

HEDONIC CONSUMER DECISION MAKING AND IMPLICATIONS FOR THE MARKETING OF MEDIA GOODS

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I. Preface

I.1 Integrative Framework and Summary of Results

This cumulative dissertation investigates aspects of consumer decision making in hedonic contexts and its implications for the marketing of media goods through a series of three empirical studies. All three studies take place within a common theoretical framework of decision making models (shown in Figure 1), applying parts of the framework in novel ways to solve real-world marketing research problems (study 1 and 2), and examining theoretical relationships between variables within of the framework (study 3). One notable way in which the studies differ is their theoretical treatment of the hedonic component of decision making, i.e. the role and conceptualization of emotions.

The role of emotions excepted, the framework in Figure 1 largely corresponds to the information processing view of behavior (Edwards 1954; Newell, Shaw, and Simon 1958; Howard and Sheth 1969; Bettman 1970), which describes humans as boundedly rational decision makers who try to maximize their expected utilities which each decision. Perhaps the most prominent representation of this view is the logical flow model developed by Howard and Sheth (1969), which in its original form is not a testable mathematical formulation, but rather an encompassing, global paradigm of buyer behavior that specifies the relationship between input variables, intervening response variables, and output variables (Hunt and Pappas 1970). According to this model, consumers recognize their needs and wants, search for information externally and internally, process the information under given constraints, and then choose the option which will deliver the highest expected utility. In the framework in Figure 1, this chain of evaluation, attitude formation, intention, and behavior relates to the information processing paradigm's output variables, while

subjective/social norms and resource constraints are among the paradigm's (more peripherally treated) "exogenous variables".

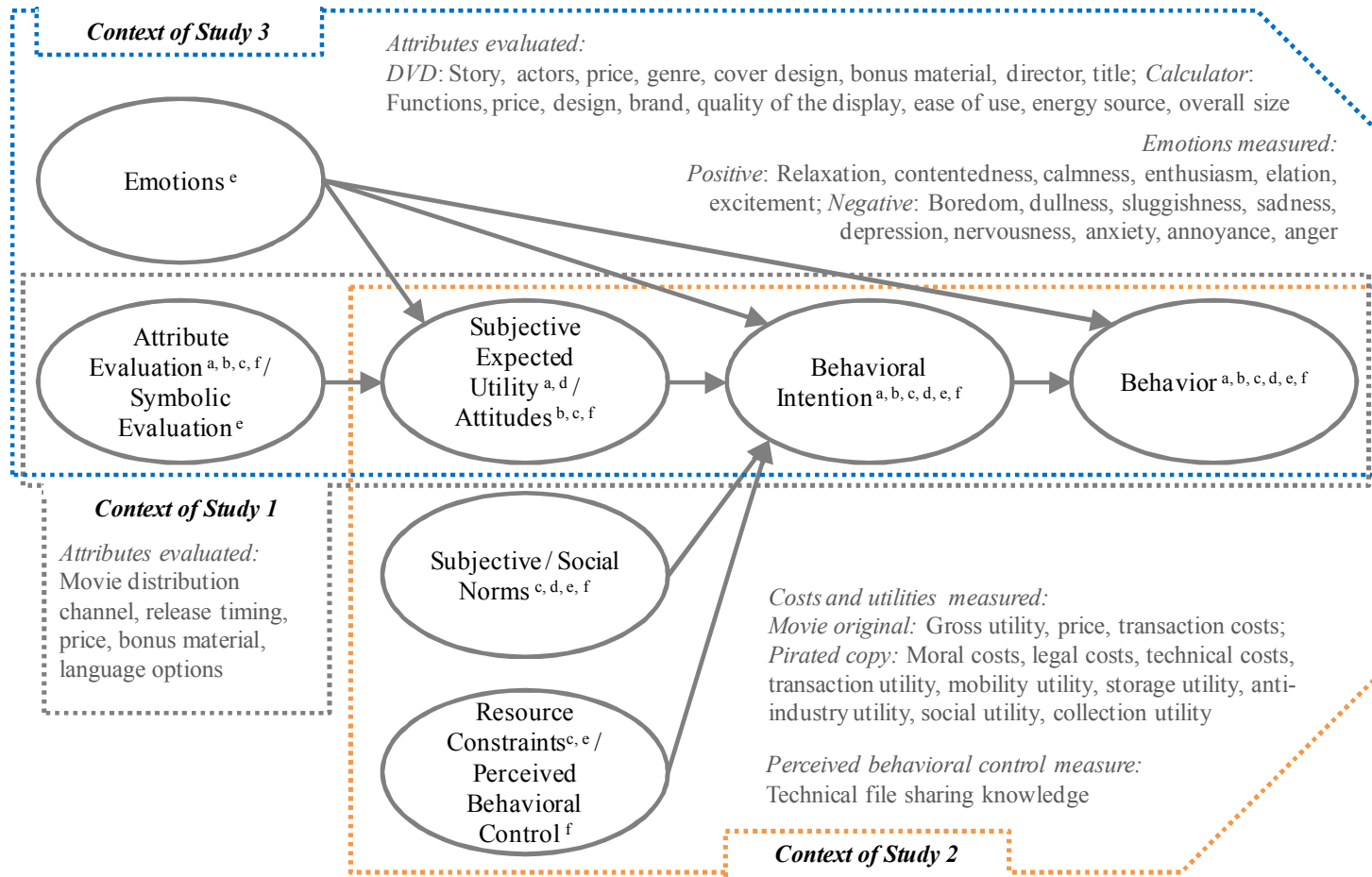
As the label "information processing view" suggests, the consumer's processing of available information in order to make a rational choice lies at the heart of this paradigm. The foundation for this was laid by Edwards (1954) in his influential article *The Theory of Decision Making*. Based on economic theories of rationality and utility, he introduced the so-called "expectancy-value models" to the psychological literature. In his Subjective Expected Utility model, the likelihood of an event's occurrence when an action is taken is the subjective probability SP of an outcome, and the desirability of this outcome is its subjective utility U . The product of subjective probability and desirability equals the subjective expected utility SEU from the action. The SEU of different alternative behaviors are compared, and the alternative with the highest SEU is chosen:

$$(1) \quad SEU = \sum_{i=1}^n SP_i \bullet U_i$$

In the realm of social psychology, Fishbein (1967) adapted this expectancy-value model to form the backbone of his theory of reasoned action. In Fishbein's variant - today considered "the most widely applied representation of attitude across many disciplines" (Bagozzi, Gürhan-Canli, and Priester 2002: 7) - beliefs b_i about the probability of the presence of attributes in an object are multiplied with evaluations e_i of these attributes. The product of belief b_i and evaluation e_i then can be summed over n attributes to determine global attitude toward the object A_{obj} . In turn, A_{obj} determines the intention to act, which should trigger the corresponding behavior:

$$(2) \quad A_{Obj} = \sum_{i=1}^n b_i \bullet e_i$$

Figure 1: Integrative Framework of Decision Making Models



- | | |
|--|--|
| a) <i>Subjective Expected Utility Model</i> (Edwards 1954) | d) <i>Theory of Social Interactions</i> (Becker 1974) |
| b) <i>Expectancy-Value Model, Theory of Reasoned Action</i> (Fishbein 1967; Fishbein and Ajzen 1975) | e) <i>Part of Experiential View of Consumer Behavior</i> (Holbrook and Hirschman 1982) |
| c) <i>Part of Information Processing View of Consumer Behavior</i> (Howard and Sheth 1969) | f) <i>Theory of Planned Behavior</i> (Ajzen 1991) |

The methodological background of study 1 in this dissertation, titled *The Last Picture Show? Timing and Order of Movie Distribution Channels*, can be traced to these attribute- and utility-based views of decision making. The study's research question centers on determining the optimal timing and order of motion picture releases across sequential distribution channels in terms of either producer- or industry-revenue maximization. Movies as well as other media goods are traditionally distributed across distinct sequential channels (e.g., theaters, home video, video-on-demand). This so-called "release windowing" has become one of the most contentious issues of debate within the film industry, with stakeholders fearing cannibalization of their respective distribution channel revenues and escalating the conflict to open threats and strategic boycotts. The reported study is the first to simulate the effects of timing, order, and pricing variations on consumer choices - and hence revenues - across four sequential distribution channels.

To achieve this, we draw on a particular consumer choice modeling technique, conjoint analysis. Based on prior research in mathematical psychology, conjoint analysis in marketing was developed in the late 1960s with the idea of estimating utility functions and component (i.e. attribute) utilities of objects, given a set of rank-order choices (Green and Rao 1971). In line with this idea, study 1 estimates consumer utility functions and attribute utilities of movie distribution channels by presenting participants with choices between consuming movies in different settings, systematically varying the underlying channel attributes, and capturing their first choice of distribution channel. Based on the estimated utility functions, we then systematically simulate consumer choices for novel distribution scenarios and integrate these choices with a behavioral model that takes into account success-breeds-success effects, repeat purchases, and hedonic saturation. Variables such as emotions, social norms, or resource constraints are not explicitly considered in this model, though they may implicitly influence the choice process. As such, out of the three studies presented in this dissertation, the choice-based conjoint approach in study 1 is

philosophically closest to a “pure” information processing view of the rational decision-maker exclusively focused on attributes and utility maximization.

In terms of the real-world implications of study 1, the empirical results suggest that the studios that produce motion pictures can increase their revenues by more than 16 percent through sequential distribution chain timing and order changes when applying a common distribution model for all movies in a country, and that revenue-maximizing structures differ strongly between countries. Under the conditions of the study, we find that a simultaneous release of movies in theaters and on rental home video generates maximum revenues for movie studios in the U.S., while having devastating effects on other players such as theater chains. We discuss different scenarios and their implications for movie studios and other industry players, and critically reflect on barriers for an implementation of the revenue-maximizing distribution models.

Study 2 of this dissertation, titled *Consumer File Sharing of Motion Pictures*, represents a follow-up to a research question left open by study 1. It examines the economic impact of illegal peer-to-peer file sharing on movie consumption choices, and thus distribution channel revenues. Similarly, the theoretical model we choose to study this phenomenon represents a follow-up development in economic and psychological decision making research. By 1975, Fishbein and Ajzen had extended Fishbein’s (1967) earlier expectancy-value model into the Theory of Reasoned Action, which now accounted for subjective norms, i.e. a person’s perception of how others want him/her to behave, and his/her motivation to comply. In the realm of economics, Becker (1974; 1992) had turned his attention to research areas that had traditionally been the domain of sociology, studying crime, drug addiction, discrimination, or family relationships from an individual-utility maximization perspective. In his framework, social feelings of guilt, obligation, duty, altruism, or love have positive or negative utility, and can therefore be subjected to an economic cost-benefit analysis of “social income”. To assess the behavioral drivers of

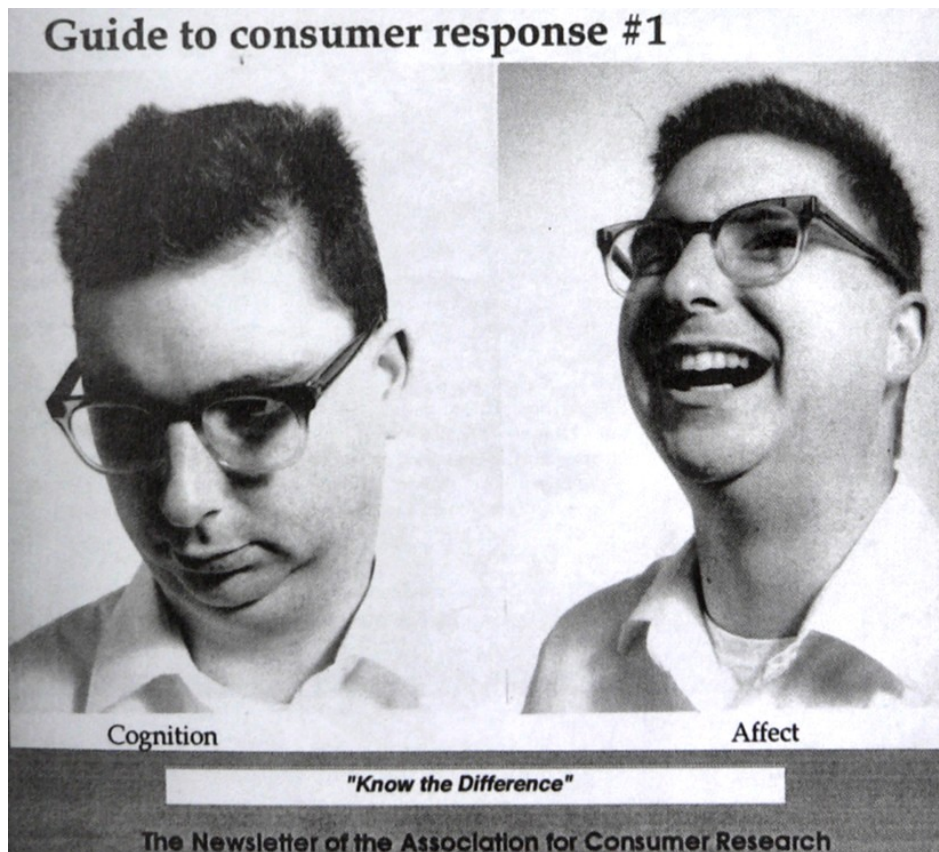
movie file sharing, we turn to a Beckerian utility analysis that, among other factors, includes the moral costs of unethical behavior, the emotional cost of fearing legal action, the “Schadenfreude” utility of harming movie studios perceived as greedy, and the social utility of impressing one’s friends with freely acquired movies. The perceived behavioral control variable in Figure 1 is captured through measuring the consumer’s technical knowledge, which is a prerequisite for engaging in peer-to-peer filesharing. Our results suggest that “Schadenfreude” utility and technical knowledge (which results in lowered search costs) are indeed among the significant drivers of file sharing behavior, while moral costs are among the significant deterrents.

In relation to the framework in Figure 1 it should be noted that while our analysis takes a selection of emotions into account, it follows the traditional Beckerian approach, subsuming feelings of fear, guilt, gloating and pride under the same utility-maximizing cost-benefit analysis that also includes economic transaction, search, substitution, and purchasing cost. As such, unlike study 3, it is not grounded systematically in either appraisal theories or dimensional theories of emotion.

As for the economic effects of file sharing behavior, these had been hotly contested prior to our study. Whereas industry advocates and some scholars postulated a cannibalistic effect on commercial forms of movie consumption, other researchers denied this effect, though evidence was lacking on both sides. Our study estimates the economic effects based on data from a controlled longitudinal panel study of 1,075 German consumers. The data contains information on the consumers’ behavioral intentions and actual behaviors toward consuming 25 new motion pictures, allowing us to study more than 10,000 individual file sharing opportunities. Using a series of ReLogit regression analyses and applying partial least squares structural equation modeling, we find evidence of substantial cannibalization of theater visits, DVD rentals, and DVD purchases, responsible for annual revenue losses of \$300 million in Germany.

Study 3, titled *Augmenting the Expectancy-Value Model with a Dimensional Model of Emotion: Predicting Consumer Behavior for Hedonic versus Utilitarian Products*, ultimately examines the role and conceptualization of emotions within the integrative framework in Figure 1. In 1982, Holbrook and Hirschman (1982: 132) stated that the information processing view had “become so ubiquitous in consumer research that, like fish in water, many researchers may be relatively unaware of its pervasiveness”, a sentiment echoed still twenty years later by Bagozzi, Gürhan-Canli, and Priester (2002). They therefore formulated the “experiential view”, which contrasted attribute beliefs/knowledge with fantasies/daydreams, tangible/objective benefits with symbolic/subjective ones, attitudes with emotions, and utility with aesthetic value. Like the information processing view, the experiential view was not developed as a testable, mathematical model, but rather as an encompassing perspective of consumer behavior. The differences between the two paradigms have sometimes been misinterpreted as a clearly demarcated boundary, with consumer behavior falling either into the information processing or the experiential category. Figure 2 shows a parody of this exaggerated dichotomy which was published on the cover of a 1994 newsletter of the Association for Consumer Research.

Figure 2: Guide to consumer response #1



Source: Association for Consumer Research (1994)

Holbrook and Hirschman (1982: 138), however, believed that “abandoning the information processing approach is undesirable, but supplementing and enriching it with an admixture of the experiential perspective could be extremely fruitful.” This is the aim of study 3: To systematically assess of the role of emotions in decision making vis-à-vis the classical expectancy-value model described earlier, and to improve the expectancy-value model’s predictive power by augmenting it with a dimensional model of emotion. Moreover, the emotions literature has evolved the theoretical distinction between anticipatory and anticipated emotions, yet research which examines the differential role of these two constructs in consumer decision making remains scarce. Study 3 tackles these issues empirically via an experiment involving 308 college students who face actual purchasing decisions for hedonic and utilitarian products.

The results of this study suggest that the operationalization of emotion in dimensional theories as bipolar constructs, even though very intuitive and parsimonious, may be somewhat misleading, as our confirmatory factor analysis reveals the concurrent experience of “mixed”, unipolar emotions. The analysis also shows that anticipatory and anticipated emotions can indeed be distinguished empirically, and that they impact the decision-making framework depicted in Figure 1 at different stages. We also find that predictions of attitudes and behavioral intentions can be significantly improved, above and beyond the explanatory power of attribute-utility evaluations, by including emotions in the analysis – not only for hedonic products such as motion picture DVDs, but surprisingly also for utilitarian products such as scientific calculators.

I.2 Publication of Studies and Contribution of Co-Authors

Study 1 was published in the *Journal of Marketing* (Hennig-Thurau, Henning, Sattler, Eggers and Houston 2007) after three rounds of peer review guided by four anonymous reviewers and editor Prof. Roland Rust. The initial submission took place in July 2006 and the revised paper was accepted for publication in January 2007. An earlier draft was presented by me at the *2006 AMA Summer Educators' Conference* and published as an abstract in the conference proceedings (Hennig-Thurau, Henning, Sattler, Eggers and Houston 2006). The research question, theoretical framework, and empirical design were jointly developed by me and Prof. Hennig-Thurau. The conjoint analysis and market simulations were carried out and written up by Prof. Henrik Sattler and Dr. Felix Eggers with input from Prof. Hennig-Thurau, while the external validation of the market simulations and the scenario analyses based on the conjoint estimations were carried out by me. The analysis of industry implications was jointly written up by me and Prof. Hennig-Thurau, with contributions from Prof. Mark Houston.

Study 2 was also published in the *Journal of Marketing* (Hennig-Thurau, Henning, and Sattler 2007), again after three rounds of peer review with four anonymous reviewers led by editor Prof. Rust. The initial version was submitted in September 2005, and the revised paper (based on a longitudinal data collection over the course of one year) was eventually accepted for publication in April 2007. An earlier draft, based on my diploma thesis (Henning 2004), was presented at the *2005 AMA Summer Educators' Conference* where it won the *Best Paper in E-Commerce and Technology Award* as well as the *Best Overall Conference Paper Award* and was published as an abstract in its proceedings (Henning and Hennig-Thurau 2005). The research question, theoretical framework, study design and empirical analysis in the earlier versions were developed by me. In the final published version, the theoretical framework, study design and the questionnaire were jointly developed by me and Profs. Hennig-Thurau and Sattler. Access, randomization and management of the longitudinal survey panel were conducted by Prof. Sattler. Analysis of descriptive statistics was carried out by me, PLS modeling of file sharing determinants was jointly carried out by me and Prof. Hennig-Thurau, and ReLogit analysis of file sharing effects was performed by Prof. Hennig-Thurau. The interpretation of results and their implications for the film industry were jointly written up by me and Prof. Hennig-Thurau, with contributions from Prof. Sattler.

At the time of this writing, Study 3 is under review for publication at *Psychology & Marketing* (Henning and Hennig-Thurau 2010). Earlier versions of this study were presented at the *Cognition and Emotion in Economic Decision Making - Workshop* and the *2008 AMA Summer Educators' Conference*, with abstracts being published in the respective proceedings (Henning 2007, Henning and Hennig-Thurau 2008). The research question and experimental design were developed by me, with feedback from Prof. Hennig-Thurau. The empirical analysis and write-up were carried out by me, with editorial input from Prof. Hennig-Thurau.

1 The Last Picture Show? Timing and Order of Movie

Distribution Channels

“Ten years from now, we’ll release a film and you’ll be able to consume it however you want.”

Yair Landau, Vice Chairman of Sony Pictures (Smith 2005, p. 52)

1.1 Introduction

Sequential distribution describes a marketing strategy that is designed to maximize producer income by making a product available to consumers in different markets in succession (Hennig-Thurau, Houston, and Walsh 2006; Vogel 2004).

Sequential distribution is used mainly to market entertainment products, including electronic games and books (Lehmann and Weinberg 2000). A primary challenge facing practitioners and marketing scholars regarding sequential distribution strategy is *when* and in *which order* to enter sequential channels to maximize producer revenue.

This paper addresses this challenge empirically by studying the motion picture industry, an industry that relies heavily on sequential distribution (Eliashberg, Elberse, and Leenders 2006; Lehmann and Weinberg 2000). Traditional distribution for a film begins with a theater premiere, followed by a release to retail markets (rental or sale of DVDs), display on premium satellite or cable channels, and, eventually, television. As revenues generated by non-theatrical markets exceed theatrical box-office grosses (e.g., U.S. box-office of \$9 billion in 2005 compared to revenues of \$24.9 billion through DVD/VHS sales and rentals, MPAA 2006b; EMA 2006), and new channels such as video-on-demand (VOD) enter the scene, this traditional sequencing of channels has come under siege by film studios (Stanley 2005) which are articulating interest in opening non-theatrical channels earlier and even changing the established order of

channels. For example, Warner Bros. Entertainment chairman Barry Meyer publicly envisions major movies debuting “on DVD simultaneously with their theatrical release,” proposing that future premieres “will be in Wal-Mart” (Bond 2005) and that theater revenues will be mere “added value.” As a result, the window between the theatrical and home video release of a motion picture is shrinking (Saccone 2005), with consumers being able to (pre)order the DVD of a movie even before it has opened theatrically in some major export markets. Such fundamental shifts in sequencing strategies would almost certainly affect players such as theater owners (Eliashberg, Elberse, and Leenders 2006; Vogel 2004). John Fithian, president of the National Association of Theater Owners, considers timing and order changes as “the biggest threat to the viability of the cinema industry today” (in CBC 2006, p. 1). So, with the growth of alternative ways to watch films, will movie theaters soon see their “last picture show?”

The impact that timing and order changes would have on movie studio revenues and profits is unclear. The current industry discussion is clearly dominated by speculation based on proprietary consultancy reports for which the underlying data, assumptions, and analyses are not open for verification. For example, a J.P. Morgan report suggests that a simultaneous release of a film in theaters and on DVD would lead to an overall 36% increase in studio revenues (Snyder 2005a). In terms of scholarly research, a limited number of researchers have studied the effect that changes in sequential distribution timing could have for studios (e.g., Lehmann and Weinberg 2000), but extant studies present either theoretical models of specific aspects of the sequential distribution process (Prasad, Bronnenberg, and Mahajan 2004) or empirical models that are based on aggregated past market data (Frank 1994; Lehmann and Weinberg 2000). No research has yet modeled the multi-stage sequential chains that reflect normal marketplace conditions, i.e., involving three or more channels and two or more release windows that have to be optimized simultaneously, and none has modeled the effects that

order changes would have on studio revenues. Also, previous research has not looked at regional differences, despite the influence that cultural variables can have on the consumption of entertainment products (Hennig-Thurau, Walsh, and Bode 2004) and the importance of export markets for U.S. entertainment industries (about half of motion picture revenues come from non-U.S. markets; OMSYC 2002).

The goal of this paper is to identify sequential distribution configurations that maximize movie studio revenues. The approach employed here extends the existing literature in three ways. We (1) consider multiple channels that consumers face in reality, (2) use individual-level discrete choice consumer data which enables us to model potential market configurations such as simultaneous releases in theaters and other channels (e.g., home video) whose economic appeal cannot be assessed by past market data, and (3) account for country differences. Drawing from the existent literature on sequential distribution, we develop an integrative framework of sequential distribution's impact on studio revenues and use this framework to present a sequential distribution net present value model. Combining a discrete-choice conjoint design with self-reported customer data, we apply our model to three leading motion-picture markets (the U.S., Japan, and Germany) by drawing on random samples for each of these markets and a total of 1,770 consumers to allow for market-specific effects. We use the model to systematically test the effects that changes in the timing and order of the windows of the sequential distribution chain would have on consumer choices and, subsequently, movie studio revenues in the different countries. We isolate configurations of the sequential distribution chain that, under the given assumptions, provide optimal payoffs to the movie studio and differentiate our findings for different movie genres. We discuss these results and highlight potential obstacles that studios might face when changing the existing distribution structure.

1.2 Sequential Distribution of Motion Pictures: Literature and Conceptual Framework

1.2.1 Overview of Channel Timing and Order Research

Extant literature on sequential distribution that deals with the optimal timing and order of channels is rare. The few existing studies on this topic have identified a number of sequential distribution chain characteristics which we use as central elements of our conceptual model of sequential distribution (Frank 1994; Lehmann and Weinberg 2000; Luan 2005; Prasad, Bronnenberg, and Mahajan 2004). While most authors recommend the current theater-to-home video window to be shortened, no study does take into account the multi-channel nature of movie distribution today when modeling the effect of window length changes.

Moreover, no academic research has yet addressed the potential impact that order changes in the sequential chain might have on studio revenues. Most studies of sequential distribution treat the order of motion picture channels as fixed, and some argue that to open a movie in any channel other than theaters is “suicidal” (Frank 1994, p. 125). Basically, two arguments are used in the extant literature to support the current sequence of motion picture channels. First, it is argued that products should be distributed first through channels that generate the “highest revenues over the least amount of time” and then cascaded down to markets that return less revenue per unit time (Eliashberg, Elberse, and Leenders 2006, p. 27). Second, the power to attract public “buzz” is seen as exclusive to the theatrical channel (Lippman 2000). These arguments, however, are being challenged by current market conditions. Beyond the overall higher revenues earned by films in ancillary markets, studio channel margins now are clearly higher for DVD sales than for theater “sales” (Blume 2004; Cohen 2003; Vogel 2004). Also, as other cultural products such as music and books are well known for their ability to stimulate huge

media “buzz” for openings in retail stores, “[i]t isn’t that radical a proposition that movies could follow that same path” (Gentile 2005). Consistent with these arguments, Eliashberg, Elberse, and Leenders (2006, p. 27) conjecture “that new movies on PPV [pay-per-view] or VOD prior to the theatrical release could be sold to millions of viewers [...]” Overall, these contrasting views suggest that an empirical examination of sequential channel order changes is merited.

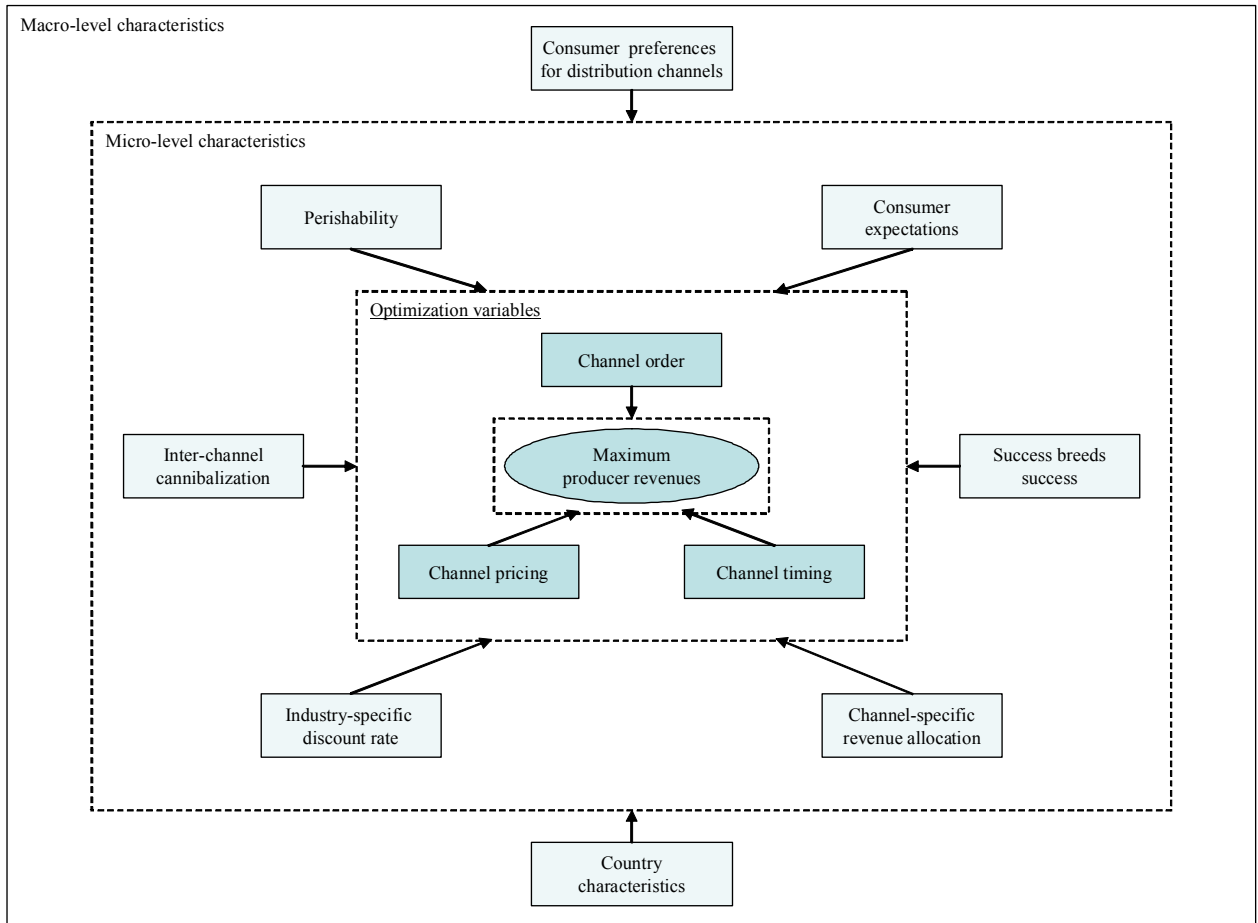
1.2.2 Conceptual Framework for Studio-Revenue Optimization

Drawing on extant research on sequential distribution, we now present a conceptual framework for sequential distribution optimization. As illustrated in Figure 3, the framework postulates that maximum studio revenues depend upon three optimization variables: the timing of distribution channels, the order in which these channels open, and the price for which the product is made available in each channel. Further, it proposes that these optimization variables are influenced by a number of micro-level and macro-level factors.

Micro-level factors. We argue that the revenue-maximizing channel configuration essentially depends upon six micro-level characteristics of sequential distribution chains. These factors include four that are suggested by the extant literature: inter-channel cannibalization, perishability, customer expectations, and success-breeds-success effects, as well as two specific financial factors: the industry-specific discount rate and the channel-specific revenue allocation.

Figure 3: A Conceptual Framework of Sequential Distribution Revenue

Maximization



With regard to *inter-channel cannibalization*, we assume that the release of a movie in a second channel has the potential to cannibalize revenues from an existing channel due to consumers’ willingness to switch between channels. Inter-channel cannibalization has been first discussed by Frank (1994) who, modeling the interrelations between theater visits and home video rental revenues, found that cannibalization takes place if a film is released on video “too early” (Frank 1994). Lehmann and Weinberg (2000) also considered channel cannibalization between theater and video releases, suggesting that the size of each market should determine the delay period. In addition, cannibalization is reflected by industry thinking that “[a] good movie is a good movie, regardless of where it's shown” (Bregman, in Arnold 2005). As argued by Prasad,

Bronnenberg, and Mahajan (2004), cannibalization effects can be either complete or partial, depending on consumers' perceptions of substitutability between movie channels.

Concerning *perishability*, we draw on Frank (1994), Lehmann and Weinberg (2000), and Prasad, Bronnenberg, and Mahajan (2004) who propose a 'wear out' effect, which exists if a film is "too old" when released in secondary channels. Adapting their argument, we assume that the revenues generated by movies in subsequent channels should be affected by the time elapsed since the movie was first available, with demand declining over time. This assumption is shared by industry executives, such as Bob Chapek, the president of Buena Vista Home Entertainment, who compared a movie "to a melting ice cube. The longer it sits, the smaller it becomes" (Dutka 2005).

Regarding *customer expectations*, Prasad, Bronnenberg, and Mahajan (2004) have argued that, as studios shorten the time between a film's theatrical run and its rental availability, consumers will strategically defer their consumption of the movie in the first channel because they expect the movie to be available soon in another channel that they prefer for certain reasons (e.g., lower price or multiple viewings). Building on this, we assume that consumers have expectations regarding the release of a motion picture in subsequent channels, and that these expectations will influence channel choice, such as passing up a theater visit in lieu of a later rental or purchase (Prasad, Bronnenberg, and Mahajan 2004). These expectations can be based on experience, but also on information from retailers and media (e.g. movie-related websites). For example, STAR WARS: EPISODE III was the bestselling DVD on Amazon.com in Germany the week before the movie was released to German theaters, with customers receiving emails from the online retailer inviting them to preorder the DVD for the new movie.

With regard to *success-breeds-success* (SBS) effects, Prasad, Bronnenberg, and Mahajan (2004) demonstrate the existence of complementary effects between channels by linking the success of the movie in theaters to video revenues. We distinguish between

multiple-purchase SBS and information-cascading SBS. In multiple-purchase SBS, an individual consumer pays to see a movie more than once, with the first viewing causing a desire for subsequent viewings (Luan 2005). Multiple purchasing will affect subsequent channel revenues until the movie can be purchased by the consumer (i.e., when the consumer can then view the film repeatedly without additional cost). In contrast, information-cascading SBS refers to the impact that a movie's success in one channel can have on *other* consumers' behavior in subsequent channels. Information-cascading SBS can be based on either personal experiences that are shared (i.e., word-of-mouth, Liu 2006; or informed cascades, DeVany and Walls 2002) or box office results that are made public (i.e., uninformed cascades; DeVany and Lee 2001). Although information-cascading SBS effects have so far been stirred by movies' theatrical releases, we argue that they could be similarly created in other channels such as DVD sales or video-on-demand, if movies were to be released there first. Empirical evidence for SBS in a movie context has been reported by Elberse and Eliashberg (2003) and Hennig-Thurau, Houston, and Walsh (2006).

Finally, distribution chain decisions are also influenced by specific financial factors. The industry-specific *discount rate* has to be considered, as future revenues have to be discounted due to risk and opportunity costs, which reduce the attractiveness of delayed channel openings. When the movie BUBBLE was the first to receive a simultaneous release in theaters, on DVD, and on pay per view in January 2006, its producer highlighted "the accelerated timetable for getting our money back" as an anticipated benefit (Bowles, in Box Office Mojo 2006). Also, the *revenue share* received by the studio in each channel constitutes a key criterion for the optimal sequential channel structure because revenues are divided between different players (e.g., theater chains and studios) in each channel, and the percentage that accrues to the studio differs across channels.

Macro-level factors. The micro-level characteristics and the revenue-maximizing channel structure that can be derived from them are influenced by the macro-level factors of channel preference and country. Specifically, micro-level characteristics are influenced by the consumers' preferences towards distribution channels such as movie theaters, DVD purchases, DVD rentals, and online downloading (Vogel 2004), all of which must be considered simultaneously. Channel preferences clearly differ; while some consumers prefer going to the movies ("I love the mythos of the darkened theater", customer statement in Puig 2005), others argue that "There's no place like home" (Clark 2005). This channel preference determines, among others, the extent of inter-channel cannibalization and perishability, because strong preferences for a certain channel limit the degree of cannibalization between channels and reduce the impact that perishability might have on channel revenues. The second macro-level factor that we consider is country characteristics. A wealth of research suggests that consumers across countries differ in their decision-making processes. In a film context, cultural factors (e.g., Hennig-Thurau, Walsh, and Bode 2004) and informational factors (e.g., Elberse and Eliashberg 2003) might explain these differences. Such country characteristics affect the expectations consumers will have towards the opening of secondary channels, as well as the extent of multiple purchasing and the role of word-of-mouth and charts for movie consumption. They might also affect the financial parameters of our framework.

1.3 A Net Present Value Model of Movie Studio's Sequential Distribution Revenues

1.3.1 General Considerations

Using the sequential distribution framework described above, we now develop a net present value model of movie studio revenues. In contrast to studies that focus on overall industry revenues and other shared outcomes (Frank 1994; Luan 2005), we

consider the revenues that each channel returns to the *movie studio* as decisive for determining the optimal sequential channel structure. This is based on the consideration that an individual firm's channel decisions are not made to maximize overall industry revenues, but to generate maximum revenues for that individual player.

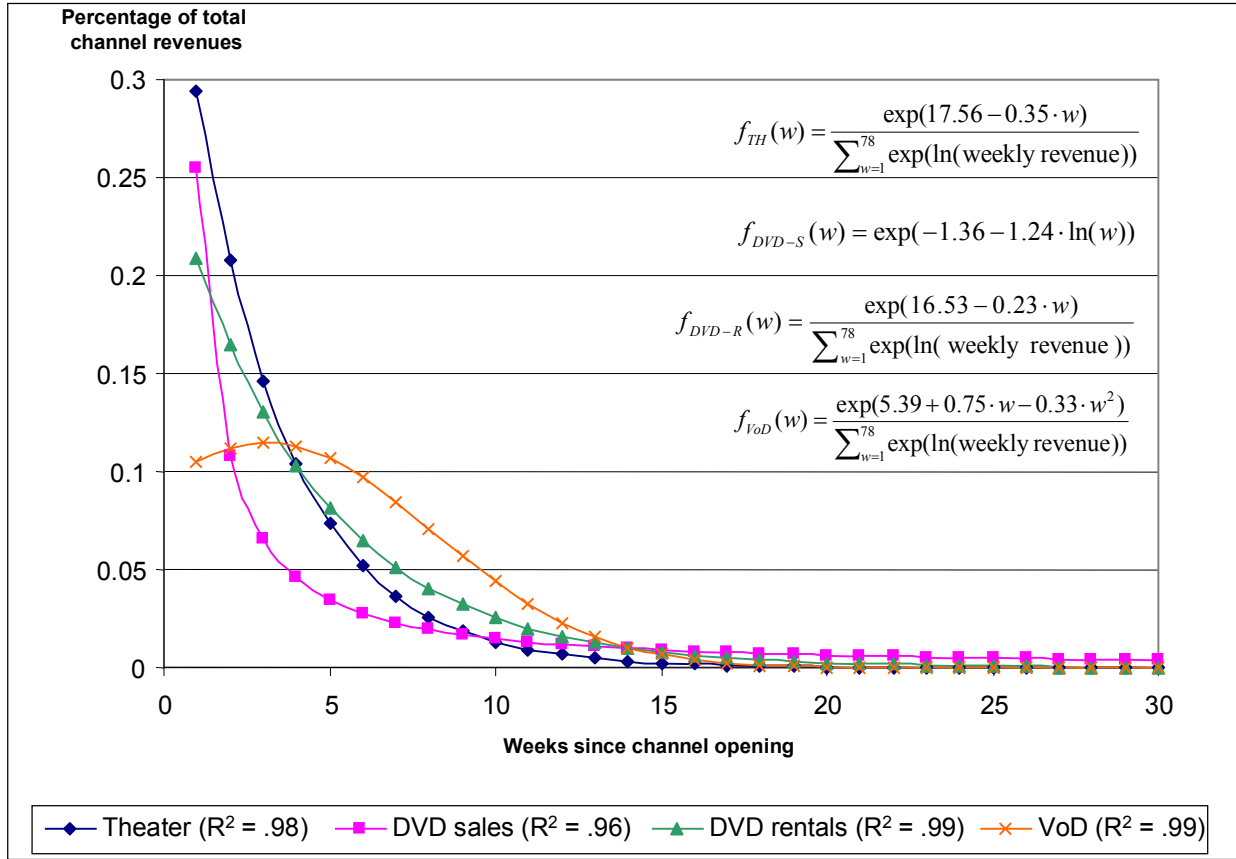
In our model, we argue that the revenues that are generated by a movie are the result of consumers' choices between different channels when the movie becomes available. To adequately cover the multi-channel nature of motion-picture distribution, we include four channels among which the consumer can chose (movie theater consumption, DVD purchases, DVD rentals, download-to-rent VOD).¹ In addition to consumer expectations regarding release dates which are modeled as known, the model accounts for the effects of inter-channel cannibalization and perishability on consumer-decision making because consumers can choose consciously between different channels, taking into account the respective opening dates in each channel vis-à-vis the consumer's willingness to accept a consumption delay. By modeling channel preference at the level of the individual consumer as part of the customer's choice decision, the model also considers varying degrees of inter-channel substitution. Moreover, the model accounts for inter-channel effects, with channel revenues being influenced by multiple-purchase SBS and both informed-cascading SBS (e.g., through word-of-mouth) and uninformed-cascading SBS (e.g., through box office data).

¹ VOD is an umbrella concept which summarizes different media services under a common label. In this paper, we focus on download-to-rent VOD, the dominant model when the empirical study was conducted, which allows consumers to watch a movie that has been downloaded from the internet for a limited period of time (usually 24 hours). To increase readability, we use the terms VOD and download-to-rent VOD interchangeably.

As channel revenues do not flow back instantly after the channel's opening, we model the weekly percentage of the channel specific revenue return as a function $f(w)$ of the number of weeks w after opening. To estimate $f(w)$, we used weekly revenue data for the studio movies released in 2005 provided by *IMDBpro* (for theaters), *Video Business* magazine (DVD rental), *Nielsen VideoScan* (DVD sales), and an anonymous Hollywood studio (VOD).² We fitted different regression models to mirror this data, assuming that the weekly percentage of revenue return becomes zero after 78 weeks (i.e., 1.5 years), which was implied by the actual revenue distribution patterns. For theatrical revenues and DVD rental returns, log-linear functions fitted best with the industry data, while for DVD sales a multiplicative function had the best fit, and for VOD returns a quadratic function was found to fit best. In all cases, the fit was excellent, with R^2 's ranging from .96 to .99. The functions are given and visualized in Figure 4.

² For DVD sales, theaters, and DVD rental, we were provided with aggregate level information on the weekly revenue patterns of all 2005 studio releases. Because industry wide information was not available for the VOD channel, we relied on aggregate level information on the VOD performance for one studio's 2005 movies. The VOD revenue data were monthly and interpolated to weekly revenues. To predict the percentage of revenue return from the \$ revenues, we modeled and forecasted the revenues of the respective channel for up to 78 weeks and related each predicted weekly revenue to the total amount of revenues to get the required percentage for these channels. In the case of DVD sales, we were provided with weekly percentages.

Figure 4: Revenues Distribution Over Time per Channel



The subscripts name the respective channel, with TH = theater, $DVD-S$ = DVD sales, $DVD-R$ = DVD rental, and VOD = download-to-rent video-on-demand.

1.3.2 Formal Model Description

The model is formally described as follows:

$$(1) \quad NPV = \beta_{TH} \cdot \frac{\sum_w \frac{f_{TH}(w) \cdot R_{TH}}{(1+r)^w}}{(1+r_M)^{t_{TH}}} + \beta_{DVD-S} \cdot \frac{\sum_w \frac{f_{DVD-S}(w) \cdot R_{DVD-S}}{(1+r)^w}}{(1+r_M)^{t_{DVD-S}}} + \beta_{DVD-R} \cdot \frac{\sum_w \frac{f_{DVD-R}(w) \cdot R_{DVD-R}}{(1+r)^w}}{(1+r_M)^{t_{DVD-R}}} + \beta_{VOD} \cdot \frac{\sum_w \frac{f_{VOD}(w) \cdot R_{VOD}}{(1+r)^w}}{(1+r_M)^{t_{VOD}}}$$

where NPV is the studio's net present value of a movie. R represents the revenues of a movie generated through a specific channel which are discounted with $f(w)$ for the respective channel's rate of flow (see Figure 4). We use a weekly discount rate of .183%

which equals an annual industry-specific discount rate of $r = 10\%$.³ The monthly equivalent to r was represented by r_M which is used to discount channel revenues to the opening of the first channel, t is the time difference in months between the opening of the first channel and the opening of the channel under consideration (i.e., window length), and β is the percentage of revenues allocated to the studio for each channel.

Revenues are generated through consumers' choices between different channels, with choices x being a function of the channel attributes $x = f(p, t, m, \pi)$, where p is the price consumers have to pay to see a movie, m is the medium (or channel), and π is a vector that reflects other factors such as the language in which the movie is shown and the presence of bonus material. We model a consumer's individual choice given a set of channel alternatives via the multinomial logit model:

$$(2) \quad x(i | J) = \frac{\exp(\theta_p p_i + \theta_t t_i + \theta_m m_i + \theta_\pi \pi_i)}{\sum_{j=1}^J \exp(\theta_p p_j + \theta_t t_j + \theta_m m_j + \theta_\pi \pi_j)}$$

with $x(i | J)$ being a consumer's choice share for channel i in a specific scenario with J movie consumption alternatives (including an option not to see the movie in one of the given channel alternatives, i.e., to wait for the movie to be made available on television for free) and θ being a parameter vector that reflects the consumer's preference structure for the channel attributes.

Individual-level choice shares are complemented with individual-level SBS information. It is important to model multiple-purchase SBS and information-cascading

³ While information on suitable discount rates for the valuation of movie studios is scarce, available sources cite annual discount rates of 9.0% for Sony Pictures (Sony 1997), 9.1% for Disney, 11.0% for MGM, and 11.8% for Pixar (Chalmers 2002). Thus, a discount rate of 10% seemed reasonable.

SBS on an individual level because consumers might not be equally likely to react to these effects. Accordingly, we get complemented individual-level choice quantities x' :

$$(3) \quad x'_{TH} = x_{TH} \cdot (1 + \gamma^{WoM}_{TH} + \gamma^C_{TH}) + \delta_{TH} \cdot x_{FC}$$

$$(4) \quad x'_{DVD-S} = x_{DVD-S} \cdot (1 + \gamma^{WoM}_{DVD-S} + \gamma^C_{DVD-S}) + \delta_{DVD-S} \cdot x_{FC}$$

$$(5) \quad x'_{DVD-R} = x_{DVD-R} \cdot (1 + \gamma^{WoM}_{DVD-R} + \gamma^C_{DVD-R}) + \delta_{DVD-R} \cdot x_{FC}$$

$$(6) \quad x'_{VOD} = x_{VOD} \cdot (1 + \gamma^{WoM}_{VOD} + \gamma^C_{VOD}) + \delta_{VOD} \cdot x_{FC}$$

with x being the choice share for the channel indicated by the subscript according to the multinomial logit model. γ represents channel-specific information-cascading SBS effects, where γ^{WoM} is the parameter for informed cascades (e.g., the percentage of movies seen in the respective channel exclusively due to word-of-mouth generated by previous channels) and γ^C is the parameter for uninformed cascades (e.g., the percentage of movies seen in the respective channel exclusively due to chart information from previous channels). δ_{TH} , δ_{DVD-R} , δ_{VOD} , and δ_{DVD-S} are multiple-purchase parameters for theaters, DVD rental, VOD, and DVD sales, respectively. x_{FC} represents the proportion of choice to see the movie in the channels that open first (being 0 if the movie is first made available through the channel under consideration).

Both information cascading SBS parameters γ^{WoM} and γ^C become zero if the movie is first made available through the channel under consideration. With regard to the multiple-purchase parameters, δ_{TH} , δ_{DVD-R} , and δ_{VOD} are zero if the movie is first made available through the respective channel or opens exclusively through DVD sales. In addition, we model the consumer's desire to re-watch the movie in a theater, on a rental DVD, or through VOD to be zero immediately after consuming it for the first time in a different channel and then to rise gradually over time, following an exponential saturation function. Specifically, we set $\delta = a \cdot (1 - \exp(-0.5 \cdot t))$, where a is the channel-specific repeat consumption probability of the individual consumer, i.e. the percentage of

movies watched in the channel indicated by the subscript of δ that were previously seen in other channels (here: x_{FC}). δ_{DVD-S} is also zero if the movie is first made available through this specific channel (i.e., DVD sales). However, as the consumer's desire to *own* a movie is formed immediately after viewing it in a different channel and remains constant thereafter in our model until fulfilled, the multiple-purchase parameter for the DVD sales channel is time-invariant at $\delta_{DVD-S} = a_{DVD-S}$.

The overall channel-specific revenues are calculated by taking the arithmetic mean of each channel's complemented choice quantity across all consumers (X') and multiplying it with the respective channel price. For example, theater revenues can be calculated by $R_{TH} = p_{TH} \cdot X'_{TH}$, with this information enabling us to calculate the weekly return and the NPV of studio revenues. Appendix A contains an illustrative application of the model.

1.3.3 Model Assumptions

It is important to note that the model described above is based on a number of assumptions. In line with our studio perspective, we focus on studio-produced motion pictures and the conditions under which such movies are distributed. Specifically, we assume motion pictures to be released widely in theaters (the dominant distribution model) and do not distinguish between producers and distributors of motion pictures with regard to revenue maximization, as most movies produced by a major Hollywood studio are distributed by sister companies over which the studio has complete control (e.g., Warner Bros. Pictures, Warner Bros. Pictures Domestic Distribution, and Warner Home Video are all subsidiaries of Time Warner Inc.). Related, we assume that consumers who want to see a movie in a channel that is already open are able to do so -- there are no shortages of screens at the theater or of DVD copies in rental stores and at retailers to limit consumption, with all movies being available through any channel. This is in line

with the market efficiency hypothesis which matches the reality of movie distribution quite well for wide studio releases (Hennig-Thurau, Houston, and Walsh 2006). Moreover, we assume that studio advertising is effective, with consumers being aware of new studio releases and making their channel choices deliberately, and that its effectiveness is the same for all channels. Consistent with the early announcement policy of new movies by studios and retailers, consumers are assumed to have homogeneous expectations (i.e., knowledge) about the timing of new studio movies' releases in different channels, with these expectations matching the actual release dates. Furthermore, we assume that customers watch a movie in theaters only once, which corresponds with norms reported in industry information (Hindes 1998). We also assume that success-breeds-success is not exclusive to theatrical releases, but exists for any channel in which a new movie is made available for the first time, and assume the allocation of revenues between studios and other players to be constant over the course of a movie release (i.e., the studio's share is identical in week 1 and the weeks that follow). Moreover, with our focus being on customer preferences, we do not consider potential market barriers caused by other players such as movie theaters that might hinder studios to implement certain distribution models (but discuss their impact later in the paper). Finally, we exclude piracy from our model, as the effect of such illegal consumption options on traditional distribution channels of motion pictures remains an unanswered question.

1.4 Research Design

To account for the existence of country factors and because of the enormous relevance of export markets for U.S. motion pictures (in 2005, cumulative foreign box office exceeded domestic theatrical revenues by 60%; MPAA 2006b), we applied our model not only to the U.S. market, but also to Japan and Germany, two film markets that

are important and culturally diverse. These three countries comprise 56.4 % of the worldwide theatrical market (MPAA 2003), and Japan and Germany are the world's third- and fourth-largest theatrical export markets, respectively. Further, Japan is the second largest home video market with annual revenues of \$5.5 billion; Germany is fifth with \$1.7 billion (IVF 2004).

Stratified random samples of the U.S., Japanese and German population were drawn in cooperation with a global marketing research company. With age and gender as interlocked strata, 5,094 consumers (U.S. = 1,701; Japan = 1,802; Germany = 1,591) were randomly selected from the research company's database which mirrors each country's overall population, and were invited by email to fill out an Internet questionnaire, and offered \$1 for participation. A total of 1,859 consumers responded. For quality reasons we eliminated respondents who completed the questionnaire in less than five minutes, leaving a sample of 1,770 (n = 588 in the U.S., a response rate of 34.6 %; n = 593 in Japan, 32.9 %; n = 589 in Germany, 37.0 %). Demographic characteristics of the subsamples are available upon request.

The questionnaire required respondents to participate in a number of discrete-choice tasks and to answer rating-scaled questions. To increase the realism of the choice tasks, respondents were first presented nine upcoming motion pictures and asked to choose the movie they were most interested to see.⁴ Short descriptions of the nine movies' plots, directors, and stars were provided, as were posters and trailers. An additional option for respondents was to wait until all nine movies are shown on

⁴ The nine studio-produced movies, which cover a wide range of genres, were: Harry Potter and the Goblet of Fire, Jarhead, King Kong, Perfume - The Story of a Murderer, Pink Panther, The Chronicles of Narnia, The DaVinci Code, Wallace & Gromit: The Curse of the Were-Rabbit, and X-Men 3. None had been released at the time of the data collection.


television and can be watched free of charge; consumers who voted for this option were excluded from the remainder of the questionnaire (Gilbride and Allenby 2004).

For the movie selected, seven choice sets were presented to the respondents embedded in a choice-based conjoint design (Louviere and Woodworth 1983; for conjoint work in channels contexts see for example Wuyts et al. 2004). Each choice set contained four hypothetical channel options for watching the movie (i.e., conjoint stimuli), as well as a “no-consumption” option (Figure 5). Regarding conjoint attributes, each conjoint stimuli was described by four (U.S.) or five (Japan and Germany) attributes, with attribute levels varied systematically (Table 1). Specifically, the attributes used to generate conjoint stimuli in the U.S. questionnaire were (1) the channel through which the movie was consumed, (2) the timing of availability, (3) the price a consumer has to pay to watch the movie, and (4) any additional content (e.g., deleted scenes, commentaries, etc.) made accessible to the consumer. As a result of pretesting and depth interviews with industry experts, the latter attribute was included to increase realism. In Japan and Germany, identical attributes and levels were used (with price levels transformed into Yen and Euro, respectively). As motion pictures are often presented in “dubbed” versions in theaters in these countries (i.e., movies are translated into Japanese/German), language was included in both cases as an additional attribute. Attribute level combinations which might have resulted in improbable alternatives and respondent confusion were modeled as prohibited pairs. Stimuli and conjoint choice sets were created according to a computer-generated randomized design that accounted for the design principles minimal overlap, level balance and orthogonality (Huber and Zwerina 1996).

Figure 5: Example of Conjoint Task

0% 100%

In which of the options below would you prefer to view the selected movie? If you are 100% sure that you would not choose any of these options (and only in that case!), please choose the box on the right.



The Da Vinci Code
 Dan Brown's best selling novel, lavishly brought to the screen by Oscar-winning director Ron Howard (A Beautiful Mind)! Following a murder at the Parisian Louvre, Tom Hanks and Audrey Tautou (The Fabulous Destiny of Amelie Poulain) have to solve a mystery once left behind by Leonardo Da Vinci - and which could shake the foundations of christianity....

Movie theater	DVD purchase	DVD rental	Legal online download (available for 24 hours)	
3 months after the movie's release date	6 months after the movie's release date	at the movie's release date	at the movie's release date	
\$3	\$7.75	\$17.25	\$12.50	
Movie without bonus material	Movie with a limited amount of bonus material (making-of featurette)	Movie with extensive bonus material (e.g. making-of, audio commentaries, deleted scenes)	Movie with a limited amount of bonus material (making-of featurette)	If these are the only options available, I would prefer to wait until the movie is shown on TV
<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>	<input type="radio"/>

proceed

Table 1: Attributes and Levels Included in Conjoint Study

Attribute	Description	Levels US	Levels Japan	Levels Germany
Channel	The channel (or medium) through which the movie is consumed	Movie theater, DVD purchase, DVD rental, legal Internet download	as in US design	as in US design
Timing	Time that has passed since the movie was first available for consumers through a legal channel	0 months, 3 months, 6 months, 12 months	as in US design	as in US design
Fee	The price a consumer has to pay to get access to the movie of his or her choice	\$3, \$7.75, \$12.50, \$17.25, \$22	400 Yen, 1,175 Yen, 1,950 Yen, 2,725 Yen, 3,500 Yen	3 Euro, 7.75 Euro, 12.50 Euro, 17.25 Euro, 22 Euro
Bonus material	The existence (or absence) of background information about a motion picture	Movie only, movie with a limited amount of bonus material (i.e. making-of featurette), movie with extensive bonus material (i.e., several making-of featurettes, deleted scenes, multiple audio-commentaries)	as in US design	as in US design
Language options	The language options the consumer can choose between	not included	Choice between Japanese and English audio track, Japanese audio track only	Choice between German and English audio track, German audio track only

Finally, respondents were asked to provide movie consumption-related responses that were used as proxies for the SBS parameters. To calculate the multiple consumption parameters δ , respondents were asked what percentage of movies they had seen in theaters they had later bought or rented on DVD/home video or downloaded from the

Internet for a fee (see Appendix B for full items).⁵ The exponential saturation function for the multiple consumption parameter for DVD rental and VOD was modeled to converge towards the multiple consumption value stated by the individual consumer for the respective channel. For the DVD sales channel, the multiple consumption parameter was set equal to the percentage of the individual consumer's DVDs that had been purchased after having watched a movie in theaters. With regard to information-cascading parameters γ^{WoM} and γ^C , respondents were asked what percentage of their DVD purchases, DVD rentals, and legal Internet downloads of movies they had not seen before in theaters was primarily triggered by information about the success of the movie in theaters (i.e., charts-based) or by personal information (i.e., word of mouth-based). Studio revenue shares were set according to industry information.⁶ To minimize any impact of language on the results, a translation-back translation procedure was used for the Japanese and German questionnaires.

⁵ Because movies have always been released in theaters first, we could not ask respondents for an inter-channel multiple consumption effect from home entertainment channels on theaters. Acknowledging that this is a limitation of the present study, we used the consumers' DVD rental behavior as a proxy for share simulations in which theaters are not the first channel and modeled consumers as being only half as likely to watch a movie in theaters after having watched it on DVD than vice versa (i.e., to rent it on DVD after having watched it in theaters), which can be considered a conservative assumption. With regard to theater-related SBS effects, we also adopted the respective DVD SBS parameters as a proxy for both theater-related SBS parameters in such scenarios. As reported later in this paper, sensitivity analyses show that our results are reasonably robust to variations in the levels of these parameters.

⁶ Specifically, the following shares were used: 50% of theaters revenues (the remaining 50% go to the theater owner; Blume 2004; Vogel 2004), 60% of DVD sales (40% for DVD retailer; Cohen 2003; Blume 2004; Manly 2005), 40% of DVD rental revenues (60% for DVD rental company; Rentrak 2005), and 50% of VOD revenues (50% for download company; Sweeting 2005; Manly 2005).

1.5 Results

1.5.1 Estimation and Validation of Conjoint Data

In order to compute the preference data variables x_{TH} , x_{DVD-S} , x_{DVD-R} , and x_{VOD} , individual-level partworths were estimated from the conjoint results through a Hierarchical Bayes (HB) routine (Arora and Huber 2001). A total of 10,000 burn-in iterations were used and another subsequent 10,000 iterations to generate parameter estimates, with every 10th iteration saved. Each respondent's utility was represented by the mean utility across these 1,000 draws.

Five of the seven choice tasks were randomly generated and used for partworth estimation, while the remaining two tasks were used for reliability and validity testing. With regard to test-retest-reliability, we referred to the agreement between respondents' choices in the first and seventh choice task, with the latter being a replication of the first task (Ghiselli, Campbell, and Zedeck 1981). With identical choices by 73.6% for the U.S. sample (four attributes per stimuli), 72.2% for the German sample and 68.1% for the Japanese sample (both five attributes), reliability is satisfactory for all three sub-samples. To measure predictive validity, we draw on the aggregate choice shares of a holdout task and test to what extent a model based on the partworths estimated through the choice tasks 1 to 5 is able to predict correctly the observed choice behavior within the sixth choice (holdout) task (Huber et al. 1993). To obtain share predictions, the partworths were transformed into choice shares for the respective profiles using a logit transformation (equation 2). Table 2 shows that the overall fit is good in all three countries, with predicted shares being very close to actual shares in terms of mean absolute error (MAE), root mean squared error (RMSE), and chi-square (Moore, Gray-Lee, and Louviere 1998), and clearly outperforming the chance model that assumes that each profile is equally likely to be chosen. The holdout scenario was identical with the

predicted choice in 66.0% of the U.S. sample cases and in 73.0% and 64.4% of the Japanese and German cases, respectively.

Table 2: CBC Prediction Accuracy for the Three Samples

	Actual shares (holdout)	Predicted shares	
		Chance	Estimated shares (Logit)
Movie theater	32.48	20.00	25.61
	32.04	20.00	29.96
	51.61	20.00	50.75
DVD purchase	16.84	20.00	17.13
	5.73	20.00	5.91
	9.85	20.00	8.49
DVD rental	36.05	20.00	40.70
	47.72	20.00	51.24
	22.75	20.00	25.09
Legal online	4.59	20.00	3.37
	4.89	20.00	1.58
	7.81	20.00	4.90
None	10.03	20.00	13.20
	9.61	20.00	11.31
	7.98	20.00	10.76

	Chance model	Logit model	Average Attribute Importance	
MAE	11.4140	3.2399	Channel	36.96
	15.9060	2.1574		25.98
	13.7440	2.0475		30.70
RMSE	2.7572	0.8972	Timing	12.96
	3.8122	0.5528		13.90
	3.7455	0.4922		16.62
Chi-Square	38.0104	3.5839	Fee	42.44
	72.6629	7.5524		44.36
	70.1427	2.8917		41.96
			Bonus material	7.65
				7.50
				8.14
			Language options	n.a.
				8.26
				2.58

Values in the top row belong to the U.S. sample, in the middle row to the Japanese sample and in the bottom row to the German sample. MAE = mean absolute error; RMSE = root mean squared error.

Comparing our results with real-world market data enables us to examine the external validity of our model. We applied our model and U.S. data to a situation that reflects actual market conditions observed at the time our analysis was conducted (U.S.

benchmark model: $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; Epstein 2005). We found that the studio revenues in this benchmark model match actual studio revenues per channel closely. Specifically, 23.7% of studio revenues are generated by theaters in our simulated benchmark model, while the studio shares of the actual theatrical revenues accounted for 25.3 % (or \$4.5 billion) of the studios' revenues in the U.S. in 2005. 19.2 % of our benchmark model studio revenues stem from DVD rentals mirrored in real-world DVD rental studio revenues of 19.2 % (\$3.4 billion), and 57.1% of the benchmark model studio revenues are generated by DVD sales, while actual DVD sales revenues constitute 55.5 % (\$9.8 billion) of the major studios' combined theatrical and home viewing revenues (MPAA 2006b; EMA 2006). This ability to reproduce current revenue patterns suggests reasonable external validity of the model and the applied conjoint procedure.

1.5.2 Sequential Distribution Chain Optimization: A Stepwise Approach

This research is the first to consider the timing of sequential distribution systems as a multiple window problem that requires simultaneous optimization. As several channel participants are involved, each of whom impose restrictions on the implementation of distribution chain changes, we decided to use a stepwise approach when applying our model to the data. Specifically, we test three different groups of scenarios which differ in terms of restrictedness.

Scenario group I retains the traditional order of movie distribution (i.e., $t_{TH} < t_{DVD-R}$ and t_{DVD-S} and t_{VOD} ; $t_{DVD-R} \leq t_{DVD-S}$; $t_{VOD} > t_{DVD-R}$ and t_{DVD-S}), paralleling previous work on sequential distribution in the film industry (e.g., Lehmann and Weinberg 2000). This

first scenario group is carried out with prices for all channels held constant as well as with DVD sale prices being allowed to vary.⁷ Scenario group II then lets movie studios freely decide when and in which order to open channels and how to price DVDs, with the exception that movies are not allowed to open elsewhere before being shown in theaters (i.e., $t_{TH} \leq t_{DVD-R}$ and t_{DVD-S} and t_{VOD}). This remaining restriction is then lifted in scenario group III, where any possible channel order is considered regardless of the potential obstacles that might hinder practical implementation.

Within each of the three scenario groups, we applied our model to all scenarios that met the respective constraints and calculated the studio's maximum NPV for each scenario. To avoid biases we refrain from using interpolations between the attribute levels used in our conjoint design, but use a complete enumeration approach instead. Given all constraints, scenario group I consists of four scenarios per country when DVD sales prices are fixed and 20 scenarios with flexible DVD sales prices. Scenario group II contains 320 possible scenarios per country, and scenario group III, the most flexible, contains a total of 875 scenarios per country. We begin our analyses with the U.S. data and then replicate our approach with Japanese and German samples. Table 3 summarizes the three best configurations in terms of studio NPV for each scenario group and country, and Figure 6 compares the NPV of each group's top scenario to the respective benchmark model.

⁷ Prices were held constant because the focus of our analysis is on studio revenues and all channels except DVD sales follow a revenue-sharing model in which the pricing decision lies with the respective final distributor and not with the studio (van der Veen and Venugopal 2005).

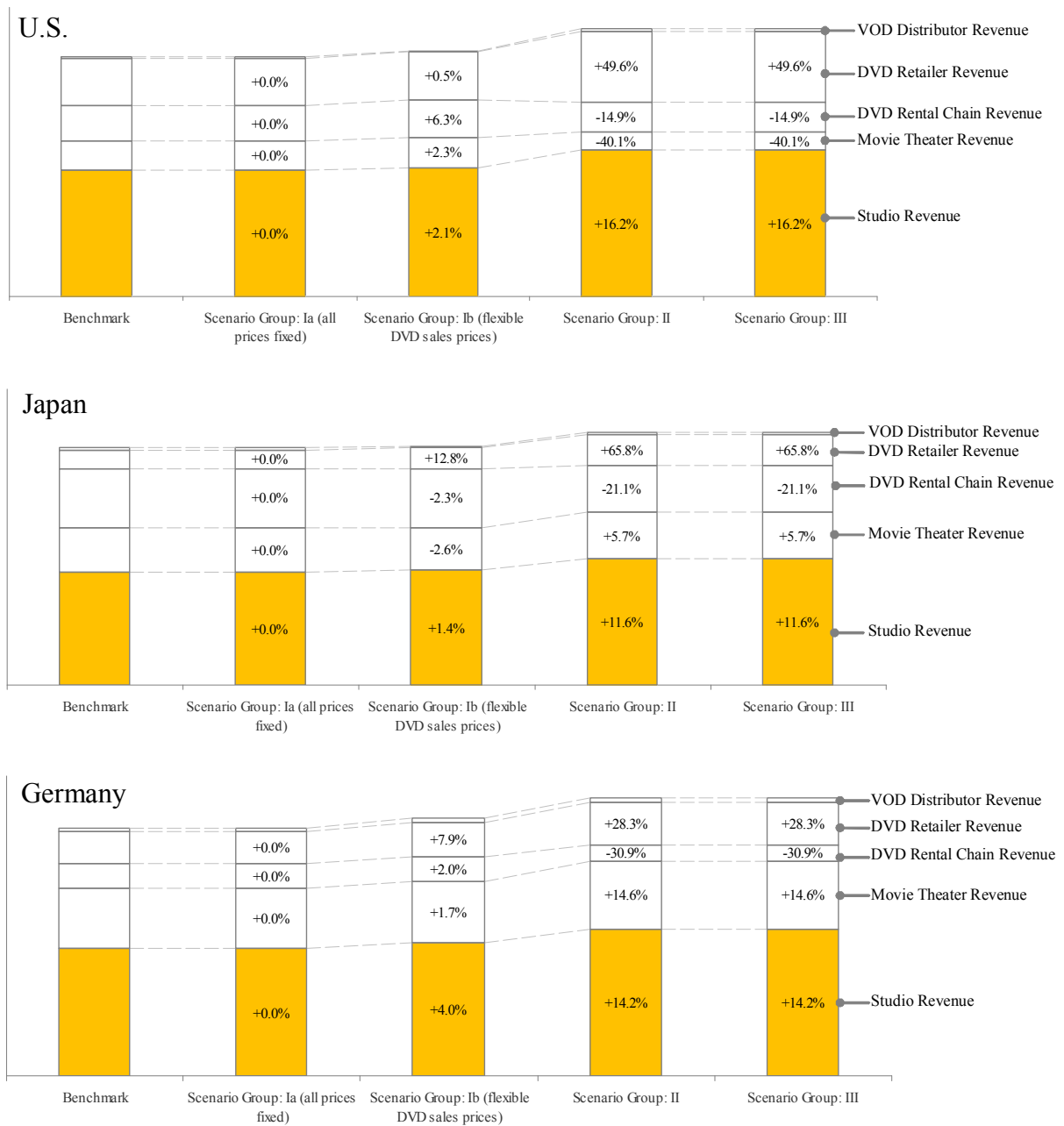
Table 3: Top Scenarios from Scenario Groups and Countries

Scenario group	Timing restrictions	Pricing restrictions	U.S.	Japan	Germany
I (with all prices fixed)	Movie Theaters < DVD Rental <= DVD Sales < VOD	Movie Theater = \$7.75; DVD Rental = \$3.00; DVD Purchase = \$17.25 (Japan: \$22.00) VOD= \$3.00	*(1) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; NPV ^S = +0.0%	*(1) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; NPV ^S = +0.0%	*(1) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; NPV ^S = +0.0%
			(2) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; NPV ^S = -1.4%	(2) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; NPV ^S = -2.1%	(2) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; NPV ^S = -2.5%
			(3) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; NPV ^S = -1.5%	(3) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; NPV ^S = -2.1%	(3) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; NPV ^S = -2.8%
I (with flexible DVD purchase prices)	Movie Theaters < DVD Rental <= DVD Sales < VOD	Movie Theater = \$7.75; DVD Rental = \$3.00; DVD Purchase >= \$3.00 and <= \$22.00; VOD: \$3.00	(1) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +2.1%	(1) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; NPV ^S = +1.4%	(1) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +4.0%
			(2) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; NPV ^S = +0.0%	(2) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; NPV ^S = +0.9%	(2) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +0.2%
			(3) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$22$; NPV ^S = -0.9%	(3) $t_{TH} = 0$; $t_{DVD-R} = 3$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$17.25$; NPV ^S = +0.5%	(3) $t_{TH} = 0$; $t_{DVD-R} = 6$; $t_{DVD-S} = 6$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; NPV ^S = +0.0%
II	Movie Theaters = 0; DVD Rental >= 0; DVD Sales >= 0; VOD >= 0	Movie Theater = \$7.75; DVD Rental = \$3.00; DVD Purchase >= \$3.00 and <= \$22.00; VOD: \$3.00	(1) $t_{TH} = 0$; $t_{DVD-R} = 0$; $t_{DVD-S} = 3$; $t_{VOD} = 0$; $p_{DVD-S} = \$22$; NPV ^S = +16.2%	(1) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; NPV ^S = +11.6%	(1) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +14.2%
			(2) $t_{TH} = 0$; $t_{DVD-R} = 0$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$22$; NPV ^S = +15.7%	(2) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$17.25$; NPV ^S = +10.1%	(2) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 0$; $p_{DVD-S} = \$22$; NPV ^S = +12.7%
			(3) $t_{TH} = 0$; $t_{DVD-R} = 0$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +15.6%	(3) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 0$; $p_{DVD-S} = \$17.25$; NPV ^S = +8.1%	(3) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$17.25$; NPV ^S = +12.7%
III	Movie Theaters >= 0; DVD Rental >= 0; DVD Sales >= 0; VOD >= 0	Movie Theater = \$7.75; DVD Rental = \$3.00; DVD Purchase >= \$3.00 and <= \$22.00; VOD: \$3.00	(1) $t_{TH} = 0$; $t_{DVD-R} = 0$; $t_{DVD-S} = 3$; $t_{VOD} = 0$; $p_{DVD-S} = \$22$; NPV ^S = +16.2%	(1) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$17.25$; NPV ^S = +11.6%	(1) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +14.2%
			(2) $t_{TH} = 0$; $t_{DVD-R} = 0$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$22$; NPV ^S = +15.7%	(2) $t_{TH} = 3$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 0$; $p_{DVD-S} = \$17.25$; NPV ^S = +11.1%	(2) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 0$; $p_{DVD-S} = \$22$; NPV ^S = +12.7%
			(3) $t_{TH} = 0$; $t_{DVD-R} = 0$; $t_{DVD-S} = 3$; $t_{VOD} = 12$; $p_{DVD-S} = \$22$; NPV ^S = +15.6%	(3) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$17.25$; NPV ^S = +10.1%	(3) $t_{TH} = 0$; $t_{DVD-R} = 12$; $t_{DVD-S} = 3$; $t_{VOD} = 6$; $p_{DVD-S} = \$17.25$; NPV ^S = +12.7%

* Benchmark scenario for the respective country; all NPV^S percentage increases/decreases are against this scenario.

t = time of release (months); p = price (dollars); TH = theater channel; DVD-S = DVD sales channel; DVD-R = DVD rental channel; VOD = download-to-rent video-on-demand

Figure 6: Revenue Changes for Top Scenario per Group (% vs. Benchmark Model)



Scenario group I results (U.S.). With fixed channel sequence and fixed prices, we find that the NPV of the current distribution configuration is optimal and cannot be increased by changes in the timing of distribution windows. Even when the pricing constraint is lifted for DVD sales (i.e., allowing DVD prices to fluctuate), the present theater-to-DVD window of six months remains superior for the studio. However, the results suggest that if the retail DVD price is set at \$22 (versus \$17.25), studio revenues

increase by 2.1% compared to the benchmark configuration. Because consumer expectations now incorporate the higher DVD retail price, choices shift slightly away from retail DVDs towards theaters, rental DVDs, and VOD.

Scenario group II results (U.S.). Removing all order constraints for home entertainment channels, except for not opening earlier than theaters, we observe major changes in terms of the channel structure that maximizes studio revenue. Under these conditions, studio revenues are maximized when movies are released simultaneously in movie theaters, on rental DVD, and in VOD, with DVDs being released for sale after a three-month window for a price of \$22. In this scenario, studio revenues increase by 16.2% compared to the benchmark constellation. However, these studio revenue gains impose a heavy cost on movie theaters which lose 40.1% of their revenues due to cannibalization. Besides movie studios, the beneficiaries of this scenario are DVD retailers whose revenues increase by 49.6%.

Examining the next-best scenarios under this constraint set, common patterns exist. The four revenue-maximizing configurations for studios all involve a simultaneous release in theaters and on rental DVD, with a DVD sales channel window of three months. Finally, the retail DVD price of \$22 is common to the nine best scenarios, suggesting that DVDs are currently priced too low to maximize studio revenue. This result is consistent with the notion that “Wal-Mart, Best Buy and other mass marketers are happily using DVDs and CDs as loss leaders and slashing prices to a level where even [rental chain] Blockbuster acknowledges it can’t compete” (Amdur 2004).

Scenario group III results (U.S.). Allowing theatrical releases to occur *after* other channels have been opened, we find that the most economically attractive scenarios remain unchanged from scenario group II. Consequently, the results suggest that a delayed theater release is not optimal for studios, since the loss of shared revenues due to severe losses by movie theaters are not offset by increases in shared revenues from gains

in the other channels. Considering the devastation such configurations would cause to movie theater chains without delivering additional revenues to the studios, channel order changes that shift theaters from the start of the distribution sequence do not appear to be a desirable strategy in the U.S. market.

Scenario analyses for foreign markets. In the restrictive scenario group I (with flexible DVD prices), strategy implications for Japan and Germany resemble those found for the U.S. In Japan, the optimal scenario employs a six-month DVD window, albeit with a slightly lower DVD retail price, and generates 1.4% more in studio revenues than the benchmark configuration. In Germany, a six-month DVD window also generates the highest revenues. By raising the retail DVD price to \$22 in this scenario, studios can increase their revenues by 4.0%, while retaining the established channel order. However, when home entertainment timing constraints are removed in scenario group II, the similarities between the U.S. and Japanese market simulations end. Although the settings now allow for simultaneous releases, the most attractive scenarios for studios retain theaters as the sole first channel. At the same time, results for Japan suggest that narrowing the theater-to-DVD sales window would increase studio revenues. Specifically, the five best scenarios in this group share the distinct pattern of releasing a movie in theaters first, opening the DVD sales channel after three months, and delaying the rental DVD release by another nine months, a configuration which would, according to our results, improve studio revenues by up to 11.6%. Contrary to the U.S. market, lower DVD retail prices increase studio revenues in Japan.

In Germany, the three revenue-maximizing configurations are basically the same as in Japan, except that DVD prices are higher and the timing of the VOD channel differs. Here, we find that the theaters and DVD retailers would also profit greatly from a three-month window for DVD sales and a 12-month windows for DVD rental and VOD, with the most attractive scenario promising studios a revenue increase of 14.2%. DVD

retailer revenues and theater revenues jump up by 28.3% and 14.6%, respectively, while the rental chains see their earnings plummet by 30.9%. Interestingly, the timing of the VOD release varies across the different revenue maximizing scenarios, ranging from an immediate opening to a 12 month delay. Although the VOD channel performs better with a shorter release window, it does not exert much influence on the studios' revenues due to limited cannibalization. As with the U.S. market, lifting the final constraint in *scenario group III* does not change the results in Japan and Germany. The best scenarios remain those found in scenario group II, with the one exception that the new second-best scenario in Japan suggests an exclusive VOD premiere, followed by a three-month window for theaters and DVD retail and a 12-month window for DVD rentals.

1.5.3 Sensitivity Analysis

Because some of the information used for model estimation was self-reported by respondents regarding their behavior under the current channel structure, we conducted a set of sensitivity analyses to see how robust our results are with regard to these measures. Specifically, we systematically varied the individual responses for all self-reported behaviors (multiple consumption SBS, word-of-mouth-based SBS, and charts-based SBS) for each channel by +/-20%. Table 4 provides the results of these analyses, showing how variations in the measures affect the respective group-best scenario's NPV change in relation to the benchmark scenario. For example, under scenario group II conditions, a 20% increase of the multiple consumption parameter for DVD purchases in Germany would result in a studio NPV increase of 15.2% compared to the benchmark model (instead of 14.2% when the multiple consumption parameter for DVD purchases is not manipulated), while a reduction of the same parameter by 20% would result in an increase of 13% in studio NPV.

Table 4: Results from Sensitivity Analyses

Scenario Group	Parameter Varied by +/- 20%	U.S.	Japan	Germany
I (with all prices fixed)		<i>Baseline: 0.0%</i>	<i>Baseline: 0.0%</i>	<i>Baseline: 0.0%</i>
	MC DVD purchase	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	MC DVD rental	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	MC VOD	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	WOM DVD purchase	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	WOM DVD rental	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	WOM VOD	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	Charts DVD purchase	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	Charts DVD rental	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
	Charts VOD	0.0% (0.0%)	0.0% (0.0%)	0.0% (0.0%)
I (with flexible DVD purchase prices)		<i>Baseline: 2.1%</i>	<i>Baseline: 1.4%</i>	<i>Baseline: 4.0%</i>
	MC DVD purchase	2.6% (1.4%)	1.0% (1.8%)	4.8% (3.2%)
	MC DVD rental	2.1% (2.1%)	1.4% (1.4%)	4.0% (4.0%)
	MC VOD	2.1% (2.1%)	1.4% (1.4%)	4.0% (4.0%)
	WOM DVD purchase	1.9% (2.2%)	1.5% (1.3%)	3.9% (4.1%)
	WOM DVD rental	2.1% (2.0%)	1.4% (1.4%)	4.0% (4.0%)
	WOM VOD	2.1% (2.1%)	1.4% (1.4%)	4.0% (4.0%)
	Charts DVD purchase	2.0% (2.2%)	1.5% (1.2%)	4.0% (4.1%)
	Charts DVD rental	2.1% (2.0%)	1.4% (1.5%)	4.0% (4.0%)
	Charts VOD	2.1% (2.1%)	1.4% (1.4%)	4.0% (4.0%)
II		<i>Baseline: 16.2%</i>	<i>Baseline: 11.6%</i>	<i>Baseline: 14.2%</i>
	MC DVD purchase	20.7% (*10.6%)	11.2% (*12.1%)	15.2% (13.0%)
	MC DVD rental	16.0% (16.5%)	11.6% (11.6%)	14.2% (14.1%)
	MC VOD	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
	WOM DVD purchase	15.9% (16.5%)	11.9% (11.3%)	14.2% (14.2%)
	WOM DVD rental	15.5% (17.2%)	11.2% (12.0%)	14.0% (14.4%)
	WOM VOD	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
	Charts DVD purchase	16.0% (16.5%)	12.0% (10.9%)	14.2% (14.1%)
	Charts DVD rental	15.7% (16.%)	11.2% (12.1%)	14.0% (14.4%)
	Charts VOD	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
III		<i>Baseline: 16.2%</i>	<i>Baseline: 11.6%</i>	<i>Baseline: 14.2%</i>
	MC DVD purchase	20.7% (*10.6%)	11.2% (*12.1%)	15.2% (13.0%)
	MC DVD rental	16.0% (16.5%)	11.6% (11.6%)	14.2% (14.1%)
	MC VOD	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
	MC theater	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
	WOM DVD purchase	15.9% (16.5%)	11.9% (11.3%)	14.2% (14.2%)
	WOM DVD rental	15.5% (17.2%)	11.2% (12.0%)	14.0% (14.4%)
	WOM VOD	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
	WOM theater	16.2% (16.2%)	11.6% (*11.6%)	14.2% (14.2%)
	Charts DVD purchase	16.0% (16.5%)	12.0% (10.9%)	14.2% (14.1%)
	Charts DVD rental	15.7% (16.%)	11.2% (12.1%)	14.0% (14.4%)
	Charts VOD	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)
	Charts theater	16.2% (16.2%)	11.6% (11.6%)	14.2% (14.2%)

Numbers before the parentheses are the group-best scenario NPV in relation to the benchmark scenario NPV when the respective parameter is increased by 20%. Numbers in parentheses are the group-best scenario NPV in relation to the benchmark scenario NPV when the respective parameter is decreased by 20%. * Under these conditions, the former group-best scenario became the second-best channel configuration by a small margin.

The pattern and magnitude of the results are, in general, substantively robust to the parameter variations. Overall, the NPV growth in the group-best scenarios in which parameters are varied differs by less than 1% from NPV growth for the original parameters. A notable exception is the variation of the individual multiple consumption

parameter for DVD purchases in U.S. scenario groups II and III, where a +/- 20% variation leads to a NPV increase of 20.7% and 10.6%, respectively, compared to an increase of 16.2% under non-varied conditions. Further support for the robustness of our results comes from the fact that the group-best scenario remains best in 230 out of 234 variations, with changes being found in only four configurations which all involve a 20% *decrease* of the multiple consumption DVD purchase parameter. Specifically, in U.S. scenario groups II and III, the DVD rental window is moved back to 12 months in the new revenue-maximizing scenario, and in the Japanese scenario groups II and III, the new top scenario features a theatrical and DVD retail opening three months after the VOD premiere, with DVD rental being delayed to a 12-month window.⁸

1.5.4 Accounting for Heterogeneity: The Impact of Movie Genres

The results reported so far assume that one distribution model will be ideal for all movies. To account for potential heterogeneity that would undermine this assumption, we examined whether genre-specific distribution models might generate additional revenues for studios. We tested the revenue potential of such a genre-specific approach by applying a two-step procedure. First, we assigned the movies in our sample to genres by

⁸ We conducted additional sensitivity analyses for the effects of potential changes in channel revenue functions and conjoint attribute utilities. Regarding channel revenue functions, modeling log-linear functions for all four channels does not change any winner scenario or NPV growth number. With regard to conjoint attribute utilities, we varied the different utilities on the individual consumer level by +/-20%, finding that the pattern and magnitude of the results are substantively robust to the variations. Specifically, the maximal reduction of NPV growth of any group-best scenario is only 1.8% compared to the respective benchmark scenario, and in 64 of the 72 varied conditions the effect on NPV growth is less than 1%. The group-best scenarios remain the same as in the non-varied condition in 62 out of 72 variations. In addition to reflecting the high reliability and internal/external validity of the conjoint results already demonstrated through established conjoint validation methods, these further analyses show that, within a reasonable range, potential changes in the consumers' perceived importance of channel characteristics (i.e., channel, timing, and price) should have only a limited effect on optimal distribution structures.

drawing on genre classifications by *IMDBpro*. This resulted in five genres (action, comedy, drama, fantasy, thriller) with two movies in each genre (one movie was assigned to two genres). Second, we repeated the optimization process used to identify general revenue-maximizing distribution models for each of the five genres, considering only the respective subsample (e.g., only respondents who selected fantasy movies).

There appear to be differences in consumer preferences. In the U.S., preferences toward rental channels are somewhat higher for comedies, while preferences toward theaters and DVD purchases are higher for action and fantasy movies, which implies moving forward rental channels for comedies and moving back the DVD rental channel behind the DVD purchase channel for action and fantasy movies. However, as a whole, genre effects on NPV outcomes are quite moderate, surpassing the general distribution model revenues by only .8% (U.S.), 1.6% (Japan), and 2.1% (Germany). Out of (3 countries*4 scenario groups*5 genres =) 60 constellations, we found only one in which a genre-specific model outperforms the general model by more than five percent (scenario group 3 in Japan for action movies, outperformance by 5.5%).

Given these relatively small revenues gains and considering that the implementation of genre-specific distribution models would likely cause consumer confusion (e.g., when new movies combine elements of two or more genres which have different distribution patterns -- EVAN ALMIGHTY, the \$250 million sequel to BRUCE ALMIGHTY, is described by its studio as “a spectacle fantasy and also a comedy”, Muñoz 2006), we will focus on the general distribution approach when discussing potential implications for the movie industry.

1.6 Discussion and Implications

This study uses a multi-indicator approach that features Hierarchical Bayes choice-based conjoint information for the intertemporal prediction of market shares. We apply an NPV model of movie studio revenues across complex and multi-window sequential distribution chains and find that by adjusting the configuration of distribution channels and the price of DVDs, motion picture studios could, all other things being equal, boost their revenues by 16.2% (or \$3.5 billion) in the United States alone. Moreover, we demonstrate that consumers' channel preferences and movie-consumption decisions clearly differ among three major markets (the U.S., Japan, and Germany), thus offering insights on how studios might fine-tune distribution strategy by country.

1.6.1 Implications for Research and the Motion Picture Industry

Our results suggest that the movie industry's current distribution model is not optimal in terms of revenue generation. Our key implication is that studio revenues can be increased by changing both the timing and order of distribution windows. The channel configuration that performs best in the U.S. includes making a film simultaneously available in theaters, DVD rental, and through VOD, followed three months later in the DVD sale channel at a price of \$22. If this configuration was to be used to distribute motion pictures in the United States, studios would receive only 12.2% of their total revenues from theaters (versus 25.3% in 2005) and only 14.1% from DVD rentals (versus 19.2% in 2005), while contributions from DVD sales would soar to 73.6% (from 55.5% in 2004), according to our findings.

Our results suggest that recent industry speculation about simultaneous channel releases, called a "death threat" by theater owners (Stanley 2005), would indeed be devastating for movie theaters. However, such a change might be financially attractive to

movie studios and DVD retailers if executed in the U.S. market, although externalities must be considered if the theater channel was to be irreparably damaged; we discuss this in more detail below. This type of simultaneous-release approach is not equally promising for studios in the major export markets of Germany and Japan where the inter-channel cannibalization of theater revenues would not be offset by DVD sales growth to the same extent as in the U.S. In fact, in these markets, our results indicate that the optimal U.S. configuration would lead to a studio revenue gain over the benchmark of only 1.8% in Germany, and even a revenue *loss* of 5.8% in Japan.

The results also imply that an *exclusive* ‘Wal-Mart premiere’ is not the most promising option for studios. In none of the three countries examined in our study do empirical results suggest that theaters should be shifted away from the start of the distribution chain. Examining the channel market shares and revenues, an exclusive movie opening in DVD retail stores would not take full advantage of multiple-purchasing behavior, as many of the consumers who would buy the DVD in such a retail-premiere scenario would also have bought it after having consumed the movie in theaters (or other rental channels) first.

Our results also suggest that the timing of the VOD channel has little influence on studio revenues. There appears to be a distinct consumer segment for VOD, but the size of the market is not strongly affected by moving the VOD release forward. For example, whereas the market share for VOD is 4.4% in the benchmark scenario, it only grows to 5.3% when a movie is initially released on VOD alongside theaters and DVD rentals in the studio revenue-maximizing U.S. scenario. It is interesting to note that this is the case despite our model assumes all movies to be available through all four channels (which is not the case in reality for VOD), a fact that signals a somewhat limited growth potential for the channel. Still, Apple CEO Stephen Jobs’ vision of offering movies through online

downloads at the same time they hit retail shelves has been likened to “walking into a lion’s den” (CinemaNow CEO Curt Marvis; Grover 2005).

Our findings underscore why potential changes to traditional channel sequences are currently at the center of Hollywood’s attention and the subject of rancorous debate. To maximize studio revenues, radical changes to the extant movie distribution model are proposed, and substantial shares of business are shifted among the various players. Most glaringly, U.S. theaters stand to lose 40% of their revenues, while DVD retailers’ revenues could increase by nearly 50%. Similarly, in the configurations that maximize studio payoff, Japanese and German DVD rental chains would face revenue losses of 21% and 31%, respectively, while their retailing counterparts could see their respective revenues jump by 66% and 28%. These results raise the question of whether U.S. theater chains or Japanese and German video rental chains would be able to scale down their operations, or whether such scenarios would be fatal. If novel distribution strategies were to trigger the disintegration of entire industry branches such as theatrical exhibition in rural areas, this outcome would not only be a financial setback for studios, but would also have widespread consequences such as a disastrous loss of cultural heritage and jobs.

How could theaters deal with such changes? One reaction might be that theaters could diversify into multi-channel operations, transforming themselves into “one-stop shops” where audiences can watch a theatrical exhibition and rent or buy the DVD afterwards (maybe receiving discounts for multiple channel consumption). Another reaction to changes to the traditional distribution model seems less speculative. Changes will be met with fierce resistance by the respective industry players who perceive a threat to their stakes. North American “[t]heater owners have already lambasted Disney CEO Bob Iger for even mentioning that he might reconsider the windows approach”, and

“Wal-Mart [...], the country's largest DVD retailer, will go bat-crazy” over attempts to change the DVD business model in favor of VOD (Grover 2005). Studios experienced a foretaste of what might happen when the simultaneous release of the film BUBBLE in multiple channels was widely met with boycotts by theaters (CBC 2006). It is therefore important to stress that our results do not include the costs that might arise from distribution model transformations, such as lost revenues caused by the boycotting of movies by theater chains, or image deterioration as a result of media debates. Could such resistance be broken by the studios? One approach would be to offer theaters compensation for accepting shorter distribution windows, e.g. a higher revenue share (Grover 2006). We ran additional sensitivity analyses to see how changes in revenue allocation would affect the attractiveness of our optimal distribution model in the U.S. We found that an allocation of 60% of box office grosses to theater owners (versus 50%) would have a very limited effect, with the revenue-maximizing structure remaining the same and studio revenues still being 13.4% higher than in the benchmark scenario.

A potential alternative would be to search, post hoc, for configurations in which every market participant gains revenues (or at least does not lose any). Our simulations suggest that such scenarios exist in the U.S. and in Germany, while we do not identify such a “win-win” configuration for the Japanese market. In the U.S., a three-month theatrical-to-DVD retail window with a higher DVD retail price, followed by the DVD rental and VOD releases another three months later, lifts studio revenues by 7.3% over the benchmark. This growth goes hand-in-hand with increases in revenues of 11.1% for DVD retailers due to the shorter window. DVD rentals and VOD gain 4.5% and 7.5% respectively because of the higher DVD price that provides them with marginal gains in choice shares, while at the same time, theater revenues are not cannibalized. The German “win-win” scenario looks quite similar, with the exception of the VOD window being 12

months. The outcome here would be a 7.6% revenue increase for studios, revenue growth of 19.1% for DVD retailers, marginal benefits for rental chains, and no changes for theaters and VOD. Even though these scenarios promise no negative effects for all parties involved, implementation would likely be met with resistance because it requires breaking with the industry tradition of opening the rental channel before (or simultaneous to) the retail channel. Rental chains would likely resist a change that promises no gains for them, but moves them further down the distribution chain. However, with DVD retailers being the co-beneficiaries in every studio revenue-maximizing configuration identified in our analyses, the studios should have powerful allies in retailing giants such as Wal-Mart (U.S.) and the Metro Group (Europe).

Altogether, this study integrates the sparse research on inter-channel effects relevant to the optimization of sequential distribution chains into a coherent model. Our model builds on characteristics of sequential distribution systems that have been identified by prior research. Any industry that relies on distribution windowing could tailor our framework and empirical approach to their context. For example, major record label SonyBMG recently has started to introduce sequential distribution to the music industry, a strategy recommended by Booz-Allen & Hamilton consultants (Bhatia, Gay, and Honey 2001). Other entertainment good producers that already employ windowing, such as book publishers and computer game developers, may benefit financially from examining the general characteristics derived in our study to gain insights into how to refine their distribution models and to increase revenues.

1.6.2 Limitations, Future Research Opportunities, and Conclusion

In addition to our modeling assumptions, this study has some limitations. The impact of distribution chain changes on piracy is not considered. Next to sequential

distribution, piracy is the movie industry's most important concern, described by the MPAA (2004a) as "the greatest threat to the economic basis of moviemaking in its 110-year history". Industry executives express concern that advanced releases on DVD or VOD might increase piracy, because high quality digital versions of movies would be accessible to potential pirates earlier in the distribution chain (Economist 2002).

However, this effect might be limited in size, as illegal copies of nearly all new movies are already available in file sharing networks prior to or during their theatrical run (Byers et al. 2004). Effective copy protection measures would certainly reduce the studios' risk associated with closing the window between theaters and home channels. Future studies should examine the impact of channel configuration on piracy.

While our model optimizes studio revenues, it ignores the costs of producing, marketing, and distributing motion pictures. While production costs will be largely unaffected by distribution chain changes, an increase in the number of DVDs sold might create economies of scale that would lower costs per DVD and increase studio profit margins. However, considering the first-copy-cost character of motion pictures with limited variable costs, revenue optimization should be a good proxy for profits. Still, future research could integrate cost and margin information.

It is important to stress that our empirical model does not explicitly consider implementation barriers to channel restructuring. Although we identify problems that would be associated with the modification of channel configurations, uncertainty remains, including the costs that might be incurred through negative responses by channel partners who have been alienated. Our "win-win" constellations would probably cause less resistance from other industry players and might be considered an acceptable compromise for all involved.

While this paper is the first to model more than two channels, our findings are limited insofar that we only include download-to-rent VOD, not download-to-own VOD. However, we assume that results would remain fairly stable, given the limited role of VOD for movie revenues and the small preferences of the respondents in our study towards VOD. The same could be said for other channels which we do not consider (e.g., mobile devices). Also, we preferred a multinomial choice scenario over a multivariate conjoint approach, i.e. asking consumers for their “first choice” in terms of watching a new movie instead of allowing them to choose multiple channels in each choice task. The latter would have required consumers to anticipate their choice behavior over time, which would have been dependent on their evaluation of the movie *after* seeing it for the first time.

We model revenue allocation between different parties as constant over time, which is true for most channels considered, but studios’ share of box office grosses often decreases with the time a movie is available in theaters. Given that the intra-channel flow of revenues remains constant across distribution models, this should not affect our results. Theater owners, however, should be aware that if movies would be shown in their venues for a shorter period in a new distribution model, the theatrical share of revenues would go down as the percentage of weeks that generate less-than-average revenues would increase. However, this is based on neither theory nor data. Similarly, while the assumption that consumers have “perfect expectations” on release times is logical, this will not be the case for every consumer and any movie release. Information asymmetries might allow studios to issue films earlier in secondary channels than consumers expect; however, consumers will learn and adapt expectations accordingly, anticipating future movies to be released earlier than announced by studios.

Although we account for key market variables, we do not control for all factors that might affect the results. For example, we do not consider movie quality, which can stimulate word-of-mouth (Liu 2006). That said, we believe that the potential for studios to differentiate distribution based on quality is limited, as a later release of “good” movies and an earlier release of “bad” movies will affect customers’ expectations. Audiences might even act strategically, staying away from theaters to prompt studios to open secondary channels earlier. Also, our results do not consider seasonality, movie competition at release, or cross-country influences (e.g., the impact of U.S. results on Germany results; see Elberse and Eliashberg 2003). Optimal structures might differ based on these factors, and thus, we suggest the role of these factors to be tested in future work.

The choice-based conjoint design reveals consumer preferences for currently non-existing, but possible, scenarios. However, the SBS parameters are based on self-reports of past consumer behavior in traditional sequential distribution sequences. While sensitivity analyses show that the self-reported data affect the results only to a limited degree, we acknowledge that no objective data is available on how SBS might evolve in different channel structures, leaving this as a challenge for future research. While our samples contain movies from major genres and we found only limited genre-specific differences in terms of revenue-maximizing distribution models, it would be laudable to replicate our findings with a different (and larger) set of movies.

In conclusion, our results suggest that the current sequential distribution configuration in the motion picture industry does not maximize revenues for the studios that produce movies. Channel configurations play an important role in motion picture success. Although theaters will not see their “last picture show” immediately, theater owners and movie audiences are almost certain to face significant changes in the near future.

2 Consumer File Sharing of Motion Pictures

2.1 Introduction

Ever since the ascent of Internet file sharing services and the parallel sharp decline of the music industry's worldwide sales, movie executives have feared that their industry would be similarly affected by illegal file sharing (*Economist* 2002). Recent figures show that around 130,000 movies are downloaded each day through file sharing networks in the United States alone (MPAA 2004b), while theatrical admissions in 2005 fell by 9% in the U.S. and even more in other major markets. Against this backdrop, the Motion Picture Association of America (MPAA) claims that “illegal movie trafficking represents the greatest threat to the economic basis of moviemaking in its 110-year history” (MPAA 2004a) and has declared “war on piracy” (Fritz 2005).

However, sound evidence for the proclaimed effect of file sharing on movie consumption is lacking. A multitude of industry reports postulate the cannibalization effect of file sharing on movie industry revenues, but the results of academic studies are inconclusive. No peer-reviewed article has yet investigated the effects of movie file sharing on commercial distribution channels, and the limited work that reports a negative effect of music file sharing on legal music consumption uses highly abstract proxies such as “Internet penetration” to measure consumer file sharing (e.g., Liebowitz 2006). At the same time, some researchers argue that file sharing does not damage the (music) industry and provide empirical (Oberholzer-Gee and Strumpf 2005) and theoretical (Gopal, Bhattacharjee, and Sanders 2005) arguments supporting the absence of a cannibalization effect—or even the presence of a *positive* effect of file sharing on legal consumption.

We shed light on this controversial issue by employing controlled longitudinal panel data from 770 to 813 consumers which encompasses information on more than

10,000 movie file sharing opportunities. We use this data to investigate whether illegal movie file sharing influences revenues generated through theatrical visits, DVD rentals, and DVD purchases and, if so, how strong the effects are. In addition, we present, for the first time, a comprehensive, theory-based model of the factors that drive consumers' movie file sharing activity. This model offers the movie industry a more thorough understanding of why consumers engage in file sharing, suggesting more effective antipiracy strategies.

The paper is structured as follows. After reviewing the relevant literature, we derive a set of hypotheses regarding the consequences and determinants of movie file sharing from extant research and utility theory. We then report our data set and use ReLogit regression analysis and partial least squares structural equation modeling to test the hypotheses. We conclude by discussing the results and implications.

2.2 Motion Picture File Sharing Literature

2.2.1 File Sharing Consequences

Industry representatives unanimously argue that illegal motion picture file sharing has a negative impact on other kinds of movie consumption, and industry-commissioned studies, such as FFA (2006a) and MPAA (2004c), support their claims. For example, in a study of movie piracy by the German Federal Film Board (FFA), respondents indicated how movie downloading or copying movies with a CD/DVD burner had influenced their consumption of motion pictures through other channels; 42% of the respondents reduced their number of movie theater visits (though 8% stated they went to the movies more often), 45% said they rented fewer DVDs, and 44% replied that they bought DVDs less often (FFA 2006a). Similarly, the findings of an eight-country study commissioned by the MPAA (2004c) indicate that “about one in four internet users (24%) have

downloaded a movie” (MPAA 2004c, p. 1) and that, on a global level, 26% of downloaders purchase movies “much less” or “a little less” often than in the past (excluding the outlier Korea lowers the unweighted mean from 26% to 14%). The insights generated by these and other industry studies are limited by their methodological approaches and lack of transparency. In all cases, the results rely on an ex-post “what-if” approach that asks consumers who have already seen movies as illegal copies (and therefore know the cinematic quality) to speculate if they would have paid for the movies if they had not been available as illegal copies.

To the best of our knowledge, no scholarly research addresses the effects of sharing illegal movie copies on commercial distribution channels. In the related context of music file sharing studies, researchers are split into two opposing groups. The first group reports a negative impact of music file sharing on industry sales (Liebowitz 2006; Michel 2006; Montero-Pons and Cuadrado-García 2006; Peitz and Waelbroeck 2004; Zentner 2006), but these studies all rely on aggregate household Internet penetration in a given city as a proxy for file sharing and do not monitor file sharing on an individual basis. Obviously, this approach raises serious questions regarding spurious correlations and paves the way for alternative explanations.

The second group of researchers question these findings and argue that file sharing has either no or a positive impact on industry revenues. Specifically, Gopal, Bhattacharjee, and Sanders (2005) propose a model of online music sharing economics and derive implications for consumer surplus and producer profits. Following the train of thought that consumer file sharing represents a form of “sampling” for experience goods, they conclude that file sharing networks lower the total costs of evaluating and acquiring experience goods, which increases purchases and industry profits. In other words, file

sharing reduces consumers' risk in evaluating new music (an argument that easily extends to movies), a major obstacle in consumer decision making.

Using a different argument, Boldrin and Levine (2002) and Grgeta (2004) model competition with sunk costs and argue that, with certain assumptions, the decreasing costs of reproduction that result from file sharing make it easier, not harder, for the producer to recoup his or her investment and that as the rate of reproduction increases, competitive rents increase. Their conclusion is based on the concept of indirect appropriability, which assumes an original product attains greater consumer utility when it can be copied and that this utility increase can be captured by the producer through a price increase. However, like Gopal, Bhattacharjee, and Sanders (2005), they do not provide empirical findings to substantiate their conclusions.

Oberholzer-Gee and Strumpf (2005) present empirical results that show no negative impact of file sharing on traditional music distribution channels. Over the course of four months, they monitor 1.75 million file downloads on file sharing networks and then match the downloads to U.S. album sales data. Their empirical analysis shows that music file sharing has no significant impact on album sales. Again, however, the generalizability of their findings is somewhat limited as the authors use the "number of German school kids on vacation" as an instrumental variable for file sharing activity to bypass endogeneity problems caused by the simultaneity of downloading and purchasing activity in their aggregate level data.

In summary, movie industry representatives argue that file sharing serves as a substitute for commercial movie consumption, while no peer-reviewed research has studied this relationship for movies, and the results from music file sharing research are inconclusive and limited by methodological constraints. Moreover, no existing study

surveys actual consumer decision making on an individual level, and no study uses longitudinal data.

2.2.2 File Sharing Determinants: The Rochelandet–Le Guel Model

Related to the consequences of movie file sharing for commercial channels are the factors that drive consumer file sharing. Research into these factors is also rare; we are not aware of a single academic study that directly addresses this question. Again, some scholars have researched file sharing determinants in the related context of music. Most authors focus on the role of individual constructs for file sharing (ethical predispositions, Gopal et al. 2004; consumer expertise, social networking, and moral judgments, Huang 2005), while Rochelandet and Le Guel (2005) attempt to integrate different drivers of sharing illegal music copies in a comprehensive model.

Building on the Beckerian consumer utility framework, Rochelandet and Le Guel (2005) propose that consumers prefer illegal copies of music over the original product (i.e., a CD) when consuming the illegal copy offers greater utility. More specifically, they argue that three groups of factors influence consumers' utility perceptions of the original and the illegal copy: (1) the utility derived from buying an original (including both gross utility and costs), (2) the costs of the illegal copy (mainly transaction costs), and (3) the degree of substitution between an original and its illegal copies. Rochelandet and Le Guel (2005) find partial support for their model from a convenience sample of 2,500 French consumers. With an ordered logit approach, the factors in their model explain 10% of the music file sharing intensity.

2.3 Consequences and Determinants of Motion Picture File Sharing

2.3.1 Motion Picture File Sharing as the Focal Construct

We define file sharing of motion pictures as consumers' consumption of illegal copies of full-length motion pictures. This definition considers not only watching but also the mere act of obtaining illegal movie copies as forms of consumption. Although these two behaviors are closely related, they are conceptually distinct because consumers not necessarily watch every illegal copy they obtain. Our use of the phrase "illegal copies" excludes original movies that consumers have the legal right to watch, such as those made available by their copyright owners to file sharing networks or Internet video forums such as *YouTube.com*, as well as commercial video-on-demand services such as *Movielink.com*. Finally, our conceptualization of file sharing involves not only accessing illegal movie copies from file sharing networks ("Internet piracy") but also the personal exchange of illegal movie copies among consumers (e.g., on CD-Rs and DVD-Rs; "hard goods piracy"), consistent with the conceptualization of movie file sharing used by the movie industry (MPAA 2006a).

2.3.2 The Effects of Motion Picture File Sharing on Commercial Channels

Consistent with a consumer utility perspective of file sharing (Rochelandet and Le Guel 2005), we propose the existence of negative (i.e., cannibalistic) effects of movie file sharing on movie consumption in the three key commercial channels, namely, theater visits, DVD rentals, and DVD sales (e.g., Liebowitz 2006; MPAA 2004c). In all three channels, we distinguish among three related but distinct potential cannibalization effects.

The first hypothesized effect refers to consumers' intentions to watch an illegal copy of a movie. We propose that when a consumer has such intentions, he or she is less

susceptible to offers from theaters, DVD rental outlets, and DVD retailers, because such intentions entail the consumer's expectation to obtain a copy of the movie for free (instead of paying for legal channels). As a consequence, the consumer will refrain from using those commercial channels. This should be the case regardless of whether the consumer actually obtains an illegal copy of the movie.

H1: A consumer's intentions to watch an illegal movie copy reduce the probability that the consumer (a) watches the movie in a movie theater, (b) rents the movie on DVD, or (c) purchases the movie on DVD.

The second hypothesized effect refers to a consumer's actual obtainment of illegal movie copies. Here we argue that consumers who have gained access to an illegal copy of a movie have a lesser probability of seeing the movie in a theater or on DVD, regardless of (a) of their original intentions toward watching an illegal copy of the movie, and (b) whether they actually watch the illegal copy. Distinguishing between consumers' intentions and their actual behavior is important from a managerial perspective, because if intentions influence commercial channel usage, the movie industry should focus its antipiracy activities on consumers who intend to watch a copy. In contrast, if actually obtaining illegal copies harms theaters and other channels, the copies should be at the core of the industry's antipiracy actions, because any obtained copy would cannibalize commercial channels regardless of consumers' intentions.

H2: For a given level of file sharing intentions, a consumer's obtainment of an illegal movie copy reduces the probability that the consumer (a) watches the movie in a movie theater, (b) rents the movie on DVD, or (c) purchases the movie on DVD.

The third hypothesized effect relates to the consumer's watching of illegal copies. We postulate that consumers who watch an illegal movie copy have a lesser probability of seeing that movie in a theater or on DVD, regardless of their original intentions toward

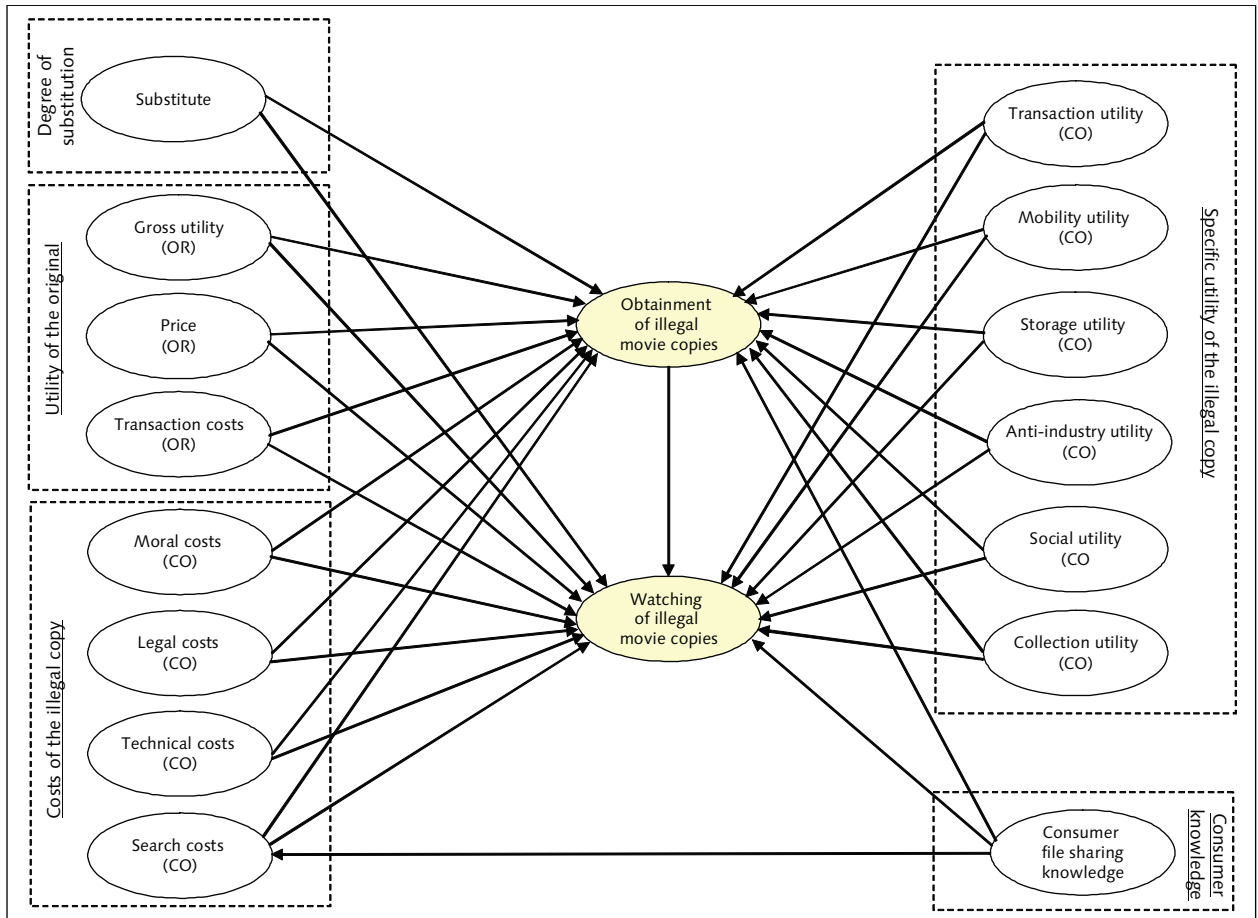
watching an illegal copy of the movie. Whereas our second hypothesis factors out what happens after the consumer obtains a copy, this third hypothesis posits that the specific act of watching the copy cannibalizes revenues. The relevance of this hypothesis stems from its associated managerial implications; it would suggest that antipiracy actions should be directed toward preventing consumers from watching obtained illegal movie copies.

H3: For a given level of file sharing intentions, the consumer's watching of the illegal movie copy reduces the probability that the consumer (a) watches the movie in a movie theater, (b) rents the movie on DVD, or (c) purchases the movie on DVD.

2.3.3 Determinants of Motion Picture File Sharing

When modeling the determinants of movie file sharing, we build on the utility-theoretic approach of Rochelandet and Le Guel (2005) but refine and extend this approach in several ways. Generally, we distinguish among five categories of factors that we expect to drive consumers' movie file sharing behavior: perceived degree of substitution between an original movie and its illegal copies, utility of the original, (transaction) costs of the illegal copy, specific utility of the copy, and consumer's file sharing knowledge. The former three categories come from Rochelandet and Le Guel (2005), while we add the latter two. We discuss the categories and the individual drivers they encompass next and summarize them in Figure 7.

Figure 7: Structural Model of File Sharing Determinants



CO = illegal movie copy; OR = original movie.

Degree of substitution. A direct implication of the utility-theoretic approach is that the degree to which a consumer perceives illegal movie copies to provide the same utility as watching the original movie in a theater or on DVD determines the intensity of consumer file sharing. This perceived degree of substitution influences the utility of the illegal copy (Rochelandet and Le Guel 2005) and therefore should have a positive effect on the intensity with which consumers obtain and watch illegal movie copies.

H4: The degree to which a consumer judges illegal movie copies as substitutes for movies in commercial channels correlates positively with the number of illegal movie copies a consumer obtains and the number of illegal copies she or he watches.

Utility of the original. A consumer's demand for illegal movie copies as substitutes of original entertainment offers is a function of the gross utility that the consumer expects to receive from watching a movie original in a theater or on DVD. Specifically, for a given degree of substitution, the original's higher gross utility will result in more illegal movie copies being obtained and watched by consumers (Rochelandet and Le Guel 2005).

Furthermore, the utility-theoretic approach implies that the costs associated with consuming a movie original also determine the original's net utility (Rochelandet and Le Guel 2005). These costs consist of the perceived price of the original and the perceived transaction costs associated with its consumption (e.g., pay for a babysitter when going to the theater). Because these costs decrease the relative attractiveness of the original compared with the illegal copy, they should correlate positively with the number of illegal movie copies obtained and watched by the consumer for a given degree of substitution.

H5a: The perceived gross utility of the original correlates positively with the number of illegal movie copies a consumer obtains and the number of illegal copies she or he watches.

H5b: The perceived costs of the original correlate positively with the number of illegal movie copies a consumer obtains and the number of illegal copies she or he watches.

Costs of the illegal copy. Because consumers usually acquire illegal copies without paying a fee, the costs of obtaining and/or watching an illegal movie copy mainly consist of transaction costs. These transaction costs comprise moral costs (e.g., ethical concerns about stealing copyrighted material; Holm 2003), legal costs (e.g., fear of sanctions; Chiang and Assane 2002), technical costs (e.g., potential file misspecifications

or viruses that could harm the consumer's computer), and search costs (e.g., time spent looking for an illegal copy) (Rochelandet and Le Guel 2005). Transaction costs reduce the attractiveness of the illegal copy compared with the original and should have a negative effect on obtaining and watching illegal movie copies.

H6: The perceived transaction costs of the illegal copy correlate negatively with the number of illegal movie copies a consumer obtains and the number of illegal copies she or he watches.

Specific utility of the illegal copy. We expand the utility-theoretic approach and argue that consumers sometimes prefer an illegal movie copy, because copies can provide consumers with specific utilities that cannot be gained by consuming the movie original. In other words, we expect some consumers to obtain and/or watch an illegal movie copy to gain a specific utility they cannot access by watching the movie in a theater or on DVD.

To develop a more thorough understanding of the specific utilities of illegal movie copies, we conducted eight qualitative, largely unstructured, in-depth interviews with experienced movie file sharers. The interviews lasted 25–45 minutes and suggested six specific file sharing utilities, which we propose positively influence consumers' movie file sharing activity:

Transaction utility. Illegal movie copies allow consumers to “make a deal” and save money compared with consuming the same movie in commercial channels. According to Thaler (1985, p. 205), such a deal can result in a transaction utility that refers not to the value of the consumed good (i.e., the movie) but to “the perceived merits of the ‘deal’,” or in other words, the customer's satisfaction and pleasure with obtaining the financial advantage associated with the copy (Grewal, Monroe, and Krishnan 1998).

Mobility utility. Illegal copies enhance consumers' mobility, because they can be stored on mobile devices (e.g., laptop computers, video iPods, PDAs), which enables consumers to carry extensive movie libraries in minimal space when traveling. Because this mobility is not possible with regular DVDs, it represents a specific utility of the copy to consumers.

Storage utility. Related, due to their non-physical character, illegal copies require less physical storage space in the consumer's domicile than purchased DVDs, which can represent a benefit for consumers.

Anti-industry utility. The movie industry is a frequent target of consumer criticism for its treatment of movies as mere commercial products rather than art, as well as for the prices it charges for movies in legal channels (e.g., Graham 2004)—an attitude which is shared by certain industry insiders (e.g., director M. Night Shyamalan calls studios “greedy, heartless, soulless, and disrespectful”; *Guardian* 2005). Consumers might consider “stealing” a movie by watching an illegal copy a legitimate kind of revenge on the industry and derive a benefit from this.

Social utility. Accumulating illegal movie copies enables consumers to establish social links with relevant others. Consumers can interact with their peers about illegal movie copies and related technology and thereby become part of a “social copying network.” This allows the consumers to demonstrate their expertise and receive social rewards for that expertise from others. Huang (2005) provides initial empirical support for such social utility.

Collection utility. The availability of illegal movie copies enables consumers to collect large numbers of movies, regardless of their financial resources. Consumer behavior literature reports that consumers derive a utility from such collecting behavior

beyond the products' functional value, and this collection utility has the potential to influence behavior (Belk 1995).

H7: The specific utility a consumer derives from an illegal movie copy correlates positively with the number of illegal movie copies the consumer obtains and the number of illegal copies she or he watches.

Consumer file sharing knowledge. In some situations, consumers are not interested in utility maximization but instead strive to “make a satisfactory choice while minimizing cognitive effort” (Hoyer 1984, p. 823). If so, the consumer's knowledge about a product category allows him or her to minimize decision-making effort yet still derive a satisfactory amount of consumption utility. Greater knowledge can reduce the consumer's cognitive effort so far that the task “is performed automatically” (Alba and Hutchinson 1987, p. 412). Accordingly, a high amount of file sharing knowledge should allow consumers to obtain and watch illegal copies with limited cognitive effort. In addition, consumer file sharing knowledge relates negatively to search costs (part of transaction costs), because knowledge reduces the time and psychological effort needed to locate an illegal movie copy.

H8a: The consumer's file sharing knowledge correlates positively with the number of illegal movie copies a consumer obtains and the number of illegal copies she or he watches.

H8b: The consumer's file sharing knowledge correlates negatively with the search costs of the illegal copy.

2.4 Testing File Sharing Consequences

In this section, we test the hypotheses that address the consequences of movie file sharing (i.e., H1–H3) using data from a controlled longitudinal sample and ReLogit logistic regression.

2.4.1 Data Collection and Sample

Understanding the effect that movie file sharing has on commercial channel usage requires a controlled longitudinal study design, which avoids biases from a priori differences in movie consumption intentions between file sharers and non-file sharers as well as speculative ex-post “what-if” questions. We collected information from a quota sample of 1,075 German consumers, using gender, age, and occupation as quota criteria. The sample mirrors the German movie-going population in terms of key demographic variables and movie consumption (see Table 5). Respondents filled out three different Internet questionnaires over the course of eight months, for which they used personalized identification numbers, so that we could connect the information provided by a respondent at different points in time and avoid multiple responses on the same questionnaire from the same respondent. Respondents received a €10 present for completing all three questionnaires, and we also raffled off additional prizes to participants.

Table 5: Sample Characteristics

Criterion	Sample	German Movie Consumer Population ^b
<i>Gender (%)</i>		
Female	52.7	51
Male	47.1	49
<i>Age Groups (%)</i>		
≤ 29	57.1	52
30-39	20.9	20
40-49	8.9	14
≥ 50	13.1	14
<i>Occupation (%)</i>		
Student/in education	40.8	35
Worker	.7	7
Employee	40.1	36
Civil servant	5.5	6
Self-employed	6.1	3
Homemaker	2.7	3
Pensioner	1.4	10
Other	2.6	-
<i>Movie consumption (per year)</i>		
Theater visits	8.2 (6) ^a	5.2
DVD purchases	4.1 (1) ^a	5.2
DVD rentals	10.3 (5) ^a	11.1

^a Number in parentheses is the median.

^b Percentages are for 2003 (FFA 2004); more recent data are not available for individual categories.

We contacted participants first in February 2006 and asked about their intentions to watch between 10 and 15 new motion pictures in a movie theater or as an illegal copy. The movies were a subset of a total of 25 movie titles covering all major studio releases in Germany in the following months, with none of the movies having been available in theaters or on DVD at that point. Five of the movies were action films, five comedies, five dramas, five children's movies, and five thrillers (the individual titles appear in

Appendix C). Each respondent began by indicating his or her preferred genres and then answered questions with regard to the movies assigned to those genres. The maximum of 15 movies (i.e., three genres) per respondent prevents cognitive overload; we also set a minimum condition of 10 movies (i.e., two genres). Participants viewed a poster of each movie, information about the director and cast, and a short synopsis of the movie's content.

We then contacted the respondents for the second time in May 2006, after each surveyed movie had been theatrically released but before they were available on DVD for either purchase or rental. In the second questionnaire, we collected information about whether respondents had seen the surveyed movies in theaters and whether they had obtained and/or watched illegal copies of the movies. Respondents also indicated whether they intended to rent and/or buy certain movie titles on DVD after these DVDs would have become available, and whether they intended to watch illegal copies of the movies. For the second questionnaire, 813 panel members responded, a satisfactory retention rate of 76%.

Finally, we provided the third questionnaire in October 2006, when 18 of the 25 surveyed movies had been available on DVD for at least four weeks, which reflects the period when studios collect approximately two-thirds of a movie's eventual total DVD rental and sales revenues.⁹ This questionnaire mainly consisted of questions about respondents' rentals and purchases of the surveyed movies on DVD, and respondents

⁹ This estimate is based on proprietary information on the weekly revenue distribution of studio movies, which we collected from *Video Business Magazine* (weekly DVD rental revenues) and *Nielsen VideoScan* (DVD purchase revenues). Also see Figure 4.

again indicated whether they had obtained and/or watched illegal copies. For this third wave, 770 respondents completed the questionnaire, for a response rate, compared with the second questionnaire, of 94.7%.

2.4.2 Measures of File Sharing and Commercial Consumption

Because file sharing can be a delicate topic, we took thorough actions to ensure respondents provided valid information about their behavior. We personally promised and gave our word as representatives of the Bauhaus-University of Weimar and the University of Hamburg that all information would be treated strictly confidentially and not given to third parties. Moreover, we paid careful attention to the wording of the file sharing items and strictly avoided describing file sharing as an illegal or immoral activity.

To measure actual file sharing behavior, we asked each respondent in all three questionnaires whether he or she had (1) obtained a copy of the movie (“Have you obtained this movie as a free copy (either downloaded from file sharing networks or gained from friends or others)?”) and (2) watched the copy (“Have you watched this movie as a free copy (either downloaded from file sharing networks or gained from friends or others)?”).¹⁰ Responses were coded 0 = “no” and 1 = “yes” in both cases. Because each of the 813 respondents to the second questionnaire reported his or her file sharing behavior for 10–15 movie titles (average number of movies per respondent = 12.65), this sample contains information about $12.65 \times 813 = 10,285$ individual file

¹⁰ None of the surveyed movies was available free of charge in a *legal* channel when the data was collected.

sharing opportunities. Respondents' intentions to watch an illegal copy of a movie were measured by asking the question "Do you plan to watch this movie as a free copy (either downloaded from file sharing networks or gained from friends or others)?," using a six-point probability scale (1 = "definitely not," 6 = "definitely").

Consumers' intentions to watch a movie in a theater (first questionnaire), rent it on DVD, or buy it on DVD (both second questionnaire) employed the same six-point scale as consumers' file sharing intentions. Questions were "Do you plan to watch this movie in a movie theater?" "Do you plan to rent this movie on DVD?" and "Do you plan to buy this movie on DVD?" Finally, we asked respondents about their actual consumption of the surveyed movies in theaters, on rental DVD, and on retail DVD, which generated three binary variables (0 = "not consumed," 1 = "consumed").

2.4.3 Descriptive File Sharing Statistics

Regarding the 25 movies in our sample, 136 respondents (17%) had obtained at least one illegal copy before the movies were released on DVD, with 242 illegal movie copies having been obtained by that time (2.4% of all file sharing opportunities). Respondents had watched 165 (68%) of these copies. The maximum number of illegal movie copies obtained by a respondent before their DVD release was 8 (out of 15 surveyed movies). Respondents intended to watch an illegal copy in 21.1% of cases before the movie's theatrical release and in 13.1% of cases before the movie's DVD release (≥ 4 on the six-point file sharing intention scale).

After the movies had been released on DVD, 141 respondents (18.5%) had obtained at least one copy of a surveyed movie; overall, a total of 342 illegal movie copies had been obtained by the time of the third survey (4.8% of the 7,146 file sharing

opportunities), with 66% of those illegal copies having been watched. At this point, the maximum number of illegal movie copies obtained by individual respondents was 11.

2.4.4 Method

We take a binary logistic regression approach to test whether movie file sharing affects theater visits, DVD rentals, and DVD sales. In binary logistic regression, a dichotomous outcome variable Y (= the respondents' decision to see a movie in commercial channels) follows a Bernoulli probability function that takes a value of 1 with probability π and 0 with probability $1-\pi$, with π varying over the observations as an inverse logistic function of a constant and a set of explanatory variables. An often overlooked characteristic of logistic regression is that it is not invariant to the relative frequency of events in the data (i.e., cases in which $Y = 1$). This is particularly relevant when the number of 1s is small compared with the number of 0s. In this situation, the logistic regression function produces biased logit coefficients that underestimate rare events (i.e., the probability that $Y = 1$; King and Zeng 2001a). Because the number of cases in which consumers see a movie in a commercial channel clearly is smaller than the number of cases in which consumers do not, we apply ReLogit regression (King and Zeng 2001a; King and Zeng 2001b). ReLogit regression estimates the same model as a standard logistic regression but corrects for logit coefficient bias and therefore does not underestimate rare event probabilities (Imai, King, and Lau 2006). As an additional benefit, ReLogit also uses "prior correction," meaning that it corrects the estimates on the basis of existing information about the fraction of 1s in the population (τ) as part of the maximum likelihood estimation process (King and Zeng 2001a). Prior correction is appropriate for our data, because we asked consumers about movies in their preferred genres (instead of all movies), and the surveyed movies are primarily major studio

releases, so that $\pi > \tau$. We calculate the τ parameters on the basis of publicly available information, with $\tau_{\text{Theater}} = .0126$, $\tau_{\text{Rental}} = .0103$, and $\tau_{\text{Purchase}} = .0040$.¹¹

2.4.5 Theater-Related Results

To account for potential differences between consumers' obtaining and watching illegal copies, we run three ReLogit models to test the impact of illegal file sharing on movie theater visits. In each model, we include the respondents' intentions to watch an illegal copy of a movie (measured in the first questionnaire) and their actual file sharing behavior (dichotomous factor, measured in the second questionnaire) as regressors and actual theater-going behavior as the binary dependent variable. To rule out potential endogenous effects which have troubled previous research on file sharing, we exclude those cases in which theatrical consumption precedes file sharing ($n = 10$), taking advantage of our individual-level longitudinal empirical design (in contrast to the aggregate level, cross-sectional design of previous studies). As a result, the independent variables in our ReLogit analyses are unaffected by the dependent variable (i.e., the consumer's theater visit).¹² In the first model (the "overall model"), we set file sharing

¹¹ We calculate τ_{Theater} by dividing the number of theater visits in Germany in 2005 (127.3 million) by the product of the number of movies released in Germany (372) and the number of German movie consumers (27.2 million). This calculation provides the percentage of all movie-going decisions that lead to a theater visit. Analogously, we calculate τ_{Rental} based on 102.9 million rentals of current feature film DVDs and τ_{Purchase} based on 39.8 million new feature film DVDs sold, with 369 new feature film DVD releases in 2005. We obtain all data used to calculate the τ parameters from SPIO (2006) and BAM (2006). π_{Theater} is .083, π_{Rental} .063, and π_{Purchase} .013. In addition, we apply the Zelig version of ReLogit, which offers minor advantages over other versions.

¹² To provide empirical evidence for the absence of endogenous effects, we conduct the Durbin-Wu-Hausman augmented regression test for endogeneity (Davidson and MacKinnon 1993). Consistent with our theoretical argument, we find the error term of the file sharing regression to be clearly non-significant in the theater visits regression equations, which means that file sharing is indeed an exogenous variable as specified and that the results are unbiased by endogeneity. We conduct the same test for the DVD rental and DVD purchase equation and again find file sharing to be exogenous.

behavior to equal 1 when the respondent has obtained an illegal copy, regardless of whether he or she has watched the copy. In the second model, file sharing behavior is 1 only when the respondent has watched the copy (“watcher model”); in the third model, file sharing behavior equals 1 when the respondent has obtained but *not* watched the copy (“non-watcher model”).

In each model, we control for the impact of the respondents’ “true” intentions to watch the movie in a theater, that is, their theater-going intentions unaffected by file sharing. We correct theater-going intentions for a potential effect of file sharing by asking respondents who indicated at least a minimum of file sharing intentions (i.e., >1 on the six-point probability scale) about their movie-going intention if a copy were not to become available. We asked this question *before* the respondents had obtained a specific copy, so respondents were able to put themselves into the situation and make valid predictions. We use the original movie-going intention score when file sharing intentions were 1 (i.e., nonexistent).

We also control for several movie characteristics, namely, the number of screens on which a movie was released (a proxy for the studio’s marketing efforts; Hennig-Thurau, Houston, and Sridhar 2006), attendance in German theaters (a proxy for word of mouth; Elberse and Eliashberg 2003), and average user rating on the Internet Movie Database (IMDb; a proxy for the valence of word of mouth; Hennig-Thurau, Houston, and Sridhar 2006). We gathered the information for these variables for the surveyed movies from *Variety* magazine and IMDb, respectively.

We report the ReLogit results for the three theater models in Table 6. All models are highly significant and shed substantial light on consumers’ theater-going decisions (Nagelkerke $R^2 = .24$). With regard to file sharing intentions, we find a negative effect on theater visits (β s between $-.09$ and $-.10$, $\exp[\beta]$ around $.91$), which is significant at $p <$

.001 in all three models. That is, an increase in file sharing intentions reduces the probability that consumers see a movie in a theater and therefore cannibalizes industry revenues.

Table 6: ReLogit Results

	Movie Theater ReLogit Model (n = 10,285)*						DVD Rental ReLogit Model (n = 7,130)**						DVD Purchase ReLogit Model (n = 7,146)***					
	Overall Model ^a		Watcher Model ^b		Non-Watcher Model ^c		Overall Model ^a		Watcher Model ^b		Non-Watcher Model ^c		Overall Model ^a		Watcher Model ^b		Non-Watcher Model ^c	
	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)	β (exp[β])	z-value (p)
Intercept	-9.57 (.912)	-27.47 ($<.001$)	-9.56 (.911)	-27.46 ($<.001$)	-9.55 (.905)	-27.43 ($<.001$)	-8.02 (.885)	-14.40 ($<.01$)	-8.01 (.881)	-14.38 ($<.01$)	-8.02 (.889)	-14.38 ($<.01$)	-8.54 (.815)	-7.82 ($<.05$)	-8.51 (.830)	-7.80 ($<.05$)	-8.613 (.805)	-7.88 ($<.05$)
File sharing intentions	-.0926 (.912)	-3.52 ($<.001$)	-.0935 (.911)	-3.57 ($<.001$)	-.0997 (.905)	-3.81 ($<.001$)	-.122 (.885)	-2.91 ($<.01$)	-.127 (.881)	-3.05 ($<.01$)	-.118 (.889)	-2.83 ($<.01$)	-.204 (.815)	-2.17 ($<.05$)	-.186 (.830)	-1.99 ($<.05$)	-.217 (.805)	-2.31 ($<.05$)
File sharing behavior	-.563 (.569)	-1.93 (.053)	-.815 (.443)	-2.09 ($<.05$)	-.0488 (.953)	-.11 (.911)	-.130 (.878)	-.36 (.720)	.465 (1.592)	1.11 (.268)	-.885 (.413)	-1.21 (.226)	1.15 (3.158)	2.42 ($<.05$)	.336 (1.399)	.43 (.667)	2.074 (7.957)	3.70 ($<.001$)
Screens (in 100)	.153 (1.165)	5.94 ($<.001$)	.152 (1.164)	5.90 ($<.001$)	.151 (1.163)	5.87 ($<.001$)	.073 (1.076)	1.06 (.290)	.073 (1.076)	1.06 (.291)	.070 (1.073)	1.02 (.309)	.289 (1.335)	1.90 (.057)	.280 (1.323)	1.85 (.065)	.281 (1.324)	1.86 (.063)
Attendance (in 1000)	.0001 (1.0001)	3.10 ($<.01$)	.0001 (1.0001)	3.14 ($<.01$)	.0001 (1.0001)	3.13 ($<.01$)	.00003 (1.000)	.13 (.893)	.00003 (1.000)	.12 (.903)	.00004 (1.000)	.19 (.852)	-.0009 (.999)	-1.79 (.074)	-.0009 (.999)	-1.71 (.087)	-.0009 (.999)	-1.72 (.086)
IMDb user rating	.347 (1.415)	7.95 ($<.001$)	.346 (1.413)	7.94 ($<.001$)	.346 (1.413)	7.94 ($<.001$)	.133 (1.142)	2.15 ($<.05$)	.132 (1.141)	2.14 ($<.05$)	.132 (1.141)	2.13 ($<.05$)	.078 (1.081)	.66 (.512)	.073 (1.076)	.62 (.536)	.082 (1.085)	.70 (.486)
Corrected theater intentions	.629 (1.88)	20.90 ($<.001$)	.629 (1.88)	20.90 ($<.001$)	.628 (1.87)	20.89 ($<.001$)	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.
Corrected DVD rental intentions	n.i.		n.i.		n.i.		.752 (2.121)	17.78 ($<.001$)	.752 (2.121)	17.78 ($<.001$)	.753 (2.123)	17.79 ($<.001$)	n.i.	n.i.	n.i.	n.i.	n.i.	n.i.
Corrected DVD purchase intentions	n.i.		n.i.		n.i.		n.i.	n.i.	n.i.	n.i.	n.i.	n.i.	1.004 (2.729)	12.12 ($<.001$)	1.012 (2.751)	12.17 ($<.001$)	1.027 (2.793)	12.29 ($<.001$)
Theater visit	n.i.		n.i.		n.i.		-.311 (.733)	-1.43 (.152)	-.298 (.742)	-1.38 (.169)	-.319 (.727)	-1.47 (.141)	.095 (1.100)	.28 (.780)	.055 (1.057)	.16 (.871)	.050 (1.051)	.15 (.882)
Log-Likelihood	4557.7		4556.2		4562.4		2454.1		2453.5		2451.1		652.5		656.7		648.5	
Chi-square (d.f.)	1089.2 (6), p $<.001$		1090.7 (6), p $<.001$		1084.5 (6), p $<.001$		387.3 (7), p $<.001$		397.9 (7), p $<.001$		400.3 (7), p $<.001$		171.2 (7), p $<.001$		167.0 (7), p $<.001$		175.1 (7), p $<.001$	
McFadden R ²	.193		.193		.192		.139		.140		.140		.208		.203		.213	
Nagelkerke R ²	.238		.238		.237		.164		.165		.166		.217		.212		.222	

* Dependent variable is actual movie theater visits (0 = no, 1 = yes). ** Dependent variable is actual DVD rental behavior (0 = no, 1 = yes). *** Dependent variable is actual DVD purchasing behavior (0 = no, 1 = yes). Notes: n.i. = variable not included in this model. ^a File sharing behavior = 1 for all cases in which the respondent obtained a copy, regardless of watching. ^b File sharing behavior = 1 when copy is obtained *and* watched. ^c File sharing behavior = 1 when copy is obtained but *not* watched.

With regard to consumers' actual file sharing behavior, the results are less clear. In the overall model, the null hypothesis that obtaining an illegal copy does not affect the probability that a consumer watches a movie in the theater cannot be rejected at the conventional $p = .05$ level. However, at $p = .053$, the risk of wrongly rejecting the null hypothesis is only slightly higher than the traditional cutoff. In the watcher model, the impact of actual file sharing behavior is significant, i.e. we find a negative effect of actual file sharing behavior on theater visits ($\beta = -.82$, $\exp[\beta] = .44$). Therefore, when a consumer watches a copy, the probability that he or she will watch the same movie in a theater declines for a given level of file sharing intentions. Finally, in the non-watcher model, the impact of actual file sharing behavior (i.e., obtaining, but not watching a copy) is insignificant ($p = .91$), with an $\exp[\beta]$ very close to 1.

These findings suggest that, in addition to the consumer's intention to watch an illegal copy, the act of watching the copy is crucial for the impact of file sharing behavior. Altogether, our data support H1a (which proposes a negative effect of file sharing intentions on theater visits) and H3a (which proposes the same effect for watching illegal copies), and the error associated with not rejecting H2a (which suspects theater visits to be hurt by consumers' obtainment of illegal copies) is only slightly greater than .05. On a side note, the corrected theater-going intentions and three movie characteristics all have the expected significant effects; they increase the probability that a consumer actually decides to see a movie in a theater.

The ReLogit results enable us to speculate about the strength of the effect that file sharing has on theater visits at the overall industry level. In a fictitious situation in which

no actual file sharing takes place (though consumers still have file sharing intentions), the number of theater visits would increase by 1.2% (from 127.5 million to 129 million visits), generating \$11.7 million in additional revenues.¹³ When actual file sharing is absent and file sharing intentions are minimal, revenues would increase by 12.6% or \$123.1 million compared with the current situation.¹⁴ Although these predictions are restricted by some methodological assumptions, the estimated losses are, by any measure, substantial.

2.4.6 DVD-Related Results

Our approach with regard to DVD rentals and sales is similar to that for theater visits. For each DVD channel, we run three ReLogit models that include respondents' intentions to watch an illegal copy of a movie (second questionnaire) and actual file sharing behavior (binary variable, third questionnaire) as regressors and actual DVD rental or purchase behavior as the binary dependent variable. Again, we exclude those cases in which respondents had consumed a movie on DVD prior to having obtained the illegal copy to rule out a potential endogeneity bias. We again distinguish an overall model, a watcher model, and a non-watcher model for both DVD channels.

¹³ Specifically, we calculate the change in channel revenues $\Delta REV_{theaters}$ as $\Delta REV_{theaters} = (\tau_{theaters}^{est} \cdot mov_{theaters} \cdot mc) - (\tau_{theaters}^{actual} \cdot mov_{theaters} \cdot mc)$, where $\tau_{theaters}^{actual}$ is the actual event probability of a consumer seeing a movie in a theater, $mov_{theaters}$ is the number of movies released in theaters in a specific year, mc is the number of movie consumers in a population, and $\tau_{theaters}^{est}$ is the event probability calculated by the ReLogit function for actual file sharing behavior ($= 0$). To apply monetary values to industry losses, we use the average 2005 ticket price in Germany.

¹⁴ We use the same equation as in footnote 13, with file sharing intentions set to 1.

In each model, we control for the impact of the respondents' intentions to rent a specific movie on DVD (in the model with DVD rental as dependent variable) or to buy a specific movie on DVD (in the model with DVD purchase as dependent variable), respectively. We correct these variables for the potential effect of file sharing with the same approach as we used for theater visits. In addition, we again control for the movie characteristics of screens, attendance, and user ratings, as well as for whether the respondents had seen the movie in a theater (binary variable).

The ReLogit results for all DVD rentals and purchase models appear in Table 6. As with theater visits, all DVD models are highly significant. The explained variance is slightly lower for DVD rentals (Nagelkerke $R^2 = .16/.17$) than for DVD purchases (Nagelkerke $R^2 = .21$), consistent with the lower cognitive preparation usually associated with rental decisions (Weinberg 2003).¹⁵ For file sharing intentions, we find significant negative effects on both DVD rentals and purchases in all models, with β s between $-.12$ and $-.13$ for rentals ($\exp[\beta]$ approximately $.89$) and between $-.19$ and $-.22$ for purchases ($\exp[\beta]$ approximately $.81$).

The results are less straightforward for actual file sharing behavior. Specifically, file sharing behavior exerts *no* significant effect on DVD rentals in all three DVD rental models. However, we find a significant impact on DVD purchases in both the overall model and the non-watcher model, though not in the watcher model. This significant impact is positive, such that greater file sharing behavior increases the number of DVDs purchased. These findings suggest that when consumers gain access to a movie copy

¹⁵ Weinberg (2003, p. 24) reports that 50% of video renters in his sample "did not have a specific title in mind when they entered the store."

(with a control for file sharing intentions) but do not watch it, their probability of purchasing the DVD is higher than it is for consumers who have not obtained an illegal copy. In such cases, the copy does not serve as a substitute for the DVD but rather stimulates consumers' desire to see the movie in a legal channel.

In summary, we find support for H1b and H1c (which state file sharing intentions to diminish DVD rentals and purchases), but neither for H2b and H2c,(which posit a negative effect of obtaining illegal copies on the two DVD channels) nor for H3b, or H3c (which argue that the watching of copies cannibalizes DVD rentals and purchases). In the case of H2c, we even find a significant positive effect instead of the proposed negative effect. As an aside, the three movie characteristics play lesser roles for DVD consumption than in the theater channel. Although in the DVD rental context, the user rating positively influences decisions to rent a specific movie on DVD, screens and theater attendance are not significant; for DVD purchase decisions, none of the movie characteristics is significant. A likely explanation is that once movies have appeared in theaters, extensive quality-related information becomes available, which is then incorporated into the consumers' intention to rent or purchase the movie on DVD.

As in the case of theater visits, we use the ReLogit estimations to speculate about the strength of the industry-wide effect of movie file sharing on DVD rentals and purchases.¹⁶ In a fictitious constellation without any illegal movie copies (but file sharing intentions remaining unchanged), DVD rentals would increase by only 0.1% (from 103.4 million to 103.5 million transactions), producing approximately \$0.5 million of

¹⁶ When calculating the industry-wide effect of file sharing on DVD rentals and purchases, we use the same approach as in the case of theater visits (see footnotes 13 and 14).

additional revenue. The positive effect of actual file sharing on DVD purchases means purchases would be 2.9% lower in such an environment (from 40.1 million to 38.9 million), resulting in industry losses of \$27.6 million. However, and more importantly, when file sharing behavior and intentions do not exist or are minimal, DVD rental transactions grow by 10.5%, generating additional revenues of \$36.9 million for the industry, and DVD purchase revenues would be boosted by \$139.5 million, or 14.7%. Accordingly, these numbers indicate that the losses caused by movie file sharing are even greater for the home entertainment channels than for the theatrical channel. Altogether, our calculations suggest that the German movie industry loses \$300 million per year due to consumer file sharing.

2.5 Testing File Sharing Determinants

2.5.1 Data, Method, and Measures

In this section, we test the hypotheses that address the determinants of consumer file sharing (i.e., H4–H8) using data collected from our quota panel sample. Specifically, the second questionnaire contained several questions pertaining to the constructs we propose influence consumer file sharing. In addition, we collect information about respondents' general file sharing behavior (i.e., not limited to the 25 movies in our sample) by asking about the absolute number of illegal movie copies they had obtained and watched during the preceding 12 months in both the first and second questionnaires.

We apply partial least squares structural equation modeling (PLS; Fornell and Cha 1994) to test the determinants hypotheses. Specifically, we employ SmartPLS (Ringle, Wende, and Will 2005), which allows the simultaneous testing of hypotheses while enabling single- and multi-item measurement and the use of both reflective and formative scales (Fornell and Bookstein 1982). The structural model shown in Figure 7 contains

three latent variables for the different facets of the original movie's utility (gross utility, price, and transaction costs), four latent variables to address the different kinds of transaction costs associated with the copy (search, moral, legal, and technical costs), and one latent variable for each of the six specific utilities of the copy (transaction, mobility, storage, collecting, anti-industry, and social utility). The model also contains the degree of substitution and the consumer's file sharing knowledge as determinants of watching and obtaining illegal copies, and links from obtaining to watching illegal copies and from file sharing knowledge to search costs.

We measure both obtaining and watching illegal copies with reflective, three-item scales that combine respondents' actual file sharing behavior with regard to the movies in our study with two more global measures. Specifically, we measured the obtainment of illegal movie copies as the number of copies of surveyed movies the consumer had actually obtained, the total number of illegal copies obtained within the year preceding the first questionnaire, and the answer to the same question from the second questionnaire. For watching illegal movie copies, we used the number of surveyed movies a respondent watched as illegal copies and the total number of watched illegal copies within the 12 months preceding the first and the second questionnaire, respectively. To measure file sharing determinants, we use existing scales when available and develop new scales for the rest, most of which take a formative nature. Except for the six specific utility variables, which we measure with one item each due to space restrictions, we use multiple items for all constructs (see Appendix D).

The reliability of the reflective scales is generally satisfactory. Obtainment and watching of illegal copies achieve alpha scores of .72 and .67, respectively, acceptable for a combination of surveyed and general past behavior, as well as the lack of established scales in the researched domain (Peter 1979). On the other reflective scales,

the alpha scores are greater than .70 in all cases. The average variance extracted is greater than .60 and composite reliability greater than .75 for all constructs.

Multicollinearity between the constructs is not an issue; all correlations among latent variables are less than or equal to .50. Table 7 lists the descriptive statistics and correlations.

Table 7: Descriptive Statistics and Correlations

	M ^a	SD ^a	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
1 Obtainment of illegal movie copies	14.04	29.76	.72																
2 Substitute	11.40	3.85	.16	n.a.															
3 Gross utility (OR)	25.35	7.75	-.14	-.07	n.a.														
4 File sharing knowledge	16.14	10.68	.31	-.00	-.15	n.a.													
5 Watching illegal movie copies	11.82	21.43	.89	.19	-.11	.29	.67												
6 Price (OR)	24.79	9.26	.09	-.10	.13	.09	.09	n.a.											
7 Transaction costs (OR)	18.78	11.49	.12	.07	-.01	-.04	.11	.08	n.a.										
8 Moral costs (CO)	11.18	3.76	-.12	-.05	.07	-.06	-.12	.05	-.01	.84									
9 Legal costs (CO)	7.56	2.49	.03	.06	-.02	-.01	.01	.06	-.00	.28	.71								
10 Technical costs (CO)	6.34	2.93	-.11	-.02	.11	-.25	-.14	-.03	-.02	.32	.34	.86							
11 Search costs (CO)	8.22	6.57	-.16	-.00	.16	-.24	-.15	-.04	.05	.22	.12	.33	n.a.						
12 Transaction utility (CO)	3.15	1.77	.17	.29	-.03	.13	.19	.05	.09	-.07	.02	-.01	-.05	n.a.					
13 Collection utility (CO)	1.53	1.00	.32	.25	-.06	.26	.29	.02	.05	-.05	.01	-.08	-.12	.22	n.a.				
14 Anti-industry utility (CO)	1.53	1.07	.22	.02	-.12	.30	.21	.06	.06	-.04	.02	.05	-.06	.21	.18	n.a.			
15 Storage utility (CO)	2.09	1.51	.24	.13	-.08	.33	.25	.04	.03	-.02	.10	-.06	-.09	.30	.34	.28	n.a.		
16 Social utility (CO)	1.41	.87	.24	.10	-.01	.25	.21	.01	.06	.04	.10	.10	.01	.29	.28	.42	.39	n.a.	
17 Mobility utility (CO)	2.65	1.81	.21	.14	-.07	.31	.23	.04	.01	-.01	.06	-.05	-.17	.29	.33	.26	.50	.30	n.a.

Numbers on the diagonal are Cronbach's alpha scores. n.a. = no alpha score calculated because the construct is measured by a formative scale or single item. CO = illegal movie copy; OR = original movie.

^a Means and standard deviations are calculated for the sum of construct items.

2.5.2 Results

We list the path coefficients, *t*-values, and total effects in Table 4. The model explains 22.1% of obtainment and 79.6% of watching illegal movie copies. In each of the five general driver categories, at least one construct has a significant direct effect on obtainment ($p < .05$), in support of our determinants hypotheses. In addition, except for gross utility of the movie original (which is negatively correlated with obtainment, instead of positively as hypothesized in H5a), all significant parameters are in the proposed directions, in general support of our hypotheses.

Table 8: Impact of Determinants of File Sharing Behavior

Effect of	On	Path Coefficient (<i>t</i> -Value)	Total Effect (<i>t</i> -Value)
<i>Utility of the original</i>			
Gross utility (OR)	Obtainment of illegal movie copies	-.071 (1.84)*	-.071 (1.84)*
Price (OR)	Obtainment of illegal movie copies	.075 (1.06)	.075 (1.06)
Transaction costs (OR)	Obtainment of illegal movie copies	.100 (2.03)**	.100 (2.03)**
Gross utility (OR)	Watching illegal movie copies	.012 (.82)	-.0503 (1.29)
Price (OR)	Watching illegal movie copies	.009 (.03)	.075 (1.02)
Transaction costs (OR)	Watching illegal movie copies	-.009 (.41)	.079 (1.68)*
<i>Costs of the illegal copy</i>			
Search costs (CO)	Obtainment of illegal movie copies	-.063 (1.79)*	-.063 (1.79)*
Moral costs (CO)	Obtainment of illegal movie copies	-.087 (2.62)**	-.087 (2.62)**
Legal costs (CO)	Obtainment of illegal movie copies	.044 (1.00)	.044 (1.00)
Technical costs (CO)	Obtainment of illegal movie copies	-.019 (.57)	-.019 (.57)
Search costs (CO)	Watching illegal movie copies	.015 (.82)	-.040 (1.15)
Moral costs (CO)	Watching illegal movie copies	.007 (.41)	-.069 (2.14)**
Legal costs (CO)	Watching illegal movie copies	-.016 (.80)	.022 (.50)
Technical costs (CO)	Watching illegal movie copies	-.040 (2.00)**	-.056 (1.78)*
<i>Degree of substitution</i>			
Substitute	Obtainment of illegal movie copies	.089 (2.66)**	.089 (2.66)**
Substitute	Watching illegal movie copies	.040 (2.16)**	.120 (4.01)**
<i>Specific utility of the illegal copy</i>			
Transaction utility (CO)	Obtainment of illegal movie copies	.012 (.34)	.012 (.34)
Collection utility (CO)	Obtainment of illegal movie copies	.178 (2.90)**	.178 (2.90)**
Mobility utility (CO)	Obtainment of illegal movie copies	-.002 (.04)	-.002 (.04)
Storage utility (CO)	Obtainment of illegal movie copies	.035 (.78)	.035 (.78)
Anti-industry utility (CO)	Obtainment of illegal movie copies	.064 (1.70)*	.064 (1.70)*
Social utility (CO)	Obtainment of illegal movie copies	.085 (1.46)	.085 (1.46)
Transaction utility (CO)	Watching illegal movie copies	.019 (.93)	.030 (.80)
Collection utility (CO)	Watching illegal movie copies	-.018 (.69)	.138 (2.07)**
Mobility utility (CO)	Watching illegal movie copies	.036 (1.56)	.035 (.92)
Storage utility (CO)	Watching illegal movie copies	.029 (1.39)	.060 (1.32)
Anti-industry utility (CO)	Watching illegal movie copies	.010 (.52)	.066 (1.73)*
Social utility (CO)	Watching illegal movie copies	-.022 (.90)	.053 (.97)
<i>File sharing knowledge</i>			
File sharing knowledge	Obtainment of illegal movie copies	.172 (4.83)**	.187 (5.28)**
File sharing knowledge	Watching illegal movie copies	-.003 (.17)	.156 (4.60)**
File sharing knowledge	Search costs (CO)	-.236 (2.12)**	-.236 (2.12)**
<i>Additional path</i>			
Obtainment of illegal movie copies	Watching illegal movie copies	.875 (26.27)**	.875 (26.27)**

Notes: OR = original commercial movie consumption, CO = illegal movie copy. *T*-values are calculated through a bootstrapping routine with 813 cases and 500 samples.

* $p < .05$ (one-sided).

** $p < .01$ (one-sided).

8 of the 15 determinant constructs in the model have significant impacts.

Specifically, as we propose in H4, the degree of substitution between illegal copies and movie originals increases both obtainment and watching of illegal copies. Regarding the utility of the original, we find that the original's transaction costs raise the extent of obtainment, as proposed in H5b, in addition to the negative effect of the original's gross utility mentioned above. The latter effect might result from the lower reference point for the utility of the original for consumers who possess more file sharing knowledge. In other words, file sharing skills might reduce the utility consumers derive from seeing a movie in a commercial channel, because they know how to get the same movie free of charge. In support of this argument, when we add a path from file sharing knowledge to gross utility, the path from gross utility to file sharing becomes insignificant.

With regard to the transaction costs of the copy, three individual drivers are significantly correlated with file sharing, in support of H6. Whereas both search and moral costs provide hurdles to the consumer obtaining illegal copies, technical costs directly reduce the probability that a customer watches such copies. Two specific utilities of the copy enhance obtainment: perceptions of illegal movie copies as collectibles (the strongest direct effect of all determinants) and the consumer's anti-industry attitude, which makes file sharing a kind of revenge action. These findings support H7. The consumers' file sharing knowledge facilitates obtainment of illegal copies directly, as well as by lowering search costs, as we hypothesize in H8a and H8b.

As we expected, watching illegal movie copies correlates strongly with the extent of obtainment. Except for technical costs and degree of substitution, which also exhibit significant direct paths to watching illegal movie copies, all determinant constructs in the model influence illegal watching not directly but only through obtainment, which serves as a full mediator.

2.6 Discussion, Implications, and Limitations

Massive speculation about the potential impact of consumer file sharing of motion pictures swirls around the movie industry. Although industry representatives claim illegal movie copies cause revenue losses, no peer-reviewed study has yet tested these claims. Existing research findings from adjacent industries such as music have been inconclusive, with all previous studies either lacking empirical data or using questionable proxies for file sharing, such as consumers' Internet usage. Drawing on a longitudinal quota sample of German consumers, we use information about consumers' file sharing intentions and behavior toward a set of actual movie titles and thereby test for the impact of movie file sharing on movie consumption in commercial channels. The controlled longitudinal design avoids biases from a priori differences between file sharers and non-file sharers. It also enables us to correct our measures of legal movie consumption intentions for potential biases caused by the availability of illegal movie copies, so that our estimates are unbiased by potentially unreliable "hindsight measures." In addition, ours is the first study to test a theory-based model of file sharing determinants in a motion picture context and significantly extends current knowledge about the drivers of consumer file sharing.

To determine the potential impact of file sharing on commercial channel consumption, we use ReLogit analysis, which corrects for logit coefficient bias, and find among our sample of 813 German consumers that illegal file sharing hurts theatrical box office revenues. The consumers' intentions to view an illegal copy of a new movie reduces consumers propensity to attend theaters. This finding suggests that file sharing intentions (which imply the consumer's expectation of being able to obtain a copy of a certain movie for free) limit the consumer's interest in legal channel consumption, which then leads him or her to forego consumption in these channels regardless of whether the consumer actually obtains an illegal copy of the movie. We find that obtaining an illegal movie copy

(controlling for file sharing intentions) significantly impacts legal consumption only when the consumer has actually watched the copy. In addition, consumers' intentions to watch a movie copy significantly reduce the number of DVD rentals and purchases. Obtainment of illegal copies does not affect rental transactions and exerts a positive impact on DVD purchases when the consumer has not watched the copy. The latter effect means that an illegal movie copy can function as a cue for purchasing the DVD of a movie. In cases where the copy obtained by the consumer is broken or of a low quality, it can be argued that the consumer's positive anticipation of watching the movie is re-routed into a purchasing act. If the copy is working, the mere presence and resulting salience of the copy seems to heighten the consumer's emotional and intellectual involvement with the movie title, which subsequently stimulates the consumer to purchase the DVD of the movie (i.e., to "go for the original"). However, the positive impact of obtainment on DVD purchases is clearly less strong than the negative impact of file sharing intentions. We calculate an overall annual industry loss of \$300 million in Germany, which represents approximately 9.4% of the total industry revenues in 2005. Even when taking into account the assumptions of our method and sample, we consider these numbers substantial.

Three major implications arise from these results. First, the movie industry is right to proclaim that consumer file sharing destroys a significant amount of its revenues. Second, consumers' intentions to engage in file sharing cause them to forgo theater visits, legal DVD rentals, or legal DVD purchases. Therefore, decreasing consumers' intention to watch illegal movie copies may be the most powerful way to fight movie piracy. A reduction in the number of illegal copies would have a much lesser (or even no) impact on piracy, as long as intentions remain unaffected. Third, though our nationwide estimates represent bold numbers, they also demonstrate that recent industry claims exaggerate the true impact of file sharing. Some industry representatives argue that each illegal copy represents a lost theater

visit (Valenti 2004)—an effect more than twice that of our ReLogit-based estimate.

Similarly, the MPAA recently reported that industry losses due to piracy are \$491 million in Germany per year (MPAA 2006a), exceeding our controlled longitudinal estimate by 73%.

We also can offer insight into the role of file sharing by comparing our loss estimates with the industry's overall economic development. Specifically, German theatrical revenues declined by 16.6% in 2005, which exceeds our 12.6% loss estimate for theater revenues and thereby suggests other factors are contributing to the movie industry's crisis. This suggestion becomes even more persuasive when considering that movie file sharing grew by only 15.5% in 2005 (FFA 2006a), so it logically should be responsible for only a small portion of the 2005 revenue decline. Assigning file sharing the role of the leading culprit might mean overlooking other threats of similar or even larger proportions. The declared "war on movie piracy" might limit the industry's ability to cope with, and draw its attention away from, societal developments, such as massive increases in consumer spending on video/computer games and cell phones. Consumers clearly have increased spending on home video titles; DVD sales grew by double-digit figures to record numbers (Snyder 2005b), and a substitution effect is likely between theater visits and alternative kinds of movie consumption (Lehmann and Weinberg 2000). Therefore, movie studios might be contributing to shrinking attendance figures themselves by promoting other distribution channels such as DVD sales and legal online services.

With regard to the determinants of illegal consumer file sharing, we adapt the utility-theoretic approach of Rochelandet and Le Guel (2005) and identify five categories of potential influencers. This approach clarifies file sharing and moves beyond the simplistic explanation, "because it's free" (e.g., MPAA 2004c). With our quota sample of 813 consumers, we test the impact of these drivers and their associated variables simultaneously through PLS. Our model explains more than twice the amount of variance of obtaining

illegal copies than that achieved by previous studies (Rochelandet and Le Guel 2005). The PLS results highlight that each driver category contributes to consumer file sharing, though to differing extents. The three drivers that exert the strongest direct impact are the collecting utility of the copy, consumers' file sharing knowledge, and transaction costs of the original; we present the first two drivers for the first time here.

Our analysis also shows that file sharing occurs because of various factors, several of which offer antipiracy organizations very specific starting points for countermeasures. Specifically, stressing the unethical element of appropriating copyrighted content without compensating the copyright owner in marketing campaigns could increase the moral costs of illegal file sharing and lower file sharing activities. Similarly, because the transaction costs of commercial channels motivate consumer file sharing, movie producers should think about ways to reduce them. When watching a movie in theaters during its opening weekend is the only way to access a new movie legally, customers must pay the accompanying transaction costs that go far beyond the ticket price (e.g., babysitters and concession prices can make a single movie easily cost \$50; Puig 2005) and therefore feel pushed toward illegal channels such as file sharing. Making movies available through new channels, such as video-on-demand, that involve lower transaction costs for the consumers and shortening the time gap between the theater and home entertainment channels might be an appropriate way to win back transaction cost-sensitive consumers. However, this strategy could cause other problems, such as increased interchannel cannibalization (Lehmann and Weinberg 2000). Yet another starting point for reducing file sharing considers the degree of substitution perceived by the customer. Although substitutability lies in the eye of the beholder, studios may want to stress the uniqueness of legal movie consumption or add features and elements to legal movie consumption that can hardly be included in illegal copies. Such elements might include events in the theater that stress the social element of movie-going or attractive

packaging of movies on DVD. The latter seems particularly relevant, because it would reduce the relative collector value of illegal copies, the main single driver of movie file sharing.

However, other measures will be less effective for reducing movie piracy, particularly if they focus on legal costs (i.e., the consumer's fear of legal persecution). Such actions appear largely ineffective for limiting file sharing; we find no significant impact of legal costs on obtaining illegal copies in our PLS analysis, despite the intimidation studios have attempted to exert on file sharers in recent campaigns. In other words, the movie industry's initial reaction to the threat of movie file sharing—suing its own customers—appears to be misguided.

As with every study, our results are limited to a certain extent. First, our analysis uses a set of 25 movies from 2006 to test the effects of file sharing on commercial consumption and investigate its drivers. Because this set represents a snapshot, it is unclear how the results might differ for different movies and a different time frame. However, our sample covers all major pictures released in the time period, which gives us confidence that the results are stable. Second, in terms of generalization, our sample covers respondents from Germany, a major international market, but we can only speculate about other markets, such as North America. Because Germany and North America are similar in terms of several facets of movie consumption (e.g., U.S. films achieve a market share of 80% in Germany, movies' successes are highly correlated in the two countries, comparable Internet diffusion rates), we expect the findings to be similar for North America but cannot provide empirical evidence to substantiate this. Similarly, though we provide strong evidence of cannibalization by illegal copies, and though the similarities between movies and other entertainment products suggest the same effects to take place in those industries, our study cannot ensure cross-industry generalizations. Third, though our sample systematically

mirrors the German movie consumer population in demographics, we concede it is not a true random sample. However, post hoc comparisons show that other criteria, such as movie consumption patterns, are similar between the sample and the relevant population. Fourth, our measurement approach enables us to separate the effects of consumer file sharing intentions and behaviors on movie consumption on the basis of a controlled longitudinal study, but the survey method means we must rely on consumer self-reported data instead of on “objective” data. We believe this limitation does not strongly affect the results though, because we use actual movie titles, measure specific behavioral variables, and avoid any kind of moral bias in the questionnaires. Fifth, we acknowledge that the consumer x movie observations in our data are not completely independent, which, however, reflects reality as some consumers will watch several movies in a given period while other consumers will watch only one. Sixth and final, we had to develop several scales ourselves because of the limited extant research on movie file sharing. Although these scales indicate solid reliability and validity, further research into their quality would certainly be helpful. This recommendation is particularly applicable to those determinant variables that we measure using single items.

3 Augmenting the Expectancy-Value Model with a Dimensional Model of Emotion: Does It Matter if the Product Is Hedonic or Utilitarian?

3.1 Introduction

Ever since its inception, the “information processing view” has been the predominant paradigm of consumer behavior research (Bagozzi, Gürhan-Canli, & Priester, 2002). This paradigm, which originated with Howard and Sheth’s (1969) model of bounded rationality and the expectancy-value models developed by Edwards (1954) and Fishbein and Ajzen (1975), mainly regards consumers as logical problem solvers and “thinking machines” (Shiv & Fedorikhin, 1999, p. 290). Prominent researchers now increasingly contend that the information processing paradigm paints an incomplete picture of consumer decision making. Although it can explain and predict the consumption of functional, utilitarian goods, its adequacy for hedonic consumption decisions, in which “less experience is available, where the problem is not well-structured, and where emotional reactions are important” (Phillips, Olsen, & Baumgartner, 1995, p. 284; see also Hirschman & Holbrook, 1982), appears questionable.

In turn, the role of affect¹⁷ has become a central research topic in consumer research in the past decade (Cohen, Pham, & Andrade, 2008). Studies document apparent aberrations

¹⁷ Regarding the terms affect, emotion, and mood, often used interchangeably, we follow the definitions offered by Ekman and Davidson (1994), according to which affect is an umbrella concept that encompasses both emotions and moods. Moods are longer lasting, less intense, and less directly coupled with action tendencies than are emotions; emotions typically are intentional (meaning that they have a specific referent object) whereas moods are generally non-intentional, global, and diffuse.

from rational expectancy-value decision making, such as preference reversals when focusing on anticipated emotions instead of focusing on product attributes (Caruso & Shafir, 2006; Shiv & Huber, 2000), the reliance on affect versus cognition under processing constraints (Shiv & Fedorikhin, 1999), the impact of body feedback, meta-cognitive feelings and moods on choice (Förster, 2004; Lee, 2004; Pham, 2004; Schwarz, 2004), or the importance of contextual factors in determining affect and preferences (Bateman, Dent, Peters, Slovic, & Starmer, 2007; Simonsohn, 2007).

As happens in most new research streams though, there have been setbacks too. The proliferation of research on seemingly contextual affective influences on behavior and the limited integration of new findings into established information processing frameworks have led to growing concerns among decision-making researchers. Such concerns have prompted questions such as the one cited by Schwarz (2006, p. 20): “Whatever happened to Fishbein and Ajzen’s theory of rational behavior and other such models? All we hear about from psychologists these days is how funny little things make people feel one way or another, influencing what they like and do.”

This research attempts to address such concern by assessing the compatibility of the flourishing emotion research stream with cognitively dominated attitude-theory decision making models. The manuscript begins with a theoretical discussion of whether Fishbein and Ajzen’s (1975) expectancy-value model (EVM) of attitude, “the most widely applied representation of attitude across many disciplines” (Bagozzi et al., 2002, p. 7), is sufficient to capture the influence of emotion on decision making. Then, the EVM is augmented with anticipatory and anticipated emotion constructs (Bagozzi, Baumgartner, Pieters, & Zeelenberg, 2000), drawing on Larsen and Diener’s (1992) circumplex model of emotion. With a controlled experiment involving 308 college students faced with actual purchase decisions, the authors test whether the augmented EVM performs better than the traditional

EVM in predicting overall evaluations and attitudes, purchase intentions, and actual behavior, using a series of multistage linear and logistic regressions. This analysis is performed for the consumption of both hedonic and utilitarian products and test for differences between these two consumption contexts. Finally, the results are discussed and implications for researchers are offered.

3.2 The Link between the Expectancy-Value Model and Emotion in Extant Research

3.2.1 The Influence of the Expectancy-Value Model

Using economic theories of rationality and utility as a foundation, Edwards (1954) introduced expectancy-value models to psychological literature. According to his theory of subjective expected utility, the likelihood of an event's occurrence when an action is taken is the subjective probability SP of an outcome, and the desirability of this outcome is its subjective utility U . The product of subjective probability and desirability equals the subjective expected utility SEU from the action:

$$(3) \quad SEU = \sum_{i=1}^n SP_i U_i$$

In the realm of social psychology, Fishbein (1967) adapted this expectancy-value model to form the backbone of his theory of reasoned action. In Fishbein's variant - today considered "the most widely applied representation of attitude across many disciplines" (Bagozzi et al., 2002, p. 7) - beliefs b_i about the probability of the presence of attributes in an object get multiplied with evaluations e_i of these attributes. In studies of consumer behavior, b_i often is replaced with w_i , or the importance weight of the attribute (the so-called adequacy-importance formulation of the EVM), because a consumer often knows with certainty whether an attribute is present or absent in a decision object (Mazis, Ahtola, & Klippel, 1975). The product of belief b_i (or importance w_i) and evaluation e_i then can be

summed over n attributes to determine global attitude toward the object A_{obj} . In turn, A_{obj} determines the intention to act, which, according to EVM, should trigger the corresponding behavior (Fishbein & Ajzen, 1975):

$$(4) \quad A_{Obj} = \sum_{i=1}^n b_i e_i$$

3.2.2 EVM and Measures of Emotion

One of the main criticisms directed at the EVM by emotion researchers is its conceptualization of evaluation e_i . Fishbein and Ajzen (1975, p. 11) use the terms “evaluation” and “affect” synonymously, arguing that no reliable empirical distinction can be made between a person’s judgment that an object makes him or her *feel* good and the evaluation that the object *is* good. Their assessment derives from earlier observations that failed to establish discriminant validity among the cognitive, affective, and conative components of the classic tripartite model of attitude (Ajzen & Fishbein, 2005), which may have been due “to a failure to adequately differentiate between evaluative measures [...] and antecedent or subsequent processes, which might be feeling-based” (Cohen et al., 2008, p. 297).

However, as theories of emotion have become more fine-grained and measurement methods advanced, several studies have empirically demonstrated the discriminant validity between evaluations and affect (Breckler & Wiggins, 1989; Richard, van der Pligt, & de Vries, 1996; Bodur, Brinberg & Coupey, 2000), and several theoretical arguments distinguish affect and evaluation. These arguments broadly can be grouped into four main categories: conceptual breadth, possibility versus probability, dynamic appraisals versus static predispositions, and temporal focus. These categories represent underlying features of evaluations versus affect and highlight where these constructs differ:

- *Conceptual breadth.* Affect encompasses the entire spectrum of human moods and emotions, whereas evaluative liking or disliking is widely considered just a tiny subset of this broad spectrum (Allen, Machleit, & Kleine, 1992).
- *Possibility versus probability.* Whereas affect is sensitive to mere possibility and can influence intentions, even when the probability of an outcome is nearly zero, attitudes usually are conceptualized as a direct function of probability and thus are very weak when the probability is close to zero (Loewenstein, Weber, Hsee, & Welch, 2001; MacInnis & de Mello, 2005).
- *Dynamic appraisals versus static predispositions.* Attitudinal evaluations are defined as a consumer's learned, static predispositions that are activated when the consumer is confronted with the stimulus object. Emotional reactions depend instead on context-sensitive dynamic appraisals (Bagozzi et al., 2003).
- *Temporal focus.* Whereas attribute evaluations are traditionally measured as preconsumption judgments, affective reactions include the consumer's actual and expected emotions before, during, and after consumption (Bagozzi, Dholakia, & Basuroy, 2000; Richard et al., 1996).

3.2.3 The Role of Emotions for Attitude and Behavior

While emotions and evaluation can be theoretically (and empirically) distinguished, as shown above, there is considerable debate about how emotions affect consumers' decision making—by functioning as an antecedent of attitude, by influencing behavior in addition to attitudes, or by both.

Regarding emotions as attitude antecedents, Cohen and colleagues (2008, p. 309) perceive an emerging consensus that emotions are “one of several potential antecedents or determinants of overall evaluation or attitude.” Early evidence for this position was provided by Breckler and Wiggins (1989), who showed in the context of blood donations

that evaluations and emotions, as measured by Izard's (1972) differential emotion scale (DES), are distinguishable components of overall attitude. Kempf (1999) studied the effects of two emotion dimensions (pleasure and arousal) and expectancy-value (measured as the product of attribute evaluations, attribute beliefs, and belief confidence) on product trial evaluations for a computer game and grammar checker software. Her results suggest that pleasure and arousal are antecedents of A_{obj} for hedonic products, whereas expectancy-value is not. Conversely, pleasure and expectancy-value are antecedents of A_{obj} for utilitarian products, whereas arousal is not. Bodur et al. (2000) showed that affect, as measured by arousal, elation, pleasantness and distress constructs, has a direct effect on attitudes towards risky behaviors. A related stream of research on persuasion and the elaboration likelihood model has emphasized the role of affect as a significant antecedent of attitude, moderated by message elaboration and involvement (e.g. Batra & Stayman, 1990; Petty, Schumann, Richman, & Strathman, 1993; Petty & Cacioppo, 1986). In particular, Mano (1997) found evidence for indirect effects of the pleasure and arousal emotion dimensions on A_{obj} (mediated by elaboration and thought positivity) as well as direct effects of pleasure on A_{obj} in one experimental condition.

Regarding the effect of emotions on behavior, human emotions appear to have evolved as drivers of behavior because of their approach/avoidance function (for a review, see Ekman & Davidson, 1994)—positive emotions impel the person experiencing them to approach the emotions' referent object, whereas negative emotions elicit avoidant behavior. However, it is unclear whether this effect exists above and beyond the effect of attitude. Again in the context of blood donations and employing the DES as a measure of emotion, Allen and colleagues (1992) demonstrated that emotions can have a direct effect on behavior, not explained by attitudes. They limit their study to behaviors for which previous experiences were not freely chosen. Richard and colleagues (1996) empirically showed that

attitudes and anticipated emotions have parallel effects on behavioral intentions for four different behaviors (i.e., eating junk food, using soft drugs, drinking alcohol, and studying), but measure both attitudes and emotions with the same three semantic differential measures. Most recently, Perugini and Bagozzi (2001) have augmented the theory of planned behavior with desires, frequency, and recency of past behavior, as well as a selection (not explained theoretically) of positive and negative anticipated emotions added as independent variables for two utilitarian behaviors (bodyweight regulation and studying). They find that the variance explanation of intentions and behavior increases significantly when they include emotion constructs.

This research builds on these findings and extends them. It is the first study which comprehensively tests the influence of emotion on all three stages of decision making (namely, attitude formation, intention formation, and behavior) and systematically analyzes potential differences between hedonic and utilitarian behaviors across all three stages, extending knowledge of how emotions affect consumers' decision making. This research aims to overcome limitations inherent with the studies listed above, such as the consideration of only an overall "good/bad" evaluation as attitude—instead of measuring attitude as a result of $b_i \times e_i$ (or $i_i \times e_i$)—which makes it nearly impossible to differentiate between the effects of evaluations (as conceptualized in the expectancy-value or adequacy-importance models) versus emotions on the formation of A_{obj} , intentions, and actual behavior.¹⁸ The authors also account for the recently suggested distinction between "anticipatory emotions" and "anticipated emotions" (Cohen et al., 2008).

¹⁸ A noteworthy exception is the study by Kempf (1999).

3.3 Augmenting the Expectancy-Value Model: Hypothesis Development

To augment the EVM with measures of affect, this research draws on Larsen and Diener's (1992) circumplex model of emotion. The circumplex model groups emotions into two bipolar dimensions based on empirical associations: pleasant versus unpleasant affect and high activation versus low activation. Dimensional models of emotions such as this one have been criticized because they do not provide any insights into the conditions that give rise to the different emotion states, in contrast with appraisal theory models that conceptualize emotions as discrete entities and explain their genesis (for an overview, see Bagozzi et al., 2000). However, this research is concerned not with the antecedents of emotions but rather their consequences in the decision making process, so dimensional models are adequate due to their parsimony and intuitiveness (Bagozzi, Gopinath, & Nyer, 1999).

Traditionally, dimensional models of emotion such as Larsen and Diener's (1992) or the PA/NA model by Watson & Tellegen (1985; "PA/NA") rely on just two bipolar dimensions anchored in phenomenologically opposing emotions, e.g. "elated/euphoric" on one end of the scale and "dull/drowsy" on the other end. This implies that these emotions are conceptualized as perfectly mutually exclusive. However, recent research has shown that consumers can experience different emotions at the same time, a phenomenon referred to as "mixed emotions" (e.g., Aaker, Drolet, & Griffin 2008). To account for such non-exclusiveness of pleasant and unpleasant affect, four unipolar emotion constructs listed in Table 9 are conceptualized, instead of using two bipolar dimensions as in Watson and Tellegen's (1985) or Larsen and Diener's (1992) model.

Table 9: Emotion Constructs

	Unpleasant Affect	Pleasant Affect
High Activation	“ <i>Negative High Activated (NegHA)</i> ”: Distressed, annoyed, fearful, sad	“ <i>Positive High Activated (PosHA)</i> ”: Enthusiastic, elated, excited
Low Activation	“ <i>Negative Low Activated (NegLA)</i> ”: Bored, sluggish, dull	“ <i>Positive Low Activated (PosLA)</i> ”: Relaxed, content, serene

Source: Adapted from Larsen & Diener, 1992.

Bagozzi and colleagues (2000) also stress that currently experienced and future emotions should be differentiated in consumer decision making. Consumers’ a priori experience of emotions felt during or after a future event, brought about by their mental simulation of these events, has been termed anticipated emotions, affective expectations, affective forecasts, or how-do-I-feel-about-it heuristics (e.g., Mellers, Schwartz, & Ritov, 1999; Pham, 1988; Wilson & Gilbert, 2005). Yet Bagozzi and colleagues (2000, p. 50) assert that “little is known [especially] about positive anticipated emotions, even though it is likely that many consumer behaviors are the result of, say, the anticipation of future joy.”

Scholars also have debated whether anticipated emotions are genuinely experienced in the present, when the expectation about the future is formed, or whether they are mere cognitive predictions about future emotional states. Mellers and colleagues (1999) find for the former, whereas Bagozzi and colleagues (2000) declare the point an open research question. Cohen and colleagues (2008) consider both possibilities equally valid and make a theoretical distinction between “anticipatory emotions” (i.e., currently experienced emotions that result from mental simulations of future events) and “anticipated emotions” (i.e., mere cognitive beliefs about future emotional states).

If anticipatory and anticipated emotions can indeed be distinguished empirically, they may also exhibit differential effects on the different stages of decision-making. For example, both anticipatory emotions and A_{obj} are conceptually anchored in the present:

Anticipatory emotions are what the consumer is *currently* experiencing, and A_{obj} measures his *current* evaluation of object. Anticipated emotions and behavioral intentions, on the other hand, are expectations of *future* emotions and behavior. In terms of the Expectancy-Value Model, anticipatory emotions may therefore have a stronger influence on A_{obj} than anticipated emotions do, while anticipated emotions may have a stronger influence on behavioral intentions than anticipatory emotions do. Following this logic, conceptual differences between the evaluation component of attitudes and emotions, and the effect of emotions on consumer decision making, as demonstrated in emotions literature, it is argued that adding emotions to the expectancy-value model may increase the variance explanation associated with the model's established outcomes, namely, attitudes, purchase intentions, and actual purchases. Formally:

H1: The variance explanation of the three decision-making stages—(a) attitude toward the object, (b) purchase intentions, and (c) actual purchases—will increase significantly when the EVM includes anticipatory and anticipated emotion dimensions.

Moreover, it is argued that emotions may become more important in decision making when the product is perceived as hedonic as opposed to utilitarian. By definition, hedonic consumption is the facet of consumer behavior which relates to “multisensory, fantasy and emotive aspects” of the product usage experience (Hirschman & Holbrook, 1982, p. 92). When consuming hedonic products, consumers pay more attention to the emotional outcome of the consumption episode; in certain instances, such as the consumption of movies, the emotional outcome may itself be the goal of consumption (Neelamegham & Jain, 1999). Contemplating the consumption of hedonic products thus can trigger mood management and mood protection strategies (Caruso & Shafir, 2006).

As Pham (1998) argues, affective reactions are perceived to be more representative of hedonic consumption episodes than of utilitarian consumption episodes. As a result of this

representative heuristic, even when emotions are present to a similar extent in both scenarios, consumers are more likely to infer that their emotional responses have been elicited by the stimulus object itself (rather than by external circumstances) when the product is hedonic rather than utilitarian, and so they are more likely to rely on their emotions in the decision making process. It is expected that the impact of emotions on the outcomes of the expectancy-value model is greater for products perceived as hedonic than for products perceived as utilitarian:

H2: The influence of anticipatory and anticipated emotions on (a) attitude toward the object, (b) purchase intentions, and (c) actual purchases is significantly greater when the product is perceived as hedonic rather than utilitarian.

3.4 Empirical Test of the Augmented EVM Model

To test the EVM model, augmented with emotions, a controlled experiment with motion picture DVDs and scientific pocket calculators as experimental stimuli for the hedonic versus utilitarian consumption context manipulation was performed. The choice of these stimuli reflects several reasons. Both products are multi-attribute offerings, are in the same price range, and are common, such that the majority of the population likely has had personal experiences with them.

Many studies which probe the role of emotion in judgment and decision-making manipulate affect through film clips (e.g. Lerner, Small, & Loewenstein, 2004), stories and introspection about emotional episodes (e.g. Tice, Bratslavsky, & Baumeister, 2001), or bogus feedback about personal performance (e.g. Forgas & Bower, 2000). The goal of this research, however, is not to manipulate emotion directly in such a fashion, but to recreate an actual purchasing decision in hedonic and utilitarian consumption contexts. Therefore,

product-generated emotions and evaluations were measured to test whether accounting for emotions will improve behavioral prediction within the EVM framework.

3.4.1 Pretest

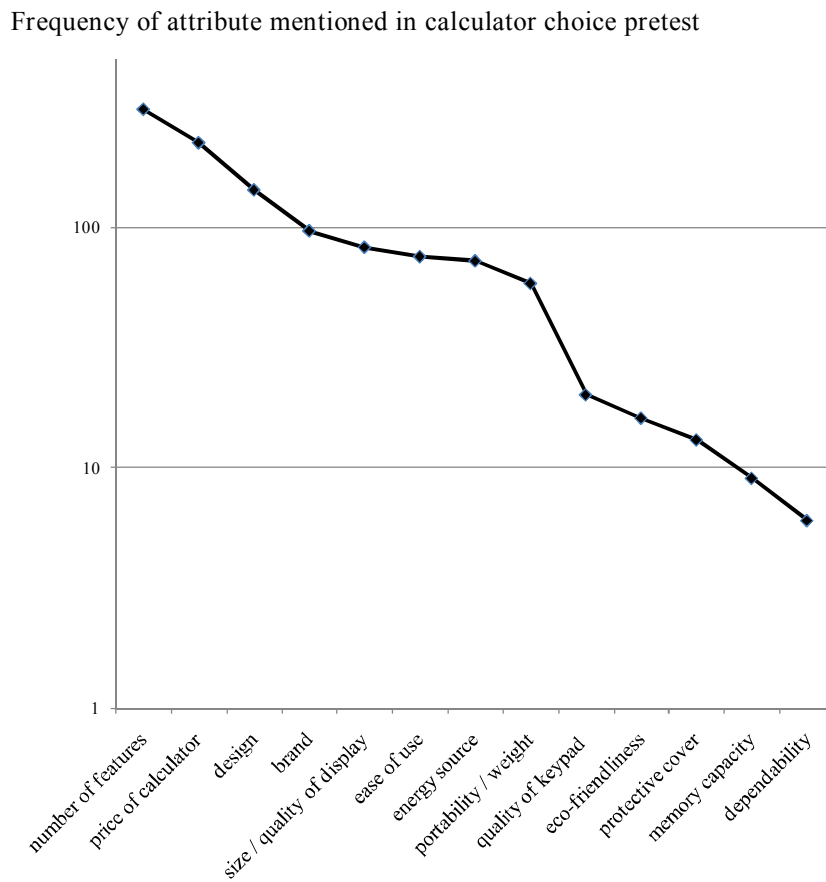
A pretest with 98 students at a German university was conducted with the goal of determining the modal salient attributes for the chosen stimuli, that is, the attributes considered by the majority of the target population when they form an attitude toward the object. The authors also controlled for differences of DVDs versus calculators on the HED/UT scale (Voss, Spangenberg, & Grohmann, 2003). The participants completed the online questionnaire, which was based on a modified rank-order elicitation technique (Breivik & Supphellen, 2003). The questionnaire contained the product images and descriptions of 10 motion picture DVDs, taken from online retailer Amazon.de, which appeared in five sets of randomized pairs. Therefore, the pretest consisted of 45 different DVD combinations. For each pair of DVDs, participants chose which they would rather buy and described the attributes they evaluated for each decision in a free response format. The procedure was then repeated for five pairs of pocket calculators.¹⁹

On average and per participant, 9.33 discrete attributes were elicited across the five choice sets in the DVD pre-test, and 11.41 discrete attributes were elicited across the five choice sets in the calculator pre-test. The attributes listed by the respondents were grouped and tabulated on the basis of the total frequency with which they were mentioned, then plotted the frequency distribution on a log-scale chart (similar to the scree plot approach in cluster analysis). This plot, listing all elicited attributes, is shown in Figure 8. For both the

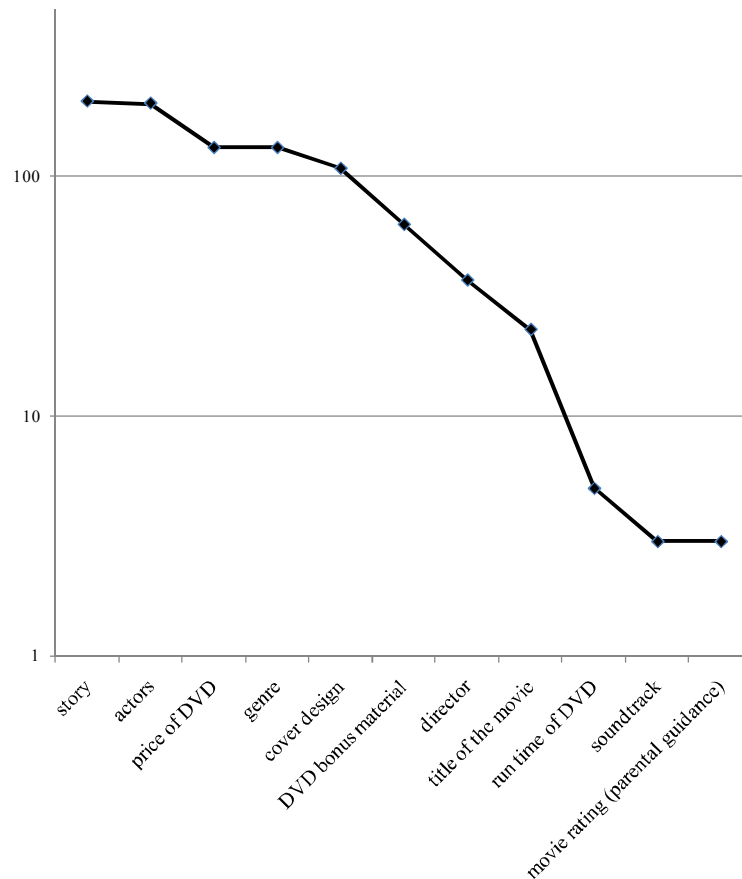
¹⁹ The list and descriptions of the 10 DVDs and 10 pocket calculators are available from the authors upon request.

DVDs and the pocket calculators, the frequency distribution curve dropped sharply after the eighth attribute, suggesting that participants usually relied on these eight attributes when forming an attitude, whereas the remaining attributes were salient only for a minority of DVD (calculator) purchasing decisions. Thus, the eight most frequently listed attributes per product were retained as the salient attributes for the experiment.

Figure 8: Scree Plot of Attribute Importance for Experimental Stimuli



Frequency of attribute mentioned in DVD choice pretest



3.4.2 Experimental Procedure

Three-hundred thirty-four students were recruited on the campus of a German university as potential participants for the main experiment. After eliminating incomplete responses and participants who had already seen the movie that was used as the stimulus in the hedonic condition, the final data set contains 308 complete cases (55.3% female).

The participants were randomly assigned to two experimental conditions. The stimulus in the hedonic condition was the motion picture DVD *Stay* (USA 2006, directed by Marc Foster, starring Ewan McGregor, Ryan Gosling, and Naomi Watts), and the stimulus in the utilitarian condition was a scientific pocket calculator, the Sharp EL-W531H. Both stimuli could be purchased at the time of the experiment from online retailers for approximately €10. The participants entered separate rooms that contained each condition's respective stimulus and a paper-based survey for measuring the hypothesized constructs.

After completing the questionnaire, they were directed into a second room, where an interviewer (the same person for both conditions and for all participants) offered them the chance to buy the DVD or calculator, for a price of €4.99. The physical separation of the survey-based intention measures and measures of actual behavior helps us reduce possible self-generated validity and interviewer compliance effects (Chandon, Morwitz, & Reinartz, 2005). The purchases were recorded as a binary measure of actual behavior. Twenty-nine of 146 (19.9%) participants in the hedonic condition and 14 of 163 (8.6%) participants in the utilitarian condition purchased the respective product.

3.4.3 Manipulation Checks and Scale Validation

To check the effectiveness of the experimental manipulation of hedonic value, the HED/UT scale developed by Voss and colleagues (2003) was used. As expected, the movie DVD scores significantly higher on the five-item HED subscale (4.69) than the calculator (3.07; $F(1, 308) = 139.25, p < .001$; Cronbach $\alpha = .880$). Likewise, the calculator scored significantly higher on the five-item UT subscale (5.13) than for the movie DVD (2.32; $F(1, 308) = 417.34, p < .001$; Cronbach $\alpha = .927$). Subsequently, only the HED subscale was used to evaluate the hedonic value of the stimuli. The attribute importance w_i and evaluations e_i were gathered for the eight attributes per stimulus, using the adequacy-importance formulation (Mazis et al., 1975). The attitude toward the object A_{obj} measure contains two items ($\alpha = .882$), and purchase intention is a single item. All the items appear in the Appendix.

In both temporal dimensions (anticipatory and anticipated), the four emotion constructs (Positive Low Activation, Positive High Activation, Negative Low Activation, Negative High Activation²⁰) were measured as reflective constructs with three to six items each, based on the emotions listed for each dimension in Larsen and Diener's (1992) circumplex model. Cronbach alphas for the constructs range from .835 to .930. The discriminant validity between the emotion constructs was assessed with a confirmatory factor analysis (employing LISREL) of the eight emotion constructs (four emotion constructs in both anticipatory and anticipated temporal dimensions). Then, the χ^2 of a model in which we allow the constructs to correlate freely ($\chi^2 = 5772.96$) was compared with several constrained models. Specifically, when constraining the correlation between any pair of anticipatory emotion constructs to 1, the chi-square increases significantly (all χ^2 differences > 528.89 , df change = 1, $p < .001$). Similarly, when constraining any pair of anticipated emotion constructs to unity, it was found that the chi-square also increases significantly (all χ^2 differences > 111.80 , df change = 1, $p < .001$). It was thus concluded that within their temporal dimensions, anticipatory and anticipated emotions exhibit discriminant validity (Bagozzi, Yi, & Phillips, 1991). The same conclusion emerges when pairs of anticipatory and anticipated emotions were constrained to unity, with the exception of two pairs that fail to exhibit discriminant validity as a result of their high correlation: anticipatory NegLoAct–anticipated NegLoAct and anticipatory NegHiAct–anticipated

²⁰ For the sake of brevity, the authors will refer to Positive Low Activation as “PosLoAct”, Positive High Activation as “PosHiAct”, Negative Low Activation as “NegLoAct”, and Negative High Activation and “NegHiAct”.

NegHiAct. This result may be explained by the finding that consumers are likely to infer their future (anticipated) emotions from their current (anticipatory) emotional experience (Wilson & Gilbert, 2003). In the calculations, this was remedied by removing the effect of anticipatory on anticipated emotions through adjusted regressions, as described subsequently. The descriptive statistics and correlations appear in Table 10.

Table 10: Descriptive Statistics and Correlations

Construct	M ^a	SD ^a	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13) ^c
1 <i>HED</i> Score	3.83	1.45	.88												
2 Adequacy-Importance ^b	191.40	52.47	.33	<i>n.a.</i>											
3 <i>Ay</i> PosLA	3.37	1.51	.16	.21	.93										
4 <i>Ay</i> PosHA	2.80	1.42	.61	.49	.18	.92									
5 <i>Ay</i> NegLA	2.43	1.37	-.40	-.30	-.11	-.33	.87								
6 <i>Ay</i> NegHA	2.29	1.18	-.09	-.20	-.37	-.14	.43	.90							
7 <i>Aed</i> PosLA	3.71	1.62	-.06	.24	.57	.11	.03	-.19	.93						
8 <i>Aed</i> PosHA	2.78	1.43	.49	.35	.12	.70	-.23	.00	.16	.91					
9 <i>Aed</i> NegLA	2.02	1.02	-.04	-.21	-.25	-.13	.39	.74	-.30	-.07	.84				
10 <i>Aed</i> NegHA	2.45	1.36	-.23	-.37	-.16	-.26	.63	.51	-.15	-.18	.60	.89			
11 <i>Aobj</i>	4.31	1.53	.55	.67	.30	.57	-.42	-.34	.24	.44	-.30	-.41	.88		
12 Purchase Intention	4.36	1.96	.31	.52	.18	.39	-.37	-.26	.22	.37	-.32	-.45	.66	<i>n.a.</i>	
13 Actual Purchase ^c	0.14	0.35	.31	.25	.02	.27	-.23	-.10	.02	.23	-.13	-.21	.33	.40	<i>n.a.</i>

Notes: Numbers on the diagonal are Cronbach's alpha scores; *n.a.* = no alpha score calculated because the construct is measured by a formative scale or single item. All correlations $r \geq |.15|$ are significant at the level of .01 (two-tailed), and all correlations $|.11| \leq r \leq |.14|$ are significant at the level of .05 (two-tailed).

^a Means and standard deviations are calculated for the average of construct items.

^b Means and standard deviations are calculated for the product of attribute importance (i_{1-8}) and attribute evaluation (e_{1-8}).

^c Point-biserial correlations (actual purchase is a binary variable with 0 = no purchase and 1 = purchase).

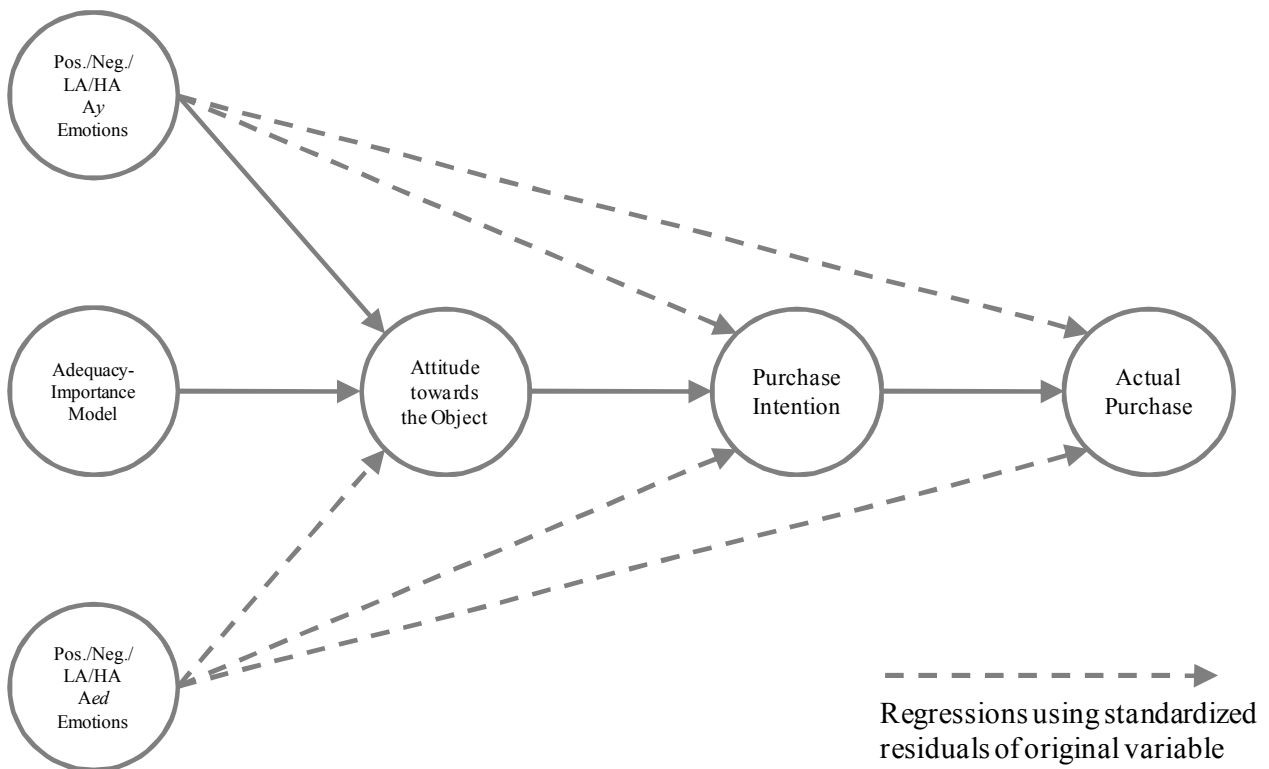
The data supports the use of four unipolar emotions instead of two bipolar dimensions. The latter conceptualization would have required that emotions are mutually exclusive, so that the unipolar scales of PosHiAct versus NegLoAct (and PosLoAct versus NegHiAct) would have to correlate with close to -1. However, the actual correlations were $r(\text{anticipatory PosHiAct, anticipatory NegLoAct}) = -.33$, $r(\text{anticipatory PosLoAct, anticipatory NegHiAct}) = -.37$, $r(\text{anticipated PosHiAct, anticipated NegLoAct}) = -.15$ and

$r(\text{anticipated PosLoAct}, \text{anticipated NegHiAct}) = -.07$, pointing to the existence of mixed emotions. This suggests that the emotion dimensions anchoring the bipolar scales are far from mutually exclusive. While having two emotion dimensions per time frame would be more parsimonious than having four, the four emotion constructs were employed due to the observed correlations and discriminant validity.

3.4.4 Results for Hypothesis 1

The hypotheses were tested with a series of adjusted multistage regression models that use the standardized residuals of the initial regression steps as independent variables in subsequent regression steps. This procedure decomposes effects in path analysis and enables us to estimate models that contain both linear and logistic relations among the variables, as is the case for the EVM outcomes of attitude, intentions, and actual purchase (Lance, 1988). In short, the purpose of calculating the residuals through multi-stage regressions is to test (1) the effect of emotions on attitude, (2) the effect of emotions on intentions that is *not already* contained in attitude, and (3) the effect of emotions on actual purchase behavior that is *not already* contained in either attitude or intention. Figure 9 shows the general augmented EVM framework, outlining which variables are exogenous and which are included as standardized residuals for each of the three regressands A_{obj} , PI , and AP .

Figure 9: Augmented EVM Framework



In the augmented EVM models, linear regressions of each anticipated PosLoAct, PosHiAct, NegLoAct, and NegHiAct emotion on its anticipatory counterpart were first run and the standardized residuals were saved. This approach removes any effect of anticipatory on anticipated emotions from subsequent regressions that involve both temporal emotion dimensions. To test H1a, A_{obj} was regressed on the adequacy-importance score, anticipatory emotion, and the anticipated emotion residuals, then compared with the “traditional” EVM model in which A_{obj} is regressed only on the adequacy-importance model. For support, H1a would require a significant increase in R^2 . The traditional EVM model attains an R^2 of .443, and the model that includes the emotion constructs produces an R^2 of .586 for A_{obj} (see Table 11).

Table 11: Path Coefficients of Traditional EVM versus Augmented EVM, n=308

Model	H1a (linear regression)				H1b (linear regression)				H1c (logistic regression)			
	Regressing A_{Obj} on:	β	p-value	R^2	Regressing PI on:	β	p-value	R^2	Regressing AP on:	B	p-value	Nagelkerke R^2 (-2LL)
Traditional EVM	Adequacy-Importance	.665	.000	.443	A_{Obj}	.662	.000	.439	A_{Obj} residuals ^d	.374	.097	.390 (173.944)
Augmented EVM	Adequacy-Importance	.435	.000	R^2 diff.: .143, $F(8,308)$ $= 12.823$, $p < .001$	A_{Obj}	.664	.000	R^2 diff.: .059, $F(8,308)$ $= 4.363$, $p = .001$	A_{Obj} residuals ^d	.387	.090	$-2LL$ diff.: 10.611, diff. in $df = 8$, $p = .225$
	Ay PosLA	.102	.014		Ay PosLA residuals ^b	-.020	.652		PI	1.553	.000	
	Ay PosHA	.279	.000		Ay PosHA residuals ^b	.004	.917		Ay PosLA residuals ^e	-.322	.122	
	Ay NegLA	-.144	.002		Ay NegLA residuals ^b	-.117	.014		Ay PosHA residuals ^e	.135	.457	
	Ay NegHA	-.111	.024		Ay NegHA residuals ^b	.006	.913		Ay NegLA residuals ^e	-.620	.043	
	Aed PosLA residuals ^a	.027	.516		Aed PosLA residuals ^c	.050	.260		Ay NegHA residuals ^e	.052	.847	
	Aed PosHA residuals ^a	.060	.119		Aed PosHA residuals ^c	.105	.013		Aed PosLA residuals ^f	-.020	.929	
	Aed NegLA residuals ^a	-.012	.790		Aed NegLA residuals ^c	-.158	.001		Aed PosHA residuals ^f	.100	.601	
	Aed NegHA residuals ^a	.001	.984		Aed NegHA residuals ^c	-.044	.351		Aed NegLA residuals ^f	.031	.916	
									Aed NegHA residuals ^f	-.068	.797	

Notes: Due to the adjusted regression procedure, there are no problems of multicollinearity (all variance inflation factors ≤ 1.71).

^a Standardized residuals of regressing each Aed on the corresponding Ay (e.g., Aed PosLA on Ay PosLA).

^b Standardized residuals of regressing each Ay on A_{Obj} .

^c Standardized residuals of regressing the residuals obtained in ^a on A_{Obj} .

^d Standardized residuals of regressing A_{Obj} on PI .

^e Standardized residuals of regressing each Ay on A_{Obj} and PI .

^f Standardized residuals of regressing the residuals obtained in ^a on A_{Obj} and PI .

As the augmented model uses more information, it must be determined whether this increase in variance explanation is trivial. However, because the R^2 difference of .143 ($F(8,308) = 12.823, p < .001$) between the two models which balances variance explanation against the amount of used information is significant, it can be claimed that the inclusion of anticipatory and anticipated emotions significantly improves the prediction of A_{obj} , in support of H1a. However, though the adequacy-importance model and all four anticipatory emotion constructs directly influence A_{obj} as expected, none of the anticipated emotion dimension residuals has a significant effect. When separate regressions for the hedonic condition and utilitarian condition subsamples were conducted, H1a holds true in both the hedonic condition (traditional EVM $R^2 = .529$, augmented EVM $R^2 = .663$, R^2 difference = .134, $F(8,146) = 6.66, p < .001$) and the utilitarian condition (traditional EVM $R^2 = .411$, augmented EVM $R^2 = .566$, R^2 difference = .155, $F(8,162) = 6.78, p < .001$). In the hedonic condition, anticipatory PosHiAct and anticipatory NegLoAct are significant at $p < .01$, and anticipated PosHiAct is significant at $p < .05$. In the utilitarian condition, on the other hand, anticipatory PosLoAct and anticipatory NegHiAct are significant at $p < .01$, and anticipatory PosHiAct is significant at $p < .05$. The adequacy-importance score is significant at $p < .001$ in both subsamples. That is, counter to the prediction, including emotion measures significantly improves the prediction of A_{obj} for not only hedonic products but also utilitarian objects.

To test H1b, each anticipatory emotion dimension and the residuals of each anticipated emotion dimension was linearly regressed on A_{obj} and the standardized residuals were saved. Consistent with the objectives of this research, this was done to obtain the

incremental effect of anticipatory and anticipated emotions on the subsequent outcome variables purchase intentions (*PI*) and actual purchase (*AP*), i.e. the effect not already included in A_{obj} ²¹. Then, the augmented EVM model was calculated as the regression of *PI* on A_{obj} and the residuals of anticipatory and anticipated emotions. Table 3 lists the results; for the augmented EVM model, R^2 reaches .488, compared with an R^2 of .439 for the traditional EVM model in which *PI* are regressed on A_{obj} only. The R^2 difference of .049 ($F(8,308) = 3.55, p < .01$) is again significant, in line with H1b. Similar to when attitudes are the dependent variable, regarding influencers of purchase intention, anticipatory NegLoAct, anticipated PosHiAct, and anticipated NegLoAct are significant, whereas the other emotions are not. H1b receives support for both hedonic (traditional EVM $R^2 = .560$, augmented EVM $R^2 = .629$, R^2 difference = .069, $F(8,146) = 3.16, p < .01$) and utilitarian (traditional EVM $R^2 = .356$, augmented EVM $R^2 = .429$, R^2 difference = .073, $F(8,162) = 2.45, p < .05$) conditions. In the former, anticipatory PosLoAct is significant, in addition to the emotions that are significant in the full sample analysis, whereas in the latter condition, only anticipated PosHiAct and anticipated NegLoAct are significant at $p < .10$.

To test H1c, each anticipated emotion was regressed on its anticipatory emotion counterpart and the residuals were saved. Next, each anticipatory emotion and each anticipated emotion residual were regressed on A_{obj} and *PI* and the residuals were saved to obtain the effects of anticipatory emotions and anticipated emotions on actual purchase (*AP*) that are not already contained in A_{obj} and *PI*. Then, A_{obj} was regressed on *PI* and the

²¹ Please note that the direction of this regression, from A_{obj} to anticipatory emotion and the anticipated emotion residuals, does not imply that the theoretical and causal relationship between these variables is suddenly reversed. Instead, the purpose is to partial out from anticipatory emotion and the anticipated emotion residuals the variance explanation of *PI* that is already contained in A_{obj} .

residuals were saved to capture the direct effect of A_{obj} on AP that is not already contained in PI . As a fourth and final step, a logistic regression of AP on PI , the A_{obj} residuals, and the residuals of anticipatory and anticipated emotion was run. For the traditional EVM model, a logistic regression of AP on PI and the A_{obj} residuals (saved from the regression of A_{obj} on PI) was calculated.

The results are also included in Table 3. For the augmented EVM model, a Nagelkerke R^2 of .438 (-2LL = 163.383) was obtained; only anticipatory NegLoAct directly influences AP . In the case of the traditional EVM model, the Nagelkerke R^2 is only .390 (-2LL = 173.994), but the likelihood ratio test (Hosmer & Lemeshow, 2004) indicates that the -2LL difference is not significant ($\chi^2 = 10.61$, $\Delta df = 8$, $p = .225$). Therefore, predictions of actual purchase do not improve significantly when anticipatory and anticipated emotion constructs were included, and H1c must be rejected. The same result occurs for both the hedonic and utilitarian condition subsamples.

3.4.5 Results for Hypothesis 2

To test H2, it was calculated whether the effects of the anticipatory and anticipated emotion variables on A_{obj} , PI , and AP in the three augmented EVM models may be moderated by the hedonic versus utilitarian conditions. To do so, the residual-centering procedure introduced by Lance (1988) was employed. For H2a, an interaction term was created first for each anticipatory emotion and each residual of the anticipated-on-anticipatory emotion regressions by multiplying the respective values with the binary condition (i.e., hedonic = 1, utilitarian = 0). Then, each interaction term was regressed on its two main effects, that is, the anticipatory emotion (anticipated emotion residual) and the hedonic (utilitarian) condition. The resulting residuals were saved used alongside the other independent variables and the main effects from the augmented EVM regression model, with A_{obj} as the outcome variable.

The results, reported in Table 11, uncover three significant interaction residual terms: anticipatory PosHiAct \times condition ($\beta = .093, p < .05$), anticipatory NegLoAct \times condition ($\beta = -.116, p < .05$), and anticipatory PosLoAct \times condition ($\beta = -.092, p < .05$). Because interaction effects represent the estimated change in the slope of Y on X1, given a one-unit change in X2 (Jaccard, Wan, & Turrisi, 1980), this means that anticipatory PosHiAct emotion (i.e. enthusiasm, elation, excitement) has a stronger positive effect, and its opposing dimension of anticipatory NegLoAct emotion (i.e. boredom, sluggishness, dullness) has a stronger negative effect on A_{obj} when the product is hedonic, in partial support of H2a. However, the positive effect of anticipatory PosLoAct emotions (i.e. relaxation, contentedness, serenity) on A_{obj} becomes weaker when the product is hedonic though, which partially contradicts H2a.

Table 12: Moderator Effects of Hedonic Condition in Augmented EVM, n=308

H2a (linear regression)			H2b (linear regression)			H2c (logistic regression)					
Regressing <i>A_{Obj}</i> on:	β	p-value	R ²	Regressing <i>PI</i> on:	β	p-value	R ²	Regressing <i>AP</i> on:	<i>B</i>	p-value	Nagelkerke R ² (-2LL)
Adequacy-Importance	.410	.000		<i>A_{Obj}</i>	.645	.000		<i>A_{Obj}</i> residuals ^e	.206	.447	
Ay PosLA	.146	.001		Ay PosLA residuals ^c	-.023	.609		<i>PI</i>	2.026	.000	
Ay PosHA	.251	.000		Ay PosHA residuals ^c	.029	.507		Ay PosLA residuals ^f	-.116	.660	
Ay NegLA	-.112	.020		Ay NegLA residuals ^c	-.120	.014		Ay PosHA residuals ^f	-.138	.505	
Ay NegHA	-.143	.004		Ay NegHA residuals ^c	-.007	.891		Ay NegLA residuals ^f	-.304	.401	
<i>Aed</i> PosLA residuals ^a	.027	.531		<i>Aed</i> PosLA residuals ^c	.016	.744		Ay NegHA residuals ^f	-.528	.227	
<i>Aed</i> PosHA residuals ^a	.077	.042		<i>Aed</i> PosHA residuals ^c	.122	.004		<i>Aed</i> PosLA residuals ^f	.244	.419	
<i>Aed</i> NegLA residuals ^a	.004	.933		<i>Aed</i> NegLA residuals ^c	-.139	.004		<i>Aed</i> PosHA residuals ^f	.190	.395	
<i>Aed</i> NegHA residuals ^a	-.071	.696		<i>Aed</i> NegHA residuals ^c	-.050	.296		<i>Aed</i> NegLA residuals ^f	.366	.285	
Hed/Ut Condition (binary)	.058	.192		Hed/Ut Condition (binary)	-.105	.027		<i>Aed</i> NegHA residuals ^f	-.633	.148	
Ay PosLA-Cond. Int.res. ^b	-.092	.027		Ay PosLA res.-Cond. Int.res. ^d	-.036	.436		Hed/Ut Condition (binary)	2.416	.001	
Ay PosHA-Cond. Int.res. ^b	.093	.021	.617	Ay PosHA res.-Cond. Int.res. ^d	.088	.035	.525	Ay PosLA res.-Cond. Int.res. ^g	-.069	.796	.508
Ay NegLA-Cond. Int.res. ^b	-.116	.014		Ay NegLA res.-Cond. Int.res. ^d	-.015	.761		Ay PosHA res.-Cond. Int.res. ^g	-.080	.678	
Ay NegHA-Cond. Int.res. ^b	.051	.288		Ay NegHA res.-Cond. Int.res. ^d	.055	.295		Ay NegLA res.-Cond. Int.res. ^g	.007	.982	
<i>Aed</i> PosLA-Cond. Int.res. ^b	-.028	.492		<i>Aed</i> PosLA res.-Cond. Int.res. ^d	-.047	.291		Ay NegHA res.-Cond. Int.res. ^g	.230	.530	
<i>Aed</i> PosHA-Cond. Int.res. ^b	.039	.302		<i>Aed</i> PosHA res.-Cond. Int.res. ^d	.010	.807		<i>Aed</i> PosLA res.-Cond. Int.res. ^g	-.255	.409	
<i>Aed</i> NegLA-Cond. Int.res. ^b	.008	.855		<i>Aed</i> NegLA res.-Cond. Int.res. ^d	-.041	.393		<i>Aed</i> PosHA res.-Cond. Int.res. ^g	-.309	.168	
<i>Aed</i> NegHA-Cond. Int.res. ^b	.018	.679		<i>Aed</i> NegHA res.-Cond. Int.res. ^d	.079	.093		<i>Aed</i> NegLA res.-Cond. Int.res. ^g	-.110	.740	
								<i>Aed</i> NegHA res.-Cond. Int.res. ^g	.413	.307	

^a Standardized residuals of regressing each *Aed* on the corresponding Ay (e.g., *Aed* PosLA on Ay PosLA).

^b Standardized residuals of regressing each HED condition × Ay (HED condition × *Aed* residual obtained in ^a) interaction term on its main effects.

^c Standardized residuals of regressing each Ay (each *Aed* residual obtained in ^a) on *A_{Obj}*.

^d Standardized residuals of regressing each HED Condition × Ay residual obtained in ^c (HED condition × *Aed* residual obtained in ^c) interaction term on its main effects.

^e Standardized residuals of regressing *A_{Obj}* on *PI*.

^f Standardized residuals of regressing each Ay (each *Aed* residual obtained in ^a) on *A_{Obj}* and *PI*.

^g Standardized residuals of regressing each HED condition × Ay residual obtained in ^f (HED condition × *Aed* residual obtained in ^f) interaction term on its main effects.

For the tests of H2b and H2c, interaction terms were analogously created by multiplying the residuals of each anticipatory and anticipated emotion contained in the augmented EVM models with the binary hedonic versus utilitarian condition, then regressed the interaction terms on the main effects to obtain the interaction residuals. Next, they were added to the respective augmented EVM model. In the linear regression with *PI* as the dependent variable, a significant anticipatory PosHiAct \times condition interaction ($\beta = .088, p < .05$) was found, which indicates that the direct effect of enthusiasm, elation, and excitement on *PI* (which is not mediated through *A_{obj}*) becomes stronger when the product is hedonic, in support of H2b (see Table 4). However, none of the other anticipatory emotion residual (anticipated emotion residual) \times condition interactions is significant. In the augmented EVM logistic regression with actual purchase as the outcome variable, no significant interaction residual term was found, which fails to provide support for H2c. Overall, support for H2 is limited, in that H2c must be fully rejected and, regarding H2a and H2b, that some but not all anticipatory emotions become more important to the decision-making process when the product is hedonic.

3.5 Discussion

Holbrook and Hirschman (1982, p. 138) suggest that “abandoning the information processing approach is undesirable, but supplementing and enriching it with an admixture of the experiential perspective could be extremely fruitful.” This is the first study that attempts to broaden the EVM by integrating it with a dimensional theory of emotion and tests the effects of emotions on the three decision-making stages: attitude formation, intention formation, and behavior. This research also accounts empirically for the distinction between anticipatory and anticipated emotions, an issue rarely addressed by

extant research, and it joins various strands of emotion research by testing the moderating effects of hedonic value in this setting.

In general, the results show that augmented EVM models explain significantly more variance of A_{obj} than does the traditional EVM, because several anticipatory and anticipated emotion constructs have strong direct effects on A_{obj} that are not captured by assessing product attribute evaluations and attribute importance (i.e., the adequacy-importance model of attitude). Similarly, the prediction of purchase intentions can be improved significantly by the inclusion of the direct effects of anticipatory and anticipated emotions that are not already contained in A_{obj} , as was demonstrated through the adjusted regressions approach. It is interesting to note that these findings hold for both hedonic and utilitarian conditions, which indicates that predictions of both global attitudes and purchase intentions for extremely utilitarian products, such as pocket calculators, can be enhanced by accounting for emotions.

An analysis of the subsamples also reveals that anticipatory emotions (vs. anticipated emotions) play a relatively bigger role in the hedonic condition (vs. the utilitarian condition). This finding may be explained by the theoretical difference between anticipatory and anticipated emotions: The latter are phenomenologically closer in nature to cognitive expectations, whereas the former are truly experienced emotions. When evaluating emotion-related hedonic products, the aforementioned representativeness heuristic (Pham, 1998) may therefore explain why anticipatory emotions are weighted more heavily in hedonic consumption decisions than anticipated emotions.

The prediction of actual purchases, however, cannot be improved significantly by adding anticipatory and anticipated emotions as predictors. Evidently, the further one moves along the decision-making stages, the weaker are the direct effects of emotion

because an increasing amount of variance is captured by the traditional EVM variables due to the adjusted regressions. Yet emotions indirectly influence *PI* through mediation by *A_{obj}* and *AP* through mediation by *A_{obj}* and *PI*. It was also found that anticipatory and anticipated emotions can be empirically distinguished, and that they influence consumer decision making at different stages. As conjectured, currently experienced (anticipatory) emotions have a stronger effect on *A_{obj}*, whereas expected future (anticipated) emotions have a stronger effect on *PI*, quite possibly due to their shared temporal anchor.

It may be argued that the relationship between anticipatory and anticipated emotions is the inverse of what is assumed in this research, i.e. anticipated emotions guiding the formation of anticipatory emotion. For example, anticipating the negative emotions associated with visiting the dentist in the future may make one feel dreadful at the moment. Or anticipating the positive emotions, e.g. elation/excitement, from the upcoming vacation may lead one to feel excited and elated right now. An alternative set of regression models (not reported in detail in the manuscript) was run incorporating this inverse relationship.²² As would be expected due to the adjusted regression methodology, reversing the causal relationship between anticipatory and anticipated emotions does not influence the R^2 or *Nagelkerke* R^2 of the Augmented EVM models, and therefore has no effect on the confirmation or disconfirmation of hypotheses. What happens, however, is that the effects of anticipated emotions generally increase, whereas the effects of anticipatory emotions generally decrease (this shift is most pronounced when *A_{obj}* is the dependent variable, and less so when *PI* and *AP* are the dependent variables). Again, this

²² Detailed information on this additional analysis is provided by the authors upon request.

is a result of the methodology, which reassigns variance explanation to anticipated emotions that was previously attributed to anticipatory emotions. This also means that the interpretation of the relative effects strengths of anticipatory versus anticipated emotions is influenced by the theoretical perspective taken. If one assumes that anticipatory guides anticipated emotion (as originally argued in this research), and thus removes from anticipated emotion all variance explanation already contained in anticipatory emotion, then the effects of anticipatory emotions will grow stronger relative to anticipated emotions, and vice versa.

In terms of the emotion circumplex model, this research shows that the emotional axis of boredom/dullness versus excitement/elation is weighted more heavily during the formation of A_{obj} when the product is hedonic rather than utilitarian. This effect decreases when PI represents the dependent variable, and it disappears when AP is the dependent variable. It is also conceivable that the choice of hedonic stimulus, a motion picture DVD, may have contributed to the higher weighting of the PosHiAct/NegLoAct dimension. For different types of hedonic consumption experiences, e.g. a massage, the PosLoAct dimension (relaxation, contentment, serenity) may be a better predictor.

3.6 Limitations and Future Research

This study contains several limitations. First, by focusing on the expectancy-value model of attitude, the authors do not control for another component of Fishbein and Ajzen's (1975) theory of reasoned action, namely, subjective norms. This construct accounts for the normative beliefs of a person's significant others, as well as the person's motivation to comply with these beliefs. In the theory of reasoned action, it is modeled to have a direct effect on intentions, parallel to (and independent of) A_{obj} . There is little doubt about the power of subjective norms in most settings studied by social

psychologists, yet their role in purchasing decisions for every day consumer goods appears more equivocal. At least five recent empirical studies based on the theory of reasoned action find no effect of subjective norms on purchase intentions or purchase behavior (Bosnjak, Obermeier, & Tuten, 2006; Helmig, Huber, & LeeFlang, 2007; Hsu, Wang, & Wen, 2006; Njite & Parsa, 2005; Wang, Chen, Chang, & Yang, 2007).

Similarly, the purchase of the pocket calculator or DVD in this study is not likely to engender strong approval or disapproval by participants' significant others, so subjective norms should not have biased the results. Nevertheless, accounting for subjective norms in further studies might prove instructive; it would be particularly interesting to examine the interplay between emotions and subjective norms in determining A_{obj} and intentions.

Second, Ajzen's (1991) extension of the theory of reasoned action, the theory of planned behavior, is ignored, which adds perceived behavioral control as an antecedent of intentions, alongside A_{obj} and subjective norms. Perceived behavioral control captures the perceived ease or difficulty associated with performing the behavior in question. In the context of this research, it is reasonable to assume that the participants did not associate any particular difficulty with the act of purchasing a simple consumer good for €4.99 and that the behavior was within their locus of control.²³

Third, as with any study that relies on survey-based (self-reported) measures of emotion, the measurement method might have introduced distortions by prompting respondents to introspect on, cognitively process, and report on their emotional states. Thus, latent and unconscious processes that otherwise would not have been salient or

²³ If participant had no cash but stated an interest in purchasing the product, we allowed him or her to return later to pay and pick up the product.

active during “normal” decision making might have become salient or activated. Conversely, respondents might not have been able to cognitively access their latent and unconscious emotional states, which would prevent their accurate reports. Therefore, though the survey-based emotion measures exhibit both internal and external validity, it could prove instructive to combine them with alternative, non–self-reported measures in additional studies. For example, physiological measures such as skin conduction resistance, blood pressure, pupil dilation, or heart rate could capture the activation dimension of emotion. However, there is great difficulty in using such autonomic nervous system measures to distinguish responses along the pleasantness dimension (Levenson, 1992). Modern brain imaging techniques, such as functional magnetic resonance imaging (fMRI), may be used to observe the activation of brain areas generally associated with pleasure and arousal, but these techniques, too, highly depend on subjective interpretations by the researcher. Moreover, physiological and neurological measures are physically intrusive (i.e., electrodes applied to the respondents’ skin or head, eye monitoring devices) or require extremely noisy machinery and claustrophobic environments. They therefore introduce their own set of problems and distortions. For decision-making studies such as this one, the most practical and unobtrusive external measure of emotion may be facial action coding. To apply the facial action coding system (FACS; Ekman & Friesen, 1978), participants would have to be filmed during the choice experiment, and specifically trained judges would then independently analyze and code the participants’ facial expressions into the emotional states they believed the participants had experienced during the experiment.

In summary, whether a researcher should augment the expectancy-value model with anticipatory and anticipated emotion constructs depends on the trade-offs he or she is willing to make, as well as the stage of decision making under investigation. For many

practical purposes, especially when the antecedents of overall attitude formation are not of interest, traditional EVM is more parsimonious and easier to handle. On the other hand, the additional variance explanation offered by anticipatory and anticipated emotions is huge for A_{obj} , considerable and significant for PI , but only marginal for AP . Thus, for researchers and practitioners alike, the augmented EVM can deliver a richer picture of the decision-making process - at least in certain conditions.

4 Summary and Implications

The results of the studies presented in this dissertation have a number of important implications both for the producers of media goods and for researchers studying hedonic consumption.

The Last Picture Show? Timing and Order of Movie Distribution Channels demonstrates that the current motion picture distribution channel configuration is neither producer-revenue nor industry-revenue maximizing, and that the optimal channel configuration is country-specific, even though common patterns exist. Since the publication of our study, theatrical-to-DVD release windows have continued to shrink at a rate of six days per year, to an average of four months and eight days in 2009 (NATO 2009). In an interesting turn of events, Sony has floated the idea of moving rental video-on-demand from the end of the sequential chain to the start - shortly after the theatrical release and before the DVD rental or sales release, at a price of \$40 per viewing - for owners of its internet-enabled Sony Bravia HD TV set (Grover 2009). Moving VOD forward at higher prices is in line with our scenarios for producer-revenue maximizing configurations, though Sony's plan excludes our scenarios' suggestion of simultaneously moving forward the DVD rental release. Sony's rationale for this is fear of piracy: Unlike DVDs, "the Bravia is a so-called closed system, which means content streamed on the sets can't be pirated" (Grover 2009). In line with our simulations predicting heavy losses for the theatrical channel as a result of moving forward the home entertainment channels, the US National Association of Theatre Owners (NATO) retaliated for Sony's suggestion by boycotting its family movie "Cloudy with a Chance of Meatballs" (Eller and Verrier 2009). In another, though mutually agreed, reshuffling of distribution windows, leading US online rental service Netflix recently signed a deal agreeing to delay rentals of new

Warner Bros. releases by 28 days *after* DVD/Blu-Ray sales commence (Cheng 2010). This release order reversal of rentals versus sales actually follows our suggestion for creating a “win-win” scenario in which *each* channel’s revenues, including theatrical, are being increased.

With our study *Consumer File Sharing of Motion Pictures* confirming the film industry’s revenue losses due to piracy, what are its implications for release window strategies? Our model shows that theatrical and DVD distribution revenues are all hurt by piracy to a significant extent. In Germany, theatres lose roughly 12.6% in revenues, DVD rentals lose 10.5%, and DVD sales lose 14.7%. Based on this, one could draw the conclusion that the optimal release window lengths in our *Last Picture Show*-study are overestimated, because the longer the waiting time for legal consumption opportunities, the higher the motivation and opportunity to engage in file sharing. This interpretation was shared by Bob Chapek, head of distribution at Disney Studios, in his renewed call for shortening the theatrical-to-DVD release window: “Studios are sitting on their hands [...] while the only ones who can exploit the product are pirates” (Eller and Verrier 2009).

On the other hand, our conceptual framework of sequential distribution revenues (Figure 3) highlights the important role of success-breeds-success effects and repeat consumption, which are strongly reduced by simultaneous releases and especially by an immediate availability of retail DVDs. Moreover, the country-specific optimality of release scenarios suggests that piracy will also affect each channel in slightly different ways in each country, e.g. due to different litigation practices, moral values concerning illegal sharing, or broadband availability. It would therefore be instructive to repeat our choice-based conjoint experiment in each major motion picture market with a study design that explicitly takes file sharing intentions into account. As in our original file

sharing study, caution would have to be taken with the questionnaire wording so as not to characterize file sharing as an illegal/immoral activity; for example, a “free copy, downloaded from the internet or obtained from friends” could be added as one of the available channels to the choice-based conjoint design. Should this design be deemed to overstate the impact of file sharing (by placing piracy squarely in the evoked set of consumption choices), general file sharing attitudes and intentions could be captured in a survey section independent of the conjoint design, so as to include them as adjustment factors in the channel-specific revenue models alongside success-breeds-success, word-of-mouth, and repeat consumption factors.

As we also point out in our file sharing study, the studios’ best chance of curbing piracy are not copy-protection mechanisms, but understanding and tackling the drivers of file sharing intentions. Based on this strategy and citing our work, Taylor, Ishida, and Wallace (2009) study file sharing intentions for music and movies. They draw on Perugini and Bagozzi’s (2001) Model of Goal-Directed Behavior, which is an extension of Ajzen’s (1991) Theory of Planned Behavior – also contained in the integrative framework of decision making models (Figure 1) underlying this dissertation – that includes desires, frequency of past behavior, and a (theoretically not explained) selection of anticipated emotion variables. Their results show that some anticipated emotions and A_{obj} towards digital piracy are indeed drivers of file sharing behavior, and they formulate a five-step action plan for content owners focused on changing attitudes towards piracy and the film/music industry, as well as raising the moral cost of piracy.

Our third study, *Augmenting the Expectancy-Value Model with a Dimensional Model of Emotion*, has direct implications for Taylor et al.’s (2009) work which aims at increasing the explained variance for file sharing intentions. Our analyses provide a more systematic approach to adding emotion measures to expectancy-value models (such as

the Model of Goal-Directed Behavior), demonstrate how anticipatory and anticipated emotions give rise to A_{obj} in the first place, and show how the variance explanation by emotions for behavioral intentions can be cleanly separated from the variance explanation by A_{obj} . It also raises the question whether our own study's choice-based conjoint design, which is philosophically closest to the information processing paradigm in excluding the role of emotion, could be enriched with an "admixture of the experiential perspective" as Holbrook and Hirschman (1982: 138) suggested. Highlighting this potential shortcoming of conjoint designs, Armitage (1997: 80) writes: "[...] it must not be forgotten that individuals have beliefs, feelings and emotions which form their attitudes when acquiring products and/or services, and it may involve utility functions and decision rules that are not adequately captured by the models of conjoint measurement." Likewise, Luce, Payne, and Bettman (1999) demonstrate that consumer do not only make trade-offs between product attributes, but also between emotional considerations.

To the best of my knowledge, there is no research yet which attempts to broaden the conjoint methodology with explicit emotion measures, or which at least examines the feasibility of doing so. At first glance, self-explicated conjoint designs would appear most suited for such an approach because, "reminiscent of the expectancy-value models of attitude theory" (Green and Srinivasan 1990: 9), they too are compositional, i.e. part-worths are calculated as the product of (separately evaluated) attribute desirability and attribute importance - which is in fact identical to the adequacy-importance formulation of attitude used in study 3 of this dissertation. However, in practice, adding emotion measures to conjoint tasks will not be as straightforward: Arguably, an emotional, hedonic appraisal of an object will first require the perception of the object as a whole, not just of its constituent parts (as in purely self-explicated approaches). Likewise,

simply adding traditional, survey-based emotion measures to decompositional conjoint designs would threaten their parsimony and real-world applicability: Participants would be asked to introspect on and report their emotions for several different products (i.e. attribute level combinations) per conjoint task and for multiple conjoint tasks in succession, in addition to having to evaluate rank-order choices. As with our study in study 3, perhaps the answer lies in finding unobtrusive, reliable, non-self-reported emotion measures which are nonetheless able to distinguish different phenomenological states. Facial action coding (Ekman and Friesen 1978) seems to be the most promising route, and computer vision research is rapidly progressing towards fully-automated facial action coding and emotion detection (Bartlett et al. 2006). Future conjoint software packages might make use of webcams to record participants' facial reactions while solving conjoint tasks, and then automatically encode detected emotions into ratio-scaled data that can be included in estimating individual utility functions. In any case, as our work demonstrates how the prediction of behavioral intentions, and thus potentially conjoint market share simulations, can be improved by including emotion measures alongside attribute and attitude measures, this could indeed be a worthwhile avenue for future research.

5 References

- Aaker, Jennifer, Aimee Drolet, and Dale Griffin (2008), "Recalling mixed emotions." *Journal of Consumer Research*, 35, 268-278.
- Ajzen, Icek (1991), "The Theory of Planned Behavior," *Organizational Behavior and Human Decision Processes*, 50, 179-211.
- Ajzen, Icek, and Martin Fishbein (2005), "The influence of attitudes on behavior," in *The Handbook of Attitudes*, D. Albarracín, B. T. Johnson, and M. P. Zanna, Eds. Mahwah, NJ: Erlbaum.
- Allen, Chris T., Karen A. Machleit, and Susan Schultz Kleine (1992), "A comparison of attitudes and emotions as predictors of behavior at diverse levels of behavioral experience," *Journal of Consumer Research*, 18 (4), 493-504.
- Amdur, Meredith (2004), "Inside Move: Studios take walk around the Block," *Variety*, (accessed September 12, 2004), [available at <http://www.variety.com/article/VR1117901641>].
- Armitage, Andrew M. D. (1997), "The application of conjoint analysis to evaluate service quality," *Total Quality Management*, 8 (2), 85-88.
- Armstrong, J. Scott, Roderick J. Brodie, and Andrew G. Parsons (2001). "Hypotheses in Marketing Science: Literature Review and Publication Audit," *Marketing Letters*, 12 (May), 171-187.
- Arnold, Thomas K. (2005), "Coming Back for Seconds, Thirds....," *USA Today*, (accessed September 26, 2005), [available at http://www.usatoday.com/life/movies/news/2005-09-26-direct-to-dvd_x.htm].

- Arora, Neeraj and Joel Huber (2001), "Improving Parameter Estimates and Model Prediction by Aggregate Customization in Choice Experiments," *Journal of Consumer Research*, 28 (September), 273-283.
- Association for Consumer Research (2004), *The Newsletter of the Association for Consumer Research*, Provo, UT: ACR.
- Bagozzi, Richard P., Hans Baumgartner, Rik Pieters, and Marcel Zeelenberg (2000), "The role of emotions in goal-directed behavior," in *The why of consumption: contemporary perspectives on consumer motives, goals and desires*, S. Ratneshwar, David Glen Mick and Cynthia Huffman, Eds. New York, NY: Routledge.
- Bagozzi, Richard P., Utpal Dholakia, and Suman Basuroy (2003), "How effortful decisions get enacted: the motivating role of decision processes, desires, and anticipated emotions," in *Journal of Behavioral Decision Making*, 16, 273-295.
- Bagozzi, Richard P., Mahesh Gopinath, and Prashanth U. Nyer (1999), "The Role of Emotions in Marketing", *Journal of the Academy of Marketing Science*, 27 (2), 184-206.
- Bagozzi, Richard P., Zeynep Gürhan-Canli, and Joseph R. Priester (2002), *The social psychology of consumer behavior*. Philadelphia, PA: Open University.
- Bagozzi, Richard P., Youjae Yi, and Lynn W. Phillips (1991), "Assessing Construct Validity in Organizational Research," *Administrative Science Quarterly*, 36, 421-458.
- BAM (2006), *Business Report zum Videomarkt 2005*, Hamburg: Bundesverband für Audiovisuelle Medien.
- Bartlett, Marian S., Gwen Littlewort, Mark Frank, Claudia Lainscsek, Ian Fasel, and Javier Movellan (2006), "Fully Automatic Facial Action Recognition in Spontaneous

- Behavior,” *7th International Conference on Automatic Face and Gesture Recognition*, New York: IEEE.
- Bateman, Ian, Sam Dent, Ellen Peters, Paul Slovic, and Chris Starmer (2007), “The affect heuristic and the attractiveness of simple gambles,” *Journal of Behavioral Decision Making*, 20, 365-380.
- Batra, Rajeev, Douglas M. Stayman (1990), “The role of mood in advertising effectiveness,” *Journal of Consumer Research*, 17, 203-214.
- Becker, Gary S. (1974), “A Theory of Social Interactions,” *Journal of Political Economy*, 82 (6), 1063-93.
- Becker, Gary S. (1992), “The Economic Way of Looking at Life,” *Nobel Lecture*, Stockholm: The Nobel Foundation.
- Belk, Russell W. (1995), *Collecting in a Consumer Society*, London: Routledge.
- Berridge, Kent, and Piotr Winkielman (2003), “What is an unconscious emotion? (The case for unconscious “liking”),” *Cognition and Emotion*, 17, 181-211.
- Bettman, James R. (1970), “Information Processing Models of Consumer Behavior,” *Journal of Marketing Research*, 8, 370-376.
- Bhatia, G. Krishan, Richard C. Gay, and W. Ross Honey (2001), “Windows into the Future: How Lessons from Hollywood will Shape the Music Industry,” *e-Insights*, 7-01, Booz-Allen & Hamilton.
- Blume, Stephen E. (2004), “The Revenue Streams: An Overview,” in *The Movie Business Book*, Jason E. Squire, ed., New York: Fireside, 331-359.
- Bodur, H. Onur, David Brinberg, and Eloise Coupey (2000), “Belief, affect, and attitude: Alternative models of the determinants of attitude,” *Journal of Consumer Psychology*, 9, 17-28.

- Boldrin, Michele and David K. Levine (2002), "The Case Against Intellectual Property," *American Economic Review*, 92 (2), 209-212.
- Bond, Paul (2005), "Theatrical-to-DVD on fast forward, film execs say," *Hollywood Reporter*, (accessed April 21, 2005), [available at http://www.hollywoodreporter.com/thr/article_display.jsp?vnu_content_id=1000892571].
- Bosnjak, Michael, Dirk Obermeier, and Tracy L. Tuten (2006), „Predicting and explaining the propensity to bid in online auctions: a comparison of two action-theoretical models," *Journal of Consumer Behaviour*, 5 (2), 102-116.
- Box Office Mojo* (2006), "'Big Momma' Jams, 'Nanny McPhee' Floats, 'Bubble' Bursts," (accessed February 7, 2006), [available at <http://boxofficemojo.com/news/?id=1997&p=1.htm>].
- Breckler, Stephen J. and Elisabeth C. Wiggins (1989), "Affect versus evaluation in the structure of attitudes," *Journal of Experimental Social Psychology*, 25, 253-271.
- Breivik, Einar, and Magne Supphellen (2003), "Elicitation of product attributes in an evaluation context: A comparison of three elicitation techniques," *Journal of Economic Psychology*, 24, 77-98.
- Byers, Simon, Lorrie Cranor, Eric Cronin, Dave Kormann, and Patrick McDaniel (2004), "An Analysis of Security Vulnerabilities in the Movie Production and Distribution Process," *Telecommunications Policy*, 28, 619-644.
- Caruso, Eugene M. and Eldar Shafir (2006), "Now that I Think about It, I'm in the Mood for Laughs: Decisions Focused on Mood," *Journal of Behavioral Decision Making*, 19, 155-69.

- CBC (2006), "U.S. cinemas back out of Soderbergh's 'Bubble'," *Canadian Broadcasting Corporation*, (accessed January 19, 2006), [available at <http://www.cbc.ca/story/arts/national/2006/01/18/bubble-soderbergh.html>].
- Chalmers, John (2002), "Finance Theory II: Asteroid Pictures, Inc.," *case study*, Massachusetts Institute of Technology, Sloan School of Management.
- Chandon, Pierre, Vicki G. Morwitz, and Werner J. Reinartz (2005), "Do Intentions Really Predict Behavior? Self-Generated Validity Effects in Survey Research," *Journal of Marketing*, 69 (April), 1-14.
- Cheng, Jacqui (2010), "Warner Bros props up decaying DVD market with Netflix pact," *Ars Technica*, (accessed February 15, 2010), [available at <http://arstechnica.com/media/news/2010/01/warner-bros-props-up-decaying-dvd-market-with-netflix-pact.ars>].
- Chiang, Eric and Djeto Assane (2002), "Software Copyright Infringement Among College Students," *Applied Economics*, 34, 157-166.
- Clark, Mike (2005), "I Love DVDs," *USA Today*, (accessed July 26, 2005), [available at http://www.usatoday.com/life/movies/news/2005-07-25-dvd-clark_x.htm].
- Cohen, Jessica R. (2003), "Media & Entertainment: A Review of 2003 Media & Entertainment Conference", *industry report*, Merrill Lynch.
- Cohen, Joel B., Michel Tuan Pham, and Eduardo B. Andrade (2008), "The Nature and Role of Affect in Consumer Behavior," in *Handbook of Consumer Psychology*, Curtis P. Haugtvedt, Paul M. Herr, and Frank R. Kardes, Eds. Boca Raton, FL: CRC Press.
- Damasio, Antonio R. (1994), *Descartes' error: emotion, reason, and the human brain*. New York: Putnam.

- Davidson, Russell and James G. MacKinnon (1993), *Estimation and Inference in Econometrics*, New York: Oxford University Press.
- DeVany, Arthur and Cassey Lee (2001), "Quality Signals in Information Cascades and the Dynamics of the Distribution of Motion Picture Box Office Revenues," *Journal of Economic Dynamics and Control*, 25 (March), 593-614.
- DeVany, Arthur and W. David Walls (2002), "Does Hollywood make too many R-rated movies? Risk, stochastic dominance, and the illusion of expectation," *Journal of Business*, 75 (July), 425-51.
- Dutka, Elaine (2005), "Battle escalates over the speedy debut of DVDs," *Los Angeles Times*, (accessed March 29, 2005), [available at <http://www.dvdverdict.com/phpBB2/viewtopic.php?t=7864&highlight=&>].
- Economist (2002), "The Oscars get Napsterized," *The Economist*, (accessed March 25, 2002), [available at http://www.economist.com/agenda/displayStory.cfm?Story_ID=1049624].
- Edwards, Ward (1954), "The Theory of Decision-Making," *Psychological Bulletin*, 51, 380-417.
- Ekman, Paul and Richard J. Davidson Eds. (1994), *The nature of emotion: fundamental questions*. New York: Oxford University Press.
- Ekman, Paul and Wallace V. Friesen (1978), *Facial Action Coding System*. Palo Alto, CA: Consulting Psychologists Press.
- Elberse, Anita and Jehoshua Eliashberg (2003), "Demand and Supply Dynamics for Sequentially Released Products in International Markets: The Case of Motion Pictures," *Marketing Science*, 22 (Summer), 329-54.

- Eliashberg, Jehoshua, Anita Elberse, and Mark Leenders (2006), "The Motion Picture Industry: Critical Issues in Practice, Current Research, and New Research Directions," *Marketing Science*, 25 (6), 638-661.
- Eller, Claudia and Richard Verrier (2009), "Studios, theaters wrangling over film release windows," *Los Angeles Times*, (accessed February 14, 2010), [available at <http://articles.latimes.com/2009/dec/26/business/la-fi-ct-windows26-2009dec26>].
- EMA (2006), 2006 Annual Report on the Home Entertainment Industry, Entertainment Merchants Association.
- Epstein, Edward J. (2005), "Downloading for Dollars," *Slate*, (accessed November 28, 2005), [available at <http://www.slate.com/id/2131124>].
- FFA (2004), "Die Kinobesucher 2003," accessed December 18, 2004, [available at http://www.ffa.de/start/download.php?file=publikationen/kinobesucher_2003.pdf].
- FFA (2006a), "Brennerstudie 2005," (accessed February 8, 2006), [available at http://www.ffa.de/start/download.php?file=publikationen/brenner_studie4.pdf].
- Fishbein, Martin (1967), "Attitude and the prediction of behavior," in *Readings in Attitude Theory and Measurement*. Martin Fishbein, ed. New York: Wiley.
- Fishbein, Martin and Icek Ajzen (1975), *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*. Reading, MA: Addison-Wesley.
- Forgas, Joseph P. and Gordon H. Bower (2000), "Mood effects on person-perception judgments," in *Emotions in Social Psychology: Essential Readings*, G. Gerrod Parrott, ed. New York, NY: Psychology Press, 204-215.
- Fornell, Claes and Fred L. Bookstein (1982), "Two Structural Equation Models: LISREL and PLS Applied to Consumer Exit-Voice Theory," *Journal of Marketing Research*, 19 (November), 440-452.

- Fornell, Claes and Jaesung Cha (1994), "Partial Least Squares," in *Advanced Methods of Marketing Research*, Richard P. Bagozzi, ed. Cambridge: Blackwell, 52-78.
- Förster, Jens (2004), "How body feedback influences consumers' evaluation of products," *Journal of Consumer Psychology*, 14, 416-426.
- Frank, Björn (1994), "Optimal Timing of Movie Releases in Ancillary Markets: The Case of Video Releases," *Journal of Cultural Economics*, 18 (June), 125-33.
- Fritz, Ben (2005), "H'w'd Chases TV Cheats," *Variety*, May 13.
- Gentile, Gary (2005), "Studios Mull Changes to Movie 'Windows'," *The Miami Herald*, (accessed August 28, 2005), [available at <http://www.miami.com/mld/miamiherald/business/national/12500564.htm>].
- Ghiselli, Edwin E., John P. Campbell, and Sheldon Zedeck (1981), *Measurement Theory for the Behavioral Sciences*. San Francisco: W.H. Freeman and Company.
- Gilbride, Timothy J. and Greg M. Allenby (2004), "A Choice Model with Conjunctive, Disjunctive, and Compensatory Screening Rules," *Marketing Science*, 23 (Summer), 391-406.
- Gopal, Ram D., Sudip Bhattacharjee, and G. Lawrence Sanders (2005), "Do Artists Benefit from Online Music Sharing?" *Journal of Business*, 79 (May), 1503-1533.
- Gopal, Ram D., G. Lawrence Sanders, Sudip Bhattacharjee, Manish Agrawal, and Suzanne C. Wagner (2004), "A Behavioral Model of Digital Music Piracy," *Journal of Organizational Computing and Electronic Commerce*, 14 (2), 89-105.
- Graham, Renee (2004), "Greedy Studios Make DVDs Not so Special," *Boston Globe*, accessed September 24, 2006, [available at http://www.boston.com/ae/movies/articles/2004/04/27/greedy_studios_make_dvds_not_so_special/].
- Green, Paul E. and Vithala R. Rao (1971), "Conjoint Measurement for Quantifying Judgmental Data," *Journal of Marketing Research*, 8 (August), 355-63.

- Grewal, Dhruv, Kent B. Monroe, and R. Krishnan (1998), "The Effects of Price-Comparison Advertising on Buyers' Perceptions of Acquisition Value, Transaction Value, and Behavioral Intentions," *Journal of Marketing*, 62 (April), 46-59.
- Grgeta, Edi (2004), "A World Where Copyright Does Not Matter: Implications of Boldrin and Levine's Model," *working paper*, University of Chicago.
- Grover, Ronald (2005), "Movie Moguls need to Face the Music," *Business Week Online*, (accessed October 29, 2005), [available at http://www.businessweek.com/bwdaily/dnflash/oct2005/nf20051018_5868_db011.htm]
- Grover, Ronald (2006), "Will Bubble Burst a Hollywood Dogma?," *Business Week*, Jan 24, p. 5-5.
- Grover, Ronald (2009), "Sony's Plan for \$40 Movies at Home," *Business Week Online*, (accessed February 14, 2010), [available at http://www.businessweek.com/bwdaily/dnflash/content/aug2009/db20090830_267810.htm].
- Guardian* (2005), "Signs Director Points to Studio Greed in Distribution Row," *Guardian Unlimited*, accessed 29 October 2005, [available at <http://film.guardian.co.uk/news/story/0,12589,1602886,00.html>].
- Helmig, Bend, Jan-Alexander Huber, and Peter S. H. Leeflang (2007), "Explaining behavioural intentions toward co-branded products," *Journal of Marketing Management*, 23, 285-304.
- Hennig-Thurau, Henning, Victor Henning, and Henrik Sattler (2007), "Consumer File Sharing of Motion Pictures," *Journal of Marketing*, 71 (October), 1-18.
- Hennig-Thurau, Thorsten, Victor Henning, Henrik Sattler, Felix Eggers and Mark Houston (2006), "Optimizing the Sequential Distribution Model for Motion Pictures", *Enhancing Knowledge Development in Marketing: Proceedings of the*

2006 AMA Summer Educators' Conference, Chicago: American Marketing Association.

Hennig-Thurau, Thorsten, Victor Henning, Henrik Sattler, Felix Eggers, and Mark Houston (2007), "The Last Picture Show? Timing and Order of Movie Distribution Channels," *Journal of Marketing*, 71 (October), 63-83.

Hennig-Thurau, Thorsten, Mark B. Houston, and Gianfranco 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*, 34 (Fall), 559-75.

Hennig-Thurau, Thorsten, Mark B. Houston, and Shrihari Sridhar (2006), "Can Good Marketing Carry a Bad Product? Evidence from the Motion Picture Industry," *Marketing Letters*, 17, 205-219.

Hennig-Thurau, Thorsten, Gianfranco Walsh, and Matthias Bode (2004), "Exporting Media Products: Understanding the Success and Failure of Hollywood Movies in Germany," *Advances in Consumer Research*, 31, 633-38.

Henning, Victor (2004), "An Empirical Study of the Effects of P2P Filesharing on the Film Industry," *diploma thesis*, Otto-Beisheim Graduate School of Management Vallendar.

Henning, Victor (2007), "The Role of Anticipated Emotions in Hedonic Consumption," *Cognition and Emotion in Economic Decision Making - Workshop Proceedings*, Rovereto: Università degli Studi di Trento.

Henning, Victor and Thorsten Hennig-Thurau (2005), "Consumer File Sharing of Motion Pictures: Consequences and Determinants", *Enhancing Knowledge Development in Marketing: Proceedings of the 2005 AMA Summer Educators' Conference*, Chicago: American Marketing Association.

- Henning, Victor and Thorsten Hennig-Thurau (2008), "The Theory of Reasoned Action: Does it Lack Emotion?," *Enhancing Knowledge Development in Marketing: Proceedings of the 2008 AMA Summer Educators' Conference*, Chicago: American Marketing Association.
- Henning, Victor and Thorsten Hennig-Thurau (2009), "Augmenting the Expectancy-Value Model with a Dimensional Model of Emotion: Does It Matter if the Product Is Hedonic or Utilitarian?," *Working paper*.
- Hindes, Andrew (1998), "The Pic That Won't Sink," *Variety*, (accessed October 14, 2005), [available at <http://www.variety.com/article/VR1117435350>].
- Hirschman, Elizabeth C. and Morris B. Holbrook (1982), "Hedonic Consumption: Emerging Concepts, Methods and Propositions.," *Journal of Marketing*, 46 (3), 92-101.
- Holbrook, Morris B. (1982), "The Experiential Aspects of Consumption: Consumer Fantasies, Feelings, and Fun," *Journal of Consumer Research*, 9 (September), 1982.
- Holm, Håkan J. (2003), "Can Economic Theory Explain Piracy Behavior?" *Topics in Economic Analysis & Policy*, 3 (1), Article 5.
- Hosmer, David W. and Stanley Lemeshow (2004), *Applied Logistic Regression (2nd ed.)*. New York: John Wiley & Sons.
- Howard, John A. and Jagdish N. Sheth (1969), *The Theory of Buyer Behavior*. New York: John Wiley & Sons.
- Hoyer, Wayne D. (1984), "An Explanation of Consumer Decision Making for a Common Repeat Purchase Product," *Journal of Consumer Research*, 11 (December), 822-829.
- Huang, Chun-Yao (2005), "File Sharing as a Form of Music Consumption," *International Journal of Electronic Commerce*, 9 (4), 37-55.

- Huber, Joel and Klaus Zwerina (1996), "The Importance of Utility Balance in Efficient Choice Designs," *Journal of Marketing Research*, 33 (August), 307-17.
- Huber, Joel, Dick R. Wittink, John A. Fiedler, and Richard Miller (1993), "The Effectiveness of Alternative Preference Elicitation Procedures in Predicting Choice," *Journal of Marketing Research*, 30 (February), 105-14.
- Hunt, Shelby D., and James L. Pappas (1972), "A Crucial Test for the Howard-Sheth Model of Buyer Behavior," *Journal of Marketing Research*, 9 (August), 346-48.
- Hsu, Tsuen-Ho, Yi-Sheng Wang, and Su-Chen Wen (2006), "Using the decomposed theory of planned behaviour to analyse consumer behavioural intention towards mobile text message coupons," *Journal of Targeting, Measurement & Analysis for Marketing*, 14 (4), 309-324.
- Imai, Kosuke, Gary King, and Olivia Lau (2006, p. 265), "Zelig: Everyone's Statistical Software, Version 2.6-3," accessed September 12, 2006 [available at <http://gking.harvard.edu/zelig/>].
- IVF (2004), *European Video Market: The Industry Overview*, International Video Federation.
- Izard, Carroll E. (1977), *Human emotions*. New York: Plenum.
- Jaccard, James, Choi K. Wan, and Robert Turrisi (1980), "The Detection and Interpretation of Interaction Effects Between Continuous Variables in Multiple Regression," *Multivariate Behavioral Research*, 25, 467-478.
- Kempf, DeAnna S. (1999), "Attitude formation from product trial: Distinct roles of cognition and affect for hedonic and functional products," *Psychology & Marketing*, 16, 35-50.
- King, Gary and Langche Zeng (2001a), "Logistic Regression in Rare Events Data," *Political Analysis*, 9 (February), 137-163.

- King, Gary and Langche Zeng (2001b), "Explaining Rare Events in International Relations," *International Organization*, 55 (3), 693-715.
- Lance, Charles E. (1988), "Residual Centering, Exploratory and Confirmatory Moderator Analysis, and Decomposition of Effects in Path Models Containing Interactions," *Applied Psychological Measurement*, 12 (2), 163.
- Larsen, Randy J. and Edward Diener (1992), "Promises and problems with the circumplex model of emotion," *Review of Personality and Social Psychology*, 13, 25-59.
- Lee, Angela Y. (2004), "The prevalence of metacognitive routes to judgment," *Journal of Consumer Psychology*, 14, 349-355.
- Lehmann, Donald R. and Charles B. Weinberg (2000), "Sales Through Sequential Distribution Channels: An Application to Movies and Videos," *Journal of Marketing*, 64 (July), 18-33.
- Lerner, Jennifer S., David A. Small, and George F. Loewenstein (2004), "Heart strings and purse strings: Carryover effects of emotions on economic decisions," *Psychological Science*, 15, 337-341.
- Levenson, Robert W. (1992), "Autonomic nervous system differences among emotions," *Psychological Science*, 3 (1), 23-27.
- Liebowitz, Stan J. (2006), "File-Sharing: Creative Destruction or Just Plain Destruction?" *Journal of Law and Economics*, 49 (April), 1-28.
- Lippman, John (2000), "Nothing Succeeds Like Past Successes," *Wall Street Journal*, November 8, 236 (29), W8.
- Liu, Yong (2006), "Word of Mouth for Movies: Its Dynamics and Impact on Box Office Revenue," *Journal of Marketing*, 70 (July), 74-89.

- Loewenstein, George F., Elke U. Weber, Christopher K. Hsee, and Ned Welch (2001), "Risk as feelings," *Psychological Bulletin*, 127 (2), 267-286.
- Louviere, Jordan J. and George Woodworth (1983), "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data," *Journal of Marketing Research*, 20 (November), 350-67.
- Luan, Jackie Y. (2005), "Optimal Inter-Release Timing for Sequential Releases," *working paper*, Yale University.
- Luce, Mary Frances, John W. Payne, and James R. Bettman (1999), "Emotional Trade-Off Difficulty and Choice," *Journal of Marketing Research*, 36 (2), 143-159.
- MacInnis, Deborah J. and Gustavo E. de Mello (2005), "The Concept of Hope and Its Relevance to Product Evaluations and Choice," *Journal of Marketing*, 69 (1), 1-14.
- Manly, Lorne (2005), "Extinction Long Seen, Video Stores Hang On," *New York Times*, (accessed August 23, 2005), [available at <http://select.nytimes.com/gst/abstract.html?res=F50D11F83A5A0C708EDDA10894DD404482>].
- Mano, Haim (1997), "Affect and persuasion: The influence of pleasantness and arousal on attitude formation and message elaboration," *Psychology & Marketing*, 14, 315-335.
- Mazis, Michael B., Olli T. Ahtola, and R. Eugene Klippel (1975), "A Comparison of Four Multi-Attribute Models in the Prediction of Consumer Attitudes," *Journal of Consumer Research*, 2 (June), 38-52.
- Mellers, Barbara, Alan Schwartz, and Ilana Ritov (1999), "Emotion-Based Choice," *Journal of Experimental Psychology: General*, 128 (3), 332-45.
- Michel, Norbert J. (2006), "The Impact of Digital File Sharing on the Music Industry: An Empirical Analysis," *Topics in Economic Analysis & Policy*, 6 (1), Article 18.

- Moore, William L., Jason Gray-Lee, and Jordan J. Louviere (1998), "A Cross-Validity Comparison of Conjoint Analysis and Choice Models at Different Levels of Aggregation," *Marketing Letters*, 9 (April), 195-207.
- Montero-Pons, Juan D. and Manuel Cuadrado-García (2006), "Digital Goods and the Effects of Copying: An Empirical Study of the Music Market," *working paper*.
- MPAA (2003), *International Entertainment Industry: 2002 Market Statistics and Analysis*, Motion Picture Association of America.
- MPAA (2004a), "Studios to Begin Suing Illegal Film File Swappers," *MPAA Press Release*, (accessed November 24, 2004), [available at http://www.mpa.org/CurrentReleases/2004_11_04_PressRelease.pdf].
- MPAA (2004b), "Respect Copyrights," accessed March 12, 2005 [available at <http://www.respectcopyrights.org>].
- MPAA (2004c), "Worldwide Internet Piracy Study," accessed March 15, 2005 [available at http://www.mpa.org/MPAAPress/2004/2004_07_08.pdf].
- MPAA (2006a), *The Cost of Movie Piracy*, Encino: MPAA.
- MPAA (2006b), *U.S. Theatrical Market: 2005 Statistics*, Motion Picture Association of America.
- Muñoz, Lorenza (2006), "Budget Overruns of Biblical Proportions," *Los Angeles Times*, (accessed October 10, 2006), [available at http://www.calendarlive.com/movies/cl-fi-ewan9oct09_0_2164715_story?coll=cl-movies].
- NATO (2009), *Major Studio Release Windows*, Washington, DC: NATO, (accessed February 14, 2010), [available at <http://www.natoonline.org/windows.htm>].
- Neelamegham, Ramya and Dipak Jain (1999), "Consumer Choice Process for Experience Goods: An Econometric Model and Analysis," *Journal of Marketing Research*, 36 (3), 373-86.

- Newell, Allen, J.C. Shaw, and Herbert A. Simon (1958), "Elements of a Theory of Human Problem Solving," *Psychological Review*, 65, 151-166.
- Njite, David, and H.G. Parsa (2005), "Structural Equation Modeling of Factors that Influence Consumer Internet Purchase Intentions of Services," *Journal of Services Research*, 5 (1), 43-59.
- Oberholzer-Gee, Felix and Koleman Strumpf (2005), "The Effect of File-Sharing on Record Sales—An Empirical Analysis," *working paper*, Harvard Business School.
- OMSYC (2002), "The World Cinema Market: Production and Exhibition," industry report, OMSYC Corp.
- Peitz, Martin and Patrick Waelbroeck (2004), "The Effect of Internet Piracy on Music Sales: Cross-Section Evidence," *Review of Economic Research on Copyright Issues*, 1 (2), 71-79.
- Perugini, Marco and Richard P. Bagozzi (2001), "The role of desires and anticipated emotions in goal-directed behaviours: Broadening and deepening the theory of planned behavior," *British Journal of Social Psychology*, 40, 79-98.
- Peter, J. Paul (1979), "Reliability: A Review of Psychometric Basics and Recent Marketing Practices," *Journal of Marketing Research*, 16 (February), 6-17.
- Petty, Robert E. and John T. Cacioppo, (1986). *Communication and persuasion: Central and peripheral routes to attitude change*. New York: Springer.
- Petty, Richard. E., David W. Schumann, Stevan A. Richman, and Alan J. Strathman (1993), "Positive mood and persuasion: Different roles for affect under high- and low-elaboration conditions," *Journal of Personality and Social Psychology*, 64, 5-30.
- Pham, Michel Tuan (1998), "Representatives, relevance, and the use of feelings in decision making," *Journal of Consumer Research*, 25 (2), 144-58.

- Pham, Michel Tuan (2004), "The Logic of Feeling," *Journal of Consumer Psychology*, 14, 360-369.
- Phillips, Diane M., Jerry C. Olson, and Hans Baumgartner (1995), "Consumption visions in consumer decision making," *Advances in Consumer Research*, 22 (1), 280-84.
- Prasad, Ashutosh, Bart Bronnenberg, and Vijay Mahajan (2004), "Product Entry Timing in Dual Distribution Channels: The Case of the Movie Industry," *Review of Marketing Science*, 2, 1-18.
- Puig, Claudia (2005), "Movies as You Like Them" *USA Today*. July 26, D1-D3.
- Rentrak (2005), "Supplier Terms – Studios," *Rentrak*, (accessed October 14, 2005), [available at <http://www.rentrakonline.com/pdfs/SupplierTerms.pdf>].
- Richard, René, Joop van der Pligt, and Nanne de Vries (1996), "Anticipated Affect and Behavioral Choice," *Basic and Applied Social Psychology*, 18 (2), 111-29.
- Ringle, Christian, Sven Wende, and Alexander Will (2005), *SmartPLS Version 2.0 M2*, www.smartpls.de.
- Rochelandet, Fabrice and Fabrice Le Guel (2005), "P2P Music Sharing Networks: Why the Legal Fight Against Copiers May Be Inefficient," *Review of Economic Research on Copyright Issues*, 2 (2), 69-82.
- Saccone, Melinda (2005), "The Incredible Shrinking Theatrical-to-DVD Window," *Video Store*, January 2, p. 29.
- Schwarz, Norbert (2004), "Meta-Cognitive Experiences in Consumer Judgment and Decision Making," *Journal of Consumer Psychology*, 14(4), 332-348.
- Schwarz, Norbert (2006), "Feelings, Fit, and Funny Effects: A Situated Cognition Perspective," *Journal of Marketing Research*, 43 (1), 20-23.

- Shiv, Baba and Alexander Fedorikhin (1999), "Heart and mind in conflict: The interplay of affect and cognition in consumer decision making," *Journal of Consumer Research*, 26 (3), 278-92.
- Shiv, Baba and Joel Huber (2000), "The Impact of Anticipating Satisfaction on Consumer Choice," *Journal of Consumer Research*, 27 (2), 202-17.
- Simonsohn, Uri (2007), "Clouds make nerds look good: field evidence of the impact of incidental factors on decision making," *Journal of Behavioral Decision Making*, 20, 143-152.
- Smith, Sean (2005), "Coming to a Theater Near You," *Newsweek*, 146, August 8, p. 52-55.
- Snyder, Gabriel (2005a), "Who's on Top?," *Variety.com*, (assessed December 25), [available at http://www.variety.com/index.asp?layout=print_story&articleid=VR1117935164].
- Snyder, Mike (2005b), "DVD Continues Spinning Success," *USA Today*, January 6.
- Sony (1997), "Annual Report 1997," *Sony Corporation*, Tokyo, Japan.
- SPIO (2006), "Schlüsseldaten Filmwirtschaft 2005", *Spitzenorganisation der Filmwirtschaft e.V.*, accessed August 28, 2006 [available at <http://www.spio.de/index.asp?SeitID=3>].
- Stanley, T. L. (2005), "Hollywood Ending?," *Advertising Age*, 76 (35), pp. 1 and 23.
- Sweeting, Paul (2005), "Cracking the Windows," *Video Business*, April 11, p. 10.
- Thaler, Richard (1985), "Mental Accounting and Consumer Choice," *Marketing Science*, 4 (Summer), 199-214.
- Tice, Dianne. M., Ellen Bratslavsky, and Roy F. Baumeister (2001), „Emotional distress regulation takes precedence over impulse control: If you feel bad, do it!," *Journal of Personality and Social Psychology*, 80, 53-67.

- Valenti, Jack (2004), "Movies in the Digital Age," summary of a speech at the MIT communications forum, accessed September 27, 2006 [available at <http://web.mit.edu/comm-forum/forums/valenti.html>].
- Voss, Kevin E., Eric R. Spangenberg, and Bianca Grohmann (2003), "Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude.," *Journal of Marketing Research*, 40 (3), 310-21.
- van der Veen, Jack A.A. and Venu Venugopal (2005), "Using Revenue Sharing to Create Win-Win in the Video Rental Supply Chain," *Journal of the Operational Research Society*, 56 (April), 757-762.
- Vogel, Harold L. (2004), *Entertainment Industry Economics: A Guide for Financial Analyses*. Cambridge: Cambridge University Press.
- Wang, Ming-Shen, Chih-Chung Chen, Su-Chao Chang, & Yung-Her Yang. (2007). Effects of Online Shopping Attitudes, Subjective Norms and Control Beliefs on Online Shopping Intentions: A Test of the Theory of Planned Behaviour. *International Journal of Management*, 24, 296-302.
- Watson, D., & Tellegen, A. (1985). Toward a consensual structure of mood. *Psychological Bulletin*, 98, 219-235.
- Weinberg, Charles (2003), "Profits out of the Picture: Research Issues and Revenue Sources Beyond the North America Box Office," *working paper*.
- Wilson, Timothy D. and Daniel T. Gilbert (2003), "Affective forecasting," in *Advances in experimental social psychology*, M. P. Zanna, Ed. Vol. 35. San Diego: Academic Press.
- Wilson, Timothy D. and Daniel T. Gilbert (2005), "Affective forecasting: Knowing what to want," *Current Directions in Psychological Science*, 14, 131-34.

Wuyts, Stefan, Stefan Stremersch, Christophe Van den Bulte, and Philip Hans Franses

(2004), "Vertical Marketing Systems for Complex Products: A Triadic Perspective,"

Journal of Marketing Research, 41 (November), 479-487.

Zentner, Alejandro (2006), "Measuring the Effect of File Sharing on Music Purchases,"

Journal of Law and Economics, 49 (April), 63-90.

6 Appendix

Appendix A: Illustrative Model Calculation

Consider a scenario with $J=5$ channel alternatives:

1. Theater visit ($=m_{TH}$) at the movie's release date, i.e. $t_{TH}=0$ months, at price $p_{TH}=\$12.50$
2. DVD rental ($=m_{DVD-R}$) at the movie's release date, i.e. $t_{DVD-R}=0$ months, at price $p_{DVD-R}=\$7.75$
3. DVD sales ($=m_{DVD-S}$) three months after the movie's release date, i.e. $t_{DVD-S}=3$ months, at price $p_{DVD-S}=\$22$
4. VOD ($=m_{VOD}$) twelve months after the movie's release date, i.e. $t_{VOD}=12$ months, at price $p_{DVD-S}=\$3$
5. Waiting for the movie to be released on television (none-option)

Given this set of alternatives and given a consumer's preference structure, option (1) might obtain choice shares of $x(TH|J)=0.25$. Thus, from 100 movie consumption occasions this consumer would visit the theater 25 times. Likewise, choice shares for the remaining channels might be $x(DVD-R|J)=0.15$, $x(DVD-S|J)=0.45$, and $x(VOD|J)=0.05$. Consequently, 10% of choice shares would be allocated to the none-option.

In this case, x_{FC} will be represented by the choice shares for theaters and DVD rental since both channels open simultaneously at the movie's release date ($t_{TH}=t_{DVD-R}=0$ months), i.e. $x_{FC}=x(TH|J)+x(DVD-R|J)=0.4$. Thus, if a consumer generally buys a DVD of a movie she has seen before in other channels in 10% of the cases ($\delta_{DVD-S}=a_{DVD-S}=0.1$) the multiple purchase effect will increase the choice shares for DVD sales by 4%. Likewise, if the consumer buys a DVD in 5% of the cases exclusively because she heard from other people that it was a success ($\gamma^{WoM}_{DVD-S}=0.05$) and in 15% of the cases exclusively due to favorable chart information ($\gamma^C_{DVD-S}=0.15$), the information-cascading SBS effect would result in an increase in choice shares of

$x_{DVD-S} \cdot (\gamma^{WOM}_{DVD-S} + \gamma^C_{DVD-S}) = 0.45 \cdot (0.05 + 0.15) = 9\%$. The total updated choice share would then be $x'_{DVD-S} = 0.45 \cdot (1 + 0.05 + 0.15) + 0.1 \cdot 0.4 = 0.58$.

With the price for a theater visit being $p_{TH} = \$12.50$ and assuming that the mean choice share for theaters across all consumers is 0.2, the expected revenue of theaters would be $R_{TH} = \$12.50 \cdot 0.2 = \2.5 . Multiplying by 100 gives a better interpretation of this result, i.e. the expected theater revenue from 100 movie consumption occasions, given the specific scenario of available channel alternatives. According to the over time revenue distribution function $f(w)$ we estimated for theaters (see Figure 2), after the first week 29.37% of the \$2.5 would flow back to theaters. This proportion then has to be discounted with the weekly discount rate of 0.183%, i.e. $(\$2.5 \cdot 0.2937) / (1.00183)$. The second week would produce another 20.74% of the total revenue that has to be discounted for two weeks, i.e. $(\$2.5 \cdot 0.2074) / (1.00183)^2$. We simulate the revenue return for up to 78 weeks in this manner. Adding up these discounted values gives the present value of the theater-specific revenues. In order to obtain the perspective of the studio, these present values have to be multiplied with the percentage of revenues that are actually allocated to the studio (see Table 3) and discounted again for the time of the window length if the channel does not open at the movie's release date, i.e. if $t > 0$ month (see equation 1).

In this example, theaters open at the movie's release date, i.e. $t_{TH} = 0$. Thus, the weekly discounted present values do not have to be discounted again. Multiplying the present values by 50%, i.e. the percentage of theater revenues allocated to the studio, eventually gives the theater-specific component of the studio's net present value of the movie in equation 1.

Appendix B: Success-Breeds-Success Questions

<i>Multiple consumption success-breeds-success</i>	
	In general: What proportion of all movies you have seen in a <u>movie theater...</u>
DVD purchase	..did you later also purchase on DVD? ___%
DVD rental	..did you later also rent on DVD in a video store? ___%
Download-to-rent VOD	..did you later also download from a legal internet service (e.g. MovieLink, CinemaNow) for a fee? ___%
<i>Word-of-mouth-based success-breeds-success</i>	
DVD purchase	Of all DVDs you have purchased so far, what proportion of those did you purchase because you missed the movie in theaters, but heard from friends or acquaintances it was good? ___%
DVD rental	Of all DVDs you have rented from a video store so far, what proportion of those did you rent because you missed the movie in theaters, but heard from friends or acquaintances it was good? ___%
Download-to-rent VOD	Of all movies you have downloaded from legal online services so far, what proportion of those did you download because you missed the movie in theaters, but heard from friends or acquaintances it was good? ___%
<i>Charts-based success-breeds-success</i>	
DVD purchase	Of all DVDs you have purchased so far, what proportion of those did you purchase because you missed the movie in theaters, but it was a huge box office success? ___%
DVD rental	Of all DVDs you have rented from a video store so far, what proportion of those did you rent because you missed the movie in theaters, but it was a huge box office success? ___%
Download-to-rent VOD	Of all movies you have downloaded from legal online services so far, what proportion of those did you download because you missed the movie in theaters, but it was a huge box office success? ___%

Appendix C: List of Movie Titles

Title	Description	Individual Responses for Theater ^a	Individual Responses for DVD ^c
<i>Bambi 2</i>	USA 2006, Family	111 (4)	110 (6; 4)
<i>Basic Instinct 2</i>	USA 2006, Thriller/Drama	561 (23)	497 (14; 7)
<i>Brokeback Mountain</i>	USA 2005, Drama/Romance	374 (81)	324 (18; 5)
<i>Capote</i>	USA 2005, Drama	375 (25)	324 (13; 2)
<i>Casanova</i>	USA 2005, Comedy/Romance	705 (33)	630 (31; 9)
<i>Da Vinci Code</i>	USA 2006, Thriller	559 (175)	- ^d
<i>Die Wilden Hühner</i>	GER 2006, Family	112 (7)	110 (3; 4)
<i>Die wilden Kerle 3</i>	GER 2006, Family	112 (7)	110 (5; 3)
<i>Die Wolke</i>	GER 2006, Drama/Romance	372 (7)	- ^d
<i>Elementarteilchen</i>	GER 2006, Drama/Romance	375 (51)	324 (14; 0)
<i>Failure to Launch</i>	USA 2006, Comedy/Romance	702 (49)	630 (42; 6)
<i>Felix 2</i>	GER 2006, Family	112 (4)	- ^d
<i>Freedomland</i>	USA 2006, Thriller	563 (0) ^b	- ^d
<i>Good Night, and Good Luck</i>	USA 2006, Thriller/Drama	559 (16)	- ^d
<i>Ice Age 2</i>	USA 2006, Family/Comedy	112 (53)	- ^d
<i>Lord of War</i>	USA 2005, Action/Thriller	451 (45)	394 (54; 5)
<i>Mission: Impossible III</i>	USA 2006, Action/Thriller	449 (66)	- ^d
<i>Pink Panther</i>	USA 2006, Comedy	702 (25)	630 (22; 3)
<i>Saw II</i>	USA 2006, Action/Horror	451 (26)	394 (23; 1)
<i>Scary Movie 4</i>	USA 2006, Comedy/Horror	698 (22)	630 (21; 4)
<i>Syriana</i>	USA 2006, Thriller/Drama	563 (53)	497 (53; 9)
<i>The New World</i>	USA 2005, Drama/Adventure	373 (2)	324 (8; 1)
<i>The Weatherman</i>	USA 2005, Comedy/Drama	703 (13)	630 (23; 6)
<i>Underworld 2: Evolution</i>	USA 2006, Action/Fantasy	451 (45)	394 (25; 11)
<i>V for Vendetta</i>	USA 2005, Action/Sci-Fi	450 (34)	394 (17; 9)

^a Number in parentheses signifies positive theater-going decisions.

^b German theatrical release canceled after disappointing U.S. box-office results.

^c Number in parentheses signifies positive DVD rental and DVD purchase decisions.

^d Movie not released on DVD at the time of the third survey.

Appendix D: Items for File Sharing Determinants

Construct	Measurement	Scale; Adapted From:
Gross utility of the movie original	(1) What are you usually willing to pay <u>when watching a new movie at the theater</u> ? (2) What are you usually willing to pay <u>when purchasing a new movie on DVD</u> ? (3) What are you usually willing to pay <u>when renting a new movie on DVD</u> ?	Formative, metric; Rochelandet and Le Guel (2005)
Price of the movie original	(1) When you go to the movies: From your experience, what do you pay for a theater ticket? (2) When you purchase a movie on DVD: From your experience, what do you pay for a DVD? (3) When you rent a movie on DVD: From your experience, what do you pay for renting a movie?	Formative, metric; Rochelandet and Le Guel (2005)
Transaction costs of the movie original	(1) How cumbersome is it to watch a chosen movie in a movie theater? (2) How cumbersome is it to purchase a chosen movie on DVD? (3) How cumbersome is it to rent a chosen movie on DVD? (4) From your experience, how high are the additional costs (beyond the price of the theater ticket) when going to the movies? (5) From your experience, how high are the additional costs (beyond the price of the DVD) when purchasing a movie on DVD? (6) From your experience, how high are the additional costs (beyond the rental price) when renting a movie on DVD?	Formative, 6 point; Rochelandet and Le Guel (2005)
Moral costs of the copy	(1) Sharing movie copies with others via Internet file sharing networks is unfair to the filmmakers. (2) Sharing movie copies is unethical. (3) When you share movie copies, you do harm to someone.	Reflective, 6 point; Huang (2005)
Legal costs of the copy	(1) The danger of being punished for sharing movie copies is high. (2) Sharing movie copies is a legally risky thing.	Reflective, 6 point; Chiang and Assane (2002)
Technical costs of the copy	(1) The danger of my PC becoming infected with computer viruses when sharing movie copies is high. (2) Sharing movie copies can entail heavy technical computer problems.	Reflective, 6 point
Search costs of the copy	(1) How cumbersome is it to download a chosen movie from file sharing networks? (2) How cumbersome is it to get a chosen movie as a copy from others?	Formative, 6 point; Rochelandet and Le Guel (2005)
Degree of substitution	(1) To what degree can a movie copy downloaded from file sharing networks or received from friends substitute viewing the movie in a theater? (2) To what degree can a movie copy downloaded from file sharing networks or received from friends substitute purchasing the movie on DVD? (3) To what degree can a movie copy downloaded from file sharing networks or received from friends substitute renting the movie on DVD?	Formative, 6 point; Rochelandet and Le Guel (2005)
Transaction	With movie copies you can make a real “deal”!	Single item, 6

Construct	Measurement	Scale; Adapted From:
utility		point; new scale
Mobility utility	You can take movie copies with you on the go, e.g. on notebook computers or video iPods.	Single item, 6 point; new scale
Storage utility	With movie copies, you can save space in your flat compared to DVD video boxes.	Single item, 6 point; new scale
Anti-industry utility	By getting movie copies, you can stick it to the movie studios and media corporations.	Single item, 6 point; new scale
Social utility	By sharing movie copies, you belong to a group of like-minded people with similar interests.	Single item, 6 point; new scale
Collection utility	Movie copies have a high collector's value.	Single item, 6 point; new scale
File sharing knowledge	<p>(1) I know several different file sharing networks.</p> <p>(2) I know how to find and download software for file sharing networks on the Internet.</p> <p>(3) I know how to set up file sharing software in order to download files from these networks.</p> <p>(4) I know how to configure firewalls in order to be able to access file sharing networks.</p> <p>(5) I know how to find and download codecs from the Internet.</p> <p>(6) I can judge from the video file format (e.g., avi, xvid-avi, divx-avi, wmv, mpeg) and the file size just about how good the image quality of the downloaded video file will be.</p>	Formative, 6 point; new scale

Appendix E: Items for Augmented EVM Models

Construct	Measurement	Scale
Hedonic value	“The DVD “Stay”/ the Sharp WriteView pocket calculator... ...is fun/ exciting/ tempting/ thrilling/ entertaining”	Ordinal seven-point scale, “not at all” - “completely”
Attribute importance w_i	“When you’re buying a DVD/ a pocket calculator, how important are the following attributes to you?” Story/ actors/ price of the DVD/ genre/ cover design/ DVD bonus material/ director/ title of the movie (<i>DVD</i>); Number of functions/ price/ design/ brand/ quality of the display/ ease of use/ energy source/ overall size (<i>Pocket calculator</i>)	Ordinal seven-point scale, “less important” - “very important”
Attribute evaluations e_i	“And how would you rate the DVD “Stay”/ the Sharp WriteView pocket calculator on these attributes?” - <i>See attribute list above</i>	Ordinal seven-point scale, “bad” - “good”
Attitude towards the Object A_{obj}	“In general... ...I think the DVD “Stay”/ the Sharp WriteView pocket calculator is good ...I like the DVD “Stay”/ the Sharp WriteView pocket calculator”	Ordinal seven-point scale, “not at all” - “completely”
Purchase Intention	“If you were offered to buy the DVD “Stay”/ the Sharp WriteView pocket calculator for €4.99: Would you buy it?”	Ordinal seven-point scale, “absolutely not” - “absolutely”
AyPosLA/ AyPosHA/ AyNegLA/ AyNegHA Emotion	“Please close your eyes for a moment and imagine seeing the movie “Stay”/ using the Sharp WriteView pocket calculator. Then please describe what you are feeling <u>right now</u> : When I imagine seeing the movie “Stay”/ using the Sharp WriteView pocket calculator, I feel... ...relaxed/ content/ calm (<i>AyPosLA</i>); enthusiastic/ elated/ excited (<i>AyPosHA</i>); bored/ dull/ sluggish (<i>AyNegLA</i>); sad/ depressed/ nervous/ anxious/ annoyed/ angry (<i>AyNegHA</i>)”	Ordinal seven-point scale, “not at all” - “completely”
AedPosLA/ AedPosHA/ AedNegLA/ AedNegHA Emotion	“Now please imagine you had already purchased the DVD “Stay” and had watched it/ had already purchased the Sharp WriteView pocket calculator and were using it regularly. How would you feel <u>after watching the movie/ after purchasing the pocket calculator and when using it regularly?</u> After watching the movie “Stay”/ after purchasing the Sharp WriteView calculator and when using it regularly, I would feel... (<i>see emotion item list</i>)	Ordinal seven-point scale, “not at all” - “completely”