ESSAYS ON THE U.S. MOTION PICTURE INDUSTRY

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This dissertation consists of a collection of essays about the U.S motion picture industry. Psychology literature proposes that emotional product attributes are central to the quality of movie consumption experiences. However such processes have been overlooked in the estimation of movie demand and quality reviewing.

Chapter 1 calibrates emotional content of a movie via a bag-of-words approach which maps a movie's plot keywords onto a set of basic human emotions. An emotional content vector is combined with other movie characteristics to build a random utility demand model for movies. The findings indicate that consumers prefer emotional variety and moderate levels of emotional complexity rather than incoherent differences. Also, the value of emotional attributes in movies is influenced by macroeconomic variables, potentially via their impact on consumer moods. As a confirmatory and supplementary analysis Chapter 1 also analyses preferences of a group of individual consumers, who rate movies online. This estimation replicates several findings from the aggregate demand model and generates further insights into consumer tastes which vary by demographic characteristics.

Chapter 2 builds on the literature which identifies the roles of movie critics as influencers of consumer choice and predictors of movie revenue by proposing a third role for movie critics: that of evaluators who signal movie quality independently of profit potential or commercial success. The relevance of this role is assessed by establishing whether critics' incentive structures favor reviews for artistic movies

which are systematically different from those of commercial movies. To this end, critics' ratings are compared with audience ratings: The positive correlation between average critics' reviews and audience reviews decreases for highly-artistic movies, which is consistent with the evaluator role permeating critical reviewing for such movies.

Chapter 3 investigates why the simple mean of critics' ratings for movies with an African American in the lead role is lower than movies with a white actor in the lead. Sources of this discrepancy can include differences in movie production and marketing expenditures, type of movie (i.e. genre, MPAA rating, emotional content, artistic and popular appeal), how good the actors are, audience tastes and time-contingent preferences of critics and audiences. Despite inclusion of these controls, results in Chapter 3 suggest that critics' ratings for movies with African American leads are up to 6 points lower and that critics favor movies where African Americans are featured in supporting roles rather than lead roles.

BIOGRAPHICAL SKETCH

Lona Fowdur is originally from Mauritius, which is where she completed her primary and secondary education. After passing her A-levels at the Queen Elizabeth High School for girls, she was awarded a scholarship by the University of Adelaide in Australia to pursue a Bachelors Degree in Finance. Upon graduation, she was invited to the Honors program, and completed an extra-year of research-oriented study in Economics. She achieved a First-Class Honors in 2002, under the supervision of Professor Kym Anderson. She spent an additional 18 months in Australia as a teaching and research assistant, and in 2004 she was accepted into the Ph.D. program in Economics at Cornell University on a Sage Fellowship. Her committee members include Vrinda Kadiyali (Chair), George Jakubson, Jeffrey Prince and Daniel Benjamin. She completed the requirements for the Masters degree in 2007 and will be earning a Ph.D. in Economics in May 2009. In June 2009, she will be joining Economists Inc, an economic consulting firm based in Washington, DC, as a senior economist.

To my parents

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CHAPTER 1

INVESTIGATING THE EMOTIONAL DRIVERS OF DEMAND FOR U.S. MOTION PICTURES

1.1. Introduction

Why do people seek entertainment? A simple answer is to be entertained. But what exactly comprises being entertained? Is it simply the pursuit of happiness? What then is common between laughing at a stand-up act, feeling anxious on a roller-coaster ride, crying at the movies, the tension of a down-to-extra-time basketball game or the quiet contentment of a walk on the beach? Utility from consuming entertainment is clearly multifaceted. How then should a researcher model demand for entertainment?

In modeling consumer choice, economists and marketers have recognized the importance of product attributes as determinants. Therefore, in addition to variables like prices, advertising, promotions, etc., consumer choice and demand has been modeled as a function of product characteristics like horse power, miles per gallon etc, for cars, and processor speed, hard drive etc, for personal computers. Researchers have documented that for entertainment, emotional product attributes (i.e. the affective responses felt by consumers as they engage with the product) are central to the quality of the consumption experience (Hirshman & Holbrook 1982). Modeling these product attributes for entertainment is likely to be harder because emotions elicited by entertainment are harder to quantify.

In this paper, we model the demand for movies in the theatrical channel. 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 & Bryant 2002). Also, any single movie can evoke a variety of emotions, e.g. surprise, horror, sadness, and joy. To measure how various emotions play out in a consumer's pursuit of happiness when watching movies, we measure the emotional content of a movie by examining its plot keywords. In addition, we include other, easier-to-measure attributes like production cost, advertising, studio, genres, MPAA ratings etc.

Plot keywords are a reasonable way to capture emotional content of a movie for the following reasons. First, they reflect information available to consumers via trailers, movie reviews, movie websites etc., which are likely to influence their choice decision. Second, while word-of-mouth and critic reviews might have more details on emotional content ("This movie will surprise you, and make you nostalgic for your childhood"), we do not have ways to capture these processes. Given we are able to parse emotional content out of plot keywords these keywords can be viewed as reasonable proxies for harder-to-obtain summaries of word-of-mouth and critic reviews. Additionally, our estimates should be viewed as conservative estimates of the impact of emotional content of movies. Our methodology allows us to answer the following questions about what consumers want in movies: Do they prefer movies with predominantly one emotion (e.g. scary) or do they prefer a mix of emotions (scary and happy)? Does demand for emotions vary by genre of movie? How have preferences for emotional content evolved over time? Do consumers demand different emotional content in movies when economic conditions are rosy versus bleak?

While there is a large literature in marketing and economics examining the motion picture industry, our paper differs from existing papers by conducting a systematic analysis of what constitutes emotional attributes in a movie. The closest papers to ours are Eliashberg & Sawhney (1994) and Neelamegham & Jain (1999). These papers look at the effect of psychological content variables of movies (measured by the degree of pleasure and arousal conferred by the plot) on individual differences in movie enjoyment in the former case and on individual movie choice in the latter case. However neither explicitly addresses specific emotions underlying choice and neither can be applied in an aggregated demand setting since they both rely on individual level psychological variables. 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).

We estimate the model for 1152 movies in theaters in 1999-2005. Our primary findings are as follows. As expected, we find that emotions play a role in movie choice. By interacting genres and emotions, we find that different subsets of emotions are relevant within each genre. We also find that changes in macroeconomic variables affect the demand for emotions. Overall, the demand for emotions seems to be driven by mood management theories established in psychology literature.

To confirm and supplement the results from the aggregate market share model, we analyze the preferences of a group of individual consumers. Since we do not have access to individual viewing/sales data, we use the ratings of a group of online reviewers who award movies a letter-grade that summarizes their level of satisfaction with the movie, pursuant to their consumption experience. Given the ordered nature of this data, we employ an ordered probit specification to capture individual preferences. In addition to serving as a robustness check for our earlier findings, this model generates several additional insights about variations in consumer preferences which emerge due to differences in consumer characteristics: we find individual differences as captured by age, gender, marital status and geographic location to be valid predictors of individual reviews and hence of preferences. These nuanced insights are potentially of use to movie distributors since audience segmentation and targeted marketing of movies are often lucrative.

A primary contribution of this paper is to provide a method to quantify the impact of psychological phenomenon on market outcomes, and do this with market data rather than laboratory data. 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 appeal is likely to matter and where verbal product descriptors are available. Examples include consumer demand for other experiential goods like books, art, concerts, amusement parks, political candidates, etc.

The rest of the paper is organized as follows. In the next section, we briefly survey the current literature on the movie industry, and the relevant literature in psychology. We describe our data in section 1.3. In section 1.4, we discuss a simple random utility framework for movie demand. We present results in section 1.5. Section 1.6 offers an ordered probit analysis of individual preferences. Section 1.7 concludes.

1.2. Literature Review: Emotions as Determinants of Choice

Movies are consumed for the emotional pleasure they provide, but they may also be chosen despite the fact that they cause negative emotions (Suomi & Harlow 1976). Interestingly, movies may be chosen not just despite, but *because* they cause negative emotions. For example, purposeful exposure to frightening scenes allows consumers to purge anxieties (Freud 1955); sad movies allow consumers to expend painful emotions, and the resolution of sad events allow consumers to construct fantasies to better cope with unhappy realities (Hirshman & Holbrook 1982). Thus movies 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 & DuBois 2006). Catharsis has also been put forth as a phenomenon underlying the reduction in violent crime pursuant to the viewing of violent movies in theaters (DellaVigna 2007). More generally, mood management theory (Zillmann & 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]. In sum, 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. 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).

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

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 & Turner 1990). In some studies researchers posit that there exist as few as two basic emotions: happiness and sadness (Weiner & 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).

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[2]. 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 which reflect emotions and which are assigned to groups on the basis of semantic relatedness; see table 1.1. We favor this 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. Further, the Shaver et al. list overlaps substantially with the lists put forth by most other researchers.

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

Table 1.1. 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
Fear	Horror	Alarm, shock, fear, fright, horror, terror, panic, hysteria, mortification
	Nervousness	Anxiety, nervousness, tenseness, uneasiness, apprehension, worry, distress, dread
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

A caveat of the Shaver et al. list is that it reflects primary emotions only and fails to distinguish between the subordinate emotions corresponding to each basic emotion. However, this weakness is not overwhelming, since Rosch (1978) suggests that "objects may first be recognized as members of their basic category and … only with additional processing can they be identified as members of their superordinate or subordinate category" (p.35). Thus, it appears possible that when consumers initially hear about a movie (through a review or word of mouth or trailers etc.), their understanding of the emotional content of the movie might not be as granular (as say after experiencing the movie). Therefore, a simpler classification of emotional content might be adequate. Rosch et al. (1976) note that information gathered at the level of basic emotions maximizes information about an emotional event, while maintaining cognitive and communicational economy.

Another caveat of the Shaver et al. list arises from the categorizations of emotions that constitute a blend of basic emotions. For example, 'jealousy' can be regarded as a mixture of 'love' and 'anger', but on the basis of how most respondents categorized jealousy, Shaver et al list jealousy as a subordinate to 'anger' only. To capture blends of basic emotions we use interaction variables between the basic emotions.

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). More generally, the role of emotions in consumer choice is well-documented (Maslow 1968).

Given this discussion on the emotional drivers of movie choice, we now turn to related literature in marketing and economics. While there is a vast literature in marketing on the motion picture industry (see Elberse et al. 2006 for a review), we focus our attention more on the directly relevant literature. 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 & 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 & Jain (1999) develop a framework to predict consumer choice and model postchoice recommendations for movies. Their 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 emotional expectations about content are a significant predictor of movie choice, while actual emotional content influence postconsumption movie evaluations and recommendations. However, as in Eliahberg & Sawhney (1994), they calibrate emotional 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 an arbitrary personality trait, we use emotions because psychologists argue that what give rise to personality traits are in fact mixtures of emotions (Plutchik 1962, 1980) and because emotions offer a more basic conceptualization and paint a richer picture of the psychological content of movies.

1.3. Data

Our dataset comprises 1152 movies from 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. 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. Since revenues and market shares are trivial below this level of theater-screening, we do not expect such truncation to bias our results.

Our theatrical revenue data is from two internet sites: Boxofficemojo.com (BM) and imdb.com (IMDB). We also use print and advertising-expenditure for each movie, which is provided by Paul Kagan and Associates. We obtained information pertaining to production studio, production budget, release date and weekly gross box office from BM. We used IMDB to collect movie genres, MPAA rating and content data. Despite the fact that both main genre and sub-genre classifications hold relevant information, we only control for the main genre and focus on the emotional dimensions as a summary measure of sub-genres because consumers may sometimes be unfamiliar with murky sub-genre listings (e.g. “neo-noir”), but they can readily process movie keyword information along dimensions of basic emotions, since emotions constitute the interface via which consumers interact with movies (Tan

1994). Further emotions represent an everyday concept that consumers can readily identify.

We hypothesize that economic conditions have an impact on consumer mood which in turn impacts their preferences for emotional content. Hence, we collect data on macroeconomic variables, namely the index of consumer confidence, the Dow Jones Industrial Average, the unemployment rate and inflation from an online source: www.economagic.com.

To compute market shares, we use yearly estimates of US population counts obtained from the US census, which we interpolate linearly to obtain weekly counts. We use a similar procedure to obtain weekly averages of national ticket prices from yearly averages which are available from the National Association of Theater Owners website: http://www.natoonline.org.

1.4. Model and Measurement Method

1.4.1. 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* takes the form:

$$U_{ijt} = \tau_{it} + \beta_i X_j + \gamma_i C_{ij} + \delta_{i1} A_{jt} + \delta_{i2} (\ln A_{jt}) + e_{ijt} \qquad (1)$$

τ_{it} represents consumer *i*'s intrinsic seasonal preference for movies. X_j is a vector of dummy variables which captures the time-invariant movie characteristics, namely the log of advertizing expenditure, log of budget, MPAA rating, production studio dummies and movie genre dummies[3]. C_j is also time-invariant and measures emotional content of movie *j* and interactions between emotion pairs. To identify the effect of time and that of macroeconomic variables on demand for emotions, we build on this vector: first by including interactions between emotional content and time (to capture the effect of time on preferences), and second by including interactions between emotional content with time as well as with respective macroeconomic variables (to capture the effect of macroeconomic variables on preferences while controlling for changes due to time alone). A_{jt} is the age of movie *j* at time *t*, i.e. the number of weeks that have lapsed since release. 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 Ainsley *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. Such a specification is important because it accounts for the presence of sleeper movies[4]. e_{ijt} is a stochastic error term which represents 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. Normalizing the intrinsic preference of not seeing a movie to zero in each week, the utility from the outside option becomes:

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[3] From this we get a log-log market share equation which follows the approach established in the literature.

[4] Unlike most movies for which demand trends down with age, sleepers tend to exhibit an 'inverted-U shaped' demand pattern

$$U_{i0t} = e_{i0t} \qquad (2)$$

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:

$$P_{ijt} = \frac{\exp(\tau_{it} + \beta_i X_j + \gamma_i C_j + \delta_{i1} A_{jt} + \delta_{i2}(\ln A_{jt})}{1 + \sum_k^{J_t} \exp(\tau_{it} + \beta_i X_k + \gamma_i C_k + \delta_{i1} A_{kt} + \delta_{i2}(\ln A_{kt})} \qquad (3)$$

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

$$\tau_{it} = \tau_t + \Delta\tau_{it}; \beta_i = \beta + \Delta\beta_{it}; \gamma_i = \gamma + \Delta\gamma_{it}; \delta_{i1} = \delta_1 + \Delta\delta_{i1}; \delta_{i2} = \delta_2 + \Delta\delta_{i2} \qquad (4)$$

We represent the consumer specific-parameters by

$$\Delta_i = \{\Delta\tau_{ij}; \Delta\beta_i; \Delta\gamma_i; \Delta\delta_{i1}; \Delta\delta_{i2}\} \qquad (5)$$

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:

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

To calculate S_{jt} we divide the weekly 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 U.S. 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 hedonic market share equation:

$$\hat{\ln}\left(\frac{Share_{jt}}{Share_{0t}}\right) = \hat{\tau}_t + \hat{\beta}X_j + \hat{\gamma}C_j + \hat{\delta}_1 A_{jt} + \hat{\delta}_2(\ln A_{jt}) \qquad (7)$$

We estimate this equation after adding interactions between genres and emotional attributes. This allows us to assess the differential impact of emotional attributes on specific genres.

1.4.2. Measure of emotional content

We use Latent Semantic Analysis (LSA). 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 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). 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 the SAT's and GRE (Landauer, Foltz, & Laham, 1998); this use prompted us to use LSA rather than competing software that perform similar functions.

LSA works by parsing a large corpus 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, and our list of six emotions, and ask the software to identify for us which plot keyword is likely to be associated with which (if any) emotion: 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 key 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

We regard such keyword lists as reasonable proxies for other sources of information available to the consumer ex-ante (trailers, plot summaries, critics' reviews, word of mouth, etc). 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. Further, since keyword lists are defined and updated by IMDB users who have seen the movie, information in keyword lists reflect movie content perceived to be relevant and likely to be passed on to others in the form of reviews and word of mouth.

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. To make the interpretation of interaction coefficients easier, we rescale these measures linearly so that they lie between 0 and 10. Examples of content scores for the above keyword list are 5.35 for joy, 5.85 for love and 5.15 for fear.

Table 1.2 includes keyword lists for two other popular movies: American Pie II and Hannibal, and table 1.3 reports the corresponding emotional content measures.

Table 1.2. Examples of keyword lists for Shrek, American Pie II and Hannibal

Movie	Keyword list
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,*

Table 1.3: Emotional content measures for 3 movies

Movie	Joy	Love	Surprise	Anger	Fear	Sadness
Shrek	5.35	5.85	5.35	5.35	5.15	4.95
American Pie II	5.85	6.30	5.00	5.20	5.35	5.30
Hannibal	5.05	5.35	4.85	5.55	5.80	5.30

Tables 1.4 and 1.5 show the average content measures by movie genre and MPAA rating respectively, and Table 1.6 shows the summary statistics for the emotional content vectors of all the movies in our sample.

Table 1.4: Average emotional content by genre

	Count	Love	Joy	Surprise	Anger	Sadness	Fear
Action/ Adventure	219	5.31	5.15	5.05	5.34	5.32	5.56
Animation	72	5.29	5.17	5.01	5.12	5.07	5.16
Comedy	332	5.63	5.33	4.92	5.26	5.20	5.35
Drama	217	5.60	5.32	4.86	5.38	5.40	5.44
Horror	155	5.39	5.15	4.97	5.42	5.46	5.74
Romantic Comedy	101	5.86	5.44	4.97	5.32	5.28	5.36
Sci-Fi Fantasy	56	5.54	5.35	4.99	5.40	5.41	5.55
Total	1152	5.27	5.53	4.95	5.32	5.30	5.46

Table 1.5: Average emotional content by MPAA rating

MPAA	Count	Love	Joy	Surprise	Anger	Sadness	Fear
G	51	5.18	5.37	5.01	5.17	5.12	5.22
PG	162	5.24	5.43	4.89	5.19	5.17	5.28
PG-13	491	5.29	5.58	4.96	5.32	5.29	5.43
R	453	5.27	5.52	4.96	5.39	5.39	5.58

Table 1.6: Summary statistics for emotional content of all movies (1152 movies)

	Love	Joy	Surprise	Anger	Sadness	Fear
Mean	5.53	5.27	4.95	5.32	5.30	5.46
Median	5.45	5.25	4.95	5.30	5.25	5.45
Standard Deviation	0.48	0.32	0.27	0.34	0.35	0.37
Minimum	4.45	4.25	4.10	4.45	4.55	4.40
Maximum	7.55	6.55	6.00	6.65	6.60	6.85
Range	3.10	2.30	1.90	2.20	2.05	2.45

The mean content scores are close to 5, which is the midpoint of the semantic proximity scale. This is because emotional content does not exhaust informational content of the keyword list, i.e. some words in the list may not connotate any emotion concept (e.g. ‘mirror’ and ‘anachronistic’ in the above list). The relatively tight cluster of emotional content measures around 5 (standard deviations range from 0.27

to 0.48) indicates that movies tend to involve a balanced combinations of all the basic emotions and that slight variations from the mean are enough to differentiate one movie from another. The higher the emotional content score, the higher the level of the corresponding emotion that consumers perceive from the keyword list. 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 1.4).

It is important to note that movies which 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.

A related paper that uses this bag-of-words method is Eliashberg, Hui and Zhang (2006). In this paper, the authors predict the rate of return of movies from movie scripts. Given that electronic scripts are not available for most movies in their sample, they extract textual information from movie spoilers. They devise an algorithm analogous to the LSA procedure to assign weights to constituent words of a document so that words which occur with the highest frequency across all documents (e.g. 'the', 'he', 'she' etc) as well as words which only occur very infrequently across all documents get a low weight. Highly weighted words tend to be action words or dialogue words and have information content about a movie's plot. Eliashberg et al.

(2006) retain 100 highest weighted words and compute the semantic proximity between these words and movie spoilers. To reduce dimensionality, they use principle components analysis and define two factors: one captures "dialogue" words and the other captures "violence" words. Since they are interested in deriving a methodology to identify successful scripts, the authors point out that a bag-of-words representation fails to capture the stories and themes which resonate with the consumer. Hence they supplement the textual information gleaned from the bag-of-words approach 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 bag-of-words and expert characterizations of content data are significant predictors of the rate of return on movies.

In our application, our use of LSA's bag-of-words approach seems appropriate for two reasons. First, we use a broader set of classifications (six key emotions and interactions) than the two-factor classification in Eliashberg et al. (2006) above; this should add descriptive richness. Second, we do 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. 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. In the absence of a way to capture sequence of emotions in a movie and given our choice of using six basic emotions rather than more complex classifications, our results are likely to provide a conservative estimate of the demand for emotions in movies.

1.5. Results

Our first set of results is in table 1.7. The results for the non-emotional content variables are consistent with existing studies (e.g. Einav (2007), Chiou (2006)); this is reassuring given the additional emotional content variables in the model. For example, both advertising and budget contribute positively to market share, which declines at an increasing rate with age. The following variables lead to higher than average market share- PG movies perform better than PG-13, Action/ Adventure movies do better than comedies.

Table 1.7: Estimated means for structural parameters of market share model

Non-emotional attributes			
Variable	Estimate	Std. Error	
Intercept	-48.789	7.320	**
Winter	0.446	0.046	**
Spring	0.152	0.046	**
Summer	0.281	0.045	**
Fall	Omitted		
BuenaVista	-0.261	0.073	**
DreamWorks	-0.189	0.086	*
Fox	-0.246	0.071	**
MGM	-0.419	0.099	**
Miramax	-0.161	0.086	
NewLine	-0.148	0.086	
Other	Omitted		
Paramount	-0.430	0.072	**
Sony	-0.738	0.079	**
Universal	-0.530	0.074	**
WarnerBros	-0.491	0.070	**
Animation	0.389	0.080	**
Action / Adventure	0.447	0.055	**
Comedy	Omitted		
Drama/BlackComedy	0.678	0.054	**
Horror	0.184	0.065	**
Romantic Comedy	-0.084	0.066	
Sci Fi / Fantasy	0.079	0.081	

Table 1.7 (continued)

MPAA:G	-0.170	0.092	
MPAA:PG	0.159	0.052	**
MPAA: PG-13	Omitted		
MPAA:R	-0.418	0.043	**
Age	0.032	0.007	**
Ln Budget	0.200	0.024	**
Ln Advertising	0.299	0.036	**
Ln Age	-1.548	0.041	**
Emotional attributes and interactions			
Variable	Estimate	Std. Error	
Love	6.600	1.462	**
Joy	2.447	2.099	
Surprise	4.446	1.763	*
Anger	-2.805	2.490	
Sadness	-5.406	2.354	*
Fear	10.077	1.826	**
Love*love	-0.026	0.127	
Love*Joy	0.734	0.289	*
Love*Surprise	-1.306	0.210	**
Love*Anger	-0.286	0.342	
Love*Sadness	-0.426	0.305	
Love*Fear	0.081	0.233	
Joy*Joy	-0.832	0.255	**
Joy*Surprise	1.506	0.291	**
Joy*Anger	-0.589	0.447	
Joy*Sadness	0.668	0.406	
Joy*Fear	-0.997	0.322	**
Surprise*Surprise	-0.710	0.155	**
Surprise*Anger	1.503	0.354	**
Surprise*Sadness	0.000	0.312	
Surprise*Fear	-1.131	0.271	**
Anger*Anger	-0.188	0.420	
Anger*Sadness	0.296	0.624	
Anger*Fear	0.049	0.441	
Sadness*Sadness	0.083	0.341	
Sadness*Fear	0.329	0.395	
Fear*Fear	-0.133	0.222	

Significance levels: 1%:** ; 5%:*

Out of the six dimensions of emotional content, four are significant: love, surprise and fear have a positive effect on market share, while sadness has a negative effect. Joy and surprise also have significant and negative coefficients on their square terms; too much joy in a movie is likely cloying, too much surprise might be too unsettling. The magnitudes of the coefficients indicate that love and fear represent the emotional attributes that consumers value the most, followed by surprise. As mentioned earlier, consumers might demand negative emotional content (fear, in this case) in movies. Some of the interaction effects are also significant.

A more detailed set of results emerges after we disaggregate the above emotional controls by genre. Table 1.8 reports the results. The statistically significant interaction coefficients between genre and distinct emotions demonstrate that consumers have different preferences for the emotional composition of movies depending on the genre. For example, while joy adds to the utility in animation, it has no impact on action/adventure and drama. Several of these results are typical, and we can justify several of our unexpected findings (e.g. preference for anger in animation, and dislike for fear in romantic comedy) via insights from media psychology: Berlyne (1971) posits that people prefer moderate levels of complexity because similitude is boring, whereas variety without coherence produces unpleasant feelings of distraction and fragmentation. For example dramas inherently produce melancholic feelings and sadness is therefore not appreciated in this genre; mood repair theories also would not support additional sadness in this genre. Similarly fear in romantic comedy can add variety without coherence and is therefore not appreciated.

Table 1.8: Estimated means for genre / emotion interactions in structural demand equation

GENRE:	Animation			Action / Adventure		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	4.876	16.105		0.266	4.798	
Joy	54.897	13.682	**	-6.659	5.754	
Surprise	7.750	9.494		-8.080	7.000	
Anger	-50.071	21.806	*	-23.614	6.777	**
Sadness	8.912	12.348		10.950	5.920	
Fear	-10.822	13.055		12.987	4.404	**
Love*love	-1.722	1.659		-0.057	0.472	
Love*Joy	8.659	3.745	*	0.525	1.083	
Love*Surprise	3.167	2.235		-0.208	0.728	
Love*Anger	-4.313	3.938		2.500	1.104	*
Love*Sadness	1.156	2.860		-3.970	0.984	**
Love*Fear	-6.106	2.847	*	0.981	0.770	
Joy*Joy	-8.543	2.303	**	-0.731	0.770	
Joy*Surprise	-3.927	2.014		2.414	0.914	**
Joy*Anger	11.422	3.149	**	6.093	1.342	**
Joy*Sadness	-12.185	2.884	**	-1.422	1.070	
Joy*Fear	2.229	2.222		-4.450	0.821	**
Surprise*Surprise	-1.356	0.564	*	-1.038	0.606	
Surprise*Anger	7.501	1.375	**	0.558	1.023	
Surprise*Sadness	-1.890	1.458		-0.419	0.856	
Surprise*Fear	-3.664	1.728	*	1.061	0.700	
Anger*Anger	-10.076	2.081	**	-5.061	1.340	**
Anger*Sadness	-0.869	3.526		4.676	2.043	*
Anger*Fear	16.320	2.349	**	1.017	1.225	
Sadness*Sadness	6.359	1.622	**	-0.327	0.932	
Sadness*Fear	-0.888	2.219		-0.328	0.900	
Fear*Fear	-2.781	1.452		-0.375	0.534	

GENRE:	Comedy			Drama		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	-3.195	2.706		13.061	3.193	**
Joy	12.069	3.398	**	-2.103	5.714	
Surprise	5.850	3.094		24.175	3.834	**
Anger	2.015	4.908		-9.537	5.207	
Sadness	7.625	4.490		-17.023	5.727	**
Fear	-2.272	3.298		14.157	5.100	**
Love*love	-0.775	0.228	**	-0.173	0.276	
Love*Joy	3.415	0.531	**	-0.446	0.748	
Love*Surprise	-1.838	0.370	**	-0.773	0.501	
Love*Anger	1.171	0.692		-3.348	0.675	**

Table 1.8. (continued)

Love*Sadness	-1.663	0.531	**	4.168	0.733	**
Love*Fear	1.039	0.417	*	-1.619	0.566	**
Joy*Joy	-1.871	0.437	**	-2.077	0.766	**
Joy*Surprise	0.032	0.494		1.579	0.849	
Joy*Anger	-4.299	0.857	**	5.591	1.108	**
Joy*Sadness	2.574	0.699	**	-1.146	1.025	
Joy*Fear	-0.331	0.601		-0.944	0.771	
Surprise*Surprise	-0.420	0.312		-1.491	0.440	**
Surprise*Anger	4.387	0.663	**	-1.704	0.873	
Surprise*Sadness	-1.630	0.594	**	-0.118	0.876	
Surprise*Fear	-1.157	0.520	*	-0.649	0.750	
Anger*Anger	-0.666	0.719		1.331	0.898	
Anger*Sadness	0.234	1.106		-0.234	1.345	
Anger*Fear	-0.294	0.807		-1.276	1.087	
Sadness*Sadness	-1.104	0.619		-2.038	0.843	*
Sadness*Fear	1.092	0.718		4.418	1.037	**
Fear*Fear	-0.008	0.456		-1.181	0.612	

GENRE:	Horror / Thriller			Romantic Comedy		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	17.780	7.314	*	10.116	5.939	
Joy	-30.041	8.227	**	-27.538	8.785	**
Surprise	-6.807	6.335		-50.270	6.821	**
Anger	-6.718	9.513		24.623	11.142	*
Sadness	-4.683	8.539		99.841	11.372	**
Fear	12.614	6.575		-69.672	8.931	**
Love*love	-1.403	0.692	*	2.526	0.573	**
Love*Joy	0.301	1.163		-0.707	0.977	
Love*Surprise	-0.581	0.941		-2.060	0.867	*
Love*Anger	-1.748	1.477		1.336	1.888	
Love*Sadness	-0.702	0.924		-3.274	1.304	*
Love*Fear	2.257	0.934	*	-2.683	1.235	*
Joy*Joy	3.105	0.774	**	-0.906	1.134	
Joy*Surprise	1.801	0.916	*	11.239	1.458	**
Joy*Anger	-0.799	1.404		-7.633	2.665	**
Joy*Sadness	-3.763	1.297	**	5.055	2.480	*
Joy*Fear	2.051	1.044	*	-0.031	1.887	
Surprise*Surprise	-0.171	0.498		1.141	0.709	
Surprise*Anger	2.501	1.267	*	-7.446	1.851	**
Surprise*Sadness	-0.378	1.045		-1.965	1.753	
Surprise*Fear	-1.741	1.094		7.209	1.177	**
Anger*Anger	0.565	1.191		4.197	2.264	
Anger*Sadness	7.128	1.778	**	-5.498	2.646	*

Table 1.8. (continued)

Anger*Fear	-6.373	1.505	**	5.371	2.621	*
Sadness*Sadness	-1.003	0.975		0.366	1.609	
Sadness*Fear	0.182	1.214		-13.441	2.079	**
Fear*Fear	0.641	0.738		8.643	1.073	**

GENRE:	Sci-fi / Fantasy		
Variable	Estimate	Std. Error	
Love	-12.858	13.007	
Joy	10.906	12.737	**
Surprise	33.619	10.166	
Anger	4.367	18.023	
Sadness	-1.922	21.120	*
Fear	49.509	24.920	
Love*love	-1.346	1.567	
Love*Joy	1.945	2.526	*
Love*Surprise	5.387	2.200	*
Love*Anger	-6.395	2.954	
Love*Sadness	-0.792	3.257	
Love*Fear	5.672	3.556	
Joy*Joy	1.618	1.930	
Joy*Surprise	-2.668	2.117	
Joy*Anger	-1.384	3.402	
Joy*Sadness	0.008	3.079	
Joy*Fear	-3.632	2.774	**
Surprise*Surprise	3.883	1.147	**
Surprise*Anger	-15.316	3.751	**
Surprise*Sadness	11.638	2.371	**
Surprise*Fear	-12.038	2.171	
Anger*Anger	2.489	4.405	*
Anger*Sadness	15.614	7.391	
Anger*Fear	0.708	4.698	
Sadness*Sadness	-2.950	4.150	**
Sadness*Fear	-18.563	5.335	**
Fear*Fear	8.441	2.962	

Significance levels: 1%:** ; 5%:*

Eliashberg and Sahwney (1994) contend that movie enjoyment at an individual level stems from a dynamic interaction between stable individual personality traits, temporary moods and the emotional content of movies. Since our focus is on aggregate data, we identify exogenous controls which potentially affect temporary moods of an aggregate audience, shifting its preferences for emotional content. Specifically, we hypothesize that the kinds of emotions that consumers will find gratifying varies with changes in their general emotional disposition. The latter can be impacted upon by economic conditions.

We investigate the impact of four macroeconomic variables: Consumer Confidence, the Dow Jones stock index, the unemployment rate and inflation on the preferences for emotions in movies. We capture the changes to preferences for emotional content induced by these variables via the inclusion of interaction variables between each macroeconomic variable and emotion/emotion pair. To disentangle changes in preferences due to these macroeconomic variables from a general trend in preferences due to time, we estimate the demand equation after including a time trend, as well as interactions between time and dimensions of emotional content.

The introduction of a time trend also allows us to assess preference trends for emotional attributes over time. We report the results in table 1.9.

The statistically significant coefficients on the interactions of joy, sadness, love and fear with time attest to progressively higher preferences for joy and sadness and progressively lower preferences for love and fear with time. In addition, relative to comedies, consumers manifest a preference for animation, action/adventure, drama and horror movies, but not for romantic comedies with time.

Table 1.9: Estimated means for interactions with time trend in structural demand equation

Interactions with Time trend			
Variable	Estimate	Std. Error	
Love	-0.050	0.012	**
Joy	0.034	0.015	*
Surprise	0.018	0.011	
Anger	0.005	0.023	
Sadness	0.055	0.020	**
Fear	-0.051	0.015	**
Animation	-0.002	0.001	**
Action / Adventure	-0.002	<0.001	**
Comedy	Omitted		
Drama	-0.003	<0.001	**
Horror	-0.002	0.001	**
Romantic Comedy	0.004	0.001	**
Sci-fi / Fantasy	-0.001	0.001	

Significance levels: 1%:** ; 5%:*

The signs on the interactions of love, sadness and fear with time as well as those on the interactions of genres with time turn out to be the exact opposite to the signs on the corresponding main emotion effects. This is an interesting finding which possibly alludes to a preference for variety as time passes: while consumers enjoy love and fear in general, results from inclusion of a time trend are consistent with the notion that consumers are getting progressively satiated with these emotions as time passes. Similarly, their dislike for sadness subsides with time. These time trends are potentially of interest to studios: While an understanding of the general preference structure of a movie audience is useful, being able to anticipate a trend in preference structures may prove to be lucrative, especially since most movies spend several months in the production process and since small differences in emotional content are enough to influence demand. Results are presented table 1.10[5].

A rise in both consumer confidence and the Dow Jones Stock Index produce very similar changes to the preference structure for emotions and genres: the preference for surprise is statistically significant and positive in both cases (surprise is a neutral emotion); the preference for animation, action/adventure, drama and horror relative to comedies is also statistically significant and positive. In addition, a rise in consumer confidence generates lower preference for joy.

In contrast, a rise in the unemployment rate generates a higher preference for joy and lower preference for fear. A rise in unemployment also causes a drop in preference for animation and horror movies. Interestingly, rising inflation generates lower preference for joy and higher preference for fear. Other preference changes induced by a rise in inflation include higher preferences for love and drama, but lower preferences for sadness and sci-fi/fantasy movies.

Summarizing the results so far, we find evidence to support the validity of emotions as movie attributes on the basis of which consumers make their movie choices. We find that a different set of emotions is preferred within each movie genre and we find that preferences for emotions change over time and with changes in macroeconomic variables. It appears that when the economic is down, consumers seek to purge their anxieties by seeking out more joy (e.g. when unemployment is high). Conversely when the economy is doing well, consumers seek more stimulation from emotions like surprise and genres like action/adventure and horror. These findings are consistent with mood management theories in psychology literature.

[5] We control for emotion/emotion and emotion/genre interactions, but do not report the coefficients.

Table 1.10: Estimated means for interactions with time trend and other macroeconomic variables in structural demand equation

	Consumer Confidence			Dow Jone Stock Index		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	-0.021	0.110		1.349	1.842	
Joy	-0.320	0.137	*	-4.016	2.179	
Surprise	0.343	0.093	**	5.385	1.452	**
Anger	-0.051	0.175		1.272	2.762	
Sadness	0.013	0.159		-4.014	2.592	
Fear	0.063	0.119		0.250	1.954	
Animation	0.009	0.004	*	0.214	0.061	**
Action / Adventure	0.008	0.003	*	0.129	0.046	**
Comedy	Omitted			Omitted		
Drama	0.017	0.004	**	0.342	0.055	**
Horror	0.009	0.004	*	0.131	0.059	*
Romantic Comedy	-0.005	0.004		-0.021	0.060	
Sci-fi / Fantasy	0.002	0.005		0.147	0.073	*
	Unemployment rate			Inflation		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	-2.007	2.407		0.068	0.014	**
Joy	6.922	2.959	*	-0.039	0.018	*
Surprise	-0.913	2.001		0.004	0.014	
Anger	0.496	4.146		-0.007	0.025	
Sadness	4.370	3.504		-0.082	0.025	**
Fear	-8.466	2.722	**	0.090	0.019	**
Animation	-0.206	0.098	*	0.015	0.045	
Action / Adventure	-0.033	0.076		-0.098	0.034	**
Comedy	Omitted			Omitted		
Drama	-0.270	0.084		0.084	0.037	*
Horror	-0.362	0.098	**	0.046	0.043	
Romantic Comedy	-0.064	0.099		-0.042	0.048	
Sci-fi / Fantasy	0.034	0.115		-0.159	0.061	**

Significance levels: 1%:** ; 5%:*

1.6. Individual demand analysis

While the market share analysis in section 5 provides aggregate information about consumer preferences, there might be more nuanced insights available for analysis of individual consumer preferences. Differences in individual preferences are plausible, and indeed likely. To confirm differences across individuals, we conduct an analysis of individual-level movie demand. However, we do not have access to individual movie viewing/sales data; instead, we use individual ratings data instead.

We gather our ratings from 'Yahoo Movies'. This website compiles user reviews from thousands of online users who award movies a summary grade lying between an 'F' and an 'A+'. Several other websites compile consumers' movie reviews, but we rely on YahooMovies.com, (YM) because it is well-known amongst the online community and it offers comprehensive coverage of wide-release movies which screened in theaters from July 2003 onwards. In addition, several YM reviewers reveal some information about their demographic profiles and the reviews are dated allowing us to match economic conditions to the time of the review. For a sample of 503 distinct wide-release movies which screened in theaters between July 2003 and March 2008, we collect a total of 4929 unique movie reviews corresponding to a total of 500 movies reviewed by 1945 reviewers. To control for the fact that some reviewers may be more lenient than others, we collect three additional movie reviews for each reviewer and compare the reviewer's average score for these three movies to the corresponding average for all reviewers (the average user review for each movie is also available from YM). We use the difference between these 2 averages as a proxy measure for the degree of leniency with which an individual reviewer grades a movie. We also control for the reviewers gender, age, marital status and geographic location. While users may have an incentive to misrepresent their personal information on online forums, such incentives are arguably less in the case of movie-discussion forums (compared to online dating sites, for example), and especially when the revelation of personal information is voluntary, as is the case for YM.

Our movie and economic condition controls follow the definitions mapped out in the aggregate demand model. In assessing the impact of economic conditions on movie reviewing, we test the hypothesis that economic conditions at the time of the review bear upon the value that individuals place on movie characteristics.

Given the ordered nature of the individual movie reviews, an ordered-response model offers a suitable framework to analyze reviews. Underlying such models is a latent but continuous descriptor of the observed grade, G^*_{ijt}, pertaining to individual $\underline{i}$'s evaluation of movie j under economic conditions t. G^*_{ijt} takes the form:

$$G^*_{ijt} = \mathbf{X'}\boldsymbol{\beta} + \varepsilon_{ijt} \quad (8)$$

β is the vector of coefficients to be estimated and X encompasses characteristics of movies and of the individuals as well as the economic conditions at the time of the review. ε_{ijt} captures an error term which is assumed to follow a normal distribution. We follow a parsimonious approach and only consider the letter grade awarded (i.e. we make no distinction between an "A+", an "A" or an "A-"). This allows us to rely on an ordered probit specification where the observed movie review is derived from the latent movie evaluation by:

$$G_{ijt} = F \quad , \quad \text{if } G^*_{ijt} \leq \mu_1$$
$$G_{ijt} = D \quad , \quad \text{if } \mu_1 \leq G^*_{ijt} \leq \mu_2$$
$$G_{ijt} = C \quad , \quad \text{if } \mu_2 \leq G^*_{ijt} \leq \mu_3$$
$$G_{ijt} = B \quad , \quad \text{if } \mu_3 \leq G^*_{ijt} \leq \mu_4$$

$$G_{ijt} = A \quad , \quad \text{if } \mu_4 \leq G^*_{ijt}$$

The μ_k's are jointly estimated threshold values which determine the observed grade a movie is expected to receive. We start by defining $X'\beta$ as follows:

$$X'\beta = \beta_0 + \beta_1 Z_i + \beta_2 Q_i + \beta_3 R_j + \beta_4 C_j{*} Z_i + \beta_5 L_t + \beta_6 L_t{*} Z_i \qquad (9)$$

Z_i is the vector of movie characteristics, which includes controls for a movie's production studio, budget, advertising expenditure, MPAA rating, emotional content and genre. R_j is a vector of consumer characteristics: gender, age and marital status, as well as the proxy measure for leniency of reviews. $R_j{*}Z_i$ represents the interaction terms between consumer characteristics and emotional content as well as between consumer characteristics and movie genres. L_t is the vector of macroeconomic variables which are controlled for one at a time (to avoid the risk of cointegration, as per section 1.5). $L_t{*}Z_i$ captures the interactions between macroeconomic conditions and movie characteristics.

We expect to see some differences between the aggregate market share and individual ratings analyses. First online reviewers might represent only a subset of the total audience for any movie, e.g. may under-represent of less technically-savvy or time-constrained viewers. Second, our ratings and market share data span different time-frames (ratings are only available from July 2003 onwards and market share data is available for more than 4 years prior); estimation of the market share model revealed that preferences change with time. Third, given that data for the market share panel spans more than twice as large a cross-section of movies; greater variability in terms of movie attributes is likely to permit the identification of a greater number of movie-attribute coefficients in the market share model than in the individual ratings model. The probit model estimates for determinants of individual ratings are reported in tables 1.11, 1.12 and 1.13.

Table 1.11: Estimated probit coefficients on movie-attributes for individual ratings model

Non-emotional attributes			
Variable	Estimate	Std. Error	
Budget	-0.001	0.001	
Advertising	0.011	0.003	**
Buena Vista	0.164	0.086	
DreamWorks	-0.063	0.103	
Fox	0.042	0.074	
MGM	0.097	0.125	
Miramax	-0.158	0.114	
New Line	0.256	0.089	**
Other	Omitted		
Paramount	-0.040	0.083	
Sony	-0.017	0.095	
Universal	0.035	0.077	
Warner Bros	-0.073	0.077	
Animation	0.166	0.342	
Action / Adventure	-0.051	0.234	
Comedy	Omitted		
Drama/BlackComedy	0.065	0.027	**
Horror	-0.141	0.280	
Romantic Comedy	0.347	0.336	
Sci Fi / Fantasy	0.451	0.340	
MPAA:G	-0.071	0.135	
MPAA:PG	-0.116	0.067	
MPAA: PG-13	Omitted		
MPAA:R	0.177	0.082	*
Emotional attributes and interactions			
Variable	Estimate	Std. Error	
Love	-2.805	1.868	
Joy	0.976	2.563	
Surprise	10.097	2.307	**
Anger	6.229	3.561	
Sadness	4.255	3.430	
Fear	5.027	2.495	*
Love*love	-0.124	0.138	

Table 1.11 (continued)

Love*Joy	0.366	0.334	
Love*Surprise	-0.515	0.266	
Love*Anger	0.904	0.444	*
Love*Sadness	0.752	0.413	
Love*Fear	-0.723	0.326	*
Joy*Joy	-0.183	0.271	
Joy*Surprise	0.831	0.420	*
Joy*Anger	-1.168	0.682	
Joy*Sadness	-0.889	0.627	
Joy*Fear	0.998	0.442	*
Surprise*Surprise	0.712	0.243	**
Surprise*Anger	-0.314	0.504	
Surprise*Sadness	0.519	0.498	
Surprise*Fear	0.144	0.402	
Anger*Anger	-0.576	0.552	
Anger*Sadness	-1.196	0.940	
Anger*Fear	1.671	0.628	**
Sadness*Sadness	0.366	0.538	
Sadness*Fear	-0.591	0.650	
Fear*Fear	-0.262	0.356	

Significance levels: 1%:** ; 5%:*

Table 1.12: Estimated probit coefficients on interactions between demographic characteristics and movie attributes for individual ratings model

	Age			Gender: Female		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	0.007	0.007		-0.0872	0.1992	
Joy	-0.005	0.009		0.0788	0.1418	
Surprise	-0.0054	0.0085		0.1204	0.1831	
Anger	0.0155	0.0125		0.0931	0.2758	
Sadness	-0.0086	0.0121		-0.3988	0.2639	
Fear	-0.0193	0.0089	*	-0.0959	0.1978	
Animation	-0.006	0.009		-0.364	0.187	
Action / Adventure	0.002	0.006		0.023	0.134	
Comedy	Omitted			Omitted		
Drama	0.004	0.006		0.028	0.150	
Horror	0.002	0.007		-0.374	0.158	*
Romantic Comedy	-0.005	0.008		-0.280	0.168	
Sci-fi / Fantasy	-0.016	0.009		-0.037	0.205	

Table 1.12. (continued)

	Marital Status: Unmarried			Geography: East Coast (relative to West Coast)		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	-0.259	0.126	*	0.274	0.182	
Joy	0.292	0.187		0.225	0.245	
Surprise	-0.228	0.172		-0.166	0.223	
Anger	0.351	0.255		-0.870	0.341	*
Sadness	-0.172	0.248		0.145	0.318	
Fear	0.037	0.184		0.423	0.239	
Animation	0.008	0.178		-0.012	0.226	
Action / Adventure	-0.243	0.116	*	0.265	0.163	
Comedy	Omitted			Omitted		
Drama	-0.155	0.142		0.132	0.187	
Horror	-0.229	0.145		0.192	0.196	
Romantic Comedy	-0.081	0.171		-0.160	0.221	
Sci-fi / Fantasy	-0.389	0.176	*	0.389	0.229	

Significance levels: 1%:** ; 5%:*

Table 1.13: Estimated probit coefficients on interactions between economic conditions and movie attributes for individual ratings model

	Consumer Confidence			Dow Jones Stock Index		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	-0.001	0.012		0.036	0.016	*
Joy	-0.025	0.011	*	-0.011	0.019	
Surprise	0.010	0.011		0.021	0.014	
Anger	-0.014	0.020		-0.068	0.025	**
Sadness	0.010	0.022		0.013	0.027	
Fear	0.022	0.014		0.008	0.020	
Animation	-0.012	0.016		-0.025	0.023	
Action/ Adventure	-0.021	0.012		0.018	0.012	
Comedy	Omitted			Omitted		
Drama	-0.003	0.010		0.036	0.013	**
Horror	0.031	0.012	**	0.018	0.014	
Romantic Comedy	-0.034	0.018		-0.012	0.018	
Sci-fi / Fantasy	-0.021	0.015		0.020	0.022	

Table 1.13. (continued)

	Unemployment rate			Inflation		
Variable	Estimate	Std. Error		Estimate	Std. Error	
Love	0.139	0.058	*	-0.0014	0.0116	
Joy	-0.003	0.078		-0.0253	0.011	*
Surprise	0.019	0.064		0.0095	0.0111	
Anger	-0.156	0.110		-0.0137	0.0199	
Sadness	-0.050	0.117		0.0103	0.0216	
Fear	0.037	0.080		0.022	0.0142	
Animation	-0.016	0.088		-0.012	0.016	
Action / Adventure	0.080	0.051		-0.021	0.012	
Comedy	Omitted			Omitted		
Drama	0.104	0.063		-0.0025	0.0102	
Horror	0.125	0.073		0.031	0.012	**
Romantic Comedy	0.014	0.079		-0.034	0.0179	
Sci-fi / Fantasy	-0.009	0.086		-0.0209	0.0151	

Significance levels: 1%:** ; 5%:*

The coefficients on the non-emotional movie characteristics reveal that similar to the aggregate choice data analysis, advertising expenditure has a positive impact on individual ratings: more advertising increases the likelihood of a movie being rated more favorably. In addition individuals tend to rank dramas (relative to comedies), higher, similar to the aggregate choice data results. One result which is different from the aggregate choice results is that individuals rate ‘R-rated’ movies (relative to ‘PG-13’ movies) higher.

We find that the main effects of demographic characteristics of consumers are insignificant. This suggests that there are no systematic differences in average leniency/ harshness of reviews across demographic consumer groups beyond what is already captured by the measure for leniency as described above (this measure is statistically significant and positive). However interactions between demographic characteristics and movie attributes, namely genres and emotional content, reveal that women rate horror movies (relative to other genres) lower than men. This result is aligned with the findings of Tamborini and Stiff (1987). Also, older individuals (relative to younger ones) rate movies with relatively higher fear-content less favorably. This finding is consistent with movie industry wisdom (Val Morgan Cinema, 2006). After controlling for age and gender, unmarried individuals (relative to their married counterparts) rank movies in the Sci-Fi and Action genres (relative to dramas), as well as movies with high (relative to low) love-content, less favorably. This is a surprising finding since industry wisdom tends to support the fact that single individuals favor high love-content. Collectively these findings demonstrate that movie rating behavior, and hence preferences, are indeed contingent upon consumer demographics.

An additional insight emerges after controlling for geographic locations of reviewers. Consumers residing along the East Coast (relative to their West Coast counterparts) tend to rank movies with comparatively lower levels of anger more favorably. Rentfrow et al (2008) survey geographic differences in personality across U.S. cities and find for example that people in the North-East tend to be more stressed on average. Assuming that such personality differences have been valid for the years spanned by our data, a preference for less anger on the East Coast may indicate a quest for mood repair whereby this group of consumers appreciates low-anger movies because such movies allow them to destress.

Next we assess how value attribution to movie characteristics changes with macroeconomic conditions, namely the index of consumer confidence, the Dow Jones Index, the unemployment rate, and the consumer price index. We find that an increase in consumer confidence increases the likelihood that a horror movie (relative to comedy) is ranked higher. However an increase in consumer confidence decreases the likelihood that a movie with high joy-content is ranked more favorably. Both of these findings reflect the results from the aggregate market share model: we found that the value of these two attributes correlated positively with consumer confidence. An increase in stock prices decreases the likelihood that movies which have high anger-content will be ranked more favorably. As stock prices increase, dramas (relative to comedies) are also ranked higher, as is the case in the aggregate market share model. The latter finding is consistent with the result in the aggregate market share model. An increase in the unemployment rate increases the likelihood that movies which have high love-content will be ranked higher. Finally an increase in the consumer price index affects the valuation of two movie attributes: the likelihood that a horror movie (relative to comedy) is ranked higher decreases, and the likelihood that a movie with high love-content is ranked higher increases. Overall we find that several preference relationships for the individual tally with those of the aggregate consumer. However the panel data for individual ratings spans a shorter time period than the market share panel and it is therefore unsurprising that several interaction coefficients for which we obtained statistical significance in the market share model are insignificant here.

To summarize the results from this section, we highlight the fact that we have found individual differences to be valid sources of differential preferences across consumer groups. Overall we find that the results for the individual consumers tend to align with those for the aggregate consumer group. In addition, the individual-level rating analysis affords us with a more detailed understanding of consumer preferences segmented on the basis of demographics and geographies.

Given that both of these segmentation criteria are valid determinants of preferences, our findings generate several implications in regards to marketing strategies employed by movie distributors. Specifically, marketing efforts which capitalize on the preferences of different demographic/geographic markets can be used to boost movie revenues by region and hence in total. In addition, assuming that preferences for wide-release movies translate into equivalent preference structures for limited-release movies, our insights regarding geographic preferences could be used by distributors to target potentially favorable markets for limited release movies. For example our results would indicate that a limited-release with low anger-content would be more favorably received on the East-Coast than in California.

1.7. Conclusion

The goal of this paper was to establish that the demand for movies is driven by their emotional content. We posited that plot keywords are a good proxy for information about the emotional content available to consumers as they make their choice of movie watching. To calibrate emotional content of a movie, we use a bag-of-words approach to map the semantic space of a movie's set of keywords onto that of basic human emotions. We build a random utility demand model using movie emotional content and other movie characteristics, and estimate it on data for 1152 movies in theaters in 1999-2005.

We show that emotional content is a significant determinant of movie demand. By disentangling the impact of emotional attributes and differences by genre, we are able to generate insights into the level of emotional complexity and variety that consumers seek in their movie experiences in general, as well as within movie genres specifically. We also find that demand for emotional attributes is affected by both macroeconomic variables and one-time economic shocks. We are able to replicate several of the findings from the aggregate market share model in an individual ratings setting, which adds to the market share model by generating more nuanced insights about consumer preferences that arise from individual characteristics. Overall, the insights from this paper are potentially of interest to both studios and theaters, who always seek to anticipate the kinds of movies that consumers will appreciate in future in making production, release and screening decisions. In addition the findings pertinent to individual preferences can be useful in audience segmentation and hence in targeted marketing of movies.

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 mood management is. Similarly, our approach can be used to examine if the demand for movies 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 would be capture time series of critics' evaluation of movies, match it with their syndication geography, and see if their preferences of movie emotions change depending on the demographics of their audience, or with their own age and experience. This is explored in Chapter 2 of this dissertation.

The methodology proposed here can be used in examining other entertainment products. An example is the book industry, where many new products have failed, and where the industry is moving towards more risk-sharing with authors. It might be possible to improve forecasts of demand for books by calibrating their emotional content.

Finally, in contrast to the bag-of-words approach used in this paper, a sequential emotional measure might provide more insights into consumer demand for emotional content in entertainment. For example, it would seem that tense middle parts followed by happy endings might be preferred to the reverse sequence. Our present methodology is unable to handle this sequence-of-words approach, and we are not aware of other methods to conduct such analyses.

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CHAPTER 2

QUALITY EVALUATION VERSUS REFLECTING AUDIENCE PREFERENCE

2.1. Introduction

Critics' opinions are especially salient in the case of experience goods where quality is unknown *ex-ante* since critics are experts who are unaffiliated with producers and therefore in a position to make independent product appraisals. Extant literature highlights the role of critical reviews in determining market outcomes for several experience goods: wines (Ashenfelter 2008), art auctions (Bauwens & Ginsburg 2000), restaurants (Chossat & Gergaud 2003), movies (Eliashberg & Shugan 1997) etc. In the case of the movie industry, more than one third of consumers indicate that they actively seek critics' reviews and about a third of filmgoers attest to choosing movies on the basis of positive reviews (Basuroy et al. 2003). In addition, movie industry wisdom upholds the view that critics are influential and that the valence of a review can make or break a movie (Eliashberg & Shugan 1997). Terry et al. (2005) validate this view by finding that a ten percent increase in critical approval generates an extra $7 million in Box Office revenues. It is therefore unsurprising that studios devote considerable resources to the management of the review process. For example they sometimes delay or forego advance screenings if they anticipate bad reviews; they organize lavish movie premieres at which they host movie critics, presumably in an attempt to coerce good reviews (Ravid et al 2006), and if they do receive good reviews, they refer to excerpts from the review when marketing the movie [6].

The literature has identified the two potential roles for movie critics which derive from the association between critical reviews and commercial success of movies: the influencer role and the predictor role. As influencers, critics act as opinion leaders who steer consumers' movie selection decisions. This effect is largest in the early weeks of a movie's release when alternative sources of movie information (e.g. word-of-mouth) are scant. As predictors, critics' ratings do not so much influence audience preference as capture movie characteristics that appeal to their audience. That is, critics' ratings are a useful explanatory variable in explaining sales or market shares because they capture movie quality. Quality is hard to measure by simply including movie genre, production budget, advertising expenses, etc. In both of these influencer and predictor roles, critics' ratings are a summary measure of, and reflect, (as well as shape in the first case) audience preference. Reinstein & Snyder (2006) summarize the difference between the two roles by defining the influence effect as the causal effect of reviews on demand, with movie quality held constant; and the prediction effect as the spurious correlation between reviews and demand, induced by their mutual correlation with quality.

However, there is a third possible role for critics: the evaluator role. This role addresses the function that critics serve by measuring and certifying quality. As influencers and predictors, critics are presumed to be making quality evaluations which align with profit or commercial potential of movies, and hence the evaluator

[6] At an extreme Sony Corporation invented fictitious film critic David Manning, who consistently gave good reviews to Sony movies, and as a result Sony incurred a fine of $1.5 million by the Connecticut Attorney General (Horn 2001).

role will likely overlap with the influencer and predictor role. However, quality can be measured independently of commercial success potential, especially when movies are appraised for their artistic worth as opposed to their commercial worth. In such instances, the overlap between the evaluator role and the influencer/ predictor roles may not be as tight. Therefore, to measure the role of critics as evaluators who review quality independently of commercial potential, we assess whether evaluations of movies with commercial success differ systematically from movies with artistic success. To this end, we compare average critics' ratings with audience ratings for both commercial and artistic movies. We find that there is a positive correlation between average critics' reviews and audience reviews (influencer/predictor roles), but that this positive correlation decreases for high-artistic appeal movies (evaluator role).

We focus on the evaluator role played by journalistic movie critics because these critics constitute a group of professional critics whose reviews are most sought after by consumers (as evidenced by compilations of journalistic reviews in several of the most notable sources of movie information, e.g. Variety Magazine, The Hollywood Reporter, Yahoo Movies, etc) and most coveted by producers (as evidenced by citations of journalistic reviews on movie promotional material like trailers, television advertisements, DVD sleeves, etc). In addition, journalistic critics face a unique dual incentive structure which helps us identify the evaluator role: Critics are employed by profit-maximizing newspapers for which it is optimal to slant news reports in the direction of audience preferences (Mullainathan & Schliefer 2005; Gentzkow & Shapiro 2006). Thus, it appears plausible, even likely, that movie critics may be encouraged to slant reviews similarly. Such behavior would also allow critics to cultivate reputation and relevance with their audiences in a market for information where substitutes for critical reviews are ubiquitously available (word-of mouth, online user reviews, talk-show coverage, etc). However, equating a newspaper's incentive of slanting with a critic's incentive to slant a review overlooks the fact that critics face an additional maximand: They may wish to further their reputation and garner greater prestige within the community of their peers by demonstrating that they are skilled enough to correctly identify movies that will be critically acclaimed. Being highly regarded among the community of critics can lead to industry perks like invitations to film festivals, movie premieres and opportunities to vote on panels of judges of artistic merit. Since artistically acclaimed movies are not always box-office hits, critics may have less incentive to apply commercial standards when reviewing such movies, in which case the evaluator and the influencer/predictor roles will not align. Further, the ability of a critic to correctly identify the quality of an artistically acclaimed movie might also serve the interests of the newspaper by their ability to serve a segment of their readership that enjoys these movies, and more broadly for the newspaper to be able to position itself as employing the best critics.

Thus, critics face a trade-off between two sets of criteria: commercial and artistic, both of which can be used to evaluate a movie. Emphasis on commercial criteria will likely induce a positive correlation between critical and audience reviews, and strengthen the influencer/predictor roles; but greater emphasis on artistic criteria, will likely mediate the positive correlation between critical and audience reviews and render the evaluator role more apparent. Greater divergence between commercial and artistic criteria, as well as higher artistic content, will result in weaker alignment between the evaluator and the influencer/predictor roles.

Holbrook 1999 and Hirschman & Pieros 1985 confirm that there are indeed substantive differences between commercial and artistic criteria: Commercial criteria reflect preferences of ordinary consumers which tend to favor attributes like enjoyability and ease to understand. Artistic criteria reflect preferences of connoisseurs or expert judges, which tend to focus on the evaluation of a movie as an art-form rather than entertainment. Artistic and commercial movies also have ostensibly distinct market outcomes: For instance artistic movies often fare better than commercial movies when it comes to garnering industry recognition. Sanders (2009) reports that even the biggest commercial hits of 2008 were not nominated for Academy Award nominations (e.g. "The Dark Knight") but other "niche-market" movies (e.g. "The Reader", "Frost/Nixon") were. Further, Deuchert et al. (2005) find that winning an Academy award contributes only marginally to increased theatrical revenues.

In this paper we assess the relevance of an evaluator role for critics by studying the strength of the correlation between critics' reviews and ordinary-consumer/popular reviews for artistic as opposed to commercial movies. As highlighted above, commercial movies tend to have lower prospects for industry recognition than artistic movies. As such, it may be harder for critics to obtain validation of their expert-evaluative skills of artistic worth when reviewing commercial movies. However their commercial evaluative skills may be judged by the extent to which their reviews align with those of ordinary consumers. Hence we hypothesize that the strength of the association between critical and popular reviews will be higher for movies of comparatively lower artistic appeal.

We test this hypothesis in two datasets, both of which are comprised of reviews of a small subset of journalistic critics referred to as cream-of-the-crop because they are employed by major print and online news publications like the New York Times and Hollywood Reporter (Rottentomatoes.com ; Metacritic.com). Our first dataset comprises a cross-section of average critics' reviews for 675 movies and the second comprises a panel of individual critics' reviews for the same cross-section of movies. Both datasets provide evidence supporting the existence of the evaluator role, i.e. of a positive correlation between critics' reviews and consumer reviews, which is mediated by artistic appeal of movies. The panel dataset yields further insights into critics' review formulation patterns by allowing us to assess how characteristics of local audiences as well as characteristics of individual critics factor into critical reviewing.

Our control for artistic appeal (which we consider untainted by critics' motive to tailor reviews to their audiences' preferences) comes from a count of the number of Critics' Choice Awards that a movie wins. These awards are decided on the basis of independent balloting of film critics by the Broadcast Film Critics Association (BFCA), the largest film critics association in the US and Canada. BFCA regroups journalistic critics from 199 print and online news media who cast anonymous and independent votes for their favorite movies at the end of each year. BFCA makes nominations and awards in multiple award categories (e.g. Best Actor, Best director, Best Screenplay, etc). Since newspaper profit-maximizing objectives do not impinge on these votes, we consider BFCA awards to be free of bias from audience preferences.

An important distinction between our work and existing work in this area is that we expand the attribute space of movies under review beyond typically considered characteristics like genre, MPAA rating, production budget, advertising expenditure and production studio, and incorporate measures of a movie's emotional content as an additional product feature. We consider emotional content as relevant because movie enjoyment hinges on the fulfillment of emotional expectations as a movie's plot devolves (Zillmann and Bryant 2002). Controlling for movie characteristics also allows us to identify the patterns of value attribution that critics use in formulating reviews. Additionally, commercially successful movies might have systematically different emotional composition (e.g. more humor, less sadness, etc.) than artistically-oriented movies.

The main contribution of this paper is to assess the relevance of the proposed evaluator role of critics; we use the divergence of this role from the established influencer/predictor roles of critics to identify it. In so doing we expand the analysis of the aggregate flow of information between experts and consumers and we offer an alternative explanation for the oft-observed differences between critics' reviews and popular reviews. Our secondary set of findings allows us to discern critics' patterns of value attribution to individual movie characteristics and local market characteristics. A thorough analysis of how critics appraise such characteristics is currently lacking in the literature, but is potentially of use to studios which seek to engineer movies which will garner greater critical acclaim, or which seek to identify markets for targeted release and advertising of movies. While the current assessment of the evaluator role is in the context of critical movie reviewing, it can be generalized to several other experience-good markets where critical reviewing occurs.

The rest of the paper is organized as follows: Section 2.2 surveys the relevant literature and formalizes the hypotheses that we seek to test in this paper. Section 2.3 outlines the data gathered for this study. Section 2.4 details the analyses and presents the results. Section 2.5 concludes.

2.2. Literature Review

Numerous studies have offered evidence for a positive relationship between aggregate critical reviews and box office performance of movies (Litman 1983 ; Litman & Kohl 1989 ; Wallace et al. 1993 ; Prag & Cassavant 1994 ; Sochay 1994 ; De Silva 1998 ; Jedidi et al. 1998 ; Terry et al. 2005). In a seminal paper, Eliashberg

& Shugan (1997) define the influencer role and the predictor role as two possible conduits via which critics' opinions feed through to Box Office revenues. As influencers critics act as opinion leaders who steer consumers' selection of movies, and as predictors they formulate opinions which reflect the degree to which a movie will align with audience preferences.

2.2.1. Evidence of the influencer and predictor roles

Evidence in favor of the prediction effect can be garnered from several studies which establish a significant correlation between reviews and revenue (e.g. Prag & Cassavant 1994 ; Terry et al 2005). Basuroy et al. (2003) propose that consumers are more responsive to negative reviews than to positive ones due to the influence effect. Reinstein & Snyder (2006) estimate the size of the influence effect by purging the prediction effect via a differences-in-differences approach: While the correlation between the valence of a review available before a movie's release and movie revenue and is due to both the influence and the predictor effect, the correlation between the valence of a review available after release and revenue generated before the review was available, is due to the prediction effect alone. Thus the revenue differences between a positively and a negatively reviewed movie and, between movies reviewed before and after release, offer an estimate of the influence effect. Basuroy et al. (2003) propose a different approach to assess the influence effect: Despite not having explicit quality controls, they argue that the differential impact of positive and negative reviews on movie revenues can be attributed to an influence effect since consumers appear more responsive to negative reviews than to positive ones, especially in the first week of release.

2.2.2. The evaluator role

Despite clear evidence demonstrating both the influencer and the predictor roles of critics, the literature seems to have sidestepped the potential evaluator role for critics. However a critic is by trade a "person, who judges, evaluates and criticizes"[7]. Cultural discourse highlights the fact that by virtue of their training, expertise and aesthetic experience, critics possess a high level of cultural capital that legitimizes their judgment of the worth of cultural offerings (Bourdieu 1986). Critical judgment of worth is distinct from ordinary judgment put forth by non-experts because critical appraisal tends to focus on aesthetic and symbolic objects which are of cultural value, while ordinary judgment tends to focus on entertainment and commoditized objects which have commercial value (Holbrook 1999). In the case of movies specifically, Holbrook (2005) finds empirical evidence supporting a statistically significant and weakly positive correlation between standards of excellence used by the average critic and those used by the ordinary consumer. Holbrook posits that the discrepancy arises because ordinary consumers place more importance on factors like enjoyment and ease to understand, while critics favor artistic value. Holbrook's study is primarily concerned with determining whether ordinary audiences have good or bad taste in relation to critics. In this paper we focus instead on an understanding of critics' behavior in the light of the dual incentive structure that they face (via employment by firms for which it is optimal to reflect audience preference and via membership to a select group of experts who also value artistic merit). Hence we propose that critics face a trade-off between the application of commercial standards (which allow critics to formulate reviews aligned with audience tastes and hence with the profit

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[7] *Dictionary.com Unabridged (v 1.1)*. Random House, Inc. http://dictionary.reference.com/browse/critic (accessed: March 29, 2009).

maximizing objectives of their employers) and artistic standards (which allow critics to gain recognition within the community of their peers). Existence of this trade-off can also help explain the existence of oft observed divergences between critics' reviews and user reviews. The present study is also methodologically different from Holbrook's study in that we control for a rich set of movie characteristics which allows us to assess how critics attribute value to movies. In addition, we supplement Holbrook's study of average critics' reviews with an assessment of individual critics' behavior to highlight how critics tailor their reviews to the characteristics of their respective audiences.

2.2.3. What motivates the tradeoff between artistic and commercial standards?

We propose that the evaluator role performed by journalistic critics occurs in the context of profit maximizing news firms which hire critics to supply signals to mass audiences. Mullainathan and Schleifer (2005) offer theoretical evidence which shows that in the market for news, it is optimal for media outlets to slant information in the direction of their audience's political biases. Gentzkow and Shapiro (2006) empirically confirm this theory and estimate the optimal political slant of different media outlets as a function of the political biases of their respective audiences. The notion of optimal slant can logically be extended to the realm of critical movie reviewing whereby it is potentially optimal for profit-maximizing firms to incentivize critics to tailor their reviews to the tastes of local audiences. In addition, by sending a signal which communicates commercial quality standards as opposed to more esoteric artistic standards, critics may be able to garner greater relevance in a market for information where ordinary consumers seek signals to inform their movie choices, and where substitutes to critics reviews are pervasively available in the form of online consumer reviews, prime-time television coverage, etc. In this paper we qualify the extent to which critics actually abstract from their commercial evaluative criteria to generate quality signals which reflect artistic criteria as the evaluator role.

It is possible to identify the strength of the evaluator role because there is a class of movies for which switching from commercial to artistic standards may offer critics a separate channel of reputation building. Such movies are of high artistic appeal, but not necessarily of high commercial appeal. More importantly, these movies are contenders for industry recognition awards (e.g. Academy Awards, Golden Globes, etc). Reviewing such movies with artistic standards in mind can afford critics an opportunity to demonstrate their expert evaluative skills which led to the correct identification of movies which are award-worthy.

Previous literature which attempts to deconstruct critical reviewing has sidestepped the evaluator role, and has also failed to assess the extent to which critics tailor their reviews to their audiences' tastes. For example Hsu and Podolny (2005) study the descriptor words which recur in the written reviews of critics at the New York Times and Variety Magazine. They focus on the degree of synonym overlap in the language used by critics to map out four different types of quantitative, one-dimensional schemas underlying the reviews. In the Hsu and Podolny's classification, a simple schema comprises reviews where words used in the review follow a bimodal distribution which cluster tightly around two modes; a complex schema comprises reviews where critics choose words which cluster tightly at several nodes along a one-dimensional continuum; an unpartitioned schema comprises reviews with words that do not exhibit any clustering patterns; and finally a robust schema involves several clusters, but words are not uniformly distributed about each node. These proposed schema do not offer any insights into what motivates the valence of a critic's review, neither do they shed any light on the incentive structure that critics face or on the information transmission mechanisms between the critic and her audience.

2.2.4. What do the averages mask?

A survey of the reviews put forth for specific movies reveals that there are often differences between the opinions of individual critics. For example, despite being the top box office performer in 2007, the movie Spiderman-3 only scored 25 points from San Francisco Chronicle critic, Mick LaSalle, while Miami Herald critic Rene Rodriguez gave it 88 points (on a 0-100 scale)[8]. Agresti & Winner (1997) confirm that there is often little agreement between critics' reviews for the same movie and Kamakura et al. (2006) capitalize on these differences to determine how informative each critic is. Heterogeneity among reviewers is not always optimal; for example from a social welfare perspective a student's final grade or the outcome of a driving test should be independent of the grader. However in the business of journalistic reviewing, dissent among critics is not necessarily sub-optimal because it allows consumers to align themselves with critics who best reflect their preferences thereby reducing the cost of acquiring informative quality signals. In a related paper, Chatterjee et al. (2007) invoke prospect theory to show that consumers who have high expectations about a movie prefer to have dissenting critics' opinions, while those who have low expectations prefer consenting opinions.

Reputation building objectives with their respective audiences, may offer a compelling explanation for systematic heterogeneity between critic's reviews. We hypothesize that heterogeneous market characteristics are a potential source of variation between critics' opinions because tailoring their reviews to reflect preferences of their individual audiences as opposed to those of the average consumer may allow critics to garner better reputation in the market within which they operate,

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[8] In our sample Spider-Man 3 was reviewed by 39 critics and obtained a mean score of 63 with a standard deviation of 15.

in addition to aligning with the profit-maximizing objectives of newspaper firms within specific markets. In chapter 1 of this thesis, we found that that consumer tastes vary by demographic groups and with economic conditions which impact on consumer moods. Hence we control for audience heterogeneity on the basis of demographics and local economic conditions to assess the extent to which critics tailor their reviews to tastes of their individual audiences.

2.3. Data

2.3.1. Movie reviews

Movie reviews of journalistic critics for over 95% of all wide-release movies which opened in theatres after 1998 are available on Metacritic.com (MC). We only consider reviews for wide release movies (movies released in more than 600 theaters nationally), since they are more likely to be reviewed by critics in all newspaper markets and have sufficient popular appeal to provide critics with an incentive to tailor their reviews to their audiences[9]. MC reviews represent the opinions of a group of critics collectively referred to as "cream-of-the-crop"; because they are highly regarded by the industry. This group comprises a total of 232 critics, employed by 48 distinct print and online news media. Since different critics use different rating scales

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[9] Given that critics ought to be predisposed to emphasize commercial standards in reviewing wide-release movies (and wide-release movies are more likely to be commercial successes than artistic appeal movies), that we do find evidence in favor of artistic appeal mediating the correlation between critics' and users' reviews (see section 4) gives added credence to our characterization of the evaluator role.

(e.g. 4 star, 5-star, letter grade, etc), MC converts each critic's review into a score on a zero-to-100 scale.

While alternative compilations of individual critic reviews are available from sources like rottentomatoes.com (RT) and yahoo!movies.com (YM), we prefer MC because it offers more comprehensive coverage of critics' reviews (all reviews available online are compiled as opposed to just a sub-sample of available reviews (as is the case with YM), and because MC appraises the favorability of reviews using a more granular scale (RT used a thumbs-up/thumbs-down appraisal format and YM uses a letter grading system).

2.3.2. Characteristics of critics

We limit the number of critics under consideration to 68 critics who are employed by one of the 11 daily newspapers for which we observe audience characteristics (See section 3.3). For each of these critics we observe experience levels (as proxied by a count of their individual reviews compiled on MC) and gender (we pool information from MC, RT and the popular press for this measure). For five critics in our sample we observe a job transfer to a different newspaper market and for each of these critics we attribute reviews to the market for which they were written, given the date of the job transfer and the approximate date of publication: Since reviews are meant to serve as a quality signal prior to consumers having seen the movie, it is reasonable to assume that reviews were published shortly before a movie's release, or shortly after release at the latest. In any case, given that only a few critics transfer from one paper to another, the timing of reviews does not bias our assessment of the evaluator role, as it would an assessment of the influencer role, for instance. Finally, it should be noted that each newspaper typically employs more than one critic, but only puts forth one review per movie, i.e. the group of critics employed by a given newspaper divvies up movies among themselves so that the newspaper puts forth a review for a maximum number of new releases.

2.3.3. Newspaper audience profile

Since it is possible that critics tailor their reviews to the preferences of their individual audiences, we gather information about the characteristics of each newspaper audience: We collect information pertaining to demographic characteristics of the audience, local economic characteristics and local tastes. We believe demographic and local economic characteristics to be relevant factors distinguishing one audience from another since in chapter 1 of the thesis we showed that these traits impact on consumer movie choice and enjoyment.

Demographics: To obtain a demographic profile of newspaper audiences we consult the Reader Profile reports, commissioned by the Audit Bureau of Circulations (ABC), a not-for-profit organization which audits newspaper circulation and maintains an electronic database of average reader demographics for most major US newspapers[10]. These reports are compiled from annual phone surveys of consumers in each newspaper's market and they provide detailed readership data pertaining to reach, readers per copy, reader demographics, etc. From these reports and for each newspaper's audience we collect information pertaining to age, race, income and education level of the average reader. It is conceivable that not all readers who attest

[10] Previous literature, (e.g. Goerge & Waldfogel 2003) use MSA (Metropolitan Statistical Area) demographics as a proxy for characteristics of the average reader, but we rely on ABC reader profiles instead since the assumption that all demographic segments have an equal predisposition to read newspapers may be flawed.

to reading a newspaper necessarily read the movie reviews section, but it is plausible that the characteristics of the overall audience reflects characteristics of the audience segment which does read movie reviews. Further, critics may not have precise information (beyond average reader characteristics), about which segments of newspaper readers read their reviews. Hence we consider Reader Profiles to be representative of mean demographic characteristics of the average reader of movie reviews as perceived by the movie critic. MC reviews for 'cream-of-the-crop' critics are available for 11 newspapers for which we have Reader Profiles. Table 2.1 summarizes the demographic characteristics of each of these newspapers from 2003 to 2007.

Table 2.1: Audience demographics

		Race		Age Group		Education	Household Income	
Newspaper	Year	White	Black	18-24	55+	College	under $35k	$100k+
Boston Globe:	2003	88	5	9	30	42	17	29
	2004	89	5	10	33	40	17	28
	2005	89	7	9	33	46	16	30
	2006	89	6	11	35	48	15	32
	2007	.	.	.	.	.	.	.
Charlotte Observer:	2003	81	17	7	34	27	23	15
	2004	80	17	10	33	30	21	14
	2005	78	19	10	33	31	24	16
	2006	80	17	11	33	30	19	25
	2007	80	17	10	36	33	20	25
Chicago Sun Times:	2003	.	.	.	.	.	.	.
	2004	.	.	.	.	.	.	.
	2005	65	31	12	32	22	22	21
	2006	65	32	16	29	22	20	23
	2007	63	31	12	34	19	24	24
Chicago Tribune	2003	.	.	.	.	.	.	.
	2004	83	12	8	36	40	14	30
	2005	83	12	9	36	40	14	30
	2006	82	13	11	37	40	14	33

Table 2.1. (continued)

	2007	80	14	10	35	40	15	35
Los Angeles Times:	2003	79	9	12	31	32	21	25
	2004	81	9	10	31	36	19	26
	2005	78	10	11	34	37	18	27
	2006	79	9	9	34	39	15	32
	2007	78	9	9	37	38	15	34
Miami Herald:	2003	76	20	9	35	28	23	17
	2004	75	22	10	34	30	24	22
	2005	76	20	11	32	29	24	23
	2006	75	21	9	36	31	24	22
	2007	74	22	10	35	29	24	26
New York Times:	2003	82	10	12	33	53	14	35
	2004	83	10	13	34	57	13	37
	2005	83	10	11	35	60	13	41
	2006	94	9	12	36	61	13	42
	2007	83	9	12	36	60	11	44
Philadelphia Inquirer:	2003	77	19	9	37	32	19	22
	2004	77	18	10	37	33	21	21
	2005	78	17	7	38	33	22	23
	2006	77	19	7	40	34	19	27
	2007	79	18	9	39	35	18	30
San Francisco Chronicle:	2003	81	6	9	33	40	13	36
	2004	77	7	7	37	48	14	36
	2005	80	6	7	36	46	14	39
	2006	79	5	7	42	50	11	44
	2007	79	5	6	44	49	11	43
Seattle Post Intelligencer:	2003	87	3	8	31	33	18	19
	2004	87	4	9	32	33	20	19
	2005	89	3	9	34	41	18	21
	2006	86	4	8	34	40	16	22
	2007	86	4	7	37	42	14	28
Washington Post:	2003	64	29	11	27	42	11	37
	2004	64	29	9	30	46	11	38
	2005	67	27	8	32	49	10	43
	2006	67	27	8	34	49	9	45
	2007	67	27	8	34	50	9	48

Local market conditions: These conditions may have some bearing on critics' reviews because they impact on the types of movies that critics (and their audiences) will like at any given point in time (in chapter 1 of this thesis we showed patterns of co-movement between macroeconomic variables and consumer preferences for movie attributes). Critics may therefore customize their reviews in accordance with the timeliness of a movie's release to prevailing local economic conditions. In so doing they may be able to put forth reviews which are more aligned with the tastes of their audiences at a given point in time. We control for local market conditions using three macroeconomic variables (unemployment rate, consumer price index (CPI) and local gas prices) in separate regressions, to avoid cointegration issues between these time-series variables. Quarterly unemployment rates and consumer price indices for each city where the newspaper companies are headquartered are obtained from the Bureau of Labor Statistics (BLS). Weekly averages of gas prices are obtained from www.economagic.com.

Tastes: In addition to demographic profiles of newspaper audiences we obtain proxies for the movie tastes of each newspaper's audience by compiling average user reviews for groups of individuals in each newspaper's geographic market. User reviews are collected from YM which allows ordinary consumers to upload a summary grade (lying between an 'F' and an 'A+', and reflecting the extent to which they enjoyed the movie). Several other websites compile consumers' movie reviews; we rely on YM because it is well-known amongst the online community and it offers comprehensive coverage of wide-release movies which screened in theaters from July 2003 onwards. We collect a total of 4929 unique movie reviews from 1945 distinct reviewers for a sample of 500 distinct wide-release movies which screened in theaters between July 2003 and March 2008. We sort these reviews by movie and by geographic location and construct an average user review for each movie and for each of 4 geographic areas: East Coast, West Coast, Midwest and South[11]. These averages serve as proxies for the movie tastes of each geographic area and hence of the newspaper market falling within that area. It is likely that tastes vary within geographic areas, but it is reasonable to assume that these regional taste measures correlate with the average tastes of newspaper audiences falling within each geographic region (the correlation between the average movie reviews put forth by our sample of online reviewers and the average reviews put forth by all YM users is 0.63).

2.3.4. Movie attributes

The movie attributes that we control for include features commonly considered in the literature, i.e. production budget and advertising revenue (obtained from Paul Kagan and Associates), MPAA rating, production studio and movie genre (from www.boxofficemojo.com). We gauge artistic appeal via a count of the number of Critics' Choice Awards that a movie wins. We considered alternative measures of artistic appeal including Academy Awards (Oscars) and Golden Globe Awards. However we favor Critics' Choice Awards because Academy awards are awarded by a community of non-experts (for example actors make up the main voting bloc: 22% of approximately 5000 voters), who may appraise commercial and not artistic standards; and the Golden Globes are awarded by a community of foreign critics who may not appraise artistic value in the same way critics in our sample do. Conversely the

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[11] Since only a small proportion of online users supply their demographic information, it is sometimes not feasible (due to lack of reviews) to construct average user reviews for each newspaper market. We therefore use averages constructed for broader geographic areas as proxies for reviews in newspaper markets falling within each area.

Critics' Choice Awards are voted upon by a large community of U.S. based critics who cast independent and anonymous ballots for the movies of their choice. In voting for the Critic's Choice Awards, critics are not constrained by the profit-maximizing objectives of the newspapers which publish their reviews and we therefore consider these awards free of bias from audience preferences and hence not reflective of commercial standards

We also measure popular appeal, which is a measure of the degree of enthusiasm that a movie generates. We use a count of the number of people who post a review on YM to this end. Holbrook (1999) confirms the validity of this count as a measure of popular appeal by finding evidence in favor of a "popularity hypothesis" (i.e. number of reviews is larger when users enjoy a movie), and evidence against an "extremity hypothesis" (i.e. number of reviews is larger when users really enjoy or really dislike a movie)[12]. We also collect average user reviews from YM. These reviews are reflective of the standards of commercial appeal that the audience applies to assess movie quality and are distinct from measures of popular appeal which capture the extent of buzz around a movie.

In addition to the above attributes we consider emotional content measures as constructed in chapter 1 of this thesis. Emotional content measures are salient because emotions give immediate meaning and significance to the movie experience (Tan 1994). The role of emotions in consumer choice is well-documented (Maslow 1968), and in the case of movies, this role is especially prevalent since consumer satisfaction hinges on the fulfillment of emotional expectations as the story unfolds (Zillmann & Bryant 2002). Further, it is possible that emotional complexity correlates with artistic

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[12] See Holbrook (1999) for an exposition of several empirical checks of the validity of the popularity hypothesis and against that of the extremity hypothesis.

appeal and we indeed find systematic differences between the levels of emotions in Award-nominated as opposed to commercial movies. The inclusion of emotional content metrics for each movie is therefore pertinent.

Some studies assess emotional content along two dimensions of psychological stimulation: pleasure and arousal (Eliashberg & Sawhney 1994, Neelamegham & Jain 1999). In Chapter 1 of this thesis we propose a more granular assessment of emotional content derived from 6 basic emotions: love, joy, surprise, sadness, fear and anger. The latter constitute the superordinate level of an emotion hierarchy which encompasses the broad range of emotions experienced by humans. In Chapter 1, emotional content is extracted from movie keywords by using Latent Semantic Analysis (LSA), a natural language processing software package which measures semantic congruence between word groups, i.e. between movie keywords (obtained from www.imdb.com) and each basic emotion. Table 2.2 reports emotional content measures for a subset of movies in our sample.

Table 2.2: Emotional content measures for 3 movies

Movie	Joy	Love	Surprise	Anger	Fear	Sadness
Shrek	5.35	5.85	5.35	5.35	5.15	4.95
American Pie II	5.85	6.30	5.00	5.20	5.35	5.30
Hannibal	5.05	5.35	4.85	5.55	5.80	5.30

Table 2.3 reports average emotional content measures for artistic and commercial movies. We observe that emotional content for all emotions, except surprise, is higher in artistic movies than in commercial movies. This suggests that artistic movies may be more emotion-laden than commercial ones.

Table 2.3: Emotional content by type of movie

Type of movie	Joy	Love	Surprise	Anger	Fear	Sadness
All	5.60	5.29	4.96	5.39	5.52	5.37
Commercial	5.57	5.27	4.96	5.37	5.51	5.35
Artistic	5.75	5.40	4.95	5.50	5.55	5.40

Table 2.4 compares the mean level of positive emotions (love and joy) and the mean level of negative emotions (anger, sadness and fear). The means for both positive and negative emotions are higher in artistic movies, but the mean of positive emotions exceeds the mean of negative motions by a greater extent for artistic movies. This possibly indicates that the mix of emotions is more complex in artistic movies than in commercial movies. Given these observed differences between the levels of emotions between artistic and commercial movies, it makes sense to include controls for emotional content in a calibration of the evaluator role of critics.

Table 2.4: Comparison of mean levels of positive and negative emotions by type of movie

Type of movie	Mean of positive emotions	Mean of Negative emotions	Balance between positive and negative emotions
All	5.44	5.42	0.02
Commercial	5.42	5.40	0.01
Artistic	5.57	5.51	0.06

2.4. Empirical determination of the evaluator role

2.4.1. Evaluator role from average reviews

We start with an assessment of the evaluator role discernible from average reviews. In this instance, we claim that critics seek to tailor their reviews to mirror overall audience preferences both because they are employed by profit maximizing firms which encourage such behavior and because they seek to build their reputation by providing an informative quality signal to the consumer. To test this claim we observe critical reviewing for a set of movies of varying artistic and popular appeal. We hypothesize that critics have a lesser incentive to reflect commercial standards of quality when reviewing movies of high artistic appeal, because they have an opportunity to pursue a different channel of reputation building in such instances, i.e. they can demonstrate their expert-evaluative skills by putting greater weight on standards of artistic appeal to identify the award-winning potential of such movies. Hence we seek to identify the extent to which critics tailor their reviews to audiences' tastes by testing the following hypothesis:

> *The correlation between average critic reviews and average user reviews is positive, but is lowered in the case of movies of high artistic appeal.*

To test this hypothesis we map the average movie grade of all movie critics, onto the grade awarded to the movie by the average consumer, controlling for artistic appeal, popular appeal and other movie attributes. We include an interaction term between average user grade and artistic appeal and estimate the following equation for the average review, $\bar{R}_i$:

$$\bar{R}_i = \delta_0 + \delta_1 UR_i + \delta_2 Z_i + \delta_3 AA_i + \delta_4 PA_i + \delta_5 AA_i{*}UR_i + \varepsilon_i \qquad (1)$$

UR_i is the average user review for movie i; Z_i is the vector of movie characteristics (it includes controls for a movie's production studio, budget, advertising expenditure, MPAA rating, emotional content and genre; AA_i and PA_i represent artistic and popular appeal respectively and $AA_i{*}UR_i$ is the interaction term between artistic and user reviews. Table 2.5 summarizes the results.

Table 2.5: Estimated parameters for average critics review equation

R^2 = 56.9% ; n= 675

Parameter	Estimate	Std. Error	
Intercept	68.483	258.293	
Average User Review	3.297	0.447	**
Critics Choice Awards	30.310	7.470	**
Popular Appeal	0.000	0.000	**
UserReview*Awards	-3.027	0.893	**
BuenaVista	2.656	2.491	
DreamWorks	1.379	2.998	
Fox	-2.293	2.161	
MGM	-3.205	3.251	
Miramax	-0.288	3.689	
NewLine	1.161	2.576	
Other	Omitted		
Paramount	1.691	2.344	
Sony	1.482	2.800	
Universal	1.088	2.377	
WarnerBros	-1.212	2.359	
Animation	12.659	3.074	**
Action / Adventure	3.109	1.946	
Comedy	Omitted		
Drama/BlackComedy	-0.962	2.365	
Horror	2.374	2.307	
Romantic Comedy	1.065	3.145	
Sci Fi / Fantasy	4.554	2.476	
MPAA:G	2.642	4.027	

Table 2.5. (continued)

MPAA:PG	-1.509	1.807	
MPAA: PG-13	Omitted		
MPAA:R	1.109	1.581	
Budget	-0.001	0.022	
Advertising	0.199	0.091	*
Love	104.148	54.504	*
Joy	5.389	72.512	
Surprise	68.384	63.855	
Anger	-225.481	104.475	*
Sadness	14.864	89.285	
Fear	16.501	67.747	
Love*love	-6.425	4.353	
Love*Joy	7.280	11.252	
Love*Surprise	-1.322	7.839	
Love*Anger	-17.784	14.411	
Love*Sadness	2.122	12.185	
Love*Fear	3.740	9.070	
Joy*Joy	-12.601	9.040	
Joy*Surprise	-12.091	11.788	
Joy*Anger	43.033	21.114	*
Joy*Sadness	7.977	17.751	
Joy*Fear	-22.303	12.869	
Surprise*Surprise	-9.457	6.473	
Surprise*Anger	13.683	14.288	
Surprise*Sadness	-12.859	13.470	
Surprise*Fear	16.239	10.927	
Anger*Anger	9.134	17.195	
Anger*Sadness	16.002	26.038	
Anger*Fear	-27.875	17.531	
Sadness*Sadness	-22.066	14.392	
Sadness*Fear	26.874	17.180	
Fear*Fear	0.250	8.739	

Significance levels: 1%:** ; 5%:*

We find evidence supporting the above hypothesis: i.e. the relationship between critics' average reviews and user average reviews is statistically significant and positive, and this relationship is mitigated for high artistic appeal movies (the coefficient on the interaction variable between artistic appeal and average user review is statistically significant and negative). In line with our a-priori expectations we find that high artistic appeal movies tend to be rated higher on average, as do movies of high popular appeal. The overall relationship between critical reviews and average user reviews is only weakly positive for high artistic appeal movies.

In addition we are able to discern critics' patterns of value attribution to specific movie attributes. For example we find that animation movies are graded 12 points higher on average relative to comedies, that the main effect of the emotion 'anger' is negative, and that critics appreciate 'anger' when it is combined with joy. Further, while critical reviewing exhibits a significant and positive correlation with movie advertising, its correlation with production budget is insignificant.

Next we address a potential endogeneity issue which would arise if critics' votes for the Critics' Choice awards are influenced by the each other. Given that we cannot find a suitable instrument for Critics' Choice Awards, we separate our sample of movies into those which are critically acclaimed and those which are not. We re-assess the correlation between critics' reviews and user reviews in both samples. We find that the coefficient on average user review is statistically significant and positive in the case of commercial movies, but statistically insignificant in the sample of artistic movies[13].

Summarizing the results so far, we have found evidence supporting a positive correlation between average critic and average user reviews, and this correlation is

[13] The coefficient on average user reviews is 3.05 and has a standard error of 0.48 in the regression with the sample of commercial movies. This coefficient is 1.55 with a standard error of 4.41 in the corresponding regression for the sample of high-artistic appeal movies.

weaker, albeit still positive for movies of high artistic appeal. However instead of representing evidence in favor of behavior patterns which is consistent with the tailoring of reviews to audience preferences, this correlation could simply be capturing the fact that critics and audiences judge movie quality along the same set of criteria, but simply allocate different weights to each set of criteria. To conclusively determine whether critics tailor reviews to audience tastes we should observe the critics' reviews changing as the characteristics of their audiences change. To this end we turn to an assessment of the evaluator role performed by critics within their respective newspaper markets.

2.4.2 Evaluator role of individual reviews

The variable of interest is now the Metacritic score which represents a scaling of the individual critic's summary grade from the corresponding rating scale that each critic uses (e.g. 4-star, 5-star, thumbs-up v/s thumbs down, letter) to a score which lies between zero and 100. Only 24 possible values along this scale have positive mass, i.e. the reviews are not distributed across a continuous scale. We therefore assess the evaluator role of individual critics using both a linear model and an ordered probit model. In the latter model, we use a parsimonious approach to group scores into classes of roughly equal frequency. Table 2.6 shows the frequency distribution of the scores for the 6104 individual critic reviews in our sample, as well as our ordered groupings and their corresponding frequencies.

We find no qualitative differences between the results from the linear model and the ordered probit model. We therefore only present and comment on results of the linear model in this section and relegate the tables of results for the ordered probit model to an appendix.

Table 2.6: Histogram of individual critics' scores

Grade	Frequency	Histogram	
0	56		
10	43	Class	Frequency
12	25		
16	4	0-40	1437
20	86		
25	384	41-50	1376
30	297		
33	3	51-70	1225
38	346		
40	193	71-80	1338
42	60		
50	1316	80-100	728
58	108		
60	145		
63	576		
67	101		
70	295		
75	1103		
80	235		
83	61		
88	274		
90	99		
91	41		
100	253		
Total	6104	Total	6104

We estimate the following model:

$$R^*_{ijt} = \alpha_0 + \alpha_1\, OMUR_{it} + \alpha_2\, AA_i + \alpha_3\, OMUR_{it} * AA_i + \alpha_4\, OMPA_{it} + \alpha_5\, Zi + \alpha_6\, C_j + \alpha_7\, L_t + \alpha_8\, L_t * Z_i \qquad (2)$$

$OMUR_{it}$ is the average user review for movie i in the critic's own newspaper market, t. AA_i is the measure of artistic appeal of movie i. $OMUR_{it} *AA_i$ is the interaction between these two variables. $OMPA_{it}$ is the measure of popular appeal of movie i in market t (this variable pertains to a count of the number of user reviews from the critic's local market). Z_i is as defined in equation (1). C_j represents characteristics of the critic, i.e. gender, experience and the newspaper market that they belong to. L_t represents characteristics of the critic's local audience. $L_t* Z_i$ represents interactions between characteristics movies and that of their local audience. These capture how critics tailor value attribution to different movie characteristics for the respective audiences that they write for. Table 2.7 shows the results.

The evaluator role:

We again find evidence in favor of the evaluator role: the likelihood of a critic rating a movie higher increases with average audience reviews in the critic's market, and this likelihood falls for movies of high artistic appeal. The overall relationship between critics' reviews and audience reviews is only weakly positive for such movies.

Given the potential endogeneity concern we raised in section 4.1, as a check of these results, we again separate out our sample of movies into artistic and commercial, and re-estimate the above equation for each sample. Again we find that the coefficient on audience reviews is statistically significant and positive in the case of commercial appeal movies and insignificant in the case of high-artistic appeal movies[14].

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[14] The coefficient on audience reviews is 1.05 and has a standard error of 0.20 in the regression with the sample of commercial movies. This coefficient is 0.051 with a standard error of 0.42 in the corresponding regression for the sample of high-artistic appeal movies.

Characteristics of critics:

Our results indicate that gender and experience of critics are not a source of systematic differences between critics' reviews. However we find that critics based in the south are likely to be less critical on average, than their counterparts based on the East coast.

Table 2.7: Estimated parameters for Individual Critics Review equation

$R^2 = 31.5\%$; n= 6104

Parameter	Estimate	Error	
Intercept	918.053	282.159	**
East	omitted		
Midwest	3.074	2.512	
South	-5.179	2.059	**
West	-3.433	1.958	
Awards	13.015	2.608	**
Own Market popularity	0.544	0.245	*
Own Market Review	1.159	0.194	**
Awards*Own Market	-0.773	0.262	**
YOUNG	-0.129	0.430	
OLD	-0.577	0.318	
COLLEGE	-0.310	0.193	
POOR	0.224	0.403	
BLACK	-0.262	0.115	*
BuenaVista	4.075	2.401	
DreamWorks	2.210	3.310	
Fox	4.223	2.071	*
MGM	0.996	3.497	
Miramax	0.841	3.427	
NewLine	8.095	2.394	**
Other	omitted		
Paramount	2.283	2.244	
Sony	1.006	2.548	
Universal	1.828	2.148	
WarnerBros	-0.692	2.138	
Animataion	16.564	2.970	**
Action / Adventure	0.498	2.001	
Comedy	omitted		
Drama/BlackComedy	6.794	2.002	**

Table 2.7. (continued)

Horror	-3.919	2.299	
Romantic Comedy	-0.059	2.585	
Sci Fi / Fantasy	2.673	2.639	
Parameter	Estimate	Error	
MPAA: G	3.965	3.372	
MPAA: PG	-3.927	1.947	*
MPAA: PG-13	omitted		
MPAA: R	1.199	1.446	
Budget	0.023	0.018	
Advertising	0.174	0.079	*
Love	63.298	51.809	
Joy	-99.813	70.132	
Surprise	-84.802	68.513	
Anger	-236.096	102.514	*
Sadness	169.311	116.157	
Fear	-141.353	76.350	
Love*love	5.651	3.753	
Love*Joy	-17.670	9.816	
Love*Surprise	0.563	7.799	
Love*Anger	-40.590	13.360	**
Love*Sadness	9.099	11.833	
Love*Fear	24.501	10.053	*
Joy*Joy	1.216	7.599	
Joy*Surprise	9.968	12.369	
Joy*Anger	51.695	21.138	*
Joy*Sadness	0.024	18.949	
Joy*Fear	-24.443	14.100	
Surprise*Surprise	-21.458	7.346	**
Surprise*Anger	35.887	15.321	*
Surprise*Sadness	-22.649	16.140	
Surprise*Fear	29.787	12.516	*
Anger*Anger	31.985	16.030	*
Anger*Sadness	-27.769	28.673	
Anger*Fear	-36.287	20.502	
Sadness*Sadness	-5.972	17.656	
Sadness*Fear	22.209	20.526	
Fear*Fear	5.959	10.361	
Critic's Experience	0.001	0.001	
Critic's Gender	0.694	1.327	

Significance levels: 1%:** ; 5%:*

Characteristics of movies

We observe some consistency in valuation of movie characteristics when we move from the model of average critics' reviews to the current model of individual reviews. Specifically, across both models critics seem to favor animation movies over other genres and advertising expenditure has a positive impact on reviews in both cases. However the present model reveals additional insights: For instance, at the individual level critics appear to favor dramas over comedies, and several more emotion-pair coefficients are significant. The differences between the two models may arise because the panel of data in the current model spans more observations, thereby producing tighter standard errors. Also the sample of movies spanned by the two datasets are not identical: in the current model we only consider movies for which we observe a local user reviews (from YM).

Characteristics of local audiences

The main effects pertaining to characteristics of local audiences do not translate into systematic differences in individual critics' reviewing patterns, except for the proportion of the audience which is black: this control exhibits a negative correlation with critics' reviews. Given the significance of this variable, we estimate a separate regression equation (which includes interactions between movie characteristics and audience demographics) to determine whether patterns of value attribution to movie characteristics changes as the audience's demographic profile changes. We find that as the proportion of college-educated individuals rises, critics attribute higher value to the emotion joy and less value to the emotion love. In addition, an increase in the proportion of individuals who belong to households that earn less than $ 35,000 per year prompts critics to put less value on the emotion 'sadness'. These changes in value attribution to movie characteristics as a result of changes in the demographic composition of their audiences are consistent with critics tailoring their reviewing patters to reflect characteristics of their audiences.

In addition to demographic composition of audiences, we assess how changes in local macroeconomic conditions can impact on critical reviewing. To this end we include interactions between local macroeconomic conditions and movie characteristics capturing genre and emotional content measures. Again we find evidence supporting changes in patterns of value attribution to movie characteristics as local conditions change. Table 2.8 reports the results.

Table 2.8: Estimated parameters for Interactions between local macroeconomic variable and movie characteristics in individual critics' reviews equation

	Consumer Price Index			Interest Rates		
Parameter	Estimate	Error		Estimate	Error	
Animation	1.838	0.609	**	1.114	0.950	
Action / Adventure	-0.155	0.374		-0.070	0.364	
Comedy	omitted			omitted		
Drama/BlackComed	0.734	0.421	*	1.992	0.559	*
Horror	-0.117	0.439		-0.436	0.430	
Romantic Comedy	0.129	0.556		0.648	0.644	
Sci Fi / Fantasy	2.398	0.598	**	0.480	0.516	
Love	0.180	0.404		-0.343	0.488	
Joy	-0.835	0.514		-0.379	0.531	
Surprise	0.521	0.419		1.567	0.454	*
Anger	-1.212	0.761		-0.799	0.902	
Sadness	1.067	0.776		-0.535	0.691	
Fear	0.200	0.526		0.484	0.564	
	Average Gas Prices			Unemployment Rate		
Parameter	Estimate	Error		Estimate	Error	
Animation	0.213	0.064	**	7.494	2.391	*
Action / Adventure	0.021	0.055		0.201	1.625	
Comedy	omitted			omitted		
Drama/BlackComed	0.133	0.051	**	1.380	1.788	
Horror	0.084	0.058		-0.486	2.049	
Romantic Comedy	0.002	0.081		0.279	2.327	
Sci Fi / Fantasy	0.377	0.076	**	12.261	2.818	*

Table 2.8. (continued)

Love	0.054	0.058		-0.288	1.628	
Joy	-0.109	0.068		-1.789	2.235	
Surprise	0.018	0.053		1.880	1.830	
Anger	-0.124	0.093		-6.165	3.335	
Sadness	0.160	0.100		6.691	3.592	
Fear	-0.014	0.067		-0.538	2.390	

Significance levels: 1%:** ; 5%:*

In summary of this section, we have found statistical evidence for a positive correlation between individual critics' reviews and the average reviews of their local audiences. In addition we find critics changing their value attribution patterns to individual movie characteristics on the basis of local audience characteristics like demographics and macroeconomic variables. Taken together, this allows us to conclude that critics may be tailoring their reviews to fit the expectations of their audiences when they formulate a review.

2.5. Conclusion

Whether as influencers of consumer movie selection, or predictors of movie profitability, critics clearly have a pivotal role in the movie industry. The purpose of this paper was to investigate a potential third role for critics as evaluators of movie quality. We argued that journalistic critics face a tradeoff between two sets of evaluative criteria when putting forth a review: artistic and commercial. This trade-off hinges on the contrast between these two sets of criteria, as well as on the existence of a dual-incentive structure whereby critics derive benefits from tailoring their reviews to audience tastes on the one hand, and to the artistic evaluations of their peers on the other. Given this trade-off, we were able to establish the relevance of the evaluator role for a subset of movies which are of high artistic appeal. Further we identified patterns of value attribution to several movie attributes, including genre, MPAA rating and emotional content. We also confirmed that systematic differences arise in the valuation of movie attributes when characteristics of the critic's audience change. Given that audience composition is exogenous, such differences are consistent with critics tailoring their reviews to audiences.

While this study allows us to establish the relevance of the evaluator role for artistic movies, we should point out that this does not suggest that critics do not perform an evaluator role when reviewing commercial movies. Rather, the suggestion is that the weight placed on commercial evaluative criteria is greater in the case of commercial movies (especially those of low artistic value) because critics' cannot gain recognition for their expert evaluative skills when putting forth reviews for movies with limited awards potential. However we cannot calibrate the strength of the evaluator role for low artistic appeal movies, given that we only have a binary measure of artistic appeal.

One possible extension of this research would be to identify a broader measure of artistic appeal (e.g. raw critics' votes for BFCA awards for all movies that received votes) and to reassess the evaluator role in the light of this measure. However we do not have access to such data. Another extension would be to investigate other sources of discrepancies between critics and audience reviews. For example Holbrook (2005) suggests that consumers and critics agree on what constitutes quality, but that the weights that each group places on the individual constituents of quality differ. Calibration of these weights could allow studios to anticipate reviews and devise adequate marketing responses for their movies. Yet another extension of this work would be to investigate exactly which movie attributes constitute artistic as opposed to commercial appeal. Finally the methodology in this chapter can be extended to other experiential goods for which experts' reviews are also available, e.g. music, books and wines.

APPENDIX

Table 2.9: Parameter estimates for ordered-probit model of individual critics reviews

Parameter	Estimate	Error	
Intercept1	50.435	16.380	
Intercept2	-0.675	0.034	**
Intercept3	-1.292	0.043	**
Intercept4	-2.247	0.059	**
East	omitted		
Midwest	0.291	0.145	*
South	-0.368	0.118	**
West	-0.206	0.113	
Awards	0.821	0.163	**
Own Market popularity	0.030	0.014	*
Own Market Review	0.056	0.011	**
Awards* Market Review	-0.046	0.016	**
YOUNG	-0.060	0.025	**
OLD	-0.057	0.018	**
COLLEGE	-0.016	0.011	
POOR	0.029	0.023	
BLACK	-0.020	0.007	**
BuenaVista	0.186	0.139	
DreamWorks	0.187	0.196	
Fox	0.217	0.120	
MGM	-0.070	0.199	
Miramax	-0.115	0.196	
NewLine	0.431	0.142	**
Other	omitted		
Paramount	0.081	0.130	
Sony	-0.060	0.146	
Universal	0.054	0.125	
WarnerBros	-0.106	0.125	
Animation	1.066	0.175	**
Action / Adventure	0.064	0.116	
Comedy	omitted		
Drama/BlackComedy	0.369	0.115	**
Horror	-0.326	0.133	*
Romantic Comedy	-0.052	0.148	
Sci Fi / Fantasy	0.117	0.152	

Table 2.9. (continued)

Parameter	Estimate	Error	
MPAA: G	0.159	0.195	
MPAA: PG	-0.272	0.115	*
MPAA: PG-13	omitted		
MPAA: R	0.123	0.084	
Budget	0.001	0.001	
Advertising	0.010	0.005	**
Love	2.749	2.974	
Joy	-4.350	4.065	
Surprise	-4.568	4.052	
Anger	-10.515	5.911	
Sadness	5.839	6.741	
Fear	-7.775	4.367	
Love*love	0.299	0.218	
Love*Joy	-1.227	0.569	*
Love*Surprise	-0.043	0.449	
Love*Anger	-1.594	0.773	*
Love*Sadness	0.409	0.684	
Love*Fear	1.273	0.582	*
Joy*Joy	0.203	0.439	
Joy*Surprise	0.573	0.722	
Joy*Anger	2.355	1.217	
Joy*Sadness	0.349	1.091	
Joy*Fear	-1.426	0.811	
Surprise*Surprise	-1.410	0.452	**
Surprise*Anger	2.148	0.902	*
Surprise*Sadness	-0.937	0.945	
Surprise*Fear	1.610	0.723	*
Anger*Anger	1.307	0.920	
Anger*Sadness	-1.686	1.661	
Anger*Fear	-1.737	1.173	
Sadness*Sadness	-0.415	1.018	
Sadness*Fear	1.662	1.179	
Fear*Fear	0.080	0.598	
Critic's Experience	0.000	0.000	
Critic's Gender	0.063	0.077	

Significance levels: 1%:** ; 5%:*

Table 2.10: Estimated probit coefficients for interactions between local macroeconomic variable and movie characteristics

	Consumer Price Index			Interest Rates		
Parameter	Estimate	Error		Estimate	Error	
Animation	0.131	0.036	**	0.062	0.054	
Action / Adventure	-0.005	0.022		-0.002	0.021	
Comedy	omitted			omitted		
Drama/BlackComedy	0.054	0.024	*	0.114	0.034	**
Horror	-0.005	0.025		-0.028	0.025	
Romantic Comedy	0.002	0.032		0.030	0.037	
Sci Fi / Fantasy	0.155	0.035	**	0.043	0.031	
Love	0.001	0.023		-0.035	0.029	
Joy	-0.039	0.030		-0.010	0.031	
Surprise	0.019	0.024		0.080	0.027	**
Anger	-0.059	0.044		-0.047	0.053	
Sadness	0.061	0.044		-0.030	0.040	
Fear	0.012	0.030		0.040	0.032	
	Average Gas Prices			Unemployment Rate		
Parameter	Estimate	Error		Estimate	Error	
Animation	0.015	0.004	**	0.535	0.171	**
Action / Adventure	0.002	0.003		0.025	0.094	
Comedy	omitted			omitted		
Drama/BlackComedy	0.009	0.003	**	0.132	0.102	
Horror	0.006	0.003		-0.020	0.117	
Romantic Comedy	0.000	0.005		-0.008	0.132	
Sci Fi / Fantasy	0.024	0.005	**	0.750	0.165	**
Love	0.002	0.003		-0.045	0.094	
Joy	-0.006	0.004		-0.072	0.128	
Surprise	-0.001	0.003		0.069	0.106	
Anger	-0.006	0.005		-0.337	0.192	
Sadness	0.009	0.006		0.394	0.206	
Fear	-0.001	0.004		-0.023	0.136	

Significance levels: 1%:** ; 5%:*

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CHAPTER 3

ARE MOVIE CRITICS RACIALLY BIASED?

3.1. Introduction

Extent literature provides evidence that racial discrimination permeates numerous aspects of society. Examples of discrimination pertaining to economic outcomes appear as differences in wages (Chandra 2000), income (Blau & Graham 1990), prices paid in consumer markets (Ayres & Siegelman 1995; Yinger 1998), credit availability (Blanchflower et al. 2003) etc. Discrimination also arises in social relations (Payne et al. 2002); in the provision of health care (van Ryn & Burke 2002); in law enforcement (Bates and Fasenfest 2006); in judicial sentencing (Abrams et al. 2006); and even in sports (Price & Wolfers 2007).

In this paper we explore race as a factor in the critical appraisal of movies. A priori, one can expect critical movie reviewing to be an unlikely context for discrimination to exist for several reasons: First Hollywood movies have often attempted to push the limits of what is socially acceptable, and movie critics are regarded as the arbiters of quality in Hollywood. Second, movie critics are employed by the news industry which has a documented liberal bias overall (Gentzkow & Shapiro 2006). Third, critics' ratings are read and assessed by a very broad audience which can potentially detect bias. But critics' ratings constitute a quality signal for a product where criteria of excellence can be very subjective and where the signal pertains to overall movie quality and not of movie stars. As a result, evidence of racial bias can be very hard to detect. This is in contrast to other markets where differentials in wages, prices, prison sentences, fouls called etc, can be readily observed. Therefore the goal of this paper is to isolate as many alternative sources of differences between critics' ratings as we can capture and to assess racial bias against African American actors in the light of such controls. Despite inclusion of these controls, we find results in this paper which contradict our a-priori expectations that movie critics are color-blind in their judgments of movies with African American actors.

We construct a dataset which tracks reviews for 771 movies released between 2003 and 2007. For each of these movies we collect reviews from a group of critics collectively referred to as cream-of-the-crop in movie industry parlance (metacritic.com; rottentomatoes.com), because they are employed by some of the most illustrious print and online publications in the U.S. Of these critics we select those who publish in newspapers for which we can observe the characteristics of corresponding audiences. We control for an extensive set of movie attributes which include measures of how good the cast members are; the type of movie (by genre, MPAA rating, emotional content and production studio); movie marketing and production expenditures; and characteristics of the critic as well as those of the audience (including a taste parameter). Nevertheless, we still find evidence of racial bias in critics' movie ratings. For movies with an African American in the lead role, we find that individual critics' ratings are up to 6 points lower on average. However we also find that critics seem to reward movies with African Americans in supporting roles with better ratings.

To assess the economic impact of critical bias against African American actors, we evaluate the impact of critics' reviews on movie market shares and find that market shares are up to about 1% lower for movies with an African American lead and up to about 2% lower for movies where both leading actors are African American. Given that we control for consumer movie ratings, we attribute this effect on shares to a causal effect, i.e. critical bias against African Americans induces a reduction in market shares. Movies in our sample earn $60M on average at the box office. While we only track movie shares during weeks where they are screened in no less than 5% of theaters nationally, we extrapolate from our results, to conclude that the negative impact of critics' ratings on shares translates to an upper limit of about $0.6M reduction in theatrical revenues on average, for movies with an African American actor in the lead, and in a $1.2M reduction for movies with two African Americans in the two main roles. In our sample of movie, only 23.5% of all movies and 21.2% of movies with African American leads breakeven[15]. Barring the sales penalty to the latter type, 2.4% more movies with African American leads would breakeven. Also theatrical revenue often correlates with sales in subsequent distribution channels like DVD, pay-per-view etc. Potential follow-on effects on total revenue are therefore likely. However these effects are outside the scope of the present analysis.

This paper ties in with several streams of literature. First and within the scope of the economics of discrimination, we assess the sources of critical bias against African Americans against three competing theories: (1) taste-based discrimination (which alludes to discrepancies in observed economic outcomes that cannot be explained away by differential characteristics of those who are discriminated against), (2) statistical discrimination (which arises when group characteristics differ on average and when every member of a group is judged on the basis of group-averages irrespective of their (often unobserved) individual characteristics), and (3) implicit discrimination (which arises when agents sub-consciously discriminate on the basis of existing stereotypes, especially when they need to make split-second decisions). We

[15] We define the breakeven point as the level of theatrical revenue which equals the sum of production and advertising expenditures. This is a simplification because on average only 55% of theatrical revenues go to the studio, the rest is retained by exhibitors.

propose taste-based discrimination as the most likely theory underlying critical bias against African American Actors. Second we assess critical reviewing in the context of media bias literature which demonstrates the optimality of slanting news reports in the direction of audience preferences (Gentzkow & Shapiro 2006; Mullainathan & Schliefer 2005) to assess whether critics' ratings merely reflect audience tastes, and find evidence of critical bias despite controls for audience characteristics, tastes and location. Third and in the context of the literature on the motion picture industry, we assess the consequences of critical bias on movie profitability and find that critical bias imposes an economic cost on movies with African American cast members. Fourth and in the context of the 'expert-ratings' literature in marketing, we generate additional insights into the aggregate flow of information between experts and consumers which show that the market's assessment of African American actors seems to be at odds with that of critics. Finally, and while testing this claim is beyond the scope of the present analysis, our findings may bear on the differential labor market outcomes literature for minority groups if critical reviewing impacts on actor-remuneration.

From an industry perspective, our findings are interesting because for several decades the majority of African Americans cast in movies were seen in subservient or stereotypical roles, and it is only in the last decade that African American actors seem to have made significant advancements in Hollywood. For example, in its eighty years of existence, the Academy Awards have only awarded 11 Oscars to African Americans, six of which were awarded between 2002 and 2009 (Khatami 2009). Robinson (2006) documents that Hollywood studios often specify a preferred race for particular roles and overwhelmingly favor white male actors for leading roles, leaving only a small proportion of roles open to African Americans for example. A recent CNN interview of Chon Noriega (UCLA Professor of Cinema and Media Studies), reports that racial stereotypes often apply to Hispanic actors as well. Noriega claims that the latter are almost always portrayed as expendable characters or as "foils for largely white characters" who define the movie (Pawolski 2009). As such it is possible that our findings reflect the broader discrimination patterns against minority groups in Hollywood.

The rest of this paper is organized as follows: Section 3.2 surveys the relevant literature on taste-based, statistical, and implicit discrimination, as well as the role of movie critics in the movie industry in general. Section 3.3 outlines the data gathered for this study and presents descriptive statistics outlining the types of movies where African Americans are more likely cast. Section 3.4 details our analyses of critics' ratings and investigates the economic impact of critics' reviews on movie sales. Section 3.5 concludes.

3.2. Literature review

3.2.1. Why do critics discriminate?

Bertrand et al. (2005) propose taste-based discrimination and statistical discrimination as two possible explanations underlying explicit racial discrimination in general. Arrow (1998) highlights the differences between these two explanations: Taste-based discrimination can be attributed to a special disutility that whites attach to contact with non-whites. As a result, racial discrepancy can persist in market outcomes despite controls for human capital and productivity in labor markets, ability to pay in commodity markets, risk assessment in credit markets etc[16]. Statistical

[16] In our case, such discrimination arises despite controls for star-power.

discrimination on the other hand, arises when differences in human capital, productivity, risk assessment etc exist on average, between race groups, but cannot be observed for specific individuals. In such cases, those who discriminate will use average characteristics of a race group as a surrogate for unobservable characteristics of an individual and this in turn generates discrepancies in the treatment of individuals from different race groups. Such discrimination is independent of the tastes of the 'discriminator'.

In the context of critical reviewing, we cannot claim that individual (or actor) productivity is unobservable since critics have the opportunity to attend movie screenings before they formulate an opinion, and hence are fully informed about the quality of the actor. As such, discrimination by critics could be attributed to taste-based discrimination.

However Bertrand et al. (2005) propose that an alternative explanation for racial discrimination could lie in implicit discrimination which is unintentional and outside of the discriminator's awareness. This type of discrimination arises because of natural stereotypes that exist about particular race groups. In the Bertrand et al. study this type of discrimination is manifested as a response time differential in computerized testing where subjects are asked to pair words that connote "African American" with words that connote "good" or "bad". This study also documents an intriguing feature of implicit attitudes which alludes to potential maniputability: For example, exposure to photographs of admired African Americans like Bill Cosby led to a decrease in anti-African American implicit attitudes. We attempt to control for implicit discrimination in the present study by including time fixed effects which potentially capture the extent of implicit bias that critics can have at any given point in time.

3.2.2. The role of critics in the movie industry

Previous literature defines two potential roles for movie critics: the influencer role and the predictor role. As influencers, critics act as opinion leaders who steer consumers' movie selection decisions, especially in the early weeks of a movie's release when alternative sources of movie information (e.g. word-of-mouth) are scant. As such critical bias against African American actors is especially problematic since it comes at a social cost to readers who are merely seeking a quality signal. As predictors, critics' ratings do not so much influence audience preference as capture movie characteristics that appeal to their audience. That is, critics' ratings are a useful explanatory variable in explaining sales or shares of movies, because they capture the audience drawing-power of movie quality. The latter is hard to measure if only movie characteristics like movie genre, production budget and advertising expenses are controlled for. For both the influencer and predictor roles, critics' ratings are a summary measure of, as well as reflect (and shape in the first case) audience preferences. Reinstein and Snyder (2006) summarize the difference between the two roles by defining the influence effect as the causal effect of reviews on demand, with movie quality held constant; and the prediction effect as the spurious correlation between reviews and demand, induced by their mutual correlation with quality.

Chapter 2 of this dissertation also explores a potential third role for movie critics, i.e. an evaluator role, whereby critics formulate a quality appraisal of movies independently of potential market success of the movie. Critics perform the evaluator role in the context of profit maximizing news firms which hire critics to supply quality signals to their readership. Mullainathan and Schleifer (2005) offer theoretical evidence which shows that in the market for news, it is optimal for media outlets to slant information in the direction of their audience's political biases and Gentzkow and Shapiro (2006) empirically confirm this theory by estimating the optimal political slant of different media outlets as a function of the political biases of their respective audiences. The notion of optimal slant can logically be extended to the realm of critical movie reviewing whereby it may be optimal for profit-maximizing firms to incentivize critics to tailor their reviews to the tastes of local audiences. In addition, by putting forth a signal which aligns with audience tastes, critics may be able to foster better reputation with their audiences. On the other hand, critics may also be motivated to put forth quality signals that align less with the standards of their audiences, but more with standards of artistic appraisal used by fellow critics since this would allow them to foster reputation within the community of their peers instead. Greater recognition among this community can lead to movie industry perks like red-carpet invitations, selection onto awards-panels, citation of reviews on movie promotional material, etc. As such, reflection of racial bias in reviewing may be indicative of preferences of the audience or of the critics' community, or both. We attempt to test the possibility that racial bias is induced by audience preferences by controlling for these via the inclusion of audience specific characteristics including demographics and taste parameters, as well as market fixed effects.

Few other papers have attempted to deconstruct the role of critics in the movie industry in an attempt to explore the existence of possible biases in critical reviewing. One such paper by Ravid et al. (2006), aims to find out whether critics exhibit a statistical bias in favor of specific movie studios. These authors demonstrate that reviews by a number of critics are indeed affected by the identity of studios and that surprisingly it is often the most reputable critics who exhibit the most biases. This study extends the notion of critical bias to the notion of race of movie stars instead.

3.3. Data

3.3.1. Movie attributes

Yahoo! Movies (YM) which is an online service provided by the Yahoo! Network provides movie information about all theatrical releases including trailers, red-carpet events, critics and consumer reviews, production studios, and names of directors and movie stars. The synopsis page for each movie also lists the names of the five main actors, i.e. the actors who played the most consequential parts of the movie, in the order that the roles matter to the plot. Specifically the name of the lead actor is listed first followed by the names of supporting actors, from the most significant role played to the least. It should be noted that the second cast member listed by YM, i.e. the first supporting actor is often female and indicates who plays the romantic interest of the lead in a movie. The next names listed tend to refer to the lead's 'sidekicks' and the villain. Collectively, this type of listing generates a precise description of the actors who are the main characters in a movie. For example the movie "Ocean's Eleven lists George Clooner (Lead), Julia Roberts (Romantic Interest), Brad Pitt (sidekick), Matt Damon (sidekick) and Andy Garcia (villain). We rely on cast information from YM because it uses a harmonized system to define top-five roles across movies. Other movie sites, like imdb.com, only list actors in the two main roles and the rest of the cast (including all cameo appearances) in alphabetical order. This does not allow us to easily infer the identities and corresponding race groups of the main cast members.

Our sample tracks the top-five cast members (in similar order as YM) of 771 wide-release movies which screened in theaters from 2003 to 2005. For each of these movies we investigate which of the top-five cast members are African American. We use a list available from Wikipedia.org. We regard this source as reliable for the following reasons: First Hollywood stars tend to be very popular, second information about them is readily available and can be readily checked, and third, given the open access format of Wikipedia, it is reasonable to assume that any wrong information about figures as popular as Hollywood Stars would be quickly corrected or disputed by fans, etc.

While actors can be from several other race-groups, for the purposes of this study, we classify all other race-groups as white since the number of actors in other minority groups (Asian/ Hispanic/ Arab etc), are much lower[17,18]. As such, if the industry discriminates against other non-white race groups as well, our results will underestimate the total extent of discrimination.

Given our race definitions, we observe 86 movies which cast African-American in lead roles; 247 movies had at least one African-American cast member and 524 movies had an all-white top-5 cast. Table 3.1 shows the racial breakdown of each of the top five cast members given their respective positions in the cast.

Table 3.1: Number of movies by race of cast member and position in cast

	Lead	Supporting 1	Supporting 2	Supporting 3	Supporting 4
Black Actor	86	78	66	77	66
White Actor	685	693	705	694	705
Total	771	771	771	771	771

[17] For instance, a recently constructed master-list of Hispanic movies in all of Hollywood history constitutes only 70 movies (Powalski 2009).

[18] Jewish actors collectively constitute an exception, but we leave an evaluation of critics' treatment of Jewish actors as an exercise for further study.

For each of the cast members, we obtain corresponding 'bankability' scores which represent a proxy for the commercial viability of each movie star. These measures were computed by The Hollywood Reporter in 2002 and are therefore invariant to the commercial success of movies in our sample period. However, given that these scores have not been updated since 2002, they may not capture the evolution of star-bankability through to 2005 (the end of our sample period). With no alternative measures for star-power, we regard 'bankability' scores as an imperfect proxy of star-power throughout our sample period. Table 3.2 shows the average bankability scores of cast members for all movies in our sample by race and by position in the cast. We observe that bankability scores for lead actors are on average higher for all movies and trend down between the lead and the fourth supporting role. Average bankability of African American actors in the lead position is on average lower than that of their white counterparts. In supporting positions, African American actors have higher average bankability for the two most important supporting.

Table 3.2: Average bankability by race of cast member and position in cast

	Lead	Supporting 1	Supporting 2	Supporting 3	Supporting 4
Black Actor	35.8	23.3	12.6	5.5	5.6
White Actor	43.5	22.4	10.1	10.7	8.2
All Actors	37.8	22.5	16.4	10.2	7.9

We control for additional movie attributes which include production budget and advertising revenue (obtained from Paul Kagan and Associates) as well as MPAA rating, movie genre and production studio (from www.boxofficemojo.com). Tables 3.3 and 3.4 show the percentages of all movies, across genre and MPAA categories, by racial composition of cast. We observe that a greater percentage of movies with African American leads tend to be dramas and Action/Adventure movies compared to movies with white leads. A greater percentage of movies with African American leads also tends to be rated PG-13, than movies with white leads.

Table 3.3: Percentage of movies by genre and racial composition of cast

Genre:	Animation	Action/ Adventure	Comedy	Horror/ Thriller	Romance	Sci-Fi/ Fantasy	Drama
Black Lead	3.49	22.09	30.23	9.30	10.47	3.49	20.93
White Lead	8.03	18.54	28.32	16.79	8.18	4.23	15.91
At least 1 Black	8.10	19.43	27.94	14.17	8.10	3.64	18.22
All white cast	7.24	18.67	28.76	16.76	8.57	4.38	15.62
All movies	7.52	18.94	28.53	15.19	15.95	8.43	4.15

Table 3.4: Percentage of movies by MPAA rating and racial composition of cast

	G	PG	PG13	R
Black Lead	2.33	19.77	48.84	29.07
White Lead	3.36	18.54	43.36	34.74
At least 1 Black cast	2.43	17.41	45.34	34.82
All white cast	3.63	19.27	43.51	33.78
All movies	3.24	18.68	43.97	34.11

Table 3.5 shows average production budgets and advertising expenditures by racial composition of cast. Movies with African American Leads tend to have lower production budgets on average. Lower budgets could be a consequence of African

American leads being paid less on average, or of their staring in movies which require fewer production resources. Similarly lower advertising expenditures could be a consequence of more targeted marketing of movies with African American leads to the African American community (e.g. in Ebony magazine), especially if African Americans are regarded as the primary market segment to which such movies appeal. But lower advertising also inherently limits the potential to get rid of stereotypes by broadcasting to larger audiences. Surprisingly however, table 3.5 also shows that movies with African American actors in supporting roles as opposed to lead roles tend to have slightly higher budgets and advertising expenditures.

Table 3.5: Average production and marketing expenditures by racial composition of cast

	Production budget ($M)	Marketing budget ($M)
Black Lead	44.82	29.09
White Lead	48.36	30.79
At least 1 Black cast	48.49	30.75
All white cast	47.72	30.49
All movies	47.97	30.57

We gauge artistic appeal via a count of the number of Critics' Choice (BFCA) Awards that a movie wins. We considered alternative measures of artistic appeal including Academy Awards (Oscars) and Golden Globe Awards. However we favor BFCAs because Academy awards are awarded by a community of non-experts (for example actors make up the main voting bloc: 22% of approximately 5000 voters), who may appraise commercial and not artistic standards; and the Golden Globes are awarded by a community of foreign critics who may not appraise artistic value in the same way critics in our sample do. Conversely the BFCA's are voted upon by a large community of U.S. based critics who are members of the Broadcast Film Critics

Association, and who cast independent and anonymous ballots for the movies of their choice. In voting for the BFCA's, critics are not constrained by the profit-maximizing objectives of the newspapers which publish their reviews and we therefore consider these awards to be reflective of true artistic quality. Of the 771 movies in our sample, 127 won at least one BFCA nomination. Of these 127 movies, 95 featured an all-white top-five cast and 8 starred a black actor in the lead position (These movies were nominated but did not win).

In addition to the above attributes we consider emotional content measures as constructed in chapter 1 of this thesis. Emotional content measures are salient because emotions give immediate meaning and significance to the movie experience (Tan 1994). The role of emotions in consumer choice is well-documented (Maslow 1968), and in the case of movies, this role is especially prevalent since consumer satisfaction hinges on the fulfillment of emotional expectations as the story unfolds (Zillmann & Bryant 2002). Some studies assess emotional content along two dimensions of psychological stimulation: pleasure and arousal (Eliashberg & Sawhney 1994, Neelamegham & Jain 1999). Chapter 1 of this dissertation proposes a more granular assessment of emotional content derived from 6 basic emotions: love, joy, surprise, sadness, fear and anger. The latter constitute the superordinate level of an emotion hierarchy which encompasses the broad range of emotions experienced by humans. Emotional content is extracted from movie keywords by using Latent Semantic Analysis (LSA), a natural language processing software package which measures semantic congruence between word groups, i.e. between movie keywords (obtained from www.imdb.com) and each basic emotion. Table 3.6 reports emotional content measures for a subset of movies in our sample.

Table 3.6: Emotional content measures for 3 movies

Movie	Joy	Love	Surprise	Anger	Fear	Sadness
Shrek	5.35	5.85	5.35	5.35	5.15	4.95
American Pie II	5.85	6.30	5.00	5.20	5.35	5.30
Hannibal	5.05	5.35	4.85	5.55	5.80	5.30

Table 3.7 reports average emotional content measures for movies by racial composition of cast. We observe that emotional content for all emotions is higher in all-white-cast movies relative to movies with at least one black cast member as well as for movies with white leads relative to black leads. Given the observed differences between the levels of emotions across types of movies, it makes sense to include controls for emotional content.

Table 3.7: Average emotional content by racial composition of cast

	Love	Joy	Surprise	Anger	Sadness	Fear
Black Lead	5.535	5.267	4.881	5.367	5.350	5.460
White Lead	5.612	5.290	4.970	5.397	5.371	5.525
Black cast	5.555	5.282	4.930	5.359	5.332	5.509
All white cast	5.625	5.289	4.973	5.408	5.385	5.520
All	5.604	5.288	4.960	5.393	5.369	5.518

In our analysis of movie sales, we also consider a movie's popular appeal which is a measure of the degree of enthusiasm that a movie generates. We use a count of the number of people who post a review on YM to this end. Holbrook (1999) confirms the validity of this count as a measure of popular appeal by finding evidence in favor of a "popularity hypothesis" (i.e. number of reviews is larger when users enjoy a movie), and evidence against an "extremity hypothesis" (i.e. number of reviews is larger when users really enjoy or really dislike a movie)[19].

3.3.2. Individual critics and user reviews

Individual critics' reviews for most movies, which screened in theaters from 1998 onwards, are available from www.Metacritic.com (MC). We only consider reviews for wide release movies (movies released in more than 600 theaters nationally), because they tend to have actors and directors who are better know and for whom we can observe a continuous measure of "bankability" or popularity scores. MC compiles reviews from a group of 232 critics collectively referred to as "cream-of-the-crop" given their clout in the industry. Since different critics use different rating scales (e.g. 4 star, 5-star, letter grade, etc), MC converts each critic's review into a score on a zero-to-100 scale. While alternative compilations of individual critic reviews are available from sources like RT and YM, we prefer MC because it offers more comprehensive coverage of critics' reviews (all reviews available online are compiled as opposed to just a sub-sample of available reviews (as is the case with YM), and because MC appraises the favorability of reviews using a more granular scale (RT used a thumbs-up/thumbs-down appraisal format and YM uses a letter grading system).

We collect user reviews from YM where ordinary consumers who have seen a movie upload a summary grade (lying between an 'F' and an 'A+', and reflecting the extent to which they enjoyed the movie). Several other websites compile consumers' movie reviews but we rely on YM because it is well-known amongst the online

[19] See Holbrook (1999) for an exposition of several empirical checks of the validity of the popularity hypothesis and against that of the extremity hypothesis.

community and it offers comprehensive coverage of wide-release movies which screened in theaters from July 2003 onwards. Given the ordered nature of the letter grading system on YM, we code each letter by a corresponding number between 0 and 12, with '0' representing an "F" and '12' an "A+".

3.3.3. Characteristics of critics' audiences

Given that movie critics may face incentives to tailor their reviews to the preferences of their audiences (see Chapter 2 of this dissertation), we construct proxies for movie preferences by geographic location of audiences: To this end we collect a total of 4929 unique movie reviews from 1945 distinct reviewers for a sample of 500 distinct wide-release movies which screened in theaters between July 2003 and March 2008. We sort these reviews by movie and by geographic location and construct an average user review for each movie and for each of 4 geographic areas: East Coast, West Coast, Midwest and South[20]. These averages serve as proxies for the movie tastes of each geographic area and hence of the newspaper market falling within that area. It is likely that taste vary within geographic areas, but it is reasonable to assume that these regional taste measures correlate with the average tastes of newspaper audiences falling within each geographic region (The correlation between the average movie reviews put forth by our sample of online reviewers and the average reviews put forth by all YM users is 0.63).

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[20] Since only a small proportion of online users supply their demographic information, it is sometimes not feasible (due to lack of reviews) to construct average user reviews for each newspaper market. We therefore use averages constructed for broader geographic areas as proxies for reviews in newspaper markets falling within each area.

In addition, we collect information pertaining to demographic characteristics of each critic's audience and local economic characteristics of each critic's market. We believe audience demographics and local economic characteristics are potential predictors of critics' reviews since in chapter 1 of the thesis I showed that these traits impact on movie choice and enjoyment.

Our demographic profile of newspaper audiences come from Reader Profile reports, commissioned by the Audit Bureau of Circulations (ABC), a not-for-profit organization which audits newspaper circulation and maintains an electronic database of average reader demographics for most major US newspapers[21]. These reports are compiled from annual phone surveys of consumers in each newspaper's market and they provide detailed readership data pertaining to reach, readers per copy, reader demographics, etc. From these reports and for each newspaper's audience we collect information pertaining to age, race, income and education levels of the average reader. While it is conceivable that not all readers who attest to reading a newspaper necessarily read the movie reviews section, it is plausible that the characteristics of the overall audience reflects characteristics of the audience segment which does read movie reviews. Further, critics may not have precise information (beyond average reader characteristics), about which segments of newspaper readers read their reviews. Hence we consider Reader Profiles to be representative of mean demographic characteristics of the average reader of movie reviews as perceived by the movie critic. MC reviews for 'cream-of-the-crop' critics are available for 11 newspapers for

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[21] Previous literature, (e.g. Goerge & Waldfogel 2003) use MSA (Metropolitan Statistical Area) demographics as a proxy for characteristics of the average reader, but we rely on ABC reader profiles instead since the assumption that all demographic segments have an equal predisposition to read newspapers may be flawed.

which we have Reader Profiles. Table 3.8 summarizes the demographic characteristics of each of these newspapers from 2003 to 2007.

Table 3.8: Audience demographics

		Race		Age Group		Education	Household Income	
Newspaper	Year	White	Black	18-24	55+	College	under $35k	$100k+
Boston Globe:	2003	88	5	9	30	42	17	29
	2004	89	5	10	33	40	17	28
	2005	89	7	9	33	46	16	30
	2006	89	6	11	35	48	15	32
	2007	.	.	.	.	.	.	.
Charlotte Observer:	2003	81	17	7	34	27	23	15
	2004	80	17	10	33	30	21	14
	2005	78	19	10	33	31	24	16
	2006	80	17	11	33	30	19	25
	2007	80	17	10	36	33	20	25
Chicago Sun Times:	2003	.	.	.	.	.	.	.
	2004	.	.	.	.	.	.	.
	2005	65	31	12	32	22	22	21
	2006	65	32	16	29	22	20	23
	2007	63	31	12	34	19	24	24
Chicago Tribune	2003	.	.	.	.	.	.	.
	2004	83	12	8	36	40	14	30
	2005	83	12	9	36	40	14	30
	2006	82	13	11	37	40	14	33
	2007	80	14	10	35	40	15	35
Los Angeles Times:	2003	79	9	12	31	32	21	25
	2004	81	9	10	31	36	19	26
	2005	78	10	11	34	37	18	27
	2006	79	9	9	34	39	15	32
	2007	78	9	9	37	38	15	34
Miami Herald:	2003	76	20	9	35	28	23	17
	2004	75	22	10	34	30	24	22
	2005	76	20	11	32	29	24	23
	2006	75	21	9	36	31	24	22
	2007	74	22	10	35	29	24	26

Table 3.8. (continued)

New York Times	2003	82	10	12	33	53	14	35
	2004	83	10	13	34	57	13	37
	2005	83	10	11	35	60	13	41
	2006	94	9	12	36	61	13	42
	2007	83	9	12	36	60	11	44
Philadelphia Inquirer:	2003	77	19	9	37	32	19	22
	2004	77	18	10	37	33	21	21
	2005	78	17	7	38	33	22	23
	2006	77	19	7	40	34	19	27
	2007	79	18	9	39	35	18	30
San Francisco Chronicle	2003	81	6	9	33	40	13	36
	2004	77	7	7	37	48	14	36
	2005	80	6	7	36	46	14	39
	2006	79	5	7	42	50	11	44
	2007	79	5	6	44	49	11	43
Seattle Post Intelligencer:	2003	87	3	8	31	33	18	19
	2004	87	4	9	32	33	20	19
	2005	89	3	9	34	41	18	21
	2006	86	4	8	34	40	16	22
	2007	86	4	7	37	42	14	28
Washington Post	2003	64	29	11	27	42	11	37
	2004	64	29	9	30	46	11	38
	2005	67	27	8	32	49	10	43
	2006	67	27	8	34	49	9	45
	2007	67	27	8	34	50	9	48

3.3.4. Characteristics of critics

We limit the number of critics under consideration to 68 critics who are employed by one of the 11 daily newspapers for which we observe audience characteristics. For each of these critics we observe experience levels (as proxied by a count of their individual reviews compiled on MC) and gender (we pool information from MC, RT and the popular press for this measure). For five critics in our sample we observe a job transfer to a different newspaper market and for each of these critics we attribute reviews to the market for which they were meant, given the date of the job transfer and the date at which the review would have been published: Since journalistic critics' reviews are meant to serve as a quality signal prior to consumers having seen the movie, it is reasonable to assume that reviews will be published shortly before a movie's release, or shortly after release at the latest. In any case, only a few critics transfer from one paper to another. Hence, the timing of reviews does not bias our assessment of critical bias against black movies. Finally, it should be noted that each newspaper typically employs more than one critic, but only puts forth one review per movie, i.e. the group of critics employed by a given newspaper divvies up movies among themselves so that the newspaper puts forth a review for a maximum number of new releases.

4.4. Analysis

4.4.1. Means comparisons of average ratings and box office sales

We start by motivating our study with a comparison of average critics' and average user reviews for movies with top-five casts of different racial composition. We do means regressions, first controlling for African American lead only and then controlling for African American actors in any of the top 5 roles. Table 3.9 shows the results for critics' ratings and user ratings respectively.

The intercepts of each of these regressions can be interpreted as the mean rating for movies with all white casts. The slope coefficients in columns (1a) and (2a) indicate the differential mean ratings for movies with an African American lead (relative to a white lead) for critics and ordinary consumers respectively: Mean critics' ratings are 4.2 points lower for movies with an African American lead, but the corresponding means show no statistical difference for ordinary consumers. Columns (1b) and (2b) indicate the differential rating for movies with African Americans in any of the top-5 roles: Critics' ratings for movies with African Americans in supporting roles is also lower than for movies with white actors, and again no such differences surface when mean ratings for ordinary consumers are compared.

Table 3.9: Average ratings by racial composition of cast

Mean Critics' Ratings		
	(1a)	(1b)
Coefficient	Mean (St.Error) Significance	Mean (St.Error) Significance
	54.78(0.62)**	54.68(0.63)**
Slope coefficients for:		
African American Lead	-4.22(1.85)*	-2.61(1.90)
African American in		
Supporting Role 1	…	-0.53(1.88)
Supporting Role 2	…	0.97(2.04)
Supporting Role 3	…	-3.21(1.91)"
Supporting Role 4	…	-4.05(1.98)*
Mean Consumer ratings		
	(2a)	(2b)
Coefficient	Mean(St.Error) Significance	Mean(St.Error) Significance)
Intercept (All white cast)	7.024(0.06)**	7.024(0.06)**
Slope coefficients for:		
African American Lead	0.319(0.20)	0.319(0.20)
African American in		
Supporting Role 1	…	…
Supporting Role 2	…	…
Supporting Role 3	…	…
Supporting Role 4	…	…

Significance levels: 1%:** ; 5%:*; 10%: "

Next we do a means regression for box-office sales to test for means differences due to race of cast members. Table 3.10 shows the results. As is the case with ordinary consumer reviews, we find no significant statistical differences, neither on the basis of the race of leads, nor of supporting cast members.

Table 3.10: Average box-office receipts by racial composition of cast

Box office Receipts ($M)		
	(a)	(b)
Coefficient	Mean(St.Error) Significance	Mean(St.Error) Significance
Intercept (All white cast)	60.00 (2.68)**	59.41 (2.91)**
Slope coefficients for:		
African American Lead	-8.49 (7.91)	-10.82 (8.71)
African American in		
Supporting Role 1	…	7.878 (8.61)
Supporting Role 2	…	4.96 (9.32)
Supporting Role 3	…	-1.74 (8.78)
Supporting Role 4	…	-2.80 (9.29)

Significance levels: 1%:**

4.4.2. Potential explanations for racial differences in critics' ratings

The racial discrepancy in critics' ratings is potentially attributable to several factors which we detail below.

Marketing: It is possible that movies with black cast members are not as well-promoted and that critics do not form a positive opinion of such movies as a result. We therefore control for studio and distributor related expenditures on movie promotion and advertising.

Genre: Since it is possible that movies with black cast members fall under genre categories which are unappreciated by critics, we add the following controls for genres: Animation, Action and Adventure, Comedy, Drama, Horror and Thriller, Romance and Science Fiction.

Artistic Appeal: Holbrook (2005) posits that by virtue of their training and expertise, critics emphasize different criteria relative to ordinary consumers when appraising movie quality: While ordinary consumers favor criteria like enjoyability and ease-to understand, critics place more weight on judging movies as an art-form rather than entertainment. To account for the possibility that movies with black-cast members fail to reflect artistic qualities, we use BFCA nominations as a control for artistic appeal.

Emotional content: If movie quality depends on emotional content and black actors tend to act better in movies with certain emotions (e.g. joy or deep sorrow), while critics have different emotional preferences (e.g. don't like joy), critical reviews will reflect this. We therefore include controls for emotional content.

Cost of actors: Critics' ratings may be reflecting the fact that black actors are simply not as good, and that black actors cost less to cast than white actors. Since a movie's budget picks up on the cost of employing the cast members, this variable is controlled for by the inclusion of a measure of the production budget.

Marketability/ commercial viability of stars: It is possible that black actors are just not as popular as white actors, which is what critics' ratings reflect. So we control for bankability of stars. Despite their bankability, black actors may get cast into relatively worse roles; however this should be reflected in a sales model as well. We do a comparison of sales for movies with black as opposed to white cast members in section 4.4.

Audience characteristics: Critics may write reviews to reflect the tastes of their audiences because they are employed by a profit-maximizing news firm for which it is optimal to slant reviews in the direction of audience preferences (See Chapter 2 of this dissertation). For example if a critic's audience is primarily white, she may write a review reflecting the tastes of such an audience. It should be noted however, that even if a critic's audience is primarily white, it is unclear from a social welfare perspective whether it is optimal for critics to express opinions which are biased against black actors, especially if the critic's readership extends beyond their respective newspaper markets.

Aside from measures of the racial composition of the audience (percentage of blacks and whites), we control for average age, education (proportion of high-school and college educated) and income (proportion of households earning under $35 000 and above $100 000). To control for aspects of audience tastes not captured by demographics, we also use average audience ratings for each movie. However this measure is potentially endogenous, given that consumer ratings may be influenced by reviews of critics' within their newspaper/geographic markets. In an alternative specification we instrument for average user ratings by using ratings of consumers outside of the critics' own newspaper market as an instrument. Circulations data from the Audit Bureau of Circulations (ABC) shows that the percentage of newspaper circulations within the Metropolitan Statistical Area (MSA) where the newspaper's headquarters are located is in excess of 90% for all the newspapers in our sample, except for the New York Times, which has about 50% of circulations in the NJ-NY-PA area, but 70% of circulations on the East coast. If critics only take into account preferences of their main audiences when formulating a review, their ratings will only correlate with ratings of consumers outside of their newspaper markets in as much as outside-market consumer ratings correlate with within-market consumer ratings. These correlations validate our choice of instrument.

Racist critics: Since all but one of the newspaper firms in our sample employ a team of movie critics (The Chicago Tribune only employs one movie critic: Roger Ebert), it is possible that critics who are most racially biased self-select into reviewing movies which have black cast members. However, we have no information about how movies are assigned to critics within newspapers. If assignments are made on the basis of movie genre or MPAA rating, our controls for movie characteristics would suffice, but if they are made on the basis of cast composition, our results will likely be picking up on the biases of the most racist critics within newspapers.

Time controls: Finally it is possible that reviews reflect the timeliness of a movie to critics and/or audiences preferences, as these preferences change over time. For example, events like the OJ Simpson trial or the election of a black president may impact on the overall bias/appreciation that critics have for the black community in general, and for African American cast members by association, thereby inducing implicit discrimination against the latter. We therefore include fixed effects for every month in our sample to capture extraneous events that might impact on contemporaneous preferences or subconscious attitudes.

4.4.3. Ratings model with control for black v/s white leads

We begin with an assessment of critics' ratings for movies with black as opposed to white lead actors. We specify the following equation for critics' ratings:

$$R_{ijt} = \alpha_0 + \alpha_1\, BlackLead_j + \alpha_2\, CriticChars_i + \alpha_3\, P\&A_j + \alpha_4\, Budget_j + \alpha_5\, Bankability_j + \alpha_6\, MovieChars_j + \alpha_7\, Newspaper_t + \alpha_8\, AudienceRating_{jt} + \alpha_9\, MarketChars_t + \alpha_{10}\, Month_j + \varepsilon_{ijt} \qquad (1)$$

R_{ijt} is the individual review of critic i for movie j in newspaper market t. $BlackLead_j$ is a dummy variable which equals one if the lead actor is black. $CriticChars_i$ is a vector of critics' characteristics which controls for critics gender and experience. $P\&A_j$ and $Budget_j$ control for movie marketing and production expenditures. $Bankability_j$ is a vector of bankability scores for each of the five top actors. $MovieChars_j$ is a vector of movie characteristics which controls for genre, MPAA rating, emotional content, production studio and artistic appeal. $Newspaper_t$ represents fixed effects for each newspaper. $AudienceRating_{jt}$ captures the movie taste of consumers within critic i's market. We will instrument for this variable using ratings of consumers outside of the critic's market using an IV approach. $MarketChars_t$ captures demographic characteristics of the critic's audience. $Month_j$ represents fixed effects corresponding to the timing of the critic's review. Finally ε_{ijt} is an idiosyncratic error term.

Following the order of the controls established in section 4.4.2 above, we estimate equation (1) using subsets of controls to test the following:

(a) Do critics rate movies with African American leads lower than those with white leads because movies with black leads are poorly marketed? To this end we only include controls for marketing and production expenditures.

(b) Are lower ratings caused because African American leads are cast into movie roles which are unappreciated by critics? In this case we add movie characteristics to the set of controls in (a).

(c) Are African American Leads worse actors? We add controls for bankability of stars to the specification in (a).

(d) Do critics formulate lower ratings to reflect the preferences of their audience? To the model in (a) we add controls for audience ratings, audience demographics and newspaper fixed effects.

(e) Are lower ratings due to exogenous events (like media coverage of race-related crime, election of African Americans to office, etc) which change critics' perception of African American Actors? To the specification in (a) we add month fixed effects.

(f) Are critics ratings lower for movies with African American Leads despite all the controls in (a) through (e)? We now run the full version of equation (1). In this specification we instrument for audience ratings using ratings of consumers outside of the critics' respective markets and use an instrumental variable approach as opposed to ordinary least squares.

Columns (a) through (f) of Table 3.11 show the results of each of the above specifications.

The differential mean coefficient on critics' ratings for movies with African American leads is negative in all of the above specifications, but is insignificant in all cases except in (d) and (f): Results in column (a) indicate that marketing differences suffice in explaining any observed mean differences for movies with African American as opposed to white leads. Column (b) results indicate that another plausible explanation for any observed mean differences could be that African American leads are cast into roles that are not appreciated by critics. Column (c) shows that differences in popularity of African American as opposed to white actors explain away the mean differences. Finally column (e) shows that exogenous events which affect critic's perceptions of African American actors may be the cause of the observed mean differences. However none of these specifications takes into account consumer preferences which introduce a potential confound: If consumers tend to like African American actors and critics ratings reflect consumer ratings, the estimated coefficient for the difference in mean ratings in (a), (b), (c) and (e) are biased. Controlling for audience preferences in (d) provides evidence of critical bias against

African American lead actors: Critics rate movies with African American lead actors on average 3.65 points lower than movies with white leads. In (f) we correct for the potentially endogenous audience taste variable and here too we find evidence of critical bias by 6.09 points on a 0-100 scale.

Table 3.11: Parameter estimates for model of critics' ratings: black lead v/s white lead actors

	(a)	(b)	(c)
R-Squared	0.046	0.281	0.052
Parameter:	Estimate (St. Dev)	Estimate (St. Dev)	Estimate(St. Dev)
BlackLeadj	-2.24 (1.76)	-0.14 (1.90)	-1.26 (2.77)
$Budget_j$	0.05 (0.016)**	0.04 (0.02)*	0.05 (0.02)**
$P\&A_j$	0.22 (0.07)**	0.14 (0.07)"	0.21 (0.07)**
$Bankability_j$	…	…	overall significant
$AudienceRating_t$	…	…	…
$CriticsChars_i$	overall significant	overall significant	overall significant
Newspaper Fixed	…	…	…
$MarketChars_t$	…	…	…
Month Fixed	…	…	…
$MovieChars_j$	…	overall significant	…
	(d)	(e)	(f)#
R-Squared	0.124	0.129	0.330
Parameter:	Estimate	Estimate	Estimate
BlackLeadj	-3.65 (1.76)*	-0.52 (1.89)	-6.09 (2.63)*
$Budget_j$	0.04 (0.02)*	0.06 (0.02)**	0.05 (0.02)"
$P\&A_j$	0.23 (0.07)**	0.29 (0.08)**	0.30 (0.11)*
$Bankability_j$	…	…	overall significant
$AudienceRating_t$	1.74(0.19)**	…	4.66 (0.93)**
$CriticsChars_i$	overall significant	overall significant	overall not
Newspaper Fixed	overall significant	…	overall not
$MarketChars_t$	overall not	…	overall significant
Month Fixed	…	overall significant	overall significant
$MovieChars_j$	…	…	overall significant

Significance levels: 1%:** ; 5%:*; 10%: "

#: IV estimates

4.4.4. Ratings model with control for black cast and black v/s white leads

Next we specify a model which considers how critics rate movies with black actors in any of the top-five roles, by controlling for the race of each actor, by adding four additional race dummies to the specifications in 4.4.3.

Table 3.12 shows the results of each of the specifications (a) to (f) of section 4.4.2. with the race dummies for each cast member included.

The results in table 3.12 indicate that the race of the lead actor is correlated with that of other cast members, since the estimated coefficient of the rating differential due to African American leads is now significant: Column (a) shows that after controlling for marketing and production expenditures, critics' ratings are race-dependent. While they rate movies with African Americans lead actors lower than those with white leads, critics also tend to rate movies with African Americans actors who play supporting roles higher compared to movies with white actors in supporting roles. In column (b), we control for movie attributes and find that the differential mean coefficient for African American lead actors is no longer significant, but that critics still have a tendency to rate movies where African Americans play the fourth supporting role comparatively higher than when these roles are played by white actors. In column (c), (d) and (e) where we control for actor bankability, audience characteristics and exogenous time factors respectively, our findings align with those from column (a): movies with African American lead actors suffer from comparatively lower ratings, but those with African American actors in supporting roles earn a premium. In column (f) we correct for endogeneity of audience tastes as in section 4.4.3. and our findings align with those of column (a)

Table 3.12: Parameter estimates for model of critics' ratings: black cast v/s white cast members

	(a)	(b)	(c)
R-Squared	0.067	0.285	0.074
Parameter:	Estimate (St. Dev)	Estimate (St. Dev)	Estimate(St. Dev)
BlackLeadj	-4.77 (1.93*)	0.56 (2.09)	-5.28 (1.97)**
$BlackSupp1_j$	-0.81 (1.95)	-1.96 (2.13)	-0.27 (1.98)
$BlackSupp2_j$	10.23 (2.02)**	0.54 (2.13)	10.77 (2.06)
$BlackSupp3_j$	2.13 (2.07)	-3.97 (2.34)"	1.61 (2.09)
$BlackSupp4_j$	4.33 (2.03)**	3.96 (2.02)*	4.95 (2.06)*
$Budget_j$	0.06 (0.016)**	0.04 (0.02)**	0.06 (0.02)**
$P\&A_j$	0.20 (0.07)**	0.14 (0.07)"	0.18 (0.07)**
$Bankability_j$	…	…	overall significant
$AudienceRating_t$	…	…	…
$CriticsChars_i$	overall significant	overall significant	overall significant
Newspaper Fixed	…	…	…
$MarketChars_t$	…	…	…
Month Fixed	…	…	…
$MovieChars_j$	…	overall significant	…
	(d)	(e)	(f)[#]
R-Squared	0.126	0.156	0.330
Parameter:	Estimate	Estimate	Estimate
BlackLeadj	-6.66 (1.96)*	-5.13 (2.14)	-15.50 (4.21)**
$BlackSupp1_j$	1.02 (1.97)	0.36 (2.28)	15.64 (4.76)**
$BlackSupp2_j$	8.32 (2.04)**	11.50 (2.11)**	9.58 (3.58)**
$BlackSupp3_j$	3.48 (2.10)"	4.50 (2.30)"	0.75 (3.52)
$BlackSupp4_j$	3.51 (2.02)"	6.93 (2.20)**	2.65 (2.79)
$Budget_j$	0.04 (0.02)*	0.06 (0.02)**	0.06 (0.03)*
$P\&A_j$	0.22 (0.07)**	0.31 (0.08)**	0.40 (0.13)**
$Bankability_j$	…	…	overall significant
$AudienceRating_t$	1.75(0.19)**	…	6.03 (1.31)**
$CriticsChars_i$	overall significant	overall significant	overall not
Newspaper Fixed	overall significant	…	overall not
$MarketChars_t$	overall not	…	overall not
Month Fixed	…	overall significant	overall significant
$MovieChars_j$	…	…	overall significant

Significance levels: 1%:** ; 5%:*; 10%: "

[#]: IV estimates

4.4.5. Analysis of Difference between critics' and audience ratings

Given the potential endogeneity concerns in sections 4.4.3. and 4.4.4., and to address possibility that our instrument for the audiences' ratings are unsuitable, we test the presence of racial bias in a regression of the difference between critics' and audience ratings. Specifically, we calibrate audience ratings (which are on a scale of 0-12 in the above analyses) so that they are on the same scale as critics' ratings, (i.e. 0-100) and compute the difference in ratings between critics and their respective audiences.

Next we run equation (1) using specification (f) of sections 4.2.1 and 4.2.2 with the difference in ratings as the dependent variable, and omitting audience ratings as an explanator. Finally another endogeneity concern would arise due to the inclusion of the control for artistic appeal if critics' ratings influence their votes for critics' awards. In separate equations, we therefore estimate racial bias by first including and then omitting the control for artistic appeal. Table 3.13 presents the results.

Results in table 3.13 are consistent with our previous findings: Specifically, we find that the presence of an African American lead causes critics to award a lower rating than their corresponding audiences, and that the presence of African Americans in supporting roles causes them to rate movies higher on average. Omitting the control for artistic appeal does not change these results.

Table 3.13: Parameter estimates for difference between critics and consumers

	(a)	(b)
R-Squared	0.235	0.262
Parameter:	Estimate (St. Error) Significance	Estimate (St. Error) Significance
BlackLeadj	-9.28 (3.17)**	-20.64 (3.50)**
$BlackSupp1_j$	…	21.89 (3.64)**
$BlackSupp2_j$	…	13.13 (3.42)**
$BlackSupp3_j$	…	1.75 (4.01)
$BlackSupp4_j$	…	1.94 (3.20)
$Budget_j$	0.02 (0.03)	0.05 (0.03)
$P\&A_j$	0.48 (0.13)**	0.51 (0.12)**
$Bankability_j$	overall significant	overall significant
Artistic Appeal	3.16(1.11)**	0.91(1.15)
$CriticsChars_i$	overall not significant	overall not significant
Newspaper Fixed Effects	overall not significant	overall not significant
$MarketChars_t$	overall not significant	overall not significant
Month Fixed Effects	overall significant	overall significant
$MovieChars_j$	overall significant	overall significant
	(c)	(d)
R-Squared	0.23	0.268
Parameter:	Estimate (St. Dev) Significance	Estimate (St. Dev) Significance
BlackLeadj	-9.44 (3.15)**	-21.04 (3.44)**
BlackSupp1j	…	22.30 (3.58)**
BlackSupp2j	…	13.94 (3.24)**
BlackSupp3j	…	1.51(3.99)
BlackSupp4j	…	2.05 (3.18)
Budgetj	0.02 (0.03)	0.05 (0.03)
P&Aj	0.57 (0.12)**	0.54 (0.12)**
Bankabilityj	overall significant	overall significant
Artistic Appeal	…	…
CriticsCharsi	overall not significant	overall not significant
Newspaper Fixed Effects	overall not significant	overall not significant
MarketCharst	overall not significant	overall not significant
Month Fixed Effects	overall significant	overall significant
MovieCharsj	overall significant	overall significant

Significance levels: 1%:** ; 5%:*; 10%:”

4.4.6. Sales Model

Having established that individual critics appear to be biased against African American leads and that they appear to favor African Americans in supporting roles, we next seek an understanding of the economic impact of overall critics' reviews on movie sales. As is standard in the literature on consumer choice, and following the exposition in Chapter 1 of this dissertation, we use a random coefficients specification (McFadden 1973; Jain et al. 1994; Rossi et al. 1993; Keane 1997), and specify the following hedonic market share equation:

$$\text{Ln}\ (\text{Share}_{jt}\ /\ \text{Share}_{0t}) = \alpha_0 + \alpha_1\ \text{Black}_j + \alpha_2\ \text{Critics}_j + \alpha_3\ \text{Critics}_j{*}\text{Black}_j + \alpha_4\ \text{UserReviewj} + \alpha_5\ \text{Bankability}_j + \alpha_6\ \text{CriticsCountj} + \alpha_7\ \text{UserCountj} + \alpha_8 \text{MovieChars}_j + \alpha_9\ \text{Month}_t + \varepsilon_{ijt} \quad (2)$$

$Share_{jt}$ / $Share_{0t}$ measures ticket sales for movie *j* in week *t* relative to the U.S. population which chooses not to see a movie in week *t*. We only track movies in weeks where they are screened wide (i.e. in more than 600 theaters nationally). Since ticket sales and hence movie sales are very low for movies not screening wide, we do not expect such truncation to bias our results. *$Black_j$* is a vector of dummies which controls for the race of each of the top-five cast members of a movie. *$Critics_j$* represents the average critics' review for movie *j* and *$Critics_j$*$Black_j$* represents the vector of interactions between average critics' reviews and *$Black_j$*. *$UserReview_j$* is the average consumer review for movie *j*. *$CriticsCount_j$* and *$UserCount_j$* respectively measure of the number of critics and consumers who review movie *j*; these variables act as proxies of popularity of the movie with each group. *$Bankability_j$* and *$Month_t$* are as defined in section 4.2. *$MovieChars_j$* includes controls for the number of movies competing for market share in any given week, as well as the number of weeks lapsed

since a movie's release (both a linear and a logarithmic term are used to account for the speed at which market share decays in the course of a movie's run (Ainsley et. al 2005)).

We first run equation (2) with a control for the race of the lead actor only, (i.e. the vectors $Black_j$ and $Critics_j{*}Black_j$ are both *nx1*, where n is the number of movies in our sample). We estimate this equation both with and without the exogenous time controls. Results are in columns (a) and (b) of table 13. Next we run equation (2) with controls for the race of all top-five actors, (i.e. the vectors $Black_j$ and $Critics_j{*}Black_j$ are both *nx5).* Again we estimate this equation both with and without the exogenous time controls. Results are in columns (c) and (d) of table 3.14.

Table 3.14: Parameter estimates for market share equations

	(a)	(b)
R-Squared	0.714	0.730
Parameter:	Estimate (St. Dev) Significance	Estimate (St. Dev) Significance
$BlackLead_j$	0.802 (0.213)**	0.697 (0.213)**
$BlackSupp1_j$	…	…
$BlackSupp2_j$	…	…
$BlackSupp3_j$	…	…
$BlackSupp4_j$	…	…
$Critics_j$	0.016 (0.002)**	0.018 (0.002)**
$Criticsj{*}BlackLead_j$	-.012 (0.004)**	-0.010 (0.004)*
$Criticsj{*}BlackSupp1_j$	…	…
$Criticsj{*}BlackSupp2_j$	…	…
$Criticsj{*}BlackSupp3_j$	…	…
$Criticsj{*}BlackSupp4_j$	…	…
$Bankability_j$	overall significant	overall significant
$AudienceReview_t$	0.015 (0.015)	0.035 (0.015)*
$CriticsCount_j$	0.006 (0.008)	0.006 (0.008)
$UserCount_j$	0.000 (0.000)**	0.000 (0.000)**
Movie Characteristics	overall significant	overall significant
Month Fixed Effects	…	overall significant

Table 3.14. (continued)

	(c)	(d)
R-Squared	0.717	0.732
Parameter:	Estimate	Estimate
BlackLeadj	0.718 (0.257)**	0.694 (0.255)**
$BlackSupp1_j$	0.616 (0.219)**	0.497 (0.219)*
$BlackSupp2_j$	-0.322 (0.224)	-0.535 (0.224)*
$BlackSupp3_j$	0.357 (0.258)	0.352 (0.255)
$BlackSupp4_j$	-0.249 (0.239)	0.106 (0.240)
$Critics_j$	0.016 (0.002)**	0.018 (0.002)**
Criticsj*BlackLeadj	-0.011 (0.005)*	-0.011 (0.005)*
Criticsj*BlackSupp1j	-0.010 (0.004)*	-0.008 (0.004)"
Criticsj*BlackSupp2j	0.006 (0.004)"	0.009 (0.004)*
Criticsj*BlackSupp3j	-0.006 (0.005)	-0.006 (0.005)
Criticsj*BlackSupp4j	0.007 (0.004)"	0.007 (0.004)
$Bankability_j$	overall significant	overall significant
$AudienceReview_t$	0.015 (0.015)	0.036 (0.015)*
$CriticsCount_j$	0.012 (0.008)	0.011 (0.008)
$UserCount_j$	0.000 (0.000)**	0.000 (0.000)**
Movie Characteristics	overall significant	overall significant
Month Fixed Effects	…	overall significant

Significance levels: 1%:** ; 5%:*; 10%:"

In all four specifications we find evidence that movies with black leads appear to earn a premium from audiences (the coefficient on $BlackLead_j$ is positive and significant at the 1% level in all cases). From specifications (c) and (d), we find that movies with black actors in first supporting roles appear to earn a market premium as well.

In all four specifications, critics' ratings are positively correlated with market shares: for every one point increase in average rating, the impact on market share is between 1.6% and 1.8 %. However this correlation decreases in the presence of a black lead (the coefficient on $Critics_j*BlackLead_j$ is negative and significant at the 1%

level in all four cases): the net correlational impact of critics' ratings on shares of movies with black leads lies between 0.4% and 0.8%.

We propose several explanations as to why the main effects of the black cast members (both lead and supporting) are positive in the market share equation. First it is possible that black actors have to go through a much more rigorous selection process to get cast. As such, while bankability may capture their commercial viability, it may not be capturing the fact that they are better at acting their parts. Second, since we are looking at an aggregate sales model, it is possible that movies with black actors are particularly successful at drawing the black audience: Fischoff *et al.* (1998) show that movies with black movie stars rank high on the all-time favorite lists of movies of the African American race group. In addition statistics compiled by the MPAA in regards to the demographics of movie audiences show that African Americans watch more movies per capita (MPAA 2008). Both these factors could account for the success of movies with black stars with the African American audience. The MPAA also documents that the greatest proportion of movie-goers fall in the 17-24 age group. Since consumers in this age-group may have grown up in a much more racially progressive environment, where an increasing number of African Americans hold important positions in society, (e.g. Barrack Obama, Colin Powell, Oprah Winfrey), it is possible that they award a premium to movies which portray African Americans in lead roles since this may be representative of a cultural ideal that they aspire to.

A possible explanation for the impact of critics' ratings on market share being lower for movies with African Americans may be that black audiences disregard critics' reviews in deciding between movies, and/or that even white audiences do not assign as much weight to critic's reviews for movies with black leads because they perceive critics to be biased in their judgment of African American actors. Since we have controlled for consumer reviews, we can attribute the reduction in market share due to critical bias against black leads to an influence effect: Shares are up to 2% lower in movies with African Americans in both the lead and first supporting roles due to critical bias against African Americans (equation (c)). Given that the movies in our sample grossed \$60M on average at the Box Office and that sales and shares are highly correlated, critical bias translates into a loss in revenue of up to \$1.2M.

3.5. Conclusion

Despite the inclusion of the controls for production and marketing expenditures, type of movie (i.e. genre, MPAA rating, emotional content, artistic and popular appeal), a measure of how good the actors are, audience preferences and time-contingent preferences of critics, we find that critics' ratings for movies with African American leads are up to 6 points lower. We also find evidence suggesting that critics seem to favor movies where African Americans are featured in supporting roles as opposed to lead roles. Aside from the potential social welfare costs of critics exhibiting biases against African American actors, there are also economic costs to the tune of up to \$1.2M which are potentially incurred by movies with African American cast members. Our results are striking because critical reviewing occurs in a very public arena where potential scrutiny by independent observers should wipe out racial biases in competitive equilibria, and because newspapers tend to display liberal biases which do not readily align with race based discrimination.

We suggest two theories that might help explain racial discrimination by critics: Taste-based discrimination and implicit discrimination. While taste-based discrimination is explicit and arises if African American actors are a source of disutility for critics, implicit discrimination can arise if critics have subconscious attitudes which create expectations that relegate roles played by African Americans to supporting positions. We attempt to rule out implicit discrimination by controlling for time variables which potentially mediate implicit discrimination (Bertrand et al. 2005). However subconscious attitudes could be time invariant, e.g. by virtue of their training and/or exposure to films released in decades prior to the 90's critics could be accustomed to movie-formulae which only cast African Americans in subordinate roles. In this case both taste-based and implicit discrimination could be potential explanations for the racial differences in ratings which we observe.

There are several ways in which this study could be extended. For example information about earnings of individual movie stars (which we unfortunately do not have access to for the entire set of actors who act in movies in our sample) could be used to supplement our 'bankability' measures. Another logical extension would be to investigate critical bias in favor or against other minority groups including female or Jewish actors for instance. Finally demographic information about movie critics could be used to identify whether the extent of discrimination is uniform across all movie critics or whether it varies by race of the critic as well.

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