# What's a Movie Worth?
## Determining the Monetary Value of Motion Pictures' TV Rights

Thorsten Hennig-Thurau, Stefan Fuchs, Mark B. Houston

### Introduction

Motion pictures are among the most valuable broadcast assets for TV stations around the globe. Industry insider Edward Jay Epstein (2005) has referred to TV as "the [Hollywood] studios' real El Dorado." TV broadcast rights account for between one quarter (Waterman, Ji and Rochet, 2007) and one third (Epstein, 2005) of studios' total revenues. More than 50% of revenues from the sale of TV rights comes from international markets (Adams Media Research, 2008); European free TV broadcasters alone pay Hollywood approximately $2.5 billion per year (Guider, 2003). For individual titles, fees can be as high as $10 million: the amount that Rupert Murdoch paid for the rights to show the movie *Titanic* for the first time on German television. For several projects, TV rights even constitute a key element in a film's financing prior to production (Dekom, 2004).

The high value of TV rights results from audiences' love of movies, which is often reflected in high ratings (e.g., more than 11 million US viewers watched the 2004 broadcast of *Harry Potter and the Sorcerer's Stone;* Marketing Charts, 2007), but also a price premium for advertisements (broadcasters pay up to five times more for ads shown during the airing of a studio motion picture than for made-for-TV films and TV series; SevenOne Media, 2008). This love (and the number and quality of viewers that result from it) can justify enormous fees such as the sum paid by Murdoch – the German airing of *Titanic* generated over $12 million in ad revenues for Murdoch (*Spiegel Online,* 2000).

A major challenge for movie studios (which seek maximum revenues) and broadcasters (which seek to avoid overspending) is to establish an appropriate transaction fee for the TV rights for a given movie – *before* that movie's airing. The existence of multiple determinants that become known at different points in the life cycle of a movie make valuation a highly complex undertaking (Litman, 1982). Currently, the sellers and buyers of such rights base their offers mainly on heuristic models and gut feelings (Schawinski, 2007).[1]

The goal of this study is to provide a theoretically grounded and scientifically rigorous means of determining the value of movie rights for TV broadcast. We pursue this goal by developing a multi-stage model of a movie's monetary TV rights value and applying it to data from a major foreign market for US films: Germany. By doing so, we contribute to a stream of research aimed at monetizing the value of movie rights and ingredients, such as stars (Wallace, Seigerman and Holbrook, 1993), Academy Awards (Nelson et al., 2001) and sequels (Hennig-Thurau, Houston and Heitjans, 2009). Our model accounts for the different points in a movie's life cycle at which broadcasters can purchase TV rights and for the increasing availability of relevant

**Thorsten Hennig-Thurau** is a professor of marketing at the University of Münster, Germany, and at the Cass Business School, City University London. A distinguished movie buff, he has published extensively in marketing, management, and media journals and is the recipient of the 2010 Mallen Award for lifetime contributions to motion picture scholarship.

**Stefan Fuchs** (PhD, Bauhaus-University of Weimar) is Vice President Entertainment, Unitymedia KabelBW Group, Cologne, Germany. Prior to joining Unitymedia, he was a senior marketing and media consultant at Booz & Company.

**Mark B. Houston** is a professor of marketing and the Eunice and James L. West Chair at Texas Christian University, Fort Worth, United States, and is President of the American Marketing Association's Academic Council. He has published over 40 papers on marketing, management and finance, several of which focus on the movie industry.

information (which influences project-related risk), over time.

## TV Rights Valuation Research

### *Movies on TV*

Accurately predicting a movie's TV ratings[2] is a key requirement for valuating TV rights (see Litman, 1982). Academic studies that address determinants of TV ratings can be divided into three groups. The first group exclusively considers content that is aired repeatedly (e.g., a TV series), but not movies (Henry and Rinne, 1984). The second group looks at movies but treats them as having homogeneous content (e.g., Goettler and Shachar, 2001). While studies in the second group reveal positive effects of movies on ratings, they do not account for the obvious heterogeneity of motion pictures. As Greenberg and Barnett (1971) noted 40 years ago, "it is improper to consider films as being perfect substitutes for each other" (p. 93).

In the third group are the few studies that include movie characteristics. Greenberg and Barnett (1971) used ordinary least squares (OLS) regression to analyze 262 movies that aired on a US network in 1968, including colour, age and type (or genre). The low $R^2$ (of .39) in combination with the limited significance of these variables forced the authors to conclude that other movie characteristics have a significant influence on TV audiences. Litman (1979b) found support for this argument; adding the theatrical success of a movie and critics' ratings while predicting TV ratings for 116 movies aired on TV in 1976–77, he explains 66% of the variance in TV ratings. In 1982 Litman replicated his initial findings with a sample of 74 movies broadcast in 1976–77, but also included more variables, namely scheduling variables, audience flow and theatrical success, explaining 64% of the variance. Although Litman used other movie-specific variables (critics' ratings, budget, awards) in a separate regression to explain theatrical success, he did not model these variables as drivers of movies' TV ratings.

In summary, extant research on TV ratings has limitations that we aim to overcome. Studies have used small convenience samples, have not systematically included movie characteristics and/or have not accounted for interrelations among these characteristics. Further, research has offered no link to the monetary value of TV rights – although Litman (1982) mentions the *possibility* of such an approach (p. 51). Finally, studies have not accounted for different points in time at which TV rights can be purchased; one can use Litman's findings for predictions only after the theatrical box office is known. Litman (1982) stresses the relevance of a multi-stage approach but does not offer a model.

### *Movie Valuation*

Although no research has isolated the financial value of a movie's TV rights, studies have monetized elements of a movie, including stars (Wallace, Seigerman and Holbrook, 1993), awards (Nelson et al., 2001) and advertising during the Super Bowl (Ho, Dhar and Weinberg, 2009). To our knowledge, the only published study to measure the value of movie rights, as a whole, is that by Hennig-Thurau, Houston and Heitjans (2009). These authors calculate the sequel value of movies using a regression approach that allows them to estimate project-specific values and account for

**Acknowledgements**
The authors wish to thank those who attended the 2009 Mallen/UCLA Workshop for Motion Picture Industry Studies for their constructive comments on this project. They wish to thank Media Control, SPIO and HSX.com for generously providing some of the data used in the research.

ABSTRACT

Motion pictures are among the most valuable products for broadcast by television stations. As a result, broadcast rights generate important revenues for the movie studios that own these assets and are often a crucial element in a film's financing. A key challenge is to determine the monetary value of the TV rights for a movie. The authors develop a multi-stage model of a movie's monetary TV rights value that accounts both for the differences in information over time and for the differences in project-related risk associated with the varying availability of information. Sellers and buyers can use the model to increase the efficiency and reduce the risk of price negotiations for the right to broadcast a movie.

KEYWORDS

TV rights, motion picture success, creative products, partial least squares

prediction risk. To date, no study has developed an approach for monetizing the value of movies' TV rights.

## A Multi-stage Model of the Monetary Value of TV Rights

We offer a model of the monetary value of US motion pictures' TV rights and then calibrate it using actual TV ratings data from Germany. A major difference between TV and other distribution channels for movies is that broadcasters purchase movie rights at a price that is determined prior to broadcast. In contrast, in theatres and home video, revenue-sharing models govern how the producer and a channel partner allocate revenues generated by a movie in a specific channel. For TV rights, the broadcasters that purchase the rights carry the risk if the movie fails to attract a sufficient audience.

### *Analytical Model of TV Rights Value*

We define the net present value (NPV) of film *f* for a broadcaster as a function of advertising revenues generated through airing of the film and the costs associated with it:

$$NPV\left(f_{s,j}\right) = \sum_{a=1}^{A} \frac{MV_a^{f(s,j)}}{\left(1+d\right)^{t_p^{f(s,j)}}} - \sum_{a=1}^{A} \frac{DC_a^{f(s,j)}}{\left(1+d\right)^{t_c^{f(s,j)}}} \quad \text{(I)}$$

where $MV$ is the monetary value of airing $\alpha$ of film $f$ for station $s$ through advertising when aired at timeslot $j$. $DC$ comprises the station's direct costs to air the film (e.g., promotion), $d$ is the monthly discount rate, $t_p$ is the time difference between the broadcaster's purchase of TV rights and the receipt of advertising revenues (in months), and $t_c$ is the time difference between the incurring of the broadcaster's direct costs and the receipt of advertising revenues. For parsimony, we do not consider potential revenues generated by sublicensing the rights to other broadcasters, indirect values of the rights and channel overhead costs; adding these aspects would not affect the estimation process.

The key variable in equation I that is unknown to broadcasters is $MV$. We define it as a function of the expected number of viewers of a movie, the length of the movie and the cost per thousand viewers:

$$MV_a^{f(s,j)} = RAT_a^{f(s,j)*} \cdot \frac{CPM}{1000 \cdot 30} \cdot \frac{L^f}{1 - MAR} \cdot MAR \cdot 60 \quad \text{(II)}$$

where $RAT^*$ is the estimated number of TV viewers in millions (i.e., TV rating), $CPM$ is the cost per thousand viewers for a 30-second ad, which is translated into cost per viewer per second, $L$ is the length of the film in minutes, and $MAR$ is the maximum advertising ratio (the percentage of minutes per hour that the broadcaster can legally use for advertising). In practice, $MAR$ differs from market to market internationally; in Germany it remains steady at around .20 (through July 2011). The term $\frac{L^f}{1-MAR}$ thus represents the expected gross air time of the movie, including advertising time. We assume advertising utilization to be 100%.

The main challenge in measuring the value of TV rights is predicting the TV ratings of a movie (i.e., $RAT^*$) that can then be transformed into a monetary measure through equation II. To meet this challenge, we develop structural models of movie TV ratings.

RÉSUMÉ

Les productions cinématographiques sont parmi les produits les plus intéressants à diffuser par les stations de télévision. Les droits de diffusion génèrent ainsi des revenus importants pour les studios qui possèdent ces actifs et constituent souvent un élément crucial du financement d'un film. La principale difficulté est de déterminer la valeur pécuniaire des droits de diffusion d'une production. Les auteurs développent un modèle en plusieurs étapes de la valeur des droits de télédiffusion d'un film qui tient compte à la fois des différences dans l'information recueillie au fil du temps et des différences entre les risques associés au projet et la disponibilité variable de l'information. Vendeurs et acheteurs peuvent utiliser le modèle pour accroître l'efficacité de la négociation de prix pour la télédiffusion d'un film et en diminuer les risques.

MOTS CLÉS

Droits de télédiffusion, succès d'un film, produits de création, moindres carrés partiels

### *Structural Models of Estimated Audience Ratings*

When one is developing prediction models for TV ratings, two issues require particular attention. First, models should acknowledge interrelationships between the drivers of ratings; this means distinguishing between direct and indirect effects of drivers on ratings, as failure to account for inter-driver effects results in distorted model parameters (e.g., Elberse and Eliashberg, 2003). Thus we assess interrelationships among drivers and ratings via nested (and simultaneously estimated) structural models.

Second, models should account for different points in time when purchases of TV rights take place *in practice* and when varying information is available. Creating separate models for the different points in time is critical for the utility of the research; models that fail to account for availability of information can be used only for post-hoc explanation, not for value estimation under uncertainty. We choose standard milestones in industry practice and develop models for four key time points for a movie: *greenlighting* (the producer commits to making a movie); *screening* (the final cut of the movie is shown to potential buyers); *US theatrical opening weekend* (US box office revenues for the opening weekend are known); and *foreign theatrical release* (foreign box office revenues are known).

In each model, we consider only variables that managers can assess at a given point in time. Causal relationships among variables provide the general structure of the different models, and we use proxy variables when definitive information on certain variables is not available at a given point in time (thus avoiding overestimating model paths). We select variables based on extant research on movie success (e.g., Moul and Shugan, 2005) and TV ratings (e.g., Goodhardt, Ehrenberg and Collins, 1987).

The variables in the greenlighting model are discussed in detail below. For the subsequent models, we identify and describe incremental variables; the details for each model are reported in Tables 2 to 5 along with the estimation results, with variable names and operationalizations being reported in Table 1. For the foreign market we use Germany, one of the world's largest TV markets and "Europe's most important market for free-to-air sales" (Westcott, 2005).

### Model I: Greenlighting

At this initial stage, limited information is available about a movie and the commercial success of the movie is unknown. Prior research suggests three general categories of variable that influence TV ratings: (a) TV variables (variables related to the airing of a movie rather than the movie itself); (b) "fit" variables (variables that describe the degree to which the nature of a movie aligns with the nature of a broadcaster); and (c) movie characteristics.

Regarding TV variables, *TV seasonality* captures the variations in TV consumption in specific months over the course of a year (Barnett et al., 1991). The *general time slot* measures variations in TV consumption at different times and different days of the week (Webster and Phalen, 1997). We also consider a *specific time slot* variable that indicates whether a movie is aired in a time slot specifically programmed for motion pictures (Greenberg and Barnett, 1971). TV *channel loyalty* captures the audience's preference for a specific channel (Goodhardt, Ehrenberg and Collins, 1987).


RESUMEN

*Las películas cinematográficas constituyen uno de los productos más valiosos para las emisoras de televisión. Los derechos de trasmisión generan, por ende, importantes ingresos para los estudios de cine propietarios de las películas trasmitidas, y con frecuencia son un elemento crucial para la financiación de una película. La determinación del valor monetario de los derechos de televisión representa un reto mayor. Los autores elaboraron un modelo de etapas múltiples para el cálculo del valor monetario de los derechos de la televisión que tenga en cuenta tanto las diferencias en la información, que surgen con el tiempo, así como las diferencias en el riesgo del proyecto relacionado con la desigual disponibilidad de la información. El modelo puede ayudar a vendedores y compradores a lograr mayores eficiencias y reducir el riesgo de las negociaciones sobre el precio del derecho de trasmisión de una película.*



PALABRAS CLAVE

*Derechos de la televisión, éxito cinematográfico, productos creativos, mínimo cuadrático parcial*

As fit variables, we consider *general movie fit,* which refers to whether a broadcaster's brand image features the airing of movies. In contrast, *genre fit* assesses the degree to which the genres of a specific movie match the brand associations of the broadcaster (Davis, 2000).

Several film characteristics are known or can be anticipated at greenlighting. Some of these are of a "global" nature, while others are "regional" – that is, specific to a particular foreign market (e.g., the German TV market). With regard to global characteristics, research has shown that a film's *genre,* representing unique dramaturgic and aesthetic patterns (Hennig-Thurau, Walsh and Wruck, 2001), influences audience appreciation of the movie (d'Astous, Colbert and Nobert, 2007), its box office success (Prag and Casavant, 1994) and its TV ratings (Litman, 1982). A film's *country of origin* informs audiences about specific aesthetic styles or kinds of narration whose attractiveness for audiences differs (d'Astous et al., 2008). We use US movies as the base category and include European movies and those that are from neither Europe nor the United States ("rest of the world") as dummies. The *production budget* of a movie (as reported in the media) informs audiences about the movie's "production value"; empirical evidence consistently links budget to box office revenues (e.g., Basuroy, Chatterjee and Ravid, 2003), and we expect a similar effect for TV audiences. Although budgets are determined at greenlighting, there remain some contingencies that can lead to a larger or smaller final budget (Rudman and Ephraim, 2004). Thus we add an uncertainty parameter – individual values are randomly distributed in a confidence interval ranging from 20% below to 20% above the "true" value. A movie's *runtime* distinguishes theatrical movies from more commercial fare, such as made-for-TV films, and serves as a marker of more valuable content for audiences (Litman, 1979a). Runtimes are only estimated at this early stage (based on the screenplay); thus we also add an uncertainty parameter of 20%.

Turning to regional characteristics, a movie's cultural familiarity refers to the use of existing brands. Because brand awareness differs between countries, it is a movie's familiarity in a specific market that should determine TV ratings, not its "global" cultural familiarity. We use *sequels* (e.g., *Transformers 2*) and *remakes* (e.g., *King Kong*) as proxies for cultural familiarity; research consistently shows that cultural familiarity has an influence on box office revenues (Hennig-Thurau, Houston and Heitjans, 2009). *Director power* and *star power* both concern branded ingredients of a movie. Audiences hold clear associations for stars and directors, who therefore can serve as early signals of a movie's appeal (Elberse, 2007). Such associations can also be expected to differ between regional markets, and we conceptualize them accordingly. While a director rarely leaves a project that has been greenlighted, the actors attached to a project are more vulnerable (Elberse, 2007); thus we add an uncertainty parameter of 20% to star power.

## Model II: Screening

At screening, potential buyers can estimate additional predictor variables based on viewing the final cut. Based on this information, the film's *financial success* in US theatres can be anticipated; we use the Hollywood Stock Exchange (HSX), a virtual stock exchange on which individuals trade fictitious stocks for actual forthcoming movies (e.g., Elberse, 2007). Also, distribution intensity in the foreign market can be estimated (we use the number of *opening weekend screens;* Elberse and Eliashberg, 2003) and *quality perceptions* of the movie by key stakeholders, namely audiences and professional critics (Holbrook and Addis, 2007), can now be assessed. In addition, because the time to the movie's airing has substantially decreased, buyers will now be able to anticipate *channel cannibalization* (i.e., the degree to which the movie's availability via other channels reduces TV ratings) at the time when the movie is aired; to account for the dynamics of channel diffusion over time, we add an uncertainty parameter of 30% to the channel cannibalization variable.

## Model III: US theatrical opening weekend

When a movie has opened in US theatres, additional information becomes available. Specifically, the level of "buzz" the movie will generate in the foreign country can be anticipated based on the reactions of US audiences, although with error (Karniouchina, 2011). Also, for several variables uncertainty is either removed (box office revenues for US opening weekend) or reduced (audience and expert quality ratings, number of screens in the foreign market).

### Model IV: Foreign theatrical release

Once a movie has been released to foreign theatres, information on *awards* (Nelson et al., 2001) and *broadcast timing* can be judged by buyers and are added to our prediction model. Further, the movie's *foreign box office performance* (Hennig-Thurau, Houston and Heitjans, 2009), its *quality perceptions* of foreign critics and audiences, and its *foreign market buzz* can be assessed without error. Thus we remove all uncertainty elements from prior equations in this model; the only exception is *channel cannibalization* (which is not yet fully determined, as the airing of the movie is still years away).

## Empirical Application: Calculating the Monetary Value of TV Rights

We now report the method and findings of a large-scale empirical study in which we use secondary data from multiple sources to estimate the parameters of the four different models and show how these parameters can be used by TV rights buyers (and sellers) to calculate the monetary value of German TV rights for individual movies.

### *Data*

Our sample consists of all full-length motion pictures that (a) premiered in US theatres from 1998 to 2002 inclusive, (b) were released in German theatres or on home video *after* their US theatrical premiere, and (c) were subsequently aired by a major German TV broadcaster for the first time by the end of 2005. These conditions were met by 674 movies that make up the final sample for models I to III. The sample for model IV consists of the 595 (out of 674) movies that were released theatrically in Germany.

### *Measures*

TV ratings were provided by AGF/GfK Fernsehforschung, a company that collects viewership data by electronically monitoring the second-by-second TV consumption of a nationwide representative panel of more than 5,000 households (Arbeitsgemeinschaft Fernsehforschung, 2011). Specifically, we use the number of viewers of a movie in Germany between 14 and 49 years of age (i.e., the information used by advertisers and broadcasters to determine advertising rates).

Table 1 provides the operationalization and data sources for all predictor constructs. We collected information from secondary sources, except for genre fit; as no objective fit data were available, we asked the research director of a leading TV station (who did not know the objective of the research) to assess the degree to which the brand image of specific German broadcasters fit with the film genres. We measure all constructs with a single item each, except for genre and channel cannibalization. Genre is a formative construct with 15 genres as indicators, while channel cannibalization consists of two formative items: (1) the number of DVD and VHS copies of the movie sold in the release year in Germany, and (2) the number of pay-TV subscribers in Germany in that year.

### *Method*

We estimate the models using partial least squares (PLS) structural equation modelling. PLS allows researchers to simultaneously estimate systems of equations with formative variables. It also estimates determinate measures for model variables that one can use for prediction. Importantly, it does not impose distribution-form requirements on the data (Fornell and Bookstein, 1982) and handles models with a large number of variables robustly (Chin, 1998). PLS iteratively minimizes the residual variance of the structural model and the measurement model until a pre-defined stop criterion is reached, and then it uses OLS to determine the structural model paths (e.g., Chin, 1998). Improvement is reached through a partial optimization approach that considers, for each variable, those model elements with which the variable is directly linked, as it iterates between the structural and the measurement model.

### *Results*

We compare all four models against a baseline model that includes only the TV variables (and thus interprets movies as homogeneous products; Goettler and Shachar, 2001). Comparisons are based on established prediction criteria,

TABLE 1

**OPERATIONALIZATION AND DATA SOURCES OF MODEL VARIABLES**

| Construct | Variable name | Operationalization | Data source |
|---|---|---|---|
| TV seasonality | Season | Average number of minutes per day of TV consumption among those aged 14–49 for the month the movie was aired (average for 1998–2005) | AGF/GfK Fernsehforschung (Media Control) |
| General time slot | Genslot | Average number of viewers (millions) among those aged 14–49 for the day and time the movie was aired (average for 1999–2005) | AGF/GfK Fernsehforschung (Media Control) |
| Specific time slot | Speslot | Dummy variable; 1 if the movie was aired by Pro7 or RTL on Sunday evening at 20:15 p.m., 0 otherwise | AGF/GfK Fernsehforschung (Media Control) |
| TV channel loyalty | Chanloy | Average market share for consumers 14–49 years of broadcaster who aired the movie (average for the 12 months preceding the airing) | AGF/GfK Fernsehforschung (Media Control) |
| General movie fit | Genfit | Percentage of German consumers who consider theatrical and made-for-TV movies as "important" or "very important" for the broadcaster that aired the movie in a representative annual survey of 3,000 consumers 14 years and over (average for 2001–05) | ARD-Trend survey |
| Genre fit | Genrefit | 5-point scale that measures the fit between the movie's genres and the broadcaster that airs the movie: 1 = very low fit, 5 = very high fit; for movies of more than one genre, genrefit is the mean score of the individual genres' fit measures | Industry expert |
| Genre | Genres | Formative construct consisting of 15 binary genre items (i.e., comedy, drama, thriller, action, horror, science fiction, adventure, animation, war, music, western, children, satire, documentary) | Blickpunkt: Film (mediabiz.de) (genre classification) |
| European film | cooE | Dummy variable; 1 if the movie was mainly produced in Europe (a European country was listed first at mediabiz.de), 0 otherwise | Blickpunkt: Film |
| Rest-of-the-world film | cooRoW | Dummy variable; 1 if the movie was mainly produced outside of Europe and the US, 0 otherwise | Blickpunkt: Film |
| Runtime | Runtime | Runtime of the movie (in minutes) | Blickpunkt: Film |
| | runtime20 | Same as runtime but with uncertainty element *UE* of 20% added to each movie; individual values are randomly distributed in a confidence interval ranging from $T+UE*T$ (upper limit) to $T-UE*T$ (lower limit), with T being the true value | Blickpunkt: Film |
| Production budget | Budget | Production budget of the movie ($ millions); missing values for 18 movies were substituted by estimates from four industry experts | IMDB (imdb.com), Variety (variety.com), Showbizdata (showbizdata.com), The Numbers (the-numbers.com) |
| | budget20 | Same as budget but with uncertainty element *UE* of 20% added to each movie (analogous to runtime20) | IMDB, Variety, Showbizdata, The Numbers, Filmexperten |
| Sequel | Sequel | Number of attendants of predecessor film (millions) | IMDB, Blickpunkt: Film |
| Remake | Remake | Index score between 0 and 5, calculated from five dummy variables: adaptation of novel, adaptation of TV series, adaptation of video game, adaptation of comic, remake of movie | IMDB |

**OPERATIONALIZATION AND DATA SOURCES OF MODEL VARIABLES**

| Construct | Variable name | Operationalization | Data source |
|---|---|---|---|
| Star power | Stars | Index score, calculated as the mean number of attendants of the previous three leading roles of a participating star who was listed on the movie poster; if a movie had multiple stars, a weighted average was calculated using an exponential decay model, with the first-listed star multiplied with factor 1, the second-listed with factor .5, the third-listed with factor .25 and the fourth-listed with factor .125 (see Hennig-Thurau, Houston and Walsh 2006) | Blickpunkt: Film |
| | star20 | Same as stars but with uncertainty element *UE* of 20% added to each movie (analogous to runtime20) | Blickpunkt: Film |
| Director power | Director | Index score, calculated as the mean number of attendants of the previous three films of the movie's director if listed on the movie poster; if a reference was made on the poster to a specific movie ("From the director of…"), the number of attendants of this movie is used instead | Blickpunkt: Film |
| US opening weekend box office revenues | USBOHSX | Closing price of movie's stock as listed on the Hollywood Stock Exchange three months prior to the US theatrical release date | HSX.com |
| | USBOOW | Box office revenues generated during movie's first weekend (Friday to Sunday) in US theatres ($ millions) | IMDB |
| US long-term box office revenues | USBOLT | Total box office revenues generated in US theatres minus USBOOW ($ millions) | IMDB |
| Quality perception by professional critics | PREV | 5-point scale of the rating of the movie by the professional reviewers of Germany's most-read movie magazine: 1 = thumbs up, 5 = thumbs down | Cinema (cinema.de) |
| | PREV20 | Dummy variable; 1 if positive rating by professional critics is expected, 0 otherwise; movies with positive expected ratings were those where PREV was above the sample median; an uncertainty element *UE* of 20% was added by randomly recoding 20% of the movies in the sample (0 → 1; 1 → 0) | Cinema |
| | PREVUS | 10-point scale (1 = very low, 10 = very high) of the weighted ratings of the movie by up to 40 US professional critics ("metascore"), with the weighting reflecting the "relevance" of each reviewer and publications; for missing values, the similarly calculated average "rotten tomato" score from a different source was used | Metacritic (metacritic.com), Rotten Tomatoes (rottentomatoes.com) |
| Quality perception by audiences | AUD | 10-point scale (1 = very low, 10 = very high) of the ratings of the movie of registered users of movie portal site ofdb.de. | Online-Filmdatenbank (ofdb.de) |
| | AUD20 | Dummy variable; 1 if a positive rating by ofdb.de users is expected, 0 otherwise; movies with positive expected ratings were those where AUD was above the sample median; an uncertainty element *UE* of 20% was added by randomly recoding 20% of the movies in the sample (0 → 1; 1 → 0) | Online-Filmdatenbank |
| | AUDUS | 10-point scale (1 = very low, 10 = very high) of the ratings by registered users of IMDB.com | IMDB |
| Opening weekend screens | Screens | Number of screens in Germany on which movie was shown on its first weekend | Blickpunkt: Film |

| OPERATIONALIZATION AND DATA SOURCES OF MODEL VARIABLES | | | |
|---|---|---|---|
| **Construct** | **Variable name** | **Operationalization** | **Data source** |
| | screens20 | 3-point scale; 1 if number of screens < 100, 2 if screens between 100 and 399, and 3 if screens > = 400; an uncertainty element *UE* of 20% was added by randomly recoding 20% of the movies in the sample to an adjacent value (1 → 2; 2 → 1 or 3; 3 → 2) | Blickpunkt: Film |
| | screens10 | Same as screens20 but with *UE* = 10% | Blickpunkt: Film |
| Channel cannibalization | chancan30 | Formative construct consisting of 2 items: number of sold DVD/VHS in Germany per year (millions) and number of average subscribers of leading German pay-TV channel per year (millions); an uncertainty element *UE* of 30% was added to each movie for both items (analogous to runtime20) | GfK (Bundesverband Audiovisuelle Medien), Premiere |
| | chancan20 | Same as chancan30 but with *UE* = 20% | GfK (Bundesverband Audiovisuelle Medien), Premiere |
| Buzz | BUZZ | Number of votes for a movie from registered users of db.de | Online-Filmdatenbank |
| | BUZZUS | Log-transformed rank of a movie on MOVIEMETER at the weekend of the US release | IMDB |
| Awards | Awards | Index score, calculated as the weighted sum of Oscar wins and nominations; weights reflected the importance of the award categories, with a best picture award = 50 points (10 points for a nomination), best actor, best actress and best director awards = 25 points (5 points for a nomination) and any other Oscar = 10 points (2 points for a nomination) (see Hennig-Thurau, Houston and Walsh 2006) | Academy of Motion Picture Arts and Sciences (oscars.org) |
| Foreign box office performance | FBOX | Number of the film's attendants in German theatres (millions) | Blickpunkt: Film |
| Broadcast timing | TSPAN | Time period between the German theatrical release of the movie and its TV premiere (in years) | AGF/GfK Fernsehforschung (Media Control), Blickpunkt: Film |

namely $R^2$, mean absolute percentage error (MAPE), MAPE weighted with actual TV ratings (wMAPE) to correct for the highly varying absolute ratings of the movies in the sample, and root mean square error (RMSE).[3] We find no substantial multicollinearity in any of the models (all variance inflation factors are below 3, except for the foreign box office model where they are below 5).

## Baseline model

Table 2 reports the baseline model parameters and their levels of significance. The TV variables explain 62.4% of the variance in TV ratings; the general and specific slot and audiences' loyalty with the channel are the strongest predictors. The MAPE for this model is 52.6%, the wMAPE is 33.6% and the RMSE is .806 million viewers.

## Greenlighting model

As also shown in Table 2, adding early movie variables increases the variance explained to 72.3%, a substantial increase of 9.9 percentage points (or 15.8%) over the baseline. Prediction accuracy is also improved, with a MAPE of 44.2% (an improvement of 8.4 points, or 16%), a wMAPE of 28.9% (4.7 points, or 14%), and an RMSE of .691 million (14.3%). Of the movie variables, we find significant parameters for the production budget, genres, stars, expected runtime, sequel, and a European country of origin (in descending path strength).

## Screening model

The additional information available at screening improves prediction accuracy further (Table 3). Variance explained for TV ratings is now 76.7%, an increase of 4.4 points (or 6%) over the greenlighting model and 14.3 points (22.9%) over the baseline. Similar improvements exist for the other accuracy criteria (MAPE = 43.9% – improved by .6%/16.5% vs. greenlighting/baseline; wMAPE = 27.2% – 5.9%/19% vs. greenlighting/baseline; RMSE = .633 – 8.4%/21.5% vs. greenlighting/baseline). The strongest direct effects on TV ratings in this model come from number of screens, expected US box office, channel cannibalization, final production budget, genres, and stars. Substantial variance is explained for the other two endogenous constructs (screens and US box office) in this structural model as well.

## US theatrical opening weekend model

As expected, the new information available at this stage reduces prediction error further (Table 4). The $R^2$ is now .788, an improvement of 2.2 points (or 2.9%) over the screening model and 16.4 points (26.3%) over the baseline. MAPE is 41.6% (improved by 5.2%/20.9% vs. screening/baseline), wMAPE is 26% (4.4%/22.6% vs. screening/baseline), and RMSE is .604 (4.6%/25.1% vs. screening/baseline). The strongest predictor of *RAT* is the US opening weekend box office, followed by the number of screens (which has gained importance as a result of reduced error for this variable), channel cannibalization, stars, and the quality perception of US audiences (another source of information that has just become available at this point in time). Explanatory power is also good, once again, for screens and US box office.

## Foreign theatrical model

As theoretically expected, prediction accuracy is highest for the final model – in other words, waiting provides an information advantage for broadcasters. As reported in Table 5, this model explains an impressive 83.3% of TV ratings variance, another improvement of 4.5 points (or 5.7%) over the US opening weekend model and 20.9 points (33.5%) over the baseline. MAPE is 35.4% (improved by 14.9%/32.7% vs. US opening/baseline), wMAPE is 22% (15.4%/34.5% vs. US opening/baseline), and RMSE is .546 (9.6%/32.3% vs. US opening/baseline). The strongest effect here comes from the newly available foreign theatrical box office variable, followed by US box office, screens, stars, and awards. Interestingly, awards have a negative effect, suggesting that, when controlling for other film characteristics, critical acclaim hurts a movie's TV ratings. The time span between foreign theatrical release and TV airing exhibits the expected negative effect on TV ratings.

In sum, the results suggest that (a) structural models predict TV ratings much better than models without movie characteristics; (b) structural models predict TV ratings to a degree that is useful (and, clearly, that is higher

TABLE 2

**ESTIMATION RESULTS FOR BASELINE AND GREENLIGHTING MODELS**

| | Baseline model | | Greenlighting model | |
|---|---|---|---|---|
| Effect of ↓ on → | RAT | | RAT | |
| Season | 0.182 | (8.04)** | 0.119 | (5.61)** |
| Genslot | 0.403 | (16.36)** | 0.313 | (12.98)** |
| Speslot | 0.308 | (9.48)** | 0.246 | (7.30)** |
| Chanloy | 0.266 | (6.17)** | 0.191 | (5.35)** |
| Genfit | -0.043 | (1.35) | -0.014 | (0.65) |
| Genrefit | 0.022 | (1.15) | 0.030 | (1.67)* |
| Genres | n/a | | 0.143 | (4.91)** |
| cooE | n/a | | 0.031 | (1.80)* |
| cooRoW | n/a | | 0.006 | (0.66) |
| runtime20 | n/a | | 0.054 | (2.25)** |
| budget20 | n/a | | 0.191 | (5.66)** |
| Sequel | n/a | | 0.055 | (1.94)* |
| Remake | n/a | | -0.026 | (1.43) |
| star20 | n/a | | 0.082 | (3.24)** |
| Director | n/a | | 0.034 | (1.34) |
| $R^2$ | 62.38% | | 72.29% | |
| $\Delta R^2$ vs. baseline model | | | 9.91% | |

*Notes:* Numbers are standardized path coefficients as estimated through PLS. Numbers in parentheses are *t* values (calculated through bootstrapping with 674 cases and 500 re-samples each). * $p < 0.10$ (two-sided); ** $p < 0.05$ (two-sided)

TABLE 3

**ESTIMATION RESULTS FOR SCREENING MODEL**

| Effect of ↓ on → | USBOHSX | | screens20 | | RAT | |
|---|---|---|---|---|---|---|
| Season | n/a | | n/a | | 0.089 | (4.40)** |
| Genslot | n/a | | n/a | | 0.282 | (13.41)** |
| Speslot | n/a | | n/a | | 0.229 | (8.16)** |
| Chanloy | n/a | | n/a | | 0.159 | (4.54)** |
| Genfit | n/a | | n/a | | 0.012 | (0.60) |
| Genrefit | n/a | | n/a | | 0.033 | (1.63) |
| Genres | 0.135 | (2.09)** | 0.053 | (1.18) | 0.091 | (2.90)** |
| cooE | -0.010 | (0.95) | 0.000 | (0.00) | 0.029 | (1.70)* |
| cooRoW | -0.008 | (0.97) | -0.071 | (2.28)** | 0.010 | (1.02) |
| Runtime | 0.063 | (1.90)* | -0.021 | (0.93) | 0.015 | (0.82) |
| Budget | 0.626 | (10.53)** | 0.278 | (4.62)** | 0.100 | (2.66)** |
| Remake | -0.033 | (1.30) | -0.010 | (0.49) | -0.028 | (1.56) |
| Sequel | n/a | | 0.041 | (1.46) | 0.036 | (1.34) |
| Stars | n/a | | 0.046 | (1.56) | 0.086 | (3.47)** |
| Director | n/a | | 0.007 | (0.33) | 0.038 | (1.53) |
| USBOHSX | n/a | | 0.210 | (4.02)** | 0.105 | (2.73)** |
| PREV20 | n/a | | 0.029 | (1.14) | 0.047 | (2.49)** |
| AUD20 | n/a | | n/a | | 0.044 | (2.40)** |
| screens20 | n/a | | n/a | | 0.179 | (8.03)** |
| chancan30 | n/a | | n/a | | -0.103 | (3.60)** |
| $R^2$ | 53.59% | | 27.58% | | 76.65% | |
| $\Delta R^2$ vs. baseline model | | | | | 14.27% | |

*Notes:* Numbers are standardized path coefficients as estimated through PLS. Numbers in parentheses are *t* values (calculated through bootstrapping with 674 cases and 500 re-samples each). * $p < 0.10$ (two-sided); ** $p < 0.05$ (two-sided); n/a no path included in model.

than shown in previous research); and (c) the information that becomes available over time increases prediction accuracy meaningfully. The last point implies a reduction of financial risk for the investor over time, which is equal to a higher risk-adjusted value and, consequently, a higher price limit, everything else being equal.

### *Value Calculation*

Through an analytical transformation procedure, we employ the PLS estimates to determine ratings estimates for individual movie titles; see Appendix 1 for a description of the transformation process. Applying our analytical model described in equations 1 and 2, we then produce estimates of each movie's monetary TV rights value.

We use the movie *Spider-Man* to exemplify this value-calculation step. We apply the parameters for broadcaster *Pro7* (which actually aired the movie), as well as industry averages. Specifically, we set CPM = €26.98 (primetime fee), MAR = .2, runtime = 121, DC = €1.6 million, and d = .007974. Regarding timing, we use $t_p$ for the different models, as reported in Table 6, and assume that direct costs are incurred at the same time that advertising revenues are flowing in ($t_c = 0$).

TABLE 4

**ESTIMATION RESULTS FOR US THEATRICAL OPENING WEEKEND MODEL**

| Effect of ↓ on → | USBOHSX | | screens20 | | RAT | |
|---|---|---|---|---|---|---|
| Season | n/a | | n/a | | 0.082 | (4.22)** |
| Genslot | n/a | | n/a | | 0.268 | (12.86)** |
| Speslot | n/a | | n/a | | 0.213 | (7.65)** |
| Chanloy | n/a | | n/a | | 0.155 | (4.37)** |
| Genfit | n/a | | n/a | | 0.009 | (0.47) |
| Genrefit | n/a | | n/a | | 0.014 | (0.85) |
| Genres | 0.162 | (3.66)** | 0.053 | (1.42) | 0.098 | (3.53)** |
| cooE | -0.065 | (3.96)** | -0.015 | (0.90) | 0.035 | (2.09)** |
| cooRoW | -0.062 | (3.06)** | -0.028 | (1.22) | 0.016 | (1.40) |
| Runtime | -0.080 | (2.03)** | -0.054 | (1.73)* | 0.025 | (1.10) |
| Budget | 0.591 | (13.56)** | 0.230 | (4.30)** | 0.052 | (1.71)* |
| Remake | -0.004 | (0.19) | -0.045 | (1.55) | -0.038 | (2.12)** |
| Sequel | n/a | | -0.024 | (0.73) | -0.004 | (0.21) |
| Stars | n/a | | 0.062 | (1.96)* | 0.102 | (4.64)** |
| Director | n/a | | 0.042 | (1.67)* | 0.038 | (1.43) |
| USBOOW | n/a | | 0.350 | (6.29)** | 0.262 | (6.44)** |
| PREVUS | 0.133 | (4.96)** | -0.099 | (1.99)** | -0.008 | (0.45) |
| AUDUS | n/a | | 0.082 | (1.68)* | 0.071 | (2.33)** |
| screens10 | n/a | | n/a | | 0.120 | (4.69)** |
| BUZZUS | n/a | | -0.192 | (4.98)** | 0.016 | (1.04) |
| chancan30 | n/a | | n/a | | -0.118 | (3.84)** |
| $R^2$ | 48.26% | | 47.38% | | 78.76% | |
| $\Delta R^2$ vs. baseline model | | | | | 16.38% | |

*Notes:* Numbers are standardized path coefficients as estimated through PLD. Numbers in parentheses are *t* values (calculated through bootstrapping with 674 cases and 500 re-samples each). * $p < 0.10$ (two-sided); ** $p < 0.05$ (two-sided); n/a no path included in model.

As risk is another key criterion for TV managers when purchasing rights (in addition to the level of ratings), we follow Hennig-Thurau et al. (2009) and employ the Value at Risk (VaR) approach and, specifically, the variance-covariance method to adjust value estimates for project risk (Sharpe and Alexander, 1990). We use the confidence level of $1 - \alpha = .80$, which is linked to a two-sided *t* value of 1.283.

Table 6 reports the (risk-free) *RAT,* MV* and *NPV* parameters for *Spider-Man* as well as risk-adjusted *VaR*, *raMV* and *raNPV* parameters. The calculations demonstrate that the value of the movie for the broadcaster increases over time as a result of (a) the reduced uncertainty in later stages, and (b) the time value of funds paid out in early rights payments (i.e., discounting). Specifically, while *Pro7* should have paid a maximum of €1.8 million for *Spider-Man* at the time the movie was greenlighted when accounting for risk, the enormous success of the movie in US and German movie theatres demonstrates its true value to be closer to €4.4 million.

TABLE 5

**ESTIMATION RESULTS FOR THEATRICAL RELEASE FOREIGN MODEL**

| Effect of ↓ on → | USBOOW | | USBOLT | | screens | | FBOX | | RAT | |
|---|---|---|---|---|---|---|---|---|---|---|
| Season | n/a | | n/a | | n/a | | n/a | | 0.084 | (4.66)** |
| Genslot | n/a | | n/a | | n/a | | n/a | | 0.265 | (13.54)** |
| Speslot | n/a | | n/a | | n/a | | n/a | | 0.181 | (6.61)** |
| Chanloy | n/a | | n/a | | n/a | | n/a | | 0.128 | (4.11)** |
| Genfit | n/a | | n/a | | n/a | | n/a | | 0.052 | (1.72)* |
| Genrefit | n/a | | n/a | | n/a | | n/a | | 0.009 | (0.69) |
| Genres | 0.185 | (3.79)** | 0.004 | (0.17) | 0.139 | (4.40)** | 0.026 | (0.84) | 0.048 | (1.86)* |
| cooE | -0.048 | (2.86)** | 0.025 | (2.07)** | -0.019 | (1.47) | 0.062 | (2.84)** | 0.020 | (1.55) |
| cooRoW | -0.048 | (2.34)** | 0.005 | (0.81) | -0.038 | (2.04)** | 0.012 | (1.17) | 0.027 | (1.99)** |
| Runtime | -0.055 | (1.69)* | 0.006 | (0.34) | -0.051 | (2.16)** | 0.087 | (2.23)** | 0.012 | (0.65) |
| Budget | 0.563 | (12.76)** | 0.035 | (1.48) | 0.251 | (6.00)** | -0.123 | (3.00)** | 0.052 | (1.78)* |
| Remake | 0.004 | (0.19) | -0.051 | (2.65)** | -0.024 | (1.39) | 0.018 | (1.23) | -0.020 | (1.49) |
| USBOOW | n/a | | 0.796 | (24.47)** | 0.548 | (14.10)** | -0.012 | (0.18) | n/a | |
| Awards | n/a | | 0.266 | (5.76)** | n/a | | 0.034 | (1.25) | -0.078 | (3.24)** |
| Sequel | n/a | | n/a | | 0.030 | (1.11) | 0.128 | (1.95)* | -0.046 | (1.92)* |
| Stars | n/a | | n/a | | 0.066 | (3.05)** | 0.024 | (1.12) | 0.084 | (4.01)** |
| Director | n/a | | n/a | | 0.043 | (1.85)* | -0.034 | (1.55) | 0.031 | (1.41) |
| PREVF | n/a | | n/a | | 0.057 | (2.46)** | 0.059 | (2.39)** | 0.015 | (1.03) |
| USBOLT | n/a | | n/a | | n/a | | 0.489 | (6.39)** | 0.089 | (2.07)** |
| AUDF | n/a | | n/a | | n/a | | -0.012 | (0.57) | 0.012 | (0.76) |
| BUZZF | n/a | | n/a | | n/a | | 0.078 | (1.47) | 0.021 | (0.81) |
| Screens | n/a | | n/a | | n/a | | 0.379 | (8.20)** | 0.088 | (1.93)* |
| chancan20 | n/a | | n/a | | n/a | | n/a | | -0.072 | (3.07)** |
| FBOX | n/a | | n/a | | n/a | | n/a | | 0.316 | (6.40)** |
| TSPAN | n/a | | n/a | | n/a | | n/a | | -0.047 | (3.01)** |
| $R^2$ | 47.08% | | 75.86% | | 73.91% | | 74.41% | | 83.33% | |
| $iR^2$ vs. baseline model | | | | | | | | | 20.95% | |

*Notes:* Numbers are standardized path coefficients as estimated through PLS. Numbers in parentheses are *t* values (calculated through bootstrapping with 595 cases and 500 re-samples each). * $p < 0.10$ (two-sided); ** $p < 0.05$ (two-sided); n/a no path included in model.

TV stations can also use this approach for making scenario-dependent valuations. For example, if *Pro7* had aired *Spider-Man* on a Sunday at 11 p.m. instead of during primetime, the *RAT** for the domestic theatrical model would have been 3.2 million (instead of 5.6 million) because of fewer viewers. The risk-free *MV* for the broadcaster (that is also affected by the lower CPM of €19.56) would have been as low as €3.8 million (instead of €9.8 million).

TABLE 6

**MONETARY VALUATION OF THE MOVIE *SPIDER-MAN* FOR GERMAN TV**

| | Baseline model | Greenlighting model | Screening model | Domestic theatrical release model | Foreign theatrical release model |
|---|---|---|---|---|---|
| $t_p^a$ | 60 | 54 | 39 | 36 | 30 |
| Standard error of the regression estimate | 0.814 | 0.703 | 0.648 | 0.619 | 0.562 |
| Results not adjusted for risk | | | | | |
| RAT* (in mil.) | 3.058 | 4.107 | 4.225 | 5.596 | 5.348 |
| MV (in mil. €) | 4.992 | 6.704 | 6.896 | 9.134 | 8.729 |
| NPV (in mil. €) | 1.499 | 2.766 | 3.459 | 5.263 | 5.279 |
| Results adjusted for risk | | | | | |
| VAR (for 1-α = .80) | 2.014 | 3.205 | 3.394 | 4.802 | 4.627 |
| raMV (in mil. €) | 3.287 | 5.232 | 5.539 | 7.838 | 7.553 |
| raNPV (in mil. €) | 0.441 | 1.807 | 2.464 | 4.289 | 4.351 |

*Notes:* $t_p^a$ is the time (of the month) that a purchasing broadcaster has to wait until a movie can be aired. VAR = Value at Risk; raMV = risk-adjusted monetary value; raNPV = risk-adjusted NPV. All monetary values are in €.

## Discussion and Implications

TV rights are an important program element for TV stations and are a key revenue source for film producers. Currently, pricing decisions for such rights are based on managers' gut feelings. This study introduces a model that enables a more theoretically sound approach to TV rights valuation, via a sequential process. One estimates the TV ratings of a movie through an equation that corresponds to the point in time in a movie's life cycle at which TV rights are being considered. Model parameters are transformed into TV ratings predictions through an analytical calculation framework and then used to calculate the monetary value of a given movie by applying an analytical NPV model.

In addition to providing managers with a valuation tool, the structural models used to predict TV ratings reveal insights into the determinants of ratings, as all models reflect assumptions of causal relationships. Key predictive variables include foreign box office results, US box office results, the number of screens on which the movie opens theatrically and a movie's star power.

Although relationships among the variables are generally found in the pattern expected, an interesting finding emerges for the quality judgements of professional critics and award givers. While the former variable has an indirect positive influence on TV ratings, the effect of awards is negative. Extant studies often find that awards drive theatre attendance, but they also find no impact on video rental (Hennig-Thurau, Houston and Walsh, 2006). Combined with our finding of a negative relation with TV ratings, it appears that awards may send quality signals that are not consistent with TV audiences' preferences, as revealed by viewing behaviour.

For researchers, the findings of this study contribute to a growing body of knowledge on the marketing of motion pictures and related cultural products, as well as on the economics of TV. While extant research has studied movie distribution via theatres and home video, the TV channel, Hollywood's "biggest profit-center" (Epstein, 2005), has remained under-researched. Future research could extend our work by adapting it for foreign TV markets beyond Germany. While structural differences between markets and differences in consumer preferences may lead to different parameter weights, the general conceptual model and empirical approach should be adaptable for other markets. Also, as the ways in which individuals consume movies on TV continue to evolve, it would be exciting to see how digital video recorders (DVRs) and Internet streaming of movies (e.g., Netflix) influence the results reported here. Interestingly, Bronnenberg, Dubé and Mela (2010) find that DVRs have not influenced consumption of consumer packaged goods, suggesting that additional research is needed to more fully understand the impact of new technologies on movie consumption behaviour via TV.

## Notes

1. In the United States, TV rights are usually negotiated as a percentage of a movie's domestic theatrical gross. While the standard is 15%, a maximum is often agreed upon to rule out extreme fees in the case of outlier hits such as *Titanic*. Similar "escalator" agreements have been applied in Europe but remain a rare exception.

2. We use the term "TV ratings" to refer to the number of consumers who view a movie on TV, not to the MPAA certification of the movie (which may be referred to as "rating").

3. We also report 1-$\alpha \leq .10$, as PLS tends to underestimate path coefficients in the structural model, which implies that the test of significance for the structural model is more conservative than for other approaches.

## References


Adams Media Research. 2008. *Film Entertainment Worldwide: The Private Equity Era*. Monterey, CA: Author.

Arbeitsgemeinschaft Fernsehforschung. 2011. *Das AGF-Fernsehpanel.* Accessed 4 March 2011 at http://www.agf.de/fsforschung/methoden/fernsehpanel.

Barnett, G., H. Chang, E. Fink and W. Richards. 1991. "Seasonality in Television Viewing: Mathematical Model of Cultural Processes." *Communication Research,* Vol. 18, nº 6, p. 755–772.

Basuroy, S., S. Chatterjee and S. Ravid. 2003. "How Critical Are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets." *Journal of Marketing,* Vol. 67, nº 4, p. 103–117.

Bronnenberg, B., J. Dubé and C. Mela. 2010. "Do Digital Video Recorders Influence Sales?" *Journal of Marketing Research,* Vol. 47, nº 6, p. 998–1010.

Chin, W. 1998. "The Partial Least Squares Approach for Structural Equation Modeling." In *Modern Methods for Business Research,* George A. Marcoulides, ed. (p. 295–336). Mahwah, NJ: Lawrence Erlbaum.

d'Astous, A., F. Colbert and V. Nobert. 2007. "Effects of Country-Genre Congruence on the Evaluation of Movies: The Moderating Role of Critical Reviews and Moviegoers' Prior Knowledge." *International Journal of Arts Management,* Vol. 10, nº 1, p. 45–51.

d'Astous, A., Z. Voss, F. Colbert, M. Caldwell and F. Courvoisier. 2008. "Product-Country Images in the Arts: A Multi-country Study." *International Marketing Review,* Vol. 25, nº 4, p. 379–403.

Davis, S. 2000. *Quotenfieber: Das Geheimnis erfolgreicher TV-Movies*. Bergisch-Gladbach: Bastei-Lübbe.

Dekom, P. 2004. "Movies, Money and Madness." In *The Movie Business Book,* 3rd ed., J. Squire, ed. (p. 100–116). New York: Fireside.

Elberse, A. 2007. "The Power of Stars: Do Star Actors Drive the Success of Movies?" *Journal of Marketing,* Vol. 71, nº 4, p. 102–120.

Elberse, A., and J. Eliashberg. 2003. "Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures." *Marketing Science,* Vol. 22, nº 3, p. 329–354.

Epstein, E. 2005. "Hollywood's Profits, Demystified: The Real El Dorado Is TV." *Slate,* 8 August. Accessed 28 November 2005 at http://www.slate.com/id/2124078/.

Fornell, C., and F. Bookstein. 1982. "Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory." *Journal of Marketing Research,* Vol. 19, nº 4, p. 440–452.

Goettler, R., and R. Shachar. 2001. "Spatial Competition in the Network Television Industry." *RAND Journal of Economics,* Vol. 32, nº 4, p. 624–656.

Goodhardt, G., A. Ehrenberg and M. Collins. 1987. *The Television Audience: Patterns of Viewing. An Update,* 2nd ed. Aldershot/Brookfield: Gower.

Greenberg, E., and H. Barnett. 1971. "TV Program Diversity: New Evidence and Old Theories." *American Economic Review,* Vol. 61, nº 2, p. 89–93.

Guider, E. 2003. "EU Probes TV Rights. H'w'd Studios and Pay TV Deals Under Fire." *Variety,* 14 January. Accessed 8 December 2005 at http://www.variety.com/index.asp?layout=print_story&articleid=VR1117878777&categoryid=1236.

Hennig-Thurau, T., M. Houston and T. Heitjans. 2009. "Conceptualizing and Measuring the Monetary Value of Brand Extensions: The Case of Motion Pictures." *Journal of Marketing,* Vol. 73, November, p. 167–183.

Hennig-Thurau, T., M. Houston and G. Walsh. 2006. "The Differing Roles of Success Drivers Across Sequential Channels: An Application to the Motion Picture Industry." *Journal of the Academy of Marketing Science,* Vol. 34, nº 4, p. 559–575.

Hennig-Thurau, T., G. Walsh and O. Wruck. 2001. "An Investigation Into the Factors Determining the Success of Service Innovations: The Case of Motion Pictures." *Academy of Marketing Science Review,* Vol. 6. http://www.amsreview.org/amsrev/theory/hennig06-01.html.

Henry, M., and H. Rinne. 1984. "Predicting Program Shares in New Time Slots." *Journal of Advertising Research,* Vol. 24, nº 2, p. 9–17.

Ho, J., T. Dhar and C. Weinberg. 2009. "Playoff Payoff: Super Bowl Advertising for Movies." *International Journal of Research in Marketing,* Vol. 26, nº 3, p. 168–179.

Holbrook, M., and M. Addis. 2007. "Taste Versus the Market: An Extension of Research on the Consumption of Popular Culture." *Journal of Consumer Research,* Vol. 34, nº 3, p. 415–424.

Karniouchina, E. 2011. "Impact of Star and Movie Buzz on Motion Picture Distribution and Box Office Revenue." *International Journal of Research in Marketing,* Vol. 28, nº 1, p. 62–74.

Litman, B. 1979a. "The Economics of the Television Market for Theatrical Movies." *Journal of Communication,* Vol. 29, nº 4, p. 20–33.

Litman, B. 1979b. "Predicting TV Ratings for Theatrical Movies." *Journalism Quarterly,* Vol. 56, nº 3, p. 590–594, 694.

Litman, B. 1982. "Decision-Making in the Film Industry: The Influence of the TV Market." *Journal of Communication,* Vol. 32, nº 3, p. 33–52.

*Marketing Charts.* 2007. "Harry Potter Casts Spell on Entertainment Industry." Thetford Center, VT: Watershed Publishing. Accessed 14 February 2011 at http://www.marketingcharts.com/television/harry-potter-casts-spell-on-entertainment-industry-980/nielsen-harry-potter-movies-on-tvjpg/.

Moul, C., and S. Shugan. 2005. "Theatrical Release and the Launching of Motion Pictures." In *A Concise Handbook of Movie Industry Economics,* C.C. Moul, ed. (p. 80–137). Cambridge: Cambridge University Press.

Nelson, R., M. Donihue, D. Waldman and C. Wheaton. 2001. "What's an Oscar Worth?" *Economic Inquiry,* Vol. 39, nº 1, p. 1–16.

Prag, J., and J. Casavant. 1994. "An Empirical Study of the Determinants of Revenues and Marketing Expenditures in the Motion Picture Industry." *Journal of Cultural Economics,* Vol. 18, nº 3, p. 217–235.

Rudman, N., and L. Ephraim. 2004. "The Finishing Touch: The Completion Guarantee." In *The Movie Business Book,* 3rd ed., J.E. Squire, ed. (p. 207–221). New York: Fireside.

Schawinski, R. 2007. *Die TV-Falle.* Zurich: Kein & Aber.

SevenOne Media. 2008. *WerbemarktReport 2007: Kommentierte Analyse der Entwicklung des Brutto-Werbemarktes 2007.* Accessed 20 March 2008 at http://appz.sevenonemedia.de/download/publikationen/WerbemarktReport_20071.pdf.

Sharpe, W., and G. Alexander. 1990. *Investments,* 4th ed. Englewood Cliffs, NJ: Prentice Hall.

*Spiegel Online.* 2000. "Untergang zu Höchstpreisen." Accessed 31 July 2011 at http://www.spiegel.de/wirtschaft/0,1518,108441,00.html.

Wallace, W., A. Seigerman and M. Holbrook. 1993. "The Role of Actors and Actresses in the Success of Films: How Much Is a Movie Star Worth?" *Journal of Cultural Economics,* Vol. 17, nº 1, p. 1–27.

Waterman, D., S. Ji and L. Rochet. 2007. "Enforcement and Control of Piracy, Copying, and Sharing in the Movie Industry." *Review of Industrial Organization,* Vol. 30, nº 4, p. 255–289.

Webster, J., and P. Phalen. 1997. *The Mass Audience: Rediscovering the Dominant Model.* Mahwah, NJ: Lawrence Erlbaum.

Westcott, T. 2005. *European Programme Rights: Movies.* London: Screen Digest. Accessed 14 June 2005 at http://www.screendigest.com/publications/reports/tv_and_broadband/european_programme_rights_movies/readmore/view.

**DESCRIPTION OF THE TRANSFORMATION PROCESS**

Having used PLS to estimate model parameters, we have to calculate predictions *a posteriori* outside of PLS as a combination of three equations. Specifically, we decompose the measurement model of the exogenous constructs, the structural model, and the measurement model of the endogenous construct TV ratings.

First, we define the exogenous measurement model equation as a transformation of the raw measures of a construct into its standardized construct score:

$$\hat{E}CV_u = \sum_g w_{ug} RV_{ug} \quad \text{(AI)}$$

where $\hat{E}CV_u$ is the estimated value of exogenous construct *u*, $RV_{ug}$ is the raw value of item $g$ used for measuring this construct, and $w_{ug}$ is a weighing parameter that links item *g* and construct *u,* which was estimated through PLS. Second, the structural model equation contains TV ratings as a dependent variable and the exogenous constructs of each stage prediction model as independent variables, and then connects them through the PLS path estimates:

$$\hat{R}ATCV = b_{RATCV0} + \sum_u b_{RATCVu} ECV_u \quad \text{(AII)}$$

where $\hat{R}ATCV$ is the estimated construct value for TV ratings, $b_{RATCVu}$ are the path coefficients linking $RATCV$ with its determinants $ECV_u$, and $b_{RATCV0}$ is a constant term ("location parameter"); both $b_{RATCVu}$ and $b_{RATCV0}$ are taken from the PLS estimation. Finally, the exogenous measurement model equation transforms the construct value of TV rating into the actual number of viewers of a movie:

$$\hat{V}iewers = \hat{R}ATRV_{RATCV1} = \frac{\hat{R}ATCV}{w_{RATCV1}} \quad \text{(AIII)}$$

where $w_{RATCV1}$ is the weight parameter of the exogenous measurement model and $\hat{R}ATRV_{RATCV1}$ is the predicted number of viewers of a movie; note that this variable differs from the original measure of $RATRV_{RATCV1}$ that we used for the PLS estimation. Inserting equations AI and AII into AIII leads to an integrated equation, AIV, which illustrates that the predicted number of viewers is a function of the items and weights of the exogenous variables:

$$\hat{V}iewers = \hat{R}ATRV_{RATCV1} = \frac{b_{RATCV0} + \sum_u b_{RATCVu} \left( \sum_g w_{ug} RV_{ug} \right)}{w_{RATCV1}} \quad \text{(AIV)}$$

An advantage of this approach is that, by using the parameters estimated for a model that considers both direct effects and indirect effects of a variable on TV ratings, one makes predictions that account for these different effects.