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The Impact of Emotional Product Attributes on Consumer Demand:

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Abstract

Demand for products is often modeled as a function of product attributes. We propose that demand for experiential or hedonic products be modeled also as a function of "emotional product attributes" or emotions that a product might elicit from consumers. Our category of interest is the U.S. motion picture industry. We calibrate emotional attributes of a movie by mapping a movie's plot keywords on a list of human emotions by using a word pattern recognition method called Latent Semantic Analysis (LSA). We propose a factor model to reduce this multidimensional representation of correlated emotional attributes to two factors – "emotional complexity" and "negative emotions". These two factors are simultaneously incorporated in a random-utility choice model of 982 movies released in theaters in 1999-2005. We find that consumers prefer movies with greater emotional complexity. Demand for movies with negative emotions is moderated by consumers' sense of well-being, as measured by the Consumer Confidence Index. Importantly, our method of capturing emotional product attributes is simple, off-the-shelf, inexpensive, and scalable to studying markets with a large number of products. Substantively, our findings combine insights from economics and psychology, and are of interest to studios and theaters in their production and release timing decisions.

Key words: emotional attributes of product, choosing positive and negative emotions, sales impact, movies.

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1. Introduction

Economists and marketers have recognized the importance of product attributes as determinants of consumer choice (e.g. Rosen 1974). Therefore, in addition to variables like prices, advertising, promotions, etc., consumer choice has been modeled as a function of product characteristics like horse power, miles per gallon etc. for cars, and processor speed, hard drive size for personal computers. But what about attributes of experiential and hedonic goods that are hard to quantify, but clearly affect choice? For example, the thrill and fear of a rollercoaster ride, or the tranquility of a walk in the woods are central to the quality of these consumption experiences (see Hirshman and Holbrook 1982).

In this paper, we measure what we term "emotional product attributes" and how these affect consumer choice; the application is to the U.S. motion picture industry for the years 1999-2005. We define "emotional product attributes" as emotions that a product might elicit from consumers. Consumers account for these emotions when they make their product choice, in exactly the same way as they take in to account the other more measurable features of a product (e.g. genre, MPAA ratings for a movie etc). The role of emotional attributes is especially rich and salient in movie choice since movies are experiential goods where satisfaction and enjoyment hinge on the fulfillment of consumers' emotional expectations as the plot devolves (Zillmann and Bryant 2002). Also, any single movie can evoke a variety of emotions, e.g. surprise, horror, sadness, and joy. We posit that in choosing among alternative movies in theaters in any given week, consumers will pick the one that has the combination of emotional attributes (and other more measurable product attributes like genre, audience ratings, etc.) that appeals to them. Specifically, we measure six emotional attributes- love, joy, surprise, anger, sadness, and fear- that Shaver (1987) classifies as primary emotions that encompass a variety of other (secondary/tertiary) emotions. We include these secondary/tertiary emotions in our measurement process as being the same as the primary emotion under which they are classified. As we will discuss in section 2, literature in psychology and media studies supports the idea of using our conceptualization of emotions as drivers of choice (Izard 1991, Foxall 2003, Tan 1994).

The key challenge in our study is the measurement of these emotional product attributes and then demonstrating that they affect choice. To do this, we posit that the emotional content of a movie can be captured by examining its "plot keywords", a term used by the internet site

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IMDB.com (Internet Movies Data Base) to represent the collection of words that capture the important elements of a movie's plot (see section 3.2 for more details to support this claim). These plot keywords are likely to be mentioned in advertisements and trailers, critical reviews and other viewers' word-of-mouth, and are therefore likely to be part of a consumer's choice process. We adopt a word pattern recognition approach to measure how these plot keywords capture emotions. Specifically, we employ Latent Semantic Analysis (LSA) software to measure how these keywords are related to the six emotions mentioned previously (see section 2 for further discussion of LSA). LSA measures the semantic distance between words. It is based on word co-occurrences; words that co-occur are considered semantically similar. For example, consider a movie that includes in its plot keywords "car crash" and "marriage". LSA determines how often a plot keyword co-occurs with each of six emotion words- love, joy, surprise, anger, sadness, and fear- based on an average person's reading/comprehension level of the English language. For example, LSA might determine that based on this level of reading/comprehension, a viewer might associate the word "car crash" most often with the word "fear" and second with the word "surprise" because these words have co-occurred in this reading corpus. Likewise, LSA might determine that "marriage" co-occurs equally often with "love" and equally with "joy". Based on this co-occurrence of words, we posit that a movie with a car-crash scene will have emotional attributes of fear and surprise, and a movie with a wedding theme will have emotional attributes of love and joy. And a movie with a wedding scene and a car-crash scene will have fear, surprise, love and joy. As can be expected, many movies are likely to have scenes that invoke all six of our measured emotions- love, joy, surprise, anger, sadness, and fear. The important differentiator across movies is the level of these emotional attributes in each of them.

Our objective is to estimate the effects of the emotional attributes of a movie on its demand. The emotional attributes are captured through numerical measures of the level of each emotion for a movie, obtained from the analysis of plot keyword data by LSA as described in the previous paragraph. In order to account for the correlation between emotional scores and to reduce the dimensionality of our measure of emotional attributes, we specify a simultaneous factor- and- consumer demand model. Therefore, rather than model demand directly as a function of these six emotional attributes (love, joy, surprise, anger, sadness and fear), we reduce them to two underlying latent factors. Our analysis shows that these factors include one that has both positive (love and joy) and negative (anger, sadness and fear) emotions; we term this factor

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emotional complexity. The other factor includes only negative emotions. We employ these latent factors along with several other movie characteristics (genre, studio dummies, time since release, seasonal dummies, advertising expenditure, etc.) in a random utility demand model for movies. This leads to a simultaneous equations model of market share and emotional attribute levels. We estimate the aggregate weekly box-office demand model for 982 movies in U.S. theaters in 1999-2005.

Our choice model estimates show that movies with combinations of all six emotions are associated with higher market shares. This suggests that consumers prefer a complex mix of emotional attributes. Moreover, after controlling for this demand of a complex mix of emotions, consumers have a preference for movies with greater negative emotions (namely anger, sadness and fear). However, this demand for negative emotions is moderated by consumers' sense of well-being (e.g. their sense of safety or confidence; see Aptor (1982, 1992) for a discussion of "protective frames") as measured by the Consumer Confidence Index. This provides empirical support to the common wisdom in industry that consumers prefer movies with more positive emotional attributes in recessionary times. Our approach enables us to estimate changes in market share associated with changes in emotional attribute levels. We find that Love is associated with the greatest increase in market share and Surprise with the least increase. Importantly, demand models that ignore emotional attributes perform worse in terms of model fit and predictive ability in our hold-out sample.

Therefore, a primary contribution of this paper is to provide evidence that, and quantify the extent to which, emotional product attributes can be directly linked to (higher) market share. Critically, we show that offering consumers a complex mix of emotional attributes can be lucrative to firms; and that simply providing positive emotional attributes will not be as profitable. Our method of measuring emotional attributes is simple, off-the-shelf, inexpensive, and scalable to studying markets with a large number of products; please see section 2 for details to support this claim. These findings highlight the need to model emotional drivers of demand, and are useful in bridging the gap between psychology and economics in understanding consumer demand.

Our findings might be of interest to both studios and theaters in their production, release timing and targeted marketing decisions. While any studio can employ focus groups and other market research methods for its own movie(s), our study establishes generalizable facts about the impact of emotional product attributes by estimating the model over weekly sales of 982 movies over seven years; this large number of movies and time series of data with varying levels of consumers' sense of well-being/economic conditions allows us to estimate robust effects across a variety of movies. Moreover, while we document the impact of emotional content on demand for movies, the method we propose here is equally applicable to studying the demand for other products and services where emotional attributes are likely to impact consumer demand and where verbal product descriptors are available. Examples include consumer demand for other experiential goods like books, political candidates, etc. More broadly, this method of parsing emotional attributes from text based content can be applied to the analysis of blogs, opinions, and other user-generated content where emotions can impact choice and where text-based descriptions are available.

Briefly comparing our paper to existing literature (see section 2 below for more details), we build on literature in consumer behavior that studies the existence of mixed emotions (Andrade and Cohen 2007, Williams and Aaker 2002). We provide market-data based proof that consumers actively *choose* mixed emotional attribute bundles; previous research has demonstrated in laboratory studies that consumers can *feel* mixed emotions (as opposed to actively demanding them in products). In the movies literature, Eliashberg and Sawhney (1994) and Neelamegham and Chintagunta (1999) measure the effect of the degree of pleasure and arousal of movie plots on stated consumer preferences for movies. Eliashberg, Hui and Zhang (2007) use semantic analysis to measure the effect of surprise endings and other variables on movie profitability. We extend this research (a) by postulating that emotional attributes (rather than plot details like surprise endings and script characteristics) and specific combinations of emotions matter to consumer choice; this finding is made possible by studying weekly sales of a large number of movies, (b) by showing how this demand for negative emotional attributes is moderated by the consumer's sense of well-being; this finding is made possible by studying movie demand over a seven-year period with varying economic conditions, and (c) by providing a method of emotional attribute measurement that can be readily scaled up to large databases; given we use easily available plot keywords rather than harder-to-find movie scripts used by Eliashberg, Hui and Zhang (2007). Such scalable methods are increasingly important in marketing as large databases are becoming the norm (Naik et. al. 2008). Importantly, our method is off-the-shelf, cheap and easy to implement, in addition to being scalable.

The rest of the paper is organized as follows. In the next section, we briefly survey the relevant literature on how emotional attributes of movies might affect movie choice. We describe our data in section 3. In section 4, we present the model and the method of estimation. The results and a series of robustness checks are presented in section 5. Section 6 concludes with directions for future research.

2. Relevant Literature: Emotions and Movie Choice

There are two broad stream of relevant literature on emotions as a driver of choice. The first research stream documents consumer preference for particular emotions or combinations of emotions, as well as their intensity. The second stream of relevant literature is on classification of emotions; this literature forms the basis of our empirical measurement of emotional content.

Consider the first stream on consumer preferences for particular emotions or combinations of emotions. Many products and services (e.g. movies, adventure sports) are consumed for the emotional pleasure (or positive emotional attributes) they provide, but they may also be chosen despite the fact that they cause negative emotions (or despite their negative emotional attributes). As Fredrickson (2000) discusses, products and experiences might be chosen not just despite, but *because* they cause negative emotions. This seeming violation of hedonism or pleasure or utility maximization (or why negative emotional attributes might provide positive utility) might be because some consumers experience these negative emotions as positive arousal (Zuckerman 1996). Other viewers might find relief after being exposed to negative emotions (Zillmann 1980). Alternatively, it is possible that consumers simultaneously experience both positive and negative emotions (i.e. mixed emotions) when exposed to negative stimuli (Andrade and Cohen 2007, Larsen, McGraw, and Cacioppo 2001, and Williams and Aaker 2002). For example, in the context of movies, sad movies allow consumers to expend painful emotions, and the resolution of sad events in movies might allow consumers to construct fantasies to better cope with unhappy realities (Hirshman and Holbrook 1982). Thus movies with negative emotions can translate into cathartic experiences that increase consumers' happiness and emotional well-being by allowing the emotional discharge of pent up anger, sadness or frustration (Scheele and DuBois 2006). Catharsis has also been put forth as a phenomenon underlying the reduction in violent crime after viewing violent movies in theaters (DellaVigna 2007).

The literature has also suggested moderators for viewers' demand for negative emotions. Apter (1982, 1992) discusses three types of "protective frames" that enable consumers to derive positive benefit from exposure to negative stimuli- the confidence frame (or feeling confident), the safety zone frame (or feeling safe), and the detachment frame (or observing the negative emotion rather than interacting with it). Andrade and Cohen (2007) show in a laboratory setting that the detachment frame is a valid moderator for viewers' co-activation of positive and negative feelings when faced with negative emotions stimuli. Another line of research suggests an alternate moderator for the demand for negative emotional attributes: mood management theory (Zillmann and Bryant 1985, Zillmann 1988) elaborates on the notion that consumers select media content in the interest of enhancing their mood states. For example Oliver (2000) finds that consumers in a negative emotional state prefer content that is likely to improve their mood while those already in a good mood gravitate towards content which helps to preserve their good mood[1]. Business press reflecting industry wisdom also supports the notion that in bad economic times, viewers want their moods to be uplifted by movies. [2]

Another relevant stream of literature to understanding how emotional product attributes might influence consumer choice of movies postulates that peak intensity of emotions influences consumers' overall evaluation of past affective episodes (Fredrickson 2000, Kahneman et. al. 1993). This is true for positive and negative peaks and ends. For example, Kahneman et al. (1993) measure negative peaks, and Baumgartner, Sujan and Padgett (1997) measure positive peaks. In extending this research to our context of emotional attributes of movies, a movie can have multiple emotions in it. Therefore it is possible that there are multiple peaks of emotional

[1] The importance of mood regulation has also been demonstrated in other media selection settings including music (Knobloch and Zillmann 2002), news (Biswas et al. 1994) and game shows (Bryant and Zillmann 1984).

[2] As Cieply (2008) says "If moviegoers have delivered a message in the last few months, it is that they want their films, for the moment, at least, to be a lot more fun than their lives". Morgenstern (2009) elaborates, "Back in the darkest days of the Great Depression, the brightest lights of the silver screen sang, danced, quipped and smooched to keep America's mind off its woes, if only for a couple of hours at a time. These days our economic prospects may not be as bleak -- at least that's the ardent hope. But there's plenty of grim stuff out there to be distracted from, and big-screen entertainments possess a singular power to take us out of ourselves…. The best Depression-era films were not just exercises in escape; they were potent fantasies that spoke to audiences in a universal language with an emotional grammar that hasn't much changed over eight decades. The point was made eloquently by a screenwriter -- a young screenwriter, as it happens -- named Dan Chariton. "Then, as now, the challenge was about coping gracefully with adversity and profound uncertainty. Fred and Ginger may have moved in wealthy circles, but their characters were often hungry hoofers, living essentially hand-to-mouth. They're not of the moneyed world, and they invariably poke fun at its emptiness and rigidity, just as the Marx Brothers and Preston Sturges did. They showed that one can live richly, even in the Depression, by virtue of one's wits and talent. If you've got an optimistic, go-with-the-flow attitude, then life will somehow sort itself out."

intensity e.g. a peak for fear, a peak for love, a peak for surprise, etc. There is another literature that shows that there is no reason to expect symmetry in the impact of these multiple peaks, even if we assume that negative stimuli cause negative affect and positive stimuli cause positive affect (as discussed previously, the mixed emotions literature questions this assumption). That is, the impact of a negative peak on consumer valuation might be very different in absolute magnitude from the impact of a positive peak (Isen 1989) Therefore, for the purposes of our study of emotional content of movies, it is important to measure the alternative peaks in the movie, and to allow asymmetry in their effects on consumer valuation and choice. This same literature also demonstrates the importance of the peaks-and-ends sequence. We are unable to measure the exact end of the movie, given the bag-of-words approach we use to measure emotions that strips out the sequence of peaks and ends. However, any emotional content of the end of the movie is measured by LSA. We discuss this in further detail in section 3.2.

The second relevant stream of literature elaborates on the various emotions a movie can capture. Movies represent dramatic enactments capable of invoking the entire spectrum of feelings consumers experience in daily life, and consumers make their movie choices on the basis of their perceptions of the subset of emotions which will be elicited by each movie.[3] To calibrate these perceptions we need a collectively exhaustive set of emotions, which captures the complete spectrum of feelings consumers experience as they engage with a movie. However, emotions and combinations of emotions are potentially countless. To circumvent this complication, we borrow a notion from emotion literature in psychology, which establishes the existence of a small set of basic, primary or fundamental emotions (Ekman et al. 1982), grouping various other emotions under these as secondary and tertiary.

Psychologists believe basic emotions to be innate and universal (Frijda 1982) and use basic emotions at the superordinate level of an emotion hierarchy, where basic emotions branch into groupings of secondary and tertiary emotions (Parrot 2001). However, since different researchers conceive basic emotion groupings differently (e.g. Ekman 1992 uses facial expressions, Arnold 1960 uses action tendencies, etc) there are some disagreements as to which specific emotions constitute the set of basic emotions (Ortony and Turner 1990). In some studies

[3] Bagozzi, Gopinath and Nyer (1999) define emotions as being distinct from moods and attitudes, and as follows "Specifically, emotions arise in response to appraisals one makes for something of relevance to one's well-being". Hence, modeling consumer choice as a function of how they might feel during and after watching the movie is appropriate.

researchers posit that there exist as few as two basic emotions: happiness and sadness (Weiner and Graham 1984), or pain and pleasure (Mowrer 1960). Others put forth as many as 11 basic emotions, namely: anger, aversion, courage, dejection, desire, despair, fear, hate, hope, love and sadness (Arnold 1960; see also Richins 1997 for 16 clusters of emotions that she calls "consumption emotion descriptors").

We rely on Shaver et al. (1987) who propose an emotion hierarchy consisting of the following six basic emotions: love, joy, anger, surprise, fear and sadness[4]. Shaver et al. classify other emotions under these six; the resultant tree structure encompasses the broad range of emotions. They derive this hierarchy from an extensive list of commonly known psychological state names that reflect emotions and that are assigned to groups on the basis of semantic relatedness (see table 1). Note that in our empirical analysis, we measure all secondary and tertiary emotions under any primary emotions as being similar to the relevant primary emotion. Therefore, these secondary and tertiary emotions contribute to the emotional product attribute measurement. We favor this six-primary-emotions construction for its simplicity. Also, this list is based on people's everyday knowledge of emotions. Therefore, this classification offers greater potential for eliciting consumer perceptions of emotional content in movies compared to emotion classifications constructed on the basis of biological processes, facial expressions, action tendencies, etc.[5] Further, the Shaver et al. (1987) list overlaps substantially with the lists put forth by most other researchers.

---Insert Table 1 here---

[4] Parrot (2001) considers love and joy as positive emotions, surprise as neutral and anger, fear and sadness as negative.

[5] A broader caveat with using emotional attributes at all is whether another psychological construct might better explain movie choices. We focus on emotional attributes as opposed to any other psychological attributes for several reasons. First, emotions are fundamental experiential and motivational processes that influence cognition and action, and are defining constructs of personality processes (Izard 1991). While personality has often been used to explain individual choice (Foxall 2003 surveys this literature), because emotions underlie personality processes, measuring emotional content is more granular. Second, media psychologists regard emotions as the interface between the consumer and the screen which gives immediate meaning and significance to the movie experience (Tan 1994).

Marketing scholars have used various psychological descriptors to study movie choice. The psychological variables considered in the literature measure the degree of pleasure and arousal consumers seek and experience from their movie choices. For example, Eliashberg and Sawhney (1994) use these measures to predict individual differences in movie enjoyment based on the match between an individual's personality and temporary moods (evaluated from survey questionnaires) and the pleasure/arousal content of movies (rated by two doctoral students who serve as objective judges). Neelamegham and Jain (1999) develop a framework to predict consumer choice and model post-choice recommendations for movies. The framework is applied in a laboratory setting where subjects are exposed to advertising as well as binary (positive and negative) reviews from critics and word of mouth. Subjects were then asked to choose one of three movies. This study finds that expectations about content characteristics are a significant predictor of movie choice, while actual content characteristics influence post-consumption movie evaluations and recommendations. However, as in Eliashberg and Sawhney (1994), they calibrate content along pleasure/arousal dimensions. These dimensions tie in with the manifestation of a personality trait in movie choice, which captures the sensation seeking nature of consumers (Zuckerman 1979). Instead of focusing on a particular personality trait, we use emotions (a) because psychologists argue that what give rise to personality traits are in fact mixtures of emotions (Plutchik 1962, 1980); and (b) because emotions offer a more basic conceptualization and paint a richer picture of the psychological content of movies. Also, it would take a significant amount of time and money to obtain subjects' evaluation of our large set of movies on various emotional content measures. Our method of measuring emotional attributes via plot keyword analysis costs less in time and money, and is objective.

Summarizing, the existing literature provides us the following guidance and opportunities in our research: the emotional content of a movie should be mapped not just on a simple positive-negative scale or on a pleasure-arousal scale; instead a richer representation of emotional variety is likely to provide richer insights in to drivers of consumer choice.

3. Data

3.1: Market and movie descriptors

Our dataset comprises 982 movies over a sampling period of 7 years: 366 weeks from January 1st of 1999 to December 29th of 2005. We follow the approach set forth in the literature (e.g. Ainslie, Dréze and Zufryden 2005, Einav 2007, Chiou 2006) and disregard movies which do not reach wide-release at any point during their theatrical run since they fit into a different and much more volatile product category which often has negligible market share. For tractability, we collect weekly data for each of these movies up to the point that they are screening in no less than 300 theaters (of about 5900 total theaters in the U.S. in 2005). Since revenues and market shares are trivial below this level of theater-screening, we do not expect such truncation to bias our results. We use data on weekly sales for 932 movies for model calibration and the remaining data for out-of-sample validation.

Our theatrical revenue data is from two internet sites: www.Boxofficemojo.com (BM) and www.imdb.com (IMDB). We also use print expenditure (i.e. cost of getting a copy of the movie to theaters) and advertising-expenditure for each movie, provided by Paul Kagan and Associates. We obtain information pertaining to the production studio, the production budget, the release date and the weekly gross box office from BM. We use IMDB to collect data on movie genres, MPAA rating and plot keywords. We measure market response in terms of quantity-based market share. This enables us to control for the choice of not watching any movie (i.e. the choice of the outside good, given that it is likely to vary over good and poor economic times). We use yearly estimates of U.S. population counts obtained from the U.S. census, which we interpolate linearly to obtain weekly counts. We use this to construct a measure of all possible viewers for a movie in any week. We use a similar procedure to obtain weekly averages of national ticket prices from yearly averages which are available the National Association of Theater Owners website, www.natoonline.org. Lastly, we obtain weekly data on the Consumer Confidence Index for the period of our data from The Conference Board (www.conference-board.org). Table 2 presents the summary statistics of these data.

---Insert Table 2 here---

3.2: Measure of emotional content

As discussed by Bagozzi, Gopinath and Nyer (1999), marketers have traditionally relied on self-reported measure of consumer emotion. In our context of trying to measure emotional content for a large number of movies well after they have run in theaters, this approach is not practical given the much larger time and money expense. Also we are trying to understand whether economic conditions might moderate how emotional attributes affect demand; this would create an additional layer of complexity in laboratory measurement. Our method of measuring emotional attributes of products is based on market choice data, and therefore provides greater external validity relative to using laboratory data to obtain stated preference data.

To generate emotional content measures for each movie, we first begin with plot keywords of movies. These keywords lists are from IMDB. Keyword lists are defined and updated by IMDB (staff and) users who have seen the movie. Each movie has on average several thousands of (viewers who have the chance to become) reviewers, and each of these reviewers has the opportunity to add to keywords. Therefore, these keywords capture the important/memorable aspects of a movie's plot, making their informational content of these keywords pertinent. Note too that keyword lists can reflect movie content that might be mentioned in trailers, advertisements, critic reviews, and word-of-mouth. It is, of course, possible and indeed likely, that these various sources of information about movie emotional content might be richer than captured by keywords. For example, given movie trailers reviews are meant to inform consumers about whether they might enjoy the movie, they might have more details on emotional content ("This movie will surprise you, and make you nostalgic for your childhood"). However, given the large number of movies and the seven-year span of the dataset, we do not have any practical way to capture the emotional content of these various sources of information (trailers, advertisements, word-of-mouth, critic reviews) used by a consumer in making movie choices. Given we are able to parse emotional content out of plot keywords alone without additional emotional attribute information that might be available from trailers, advertisement etc., our estimates should be viewed as conservative estimates of the impact of emotional content of movies.

We use the technique of Latent Semantic Analysis (LSA) for our study. LSA is a natural language processing software package developed by psychologists and linguists at the University of Colorado, Boulder to measure the semantic distance between word groups. It is based on word co-occurrences and considers words that tend to occur together as being semantically similar (Landauer and Dumais, 1997). Since structure pertaining to word order is not maintained, LSA is referred to as a bag-of-words model (Coccaro and Jurafsky 1998). Regardless, LSA infers word relations which successfully mimic human information judgments and meaning-extraction

(Landauer and Dumais, 1997). For example, LSA scores overlap those of humans on standard vocabulary and subject matter tests, it mimics human word sorting and category judgments, and accurately estimates passage coherence and the quality and quantity of knowledge contained in an essay (Landauer and Dumais, 1997). Because of these properties, LSA has been used to generate essay-grading algorithms for the Educational Testing Service which administers standardized tests like SAT and GRE (Landauer, Foltz, and Laham, 1998). It is also used by several universities as well as Rand Corporation to grade logic and grammar in essays. LSA has also been used for prior art searches for patent applications. There are several academic papers that demonstrate the usefulness of LSA in speech recognition software (Bellegarda 1998), clustering source code to better understand software structure (Maletic and Marcus 2000), to reduce dimensionality of a large set of text descriptors of facial expressions (Fasel, Monay and Gatica-Perez 2000), linking a snippet of text on a webpage to the next webpage a person might surf based on semantic similarity of texts (Blackmon et. al. 2002), collecting all relevant documents that share a common research theme (Woo, Madnick and Ziegler, 2009), etc. Given this broad academic evidence of LSA's abilities as well as its commercial usage, we saw an opportunity to use LSA in our context to extract semantic distance between plot keyword and our list of emotional attribute words.

LSA has several options in analyzing text. For our application, we chose "general reading up to first year of college", given over 90% of the U.S. adult population has graduated from high school. Some of the other options are higher and lower levels of education, and field-specific knowledge (e.g. microbiology). Our option implies that the program uses the corpus of all documents that a high school graduate might have possibly read in her/his lifetime, and then maps all these documents to all the words in the dictionary, with the documents forming columns of a matrix and the dictionary forming rows. As expected, this matrix is sparse, so it is decomposed into 300 factors via a singular value decomposition process. These factors collectively capture dimensions of 'meaning' as understood by a high-school graduate. We then take our plot summary keywords for each movie, and our list of six emotions (each with its list of secondary and tertiary emotions), and ask the software to identify for us which plot keyword is likely to be associated with which (if any) emotion (including secondary and tertiary): LSA locates the position of the plot keywords and each of our six emotions in the space spanned by the 300 factors and computes the semantic distance between plot keywords and each emotion as the cosine between the position vectors in the spanned space.

LSA's ability to mimic human information judgments is critical to generating the perceived semantic proximity between each basic emotion and the keyword lists describing each movie's plot. Consider the following keyword list for the movie Shrek:

> Gnome, Bear, Sunrise, Peter Pan, Hero, Pinocchio, Unlikely Hero, Blind, Tower, Mouse, Sunset, Bishop, Decree, Shrek, Big Bad Wolf, Robin Hood, Arrow, Comic Sidekick, Coffin, Friend, Altered Version Of Studio Logo, True Love, Wolf, Fairy, Sword And Sorcery, Courage, Hunter, Isolation, Fairy Tale, Alienation, Surprise After End Credits, Accordion, Stained Glass Window, Kiss, Midget, Reluctant Hero, Lord, Dwarf, Mirror, Sidekick, Outhouse, Beer, Torture, Transformation, Pig, Challenge, Anachronistic, Dragon, Castle, Curse, Disneyland, Donkey, Ethnic Cleansing, Fairy Tale, Flatulence, Friendship, Knight, Magic Mirror, Magic, Ogre, Spoof, Princess, Quest, Rescue, Spell, Talking Animal, Wedding, Blockbuster, Canceled Wedding, Fairy Tale Parody, Fart, Racism, Belch, Exploding Bird, Lava Filled Moat, Onion, Rope, Bridge, Swamp, Gingerbread Man, Crossbow, Destiny, Hit In Crotch, Pitchfork, Rotisserie, Skeleton, Sword, Windmill, Crude Humor, Satire, Fire Breathing Dragon

While a plot summary or movie review may include a sentence like "Donkey and Shrek rescue the princess from the dragon", the keyword list conveys the information in this sentence through the words 'donkey', 'Shrek', 'rescue' 'princess' and 'dragon'. The semantic information that LSA extracts from both the sentence and the keyword list is exactly the same given that LSA does not preserve word order and strips down sentences of ubiquitous words (like "a", "the", "in" etc). Also, repetition of the same word or similar words ("surprise" three times, or "surprise", "amazement", "wonderment") does not change the mean emotional score given the very small impact adding more words will have when compared to the large number of words in the corpus of documents that we use as a basis for determining semantic distance.

To generate emotional content measures we define each basic emotion by its corresponding list of subordinate emotions and match this definition to keyword lists. This yields measures on a scale of -1 to 1 for each basic emotion, given that LSA is computing a cosine value. We call these measures "emotional content scores". Examples of emotional content scores for the above keyword list are 0.07 for joy, 0.17 for love and 0.03 for fear.

Table 3 includes keyword lists for two other popular movies: American Pie II and Hannibal, and table 4 reports the corresponding emotional content measures. Tables 5 and 6 show the average content measures by movie genre and MPAA rating respectively. Table 7 shows the summary statistics for the emotional content scores of all the movies in our sample. Table 8 presents the correlation matrix of all emotional content measures.

---Insert Tables 3,4,5,6,7 and 8 here---

The mean emotional content scores vary between -0.01 for surprise and 0.11 for Love. The prevalence of such low scores is because emotional content does not exhaust informational content of the keyword list, i.e. some words in the list may not connote any emotion concept (e.g. 'mirror' and 'anachronistic' in the above list). The relatively tight cluster of emotional content measures (standard deviations range from 0.06 to 0.10 across emotions) indicates that movies tend to involve balanced combinations of all the basic emotions. Whether this tight distribution will hinder the estimation of the impact of emotional attributes on consumer demand is an empirical question; see section 5 for results. Given the emotional content scores measure emotional attributes of the movie, the resulting content measures are intuitive: horror movies have the highest average score for fear, romantic comedies have the highest average score for love, etc. (table 5). While this face-validity is reassuring, it also raises the (empirically answerable, please see section 5) question of whether these emotional scores will provide explanatory power over and above including genres as explanatory variables in estimating consumer demand. The average correlation across all pair of emotional content scores is 0.39, suggesting the presence of underlying constructs composed of combinations of emotions.

It is important to note that movies that are of high joy content are not necessarily of low sadness content. This is because some movies are bitter-sweet overall (e.g. dramas often involve a buildup of sadness or melancholy which is resolved by a joyful ending). Further, emotional content measures do not positively correlate with the length of keyword lists because the measures are derived from the overall meaning conveyed by keywords taken together. For example the word 'car' in conjunction with 'crash' will elicit fear, but 'car' as part of a keyword list pertaining to a documentary about the car-making will not. Since LSA distinguishes between the contexts within which words and word groups appear together, a car making documentary will have low emotional scores overall, irrespective of the length of the keyword list.

Eliashberg, Hui and Zhang (2007) also use semantic analysis to extract textual information from movie scripts. They train their algorithm on 70 movie scripts to extract word occurrence frequency. They retain 100 highest weighted words and compute the co-occurrences between these 100 words and movie spoilers. To reduce dimensionality, they use principal components analysis and define two factors: one captures "dialogue" words and the other captures "violence" words. They supplement this textual information with expert assessments of movie scripts. These experts take into account script-writing guidelines, which highlight the need for cohesive stories, unambiguous resolutions, logical endings, etc. The authors find that both their semantic measure and expert characterizations of content data are significant predictors of the rate of return on movies.

Contrast our LSA application to the Eliashberg et. al.'s (2007) semantic classification. As mentioned earlier, LSA is trained on the entire corpus of documents that a high school graduate might have read. Repetition of words or adding synonyms in plot keywords does not change the emotional scores for any movies, given the very small impact adding more words will have when compared to the large number of words ever read by a high school graduate. The Elaishberg et al. system, in contrast, is trained on a much smaller corpus (70 movies scripts) and is therefore much more sensitive to words in spoiler descriptions. Moreover, the larger corpus of LSA makes it easier for us to estimate more (more specifically, we are able to estimate six different emotions) than the two factors that Eliashberg et al. estimate.

Also, Eliashberg et al. look for surprise endings and violent scenes in the textual analysis, which are likely to be correlated with emotions (e.g. surprise endings with surprise, violent scenes with fear or anger). But they do not explicitly model emotional content of scripts in predicting movie success, nor do they include all plot characteristics that correspond to each of the six basic emotions (and the various underlying secondary/tertiary emotions). Importantly, we use readily available plot keywords rather than the harder-to-find movie scripts in their paper. This larger database of weekly sales for 982 movies over seven years allows us to make robust calculations about the impact of emotional attributes on movie shares. This large database also allows us to study the additional question of how consumers' sense of well-being (as measured by economic conditions) might moderate the impact of emotional attributes on movie shares. We also find in the empirical analysis (see next section) that our classification of emotions has explanatory power, despite not using the additional expert assessment that Eliashberg et al.

(2006) use. Note that using expert reviews for a sample as large as ours is not feasible and therefore our method can be used more easily for larger datasets. Also, LSA captures a much broader scheme of human expertise with language rather than relying on expert judgment. Therefore, for the purposes of our study, the LSA methodology is likely to be more robust. And as mentioned previously, given its ease of scalability and application, LSA can also be readily applied to other research contexts.

4. Model

We first discuss the demand model, which captures the effect of emotional content on box-office demand for movies. Next, we discuss the measurement model that explains how we incorporate the emotional content measures into the demand model.

4.1. Demand model

As is standard in the literature on consumer choice, we formulate consumer utility as following a random coefficients specification (McFadden 1973). The indirect utility of consumer *i* who chooses movie *j* in week *t* is:

$$U_{ijt} = \alpha_{ij} + x_{jt}\beta_i + \Lambda_{1i}\xi_j + \Lambda_{2i} f(\xi_j) + \varepsilon_{ijt} \tag{1}$$

ξ_j is a k-dimensional latent vector that represents the emotional product attributes of movie j and Λ_{1i} is a parameter vector that measures the preference of consumer i for such attributes. $f(\xi_j)$ is a function of ξ_j specified by the researcher, that potentially captures its interactions with other variables of interest, its polynomial expansions, etc. Later in this section we detail the measurement of this vector. α_{ij} represents consumer *i*'s intrinsic preference for movie *j*. x_{jt} is a vector of covariates including movie characteristics (MPAA rating, genre, production studio), functions of release time (season of the year, number of weeks since release[6]) and marketing variables (advertising expenditure) and production budget[7]. ε_{ijt} is a stochastic error term

[6] Both a linear and a logarithmic term in age in theatrical distribution are used in an attempt to capture the non-linear decay of demand with age. This follows Ainsle *et al.* (2005) who interpret the coefficient on the logarithmic term, as being indicative of the peak attractiveness of a movie and that on the linear term as a speed parameter representing how fast attractiveness builds and decays.
[7] We employ logarithms of advertising expenditures and production budgets, resulting in a log-log market share equation, which follows the approach established in the literature.

representing the unobserved component of consumer *i*'s utility for movie *j* at time *t* and which is assumed to be *iid* type-I extreme value distributed across consumers, movies and time periods.

A consumer's choice set also includes the outside option of seeing no movie in any week. Normalizing the intrinsic preference of not seeing a movie to zero in each week, the utility from the outside option becomes:

$$U_{i0t} = e_{i0t} \tag{2}$$

where e_{i0t} is also mean zero and *iid* type-I extreme value distributed across consumers. We also assume that each consumer's movie choices are *iid*. If there are J_t movies to choose from each week, the probability, P_{ijt} that consumer *i* chooses movie *j* in week *t* is:

$$P_{ijt} = \frac{\exp(\alpha_{ij} + x_{ijt}\beta_i + \Lambda_{1i}\xi_j + \Lambda_{2i} f(\xi_j))}{1 + \sum_{j=1}^{J_t} \exp(\alpha_{ij} + x_{ijt}\beta_i + \Lambda_{1i}\xi_j + \Lambda_{2i} f(\xi_j))} \tag{3}$$

Consumer preference parameters are represented as the sum of corresponding means for the consumer population and the consumer-specific deviations from these means:

$$\alpha_{ij} = \alpha_j + \Delta\alpha_{ij};\ \beta_i = \beta + \Delta\beta_i\ ;\ \Lambda_{1i} = \Lambda_1 + \Delta\Lambda_{1i}; \Lambda_{2i} = \Lambda_2 + \Delta\Lambda_{2i} \tag{4}$$

We represent the consumer specific-parameters by

$$\Delta_i = \{\Delta\alpha_{ij} \quad \Delta\beta_i \quad \Delta\Lambda_{1i} \quad \Delta\Lambda_{2i}\} \tag{5}$$

We denote the distribution of Δ_i by $F(\Delta_i)$, which is the cdf of the multivariate normal distribution of the consumer specific parameters. We substitute (5) into (3) and integrate over the region of support, A_{ij} of Δ_i for all consumers to obtain the aggregate market share of movie *j* in week *t*:

$$S_{jt} = \int_{A_i} P_{ijt}(\Delta_i) dF(\Delta_i) \tag{6}$$

To calculate S_{jt} we divide the weekly box-office revenues of each movie by the average ticket price in that week to get an admissions count and then divide by an interpolation of the US population in that week to obtain the market share of movie j in week t. S_{ot} is simply 1 minus the total market share of all movies showing in any given week. This specification results in the following:

$$\log\left(\frac{Share_{jt}}{Share_{0t}}\right) = \alpha_j + x_{jt}\beta + \Lambda_1\xi_j + \Lambda_2 f(\xi_j) + \varepsilon_{jt} \tag{7}$$

The movie specific fixed effects and the error terms are assumed normally distributed.

$$\alpha_j \sim N(\overline{\alpha}, \sigma_\alpha^2) \tag{8}$$

$$\varepsilon_{jt} \sim N(0, \sigma_S^2) \tag{9}$$

Next we discuss the measurement of the latent vector that represents the emotional product attributes.

4.2. Measurement model

One approach to capture the effect of emotional attributes on demand is to substitute ξ_j with the emotional content scores derived from LSA. This approach is problematic for at least three reasons. First, we know that the emotional content scores are highly correlated (table 8). Indeed preliminary analysis of the data suggests that incorporating these scores in the indirect utility function yields unstable estimates of their effects on market shares (due to the collinearity). Second, the emotional scores data are high-dimensional which could result in over-parameterization. Third, treating the emotional score data as non-stochastic might yield inconsistent estimates of the effects of emotional attributes on choice (Ashok *et al.* 2002, Sonnier and Ainslie 2009). To obviate these issues, we adopt a factor-analytic approach. This approach recognizes that we measure emotional attributes with some measurement errors, and projects the high-dimensional emotional score data on to a lower dimensional space. This allows us to infer the underlying latent constructs that capture the effects of all six emotional scores on market share. Our approach is also consistent with previous research on emotions that relies on consumer level laboratory data. Edell and Burke (1987) reduce their 52-items scale of emotions to three factors (upbeat, negative and warm feelings). Similarly, in a study of affective consumer responses to advertising, Batra and Holbrook (1990) use factor analysis to reduce 12 types of correlated responses to three underlying dimensions of emotions. Specifically, we project the LSA based emotional content scores on a set of underlying latent factors as follows.

$$e_j = \phi + \Pi \xi_j + \delta_j \tag{9}$$

where ξ_j is the k-dimensional vector of factor scores of movie *j*, Π is the (6 by k) matrix of factor loadings, and ϕ is the intercept. Since the emotional content scores are cosines bounded between -1 and 1, assuming them to be normally distributed could be a misspecification. So we apply the following transformation.

$$e_{kj} = \frac{e_{kj}^*}{\sqrt{1-(e_{kj}^*)^2}} \tag{10}$$

where e^*_{kj} is the LSA based score of movie *j* for emotion *k*., and e_{kj} is the transformed score. Later in the paper, we discuss the robustness of our results to this transformation.

Identification of factor models requires restrictions on certain parameters (see Ansari, Jedidi and Dube (2002) for an excellent description of identification issues pertaining to several models in this class, and Bartholomew and Knott (1999) for a general treatment of factor analytic models). Models that aim to confirm hypotheses about factor loadings pertaining to certain items (emotional scores in our context), impose severe restrictions on the factor loading matrix. The factor loadings of several items are *a priori* fixed to ones or zeros based on theoretical considerations. Such models are referred to as confirmatory factor analytic models. However, given the exploratory nature of our investigation, we choose to minimize the restrictions on factor loadings. The only restriction we impose without any loss of generality is that the loading of an arbitrarily chosen emotional score is one for factor 1 $(\pi_{11} = 1)$ and zero for the other factors $(\pi_{12} = 0$ for a two factor model). This serves to fix the scale of the factor scores. This flexibility comes at the cost of assuming that all dimensions of factor scores are independent. Specifically, we make the following assumptions.

$$\xi_j \sim N(0, I) \tag{11}$$

$$\delta_j \sim N(0, \sigma_e^2 I) \tag{12}$$

Since our objective is to identify the underlying emotional constructs that affect market share, and not so much to study the interdependence of constrained factors, this is a reasonable trade-off. Conditional on the factor loadings, the transformed emotional content scores follow a multivariate distribution.

$$e_j \sim MVN(\phi, \Pi\Pi' + \sigma_e^2 I) \tag{13}$$

Since the effect of emotional attributes on market share is specified through low-dimensional independent latent factors, we are able to deal with the problems associated with incorporating high-dimensional and correlated emotional scores directly into the demand model. Lastly, we discuss the choice of functional form of $f(\xi_j)$ in the demand model. One of the objectives of this research is to investigate how consumer preference for emotional attributes varies with their sense of well being, such as consumer confidence in the economy. So we specify $f(\xi_j) = \xi_j C_t$ where C_t is the Consumer Confidence Index in week *t*.[8] Later in the paper, we discuss alternate specifications of this function. This completes the description of the model.

One approach to estimate this model is to first estimate the factor model, and to then incorporate the factor score estimates into the demand model. Instead, we treat the demand model and the factor model as a simultaneous system, and estimate all parameters including the factor scores simultaneously. So the likelihood of the factor scores depends not just on the emotional content scores data but also on the market share data. This leads to improved efficiency of estimation of the factor scores (Gilbride *et al.* 2005) and avoids the attenuation bias that might arise from treating the factor scores in the demand model as non-stochastic (Sonnier and Ainslie 2009, Ashok *et al.* 2002).

We adopt a Bayesian method of model estimation, specifying proper but diffuse prior distributions of the model parameters, and then deriving their posterior conditional distributions. Given the set of conditional distributions and priors, we draw recursively from the posterior distribution of the model parameters. We use the technique of data augmentation (Tanner and Wong 1997) coupled with the Metropolis Hastings algorithm to generate the factor scores ξ_j, which leads to a Markov Chain Monte Carlo solution. We conducted extensive simulation studies which involved creation of simulated datasets as per the specified model, specification of "true" parameter values, and then employing the proposed estimation method to test for biases in parameter estimates and model convergence. We found that the parameter estimates were unbiased and conclude that the model is identified. The estimation algorithm, and details of the simulation exercises, is available from the authors. The Gibbs sampler and the Metropolis Hastings algorithm were coded in Fortran 90. Convergence was assessed on the basis of the Geweke convergence diagnostic (Geweke 1992), and by inspecting the time series of draws.

5. Results and Model Comparison

In this section, we first present the results of model estimation which provide evidence of the effect of emotional product attributes on market share. Next, we compare our model with

[8] To check the robustness of our results with respect to this measure of consumer confidence, we substituted it with the Dow Jones Industrial Average (averaged within a week) and with a dummy variable for September 11, 2001. In both cases, the effects were significant and directionally the same. The two measures are highly correlated with the Consumer Confidence Index, so we decided to incorporate one measure in the model.

baseline models to demonstrate the superior performance of our model. Finally, we present the results of several robustness checks and some additional analyses.

5.1 Results

We first discuss the results of the measurement model, estimated on 932 movies (table 9). All six emotional content scores load positively on to the first factor, with "surprise" having the lowest effect magnitude relative to the other emotions. We label this factor "emotional complexity", since it is composed of all emotions, both positive and negative, with different loadings. In contrast, only negative emotions, namely anger, sadness and fear load on to the second factor. The loadings of positive emotions on this factor are not significant. So we label this factor "negative emotions". These results suggest the presence of two underlying emotional constructs – one consisting of a complex mix of all emotions, and the other consisting of negative emotions only.

---Insert Tables 9 and 10 here---

Next, we discuss the effect of the latent factors on box office market shares (table 10). We find that both factors have a positive main effect on market share, with the effect of the first factor (emotional complexity) being greater in magnitude than that of the second factor (negative emotions). This suggests that movies with greater "emotional complexity" (as measured by the LSA method) are associated with higher box-office market share, than movies with lower emotional complexity. However, there is another independent and positive effect of negative emotions on box-office revenue over and above that of emotional complexity. These results provide evidence that previously studied classifications of emotions along positive-negative or pleasure-arousal dimensions are perhaps not very well-suited in explaining consumer choice of movies. Instead we find evidence of demand for a complex mix of emotions, in addition to a demand for negative emotions.

Interestingly, we find that the demand for negative emotions increases with consumers' sense of well-being as measured by the Consumer Confidence Index. This finding is consistent with the "protective frame" theory of Apter (1982) which postulates that when subjects (in our case movie viewers) are safe or confident, negative stimuli are less likely to generate negative emotions. This finding is also consistent with industry wisdom that in recessionary times, movies with more positive emotions do better at the box-office. This suggests that if movie studios expect consumer confidence to be low (high) at the planned time of movie release, then they might benefit from content that has a lower (greater) level of negative emotional attributes (or they might postpone their release to a time when there is greater consumer confidence in the economy, should their movie have higher negative emotional attributes)[9]. The demand for emotional complexity does not vary significantly with consumer confidence. To the best of our knowledge, this is the first empirical evidence of how emotional attributes drive market shares in a product category.

---Insert Table 11 here---

Although these results provide strong evidence of emotional attributes on market share, it is not immediately clear which specific emotions have the greatest effect, and what the magnitudes of these effects are in terms of market share. We estimate the expected increase in market share associated with an increase of 0.1 in the LSA based score of each emotion. We first estimate the moments of the posterior distributions of the factor scores conditional on the increased emotion scores. Next, we estimate the posterior mean of market shares conditional on these posterior factor scores. So our estimates of change in market shares take into account the fact that emotion scores are correlated across emotions, and load on to two independent latent constructs. See table 11 for results. We find that the mean increase in market share across emotions is 9.0%. Love is associated with the greatest increase in market share and Surprise is associated with the least increase. This finding builds on the work of Eliashberg, Hui and Zhang (2007) who found *surprise* endings to be very important to movie success. These findings suggest that movie studios could gain substantial market share by increasing the emotional attribute content of their movies. However, three caveats are in order. First, given the small range of emotional scores of the movies in our data (Table 7), an increase in 0.1 in the LSA based

[9] For an unplanned movie release delay that turned out to be strategically beneficial, consider Hale's (2009) description of the distribution travails of the Japanese Oscar-winning movie *Departed* "Once the film was finished, another long wait ensued: 13 months passed before a distributor could be found. But the delay was a godsend, both men said. Mr. Takita conjectured that the worsening economic climate primed audiences for the film. Is money the most important thing in life? he said. What is the most important thing in life? People certainly are in search of some kind of comfort, of safe haven, and whether they find that in music or in books or in films.."

score is quite high. Second, our results might be limited to the range of the emotional scores, e.g. the maximum score of Surprise in our data is 0.766, so changes in market shares by increasing the level of Surprise beyond 0.766 is difficult to predict. Third, our results suggest that consumers demand a variety of emotions in a movie, and therefore movie studios would be well advised not to increase the level of one specific emotion, but to focus on the mix of emotions that one or both factors represent.

Our estimates of the effects of other covariates on box office market share are consistent with previous literature (table 12). Greater product budget and greater advertising spend are associated with greater market share. The greater the time since a movie has been released, the lower is its market share. Animation and action based movies garner higher market share than movies of other genres. Movies rated R or G are associated with lower market share than other movies. We also observe significant studio specific effects on market share.

---Insert Table 12 here---

5.2 Model Comparison

We now demonstrate that our model has better in-sample fit and predictive ability (in a hold-out sample of weekly sales for 50 movies) than benchmark models. Our first benchmark model (Model 1) ignores emotional attributes i.e. $\xi_j = f(\xi_j) = 0$. Our second benchmark model (Model 2) assumes that there is only one underlying factor that captures the effect of emotional attributes on market share i.e. k=1. Model 3 is the proposed model. We use the log marginal density to compare across models (table 13). The log marginal density is calculated using a harmonic mean of the individual likelihoods across iterations (Newton and Raftery 1994). We find that the log marginal density of the proposed model is the greatest and that of model 1, which ignores emotional attributes, is the least. Accurately predicting market share is of great importance to marketers.

We first compare the in-sample prediction of our model with models 1 and 2. We use two well-accepted measures – the mean absolute deviation (MAD) between the predicted and actual market shares and the root mean squared error (RMSE) of market share prediction. This is based on the calibration sample of 932 movies. Both measures indicate that the in-sample prediction of our model is the greatest, and that of the model which ignores emotional attributes, the least. The

MAD of the proposed model is 16.5% lower than that of model 1 suggesting substantial improvement in predictive ability. Next, we compare the out-of-sample predictive ability across models. This is based on computing the expected market shares on a holdout sample of 50 movies, and comparing them with the actual market shares. Both measures of predictive ability indicate that our model offers significant improvement in out-of-sample predictive ability over benchmark models. This underlines the importance of incorporating emotional attributes in market share models.

---Insert Table 13 here---

5.3 Robustness Checks and Post-Hoc Analyses

Next, we discuss the robustness of our results to specific features of the data and the model. First, we transformed the LSA based emotional content score in order to avoid a distributional misspecification (equation 10). To test the robustness of our results against this specification, we estimated the model under another transformation, namely $e_{kj} = \log(e^{*}_{kj} + 1)$. Although this transformed score has no lower bound, its upper bound is log(2). We find that the significance and direction of all factor loading estimates remain unchanged, as do all the substantive results. However, the predictive ability and in-sample fit of the proposed transformation is better.

Second, one implication of our results is that higher the emotional content score of a movie, the greater will be its market share. In order to test potentially non-linear and non-monotonic relationships between emotional attributes and market shares, we specify a model where $f(\xi_j) = \xi_j^2$. This specification allows us to capture non-linear relationships of interest. We find that our estimates of the effect of ξ_j^2 are not significantly different from zero. The posterior mean of the effect of ξ_{j1}^2 is 0.032 (posterior SD = 0.027). The posterior mean of the effect of ξ_{j2}^2 is 0.007 (posterior SD = 0.005). Lack of evidence of a non-linear relationship could perhaps be driven by the low variance of emotional content scores. We conclude that there is insufficient evidence of non-linear and non-monotonic effects of emotional content scores on market shares.

Third, the effects of the latent factors on market shares could be heterogeneous across movies. It is plausible that the demand for emotional attributes varies across movie genres. For example, it could be that the demand for fear is greater in horror movies, and that for joy is greater in animation movies. We tested this proposition by specifying $f(\xi_j)$ as a vector of genre dummy variables. These effects were not significantly different from zero, so we do not find evidence of genre based heterogeneity in the effects of emotional attributes. Heterogeneity in these effects across movies could also be driven by unobserved variables. So we estimated a latent class model which assumes that each movie belongs to one of two segments. The effects of emotional factors on market share are assumed to be the same across movies within a segment, but allowed to vary across the two segments. We find that the parameter estimates of the effects of latent factors are not significantly different across segments. Since factor scores are invariant across all observations specific to a movie, a model with movie-specific random effects of latent factors is not identified. In summary, we do not find evidence of heterogeneity in the effects of emotional attributes on movie market shares. Detailed results of all of these analyses, and the associated estimation methods, are available from the authors.

Lastly, we discuss our reasons for choosing the number of latent factors to be two. Parameter estimates of a three factor model (k=3) suggest that a) the posterior 95% credible intervals of the factor loadings of all emotions on the third factor contain zero, b) the posterior 95% credible interval of the effect of the third factor on market share contains zero, and c) the log-marginal density of this model is -6484.2, which is slightly lower than that of the proposed two factor model. We conclude that the effect of the LSA based emotional scores on market shares are best captured through two underlying latent factors.

6. Conclusion

The goals of this paper were (i) to propose a scalable method of measuring emotional product attributes for experiential products and (ii) to estimate the effects of these emotional product attributes on revealed consumer choice. Our application was to weekly sales of 982 movies in the U.S. motion picture industry in 1999-2005. We used plot keywords as a proxy for emotional product attributes information available to viewers as they make the movie choices. We extract emotional content scores from these plot keywords by mapping the semantic similarity between a movie's set of keywords and a set of words of basic human emotions. We build a random utility demand model using movie emotional product attribute measures and other movie characteristics.

We show that emotional content is a significant determinant of movie demand, both in-sample and in a hold-out sample. Specifically, we find that consumers prefer mixed emotional bundles (or emotional complexity) as well as negative emotions. The preference for negative emotions, however, is moderated by consumers' sense of well-being (safety and confidence) as captured by the Consumer Confidence Index. The insights from this paper are potentially of interest to both studios and theaters, who seek to anticipate the kinds of movies that consumers will appreciate in future when making production, release timing and screening decisions. This methodology can also be used on individual-level data to investigate if there are any segments in demand for emotional product attributes; some individual characteristics to investigate are age, income, gender, consumption occasion (e.g. family outing versus date night). The methodology proposed here can be used in examining other entertainment products like books and possibly in analyzing political campaigns and other advertising strategies. The method can also be used to analyze blogs, and other user-generated content, given it is easily scalable (and off-the-shelf) and has been proven to be a superior tool in various research contexts.

There are several avenues in which this research can be extended to understand other facets of the demand for movies. For example, individual level data from different countries can give insights as to how universal the demand for emotional attributes is. Similarly, our approach can be used to examine if the demand for emotions in the secondary channel, especially in the buying (and hence repeated watching) versus renting (single watching occasion, possibly after watching in the theatre), is different from demand for emotions in the primary theatrical channel. Yet another application is to understand whether movie critics have systematically different preferences for emotional attributes relative to their audience (e.g. audience preference for joy is higher than critics), and whether this explains the difference in critics' and audience ratings for any movie. Finally, another avenue for future research is to understand the optimal emotional differentiation among competitive movies released theatrically in the same week, with special attention paid to the differences in budgets. For example, do larger-budget movies released in the same weekend have to have greater emotional differentiation from one another compared to a lower-budget movie, controlling for the overall mood of the season (e.g. greater demand for love in Christmas, and adventure in July)?

More broadly, this research highlights the relative ease with which the economics and psychology of consumer choice can be integrated. Behavioral economics is a growing field; we hope our paper will contribute both to that field and spur more work in quantitative-behavioral-marketing.

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Table 1: Basic Human Emotions (Shaver et al. 1987)

Primary emotion	Secondary emotion	Tertiary emotions
Love	Affection	Adoration, affection, love, fondness, liking, attraction, caring, tenderness, compassion, sentimentality
	Lust	Arousal, desire, lust, passion, infatuation
	Longing	Longing
Joy	Cheerfulness	Amusement, bliss, cheerfulness, gaiety, glee, jolliness, joviality, joy, delight, enjoyment, gladness, happiness, jubilation, elation, satisfaction, ecstasy, euphoria
	Zest	Enthusiasm, zeal, zest, excitement, thrill, exhilaration
	Contentment	Contentment, pleasure
	Pride	Pride, triumph
Surprise	Surprise	Amazement, surprise, astonishment
Anger	Irritation	Aggravation, irritation, agitation, annoyance, grouchiness, grumpiness
	Exasperation	Exasperation, frustration
	Rage	Anger, rage, outrage, fury, wrath, hostility, ferocity, bitterness, hate, loathing, scorn, spite, vengefulness, dislike, resentment
	Disgust	Disgust, revulsion, contempt
	Envy	Envy, jealousy
	Torment	Torment
	Suffering	Agony, suffering, hurt, anguish
Sadness	Sadness	Depression, despair, hopelessness, gloom, glumness, sadness, unhappiness, grief, sorrow, woe, misery, melancholy
	Disappointment	Dismay, disappointment, displeasure
	Shame	Guilt, shame, regret, remorse
	Neglect	Alienation, isolation, neglect, loneliness, rejection, homesickness, defeat, dejection, insecurity, embarrassment, humiliation, insult
	Sympathy	Pity, sympathy
Fear	Horror	Alarm, shock, fear, fright, horror, terror, panic, hysteria, mortification
	Nervousness	Anxiety, nervousness, tenseness, uneasiness, apprehension, worry, distress, dread

Table 2: Summary Statistics of the Data (n=982)

	Mean	SD
Log(Weekly Box Office Revenue in $)	14.790	1.462
Log(Production Budget in $)	7.585	0.498
Log(Advertising Spend in $)	7.445	0.236
Consumer Confidence Index	110.144	22.316
Release Timing		
Spring	0.240	0.427
Summer	0.265	0.441
Fall	0.249	0.432
Winter	0.247	0.431
Number of weeks from release	6.100	5.054
Genre Dummy Variables		
Comedy	0.272	0.445
Animation	0.089	0.285
Romantic	0.089	0.285
Drama	0.172	0.378
Action	0.199	0.399
Science Fiction	0.054	0.227
Horror	0.123	0.329
MPAA Rating Dummy Variables		
G	0.062	0.241
PG	0.180	0.384
PG13	0.439	0.496
R	0.319	0.466
Studio Dummy Variables		
Buena Vista	0.133	0.339
Fox	0.108	0.311
MGM	0.036	0.187
Warner Bros.	0.130	0.337
Other Studios	0.591	0.491

Table 3: Examples of Plot Keyword Lists

Movie	Keyword list
Shrek	Gnome, Bear, Sunrise, Peter Pan, Hero, Pinocchio, Unlikely Hero, Blind, Tower, Mouse, Sunset, Bishop, Decree, Shrek, Big Bad Wolf, Robin Hood, Arrow, Comic Sidekick, Coffin, Friend, Altered Version Of Studio Logo, True Love, Wolf, Fairy, Sword And Sorcery, Courage, Hunter, Isolation, Fairy Tale, Alienation, Surprise After End Credits, Accordion, Stained Glass Window, Kiss, Midget, Reluctant Hero, Lord, Dwarf, Mirror, Sidekick, Outhouse, Beer, Torture, Transformation, Pig, Challenge, Anachronistic, Dragon, Castle, Curse, Disneyland, Donkey, Ethnic Cleansing, Fairy Tale, Flatulence, Friendship, Knight, Magic Mirror, Magic, Ogre, Spoof, Princess, Quest, Rescue, Spell, Talking Animal, Wedding, Blockbuster, Canceled Wedding, Fairy Tale Parody, Fart, Racism, Belch, Exploding Bird, Lava Filled Moat, Onion, Rope, Bridge, Swamp, Gingerbread Man, Crossbow, Destiny, Hit In Crotch, Pitchfork, Rotisserie, Skeleton, Sword, Windmill, Crude Humor, Satire, Fire Breathing Dragon
American Pie II	Gay Kiss, Teen Movie, Gross, Sequel, College, Sex, Teenager, Campy, Dormitory, Friend, Lesbian, Buddhism, College Summer, Humiliation, Obsession, Urination Scene, Band, Beach, Citizens Band Radio, Embarrassment, Father Son Relationship, Masturbation Scene, Party, Pool Table, Topless, Telephone Sex, Teen Sex Comedy, Lesbian Kiss, Band Camp, Beach House, Glue, Four Best Friends, Human Relationship, Male Bonding, Self Discovery, Martial Arts, Crude Humor, Cult Favorite, Student, Masturbation, Teen, Urination, Humor, Idiot, Obscenity, Repulsive, Stupidity, Vulgarity, Obscene Older Woman Younger Man
Hannibal	Black Comedy, Shoot, Brain Eating, Phone, Cell Phone, Good Versus Evil, Woman In Jeopardy, Sequel, FBI, Cannibal, Revenge, Serial Killer, Carousel, Blood, Brain, Cannibalism, Cellular Phone, Disembowelment, Disturbing, Eating Brains, Forensic, Hanging, Hyperrealism, Kidnapping, Millionaire, Murder, Rescue, Severed Hand, Shootout, Slit Throat, Stun Gun, Surveillance Camera, Torture, Violence, Wheelchair, Product Placement, Hannibal Lecter, Boar, Disfigurement, Italy, Police, Reward, Wealthy, Self Mutilation, Dream Like, Eaten Alive, Fairy Tale, Gothic, Neo Noir, Surreal, Blockbuster, Person On Fire, Psychiatrist, Handcuffs, Bitten In The Throat, Blood Splatter, Death, Gore, Hit By Car, Shot In The Arm, Shot In The Chest, Shot In The Shoulder, Shot To Death, Throat Slitting, Human Monster, Based On Novel

Table 4: Emotional Content Scores for 3 Movies

Movie	Joy	Love	Surprise	Anger	Fear	Sadness
Shrek	0.07	0.17	0.07	0.07	0.03	-0.01
American Pie II	0.17	0.26	0.00	0.04	0.07	0.06
Hannibal	0.01	0.07	-0.03	0.11	0.16	0.06

Table 5: Mean Emotional Content Scores by Genre

	Love	Joy	Surprise	Anger	Sadness	Fear
Action	0.062	0.030	0.010	0.068	0.064	0.112
Animation	0.058	0.034	0.002	0.024	0.014	0.032
Comedy	0.126	0.066	-0.016	0.052	0.040	0.070
Drama	0.120	0.064	-0.028	0.076	0.080	0.088
Horror	0.078	0.030	-0.006	0.084	0.092	0.148
Romantic	0.172	0.088	-0.006	0.064	0.056	0.072
Sci-Fi / Fantasy	0.108	0.070	-0.002	0.080	0.082	0.110

Table 6: Mean Emotional Content Scores by MPAA Rating

	Love	Joy	Surprise	Anger	Sadness	Fear
G	0.074	0.036	0.002	0.034	0.024	0.044
PG	0.086	0.048	-0.022	0.038	0.034	0.056
PG-13	0.116	0.058	-0.008	0.064	0.058	0.086
R	0.104	0.054	-0.008	0.078	0.078	0.116

Table 7: Summary Statistics of Emotional Content Scores

	Love	Joy	Surprise	Anger	Sadness	Fear
Mean	0.106	0.054	-0.010	0.064	0.060	0.092
Median	0.090	0.050	-0.010	0.060	0.050	0.090
Std. Dev.	0.097	0.063	0.055	0.067	0.071	0.074
Minimum	-0.110	-0.150	-0.180	-0.110	-0.090	-0.120
Maximum	0.794	0.786	0.766	0.822	0.840	0.806
Range	0.904	0.936	-0.946	0.932	0.930	0.926

Table 8: Correlations Between Emotional Content Scores

	Love	Joy	Surprise	Anger	Sadness
Joy	0.728				
Surprise	0.007	0.075			
Anger	0.574	0.48	0.158		
Sadness	0.478	0.438	0.101	0.807	
Fear	0.243	0.252	0.159	0.699	0.707

Table 9: Factor Loadings of Emotion Scores on Latent Factors (Π)

Emotion	Factor 1: Emotional Complexity		Factor 2: Negative Emotions	
	Posterior Mean	Posterior SD	Posterior Mean	Posterior SD
Joy	0.523*	0.017	0.027	0.017
Surprise	0.046*	0.018	0.107	0.083
Anger	0.438*	0.024	0.429*	0.018
Sadness	0.387*	0.023	0.472*	0.019
Fear	0.208*	0.029	0.618*	0.019
Love	1* (f)	-	0 (f)	-

Note: = Posterior means of parameter estimates whose 95% credible interval does not contain zero.*
f = Fixed for identification.

Table 10: Effect of Latent Emotion Factors on Box-Office Market Share (Λ)

		Posterior Mean	Posterior SD
Factor 1: Emotional Complexity	Main Effect	0.169*	0.039
	Interaction Effect with Consumer Confidence Index	0.003	0.002
Factor 2: Negative Emotions	Main Effect	0.098*	0.042
	Interaction Effect with Consumer Confidence Index	0.010*	0.001

Note: = Posterior means of parameter estimates whose 95% credible interval does not contain zero*

Table 11: Expected Increase in Box-Office Market Share (S_{jt}/S_{0t}) associated with an Increase in Emotional Score by 0.1

Emotion	Expected increase in market share
Joy	7.81%
Surprise	1.16%
Anger	4.86%
Sadness	10.68%
Fear	12.99%
Love	16.48%

Table 12: Effect of Observed Covariates on Box-Office Market Share (β)

	Posterior Mean	Posterior SD
Log(Production Budget)	0.161*	0.048
Log(Advertising Spend)	0.460*	0.052
Consumer Confidence Index	0.004*	0.001
Release Timing (Baseline = Winter)		
Spring	-0.194*	0.023
Summer	-0.299*	0.028
Fall	-0.655*	0.025
Number of weeks from release	-0.051*	0.003
Log(Number of weeks from release)	-1.518*	0.015
Genre (Baseline = Comedy)		
Animation	1.171*	0.182
Romantic	-0.361	0.260
Drama	0.100	0.139
Action	0.485*	0.123
Science Fiction	0.084	0.191
Horror	-0.011	0.114
MPAA Rating (Baseline = R)		
G	-0.134	0.213
PG	0.265*	0.067
PG-13	0.331*	0.137
Studio (Baseline = Other) Studios)		
Buena Vista	-0.287*	0.068
Fox	-0.218*	0.073
MGM	-0.421*	0.073
Warner Bros.	0.157	0.148

Note: = Posterior means of parameter estimates whose 95% credible interval does not contain zero*

Table 13: Model Comparison

	Model 1: number of factors = 0	Model 2: number of factors = 1	Model 3: number of factors = 2
In-sample fit			
Log marginal density	-7131.4	-6759.9	-6461.6
In-sample prediction			
MAD	0.483	0.437	0.404
RMSE	0.624	0.564	0.546
Out-of-sample prediction			
MAD	0.526	0.487	0.455
RMSE	0.649	0.593	0.584