROI is in black. The percentages indicate how often each of the strategies yielded the highest ROI in 2,000 simulation runs.

The 10 strategies are investigated for three hypothetical scenarios, described by the attractions already available in the park. Scenario A is the "plain" scenario in which the two types, theme and thrill, are equally saturated (past investment in both types is €18 M) and in which there are no opportunities to take advantage of reinforcement effects (as all previous introductions occurred very long ago and are therefore "sunk"). Scenario B also eliminates the reinforcement potential, but now theme attractions are *less saturated* than thrill attractions (past investments of €12 M versus €24 M). In scenario C, theme and thrill are equally saturated (for both types the total past investments amount to €18 M), but theme now has *reinforcement potential*. For theme, only €6 M (from the total of €18 M) was invested long ago ("sunk"), whereas €12 M was invested one year ago, in year 0, and can therefore be reinforced by new theme attractions.

Figure 8 shows the ROI estimates for the 10 investment options in each of the three scenarios. For all scenarios, we obtained the result that it is more profitable to introduce the attractions as early on as possible (e.g., better to invest in year 1 than in year 2), so these are the only investment strategies we show. The reported numbers account for parameter uncertainty. For each scenario, the strategy with the highest (average) ROI is in black, and the percentages indicate how often each of the strategies yielded the highest ROI in 2,000 simulation runs. Several insights emerge from this exercise.

- *All else equal, investing in thrill attractions is more effective than investing in themed ones* (see, e.g., scenario A). Theme park managers around the world seem to share this belief. In recent years, new roller coaster rides were added in Disney's Epcot (Mission: Space), Disney World's Animal Kingdom (Expedition Everest), and Universal Studios (Revenge of the Mummy Rides), to name a few.
- *Under certain conditions, theme attractions become more effective than thrills*. This holds if thrill has become saturated because of a large presence of this type (scenario B) or if theme has a lot of reinforcement potential because of recent theme introductions (scenario C). In line with that observation, PricewaterhouseCoopers (2004–2008, p. 497) projects that an increasing number of parks will move away from their almost exclusive focus on thrill rides and add attractions that also appeal to a more family-oriented audience. Six Flags' new owners, for example, recognize that many of their parks "were one-trick ponies, thrill palaces for teens without enough other attractions to appeal to young families" (*BusinessWeek* 2006).
- *It is more efficient to invest in multiple smaller attractions than in one big attraction.* At first sight, this finding may appear in contrast with the "arms race" that currently seems to take place in the theme park industry. Indeed, several recent mega-attractions have received much press coverage. However, our finding is consistent with the emerging view that new rides that are smaller and relatively cheap may also lure visitors looking for something new (see, e.g., Schneider 2005). As a case in point, LEGOLAND California was able to achieve a record growth of 16% in 2006 because of the popularity of its relatively inexpensive ($10 M) Pirate Shore addition (Rubin 2007). A similar observation was made (albeit in a different setting) by Pauwels et al. (2004, p. 154), who

concluded that “managers need not always incur the high development and launch costs that are associated with major product innovations,” and may as well opt for smaller, but more frequent, innovations.

7. Conclusion

This paper contributes to the growing literature of models to guide decisions in the entertainment industry. Although the marketing literature offers several models to support decisions for the motion picture industry and other areas (e.g., Wierenga 2008), the theme park industry has different characteristics requiring a different modeling approach. To guide investment decisions in theme park attractions, we estimated a model that disentangles the contribution of individual attractions to total theme park attendance.

In our empirical application we found that the contribution over time is captured by a slowly extinguishing pulsing pattern, accounting for stronger effects in high seasons. Because more than 50% of the *within-year* effect is concentrated in eight weeks of the year, these are the weeks that management should adjust staffing levels to cope with increased demand. On average, attractions obtain 35% of their total impact in the year of introduction, whereas 90% materializes in the first five years following their introduction.

Our results also indicate that attractions indeed do not operate in isolation but interact with other attractions in the park’s portfolio via (negative) saturation and (positive) reinforcement effects. When planning a new attraction, one should not only consider *what* rides are already in the park but also *when* these were introduced. Indeed, to fully capitalize on the potential reinforcement effects, one should not let too much time elapse between consecutive introductions of the same type. However, at some point, the negative saturation effect will dampen the direct effect to such an extent that the addition of attractions of another type becomes more appealing. A failure to recognize this has, as indicated before, been identified as one of the key mistakes made by Six Flags. Our modeling approach may be useful to avoid such costly mistakes and to help management make the most appropriate trade-offs.

We estimated our model on data from the Efteling, a mature park with a combination of theme rides and thrill rides, not unlike the Disney parks around the world (yet at a smaller scale). Our results are directionally in line with several developments in the industry, which adds to the face validity of our results. We expect that similar effects hold for other parks that are similarly diverse and mature. Although we do not claim that the same parameter estimates will apply to other theme parks, we believe that the same underlying mechanisms are at work, especially because these mechanisms are based on well-documented individual-level phenomena such as novelty wear-off, attribute satiation, and attribute alignment.

Obviously, it would be useful to replicate our study for other theme parks. These might differ in terms of their size and location (e.g., United States, Asia) or in their types of attractions (e.g., a separate category of water attractions). To facilitate the diffusion of our model, the electronic companion provides a detailed description of the steps needed to implement the model and an artificial data set to test the implementation. In practical situations, we recommend to first estimate the model without error terms $\omega_{j,s,t}$ in Equation (3) and $\xi_{j,s,t}$ in Equation (4), in which case standard maximum likelihood suffices (instead of simulated maximum likelihood).

Other areas for future research remain. First, we could use an attribute-based model to represent the variety of the available attractions (Hoch et al. 1999). Second, our model does not impose assumptions on how repeat and first-time visitors might contribute to attendance. A simulation study by Bodapati and Gupta (2004) shows that it is very difficult to recover heterogeneity patterns from aggregate data, even for frequently bought consumer goods with many repeat purchases. These problems are likely to be amplified in a theme park setting, because there is an extreme amount of variability in interpurchase times, with an average repeat cycle of more than two years for most parks (http://www.entrepreneur.com). Nevertheless, future research could add assumptions to infer the relative contributions of first-time versus repeat visitors.

Third, it would be interesting to directly incorporate marketing-mix variables such as price and advertising spending. Fourth, our ROI calculations could be refined by also considering maintenance costs (that may vary across attractions) or by allowing for a more intricate price (revenue) structure.

We believe that our modeling approach may also be relevant in other settings. City councils, for example, may have to choose between different investment options to increase the number of tourists in their city. Should they build another concert hall or add a spectacular attraction such as a giant Ferris wheel? Similarly, what piece of art should museum directors invest in to improve the overall appeal of their collection? Or what combination of stores should a shopping mall offer? The same notions of saturation and reinforcement potential from our modeling approach may be at work in these settings.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mktsci.pubs.informs.org/.

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