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Essays on Brand Competition

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Essays on Brand Competition

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An Abstract of
A dissertation submitted to the Faculty of the
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Abstract

Essays on Brand Competition

By Anthony Koschmann

The objective of this dissertation is to investigate brand competition. The dissertation examines the strategies of brand competition across different industries and product lifecycles. Essay 1 investigates the performance of co-branded products, which feature two brands in one product offering. Theory is developed that explains brands as having two types of overall consumer judgments, functional and emotional valuations, which interact along similar or different dimensions. The research utilizes aggregate panel data of consumer packaged goods. Essay 2 explores the supply side of illegal copies of brands. A theoretical framework links together four components of the market: legal demand, legal supply, illegal demand, and illegal supply, contesting whether the illegal side acts as a pure substitute. The analysis separates effects in the launch from post-launch periods of a class of information goods. Essay 3 presents the perspective that brands in a mature category face challenges in growing the brand. A focal tool used by managers is to introduce new branded variations to retain brand loyalty but also create differentiated product offerings. However, these offerings might create variety-seeking within the brand family. Studied here is whether households are loyal to a particular variety of the brand, or engage in switching within the brand.

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Chapter 1

Overview

Brands are assets in the firm's brand portfolio, managed to create and maintain differential advantage over competitors. Present day challenges, though, require managers to consider threats beyond that of the competition. Popular press articles highlight changing demographics, the increasing quality of private label offerings, technological transformations, product proliferation, and a host of other concerns that threaten the brand's ability to compete.

Rather, the function of the brand is to *mitigate* competitive effects by creating a distinct offering that is not easily replicated by competitors, insulating the brand from commoditization. However, even creating a distinct value proposition in the mind of the consumer does not guarantee success for the brand. The reader can surely conjure a failed brand that had carved out an identity related to low prices, unique advertising, or cutting-edge products.

Brand competition is often discussed in the form of the brand competing against direct, immediate opposition. For every Coke, Ford, Windows, or McDonalds there is a respective Pepsi, Chevrolet, Mac, or Burger King. This inter-firm rivalry is the focal component of Porter's 5 Forces for the competitive intensity of an industry. In the narrative sense, this 'man-versus-man' casts the brand in stark terms of an 'us versus them' mentality in which brands cast themselves as the protagonist to their consumer base. In consideration of this, less examined is the struggle of the brand with itself. That is, the brand undertakes strategies and tactics that may be self-imposing competitive pressures – it may be engaging in *intra-firm* rivalry.

This dissertation explores this internalized competition from three views: how the brand is competing with itself, its family, and its friends. Indeed, the brand manager's strategic focus has to extend beyond direct competition. Inquiry into these competitive actions challenges the prevailing conventional wisdom surrounding competitive pressures.

For instance, Essay 1 examines the ability of the brand to compete with a branded partner as an alliance. By including a second brand in its product formulation, the brand aims to create a distinct offering in the marketplace, signaling quality, and growing its market footprint to consumers who might not usually purchase the product category. These 'co-brand' ventures represent a growing part of the managerial toolkit: noted in the essay is that this strategy has recently grown from 3.5% to 6% of all new product launches of consumer packaged goods. While co-brands have primarily been studied as a phenomena of consumer perceptions in lab studies, empirical research is lacking: two prior studies have examined the effect of co-brand choice in limited contexts of two or three products. Using a longitudinal dataset covering fourteen years, Essay 1 is the first of its kind to provide large-scale market evidence of co-brand performance: 126 products across 49 product categories. The performance of these co-branded products – when brand, category, and macroeconomic conditions are accounted for – is driven by how consumer perceptions of both brands interact with each other. Using a generalized estimation equation, the findings suggest that brands which are too similar in their perceptions have a negative effect on market performance, while complementary brands have no significant effect – contradicting the belief that consumers have a preference for complementarity. The research disputes the view that a brand manager should seek out the best partner possible. As the maxim goes, “Nobody ever got fired for hiring IBM” does not hold here: strong brands should seek out weaker partners and vice versa.

Essay 2 looks at the effects of illegal copies on brand performance – or, how the brand competes against itself. The prevailing view is that these illegal variants represent cannibalization, hindering brand performance. An alternative view is that there may be positive effects, such as a sampling mechanism for information goods or even to inspire aspirational purchases as seen in luxury goods. A challenge in research of this kind is that observing illegal activity is difficult. Using data from the motion picture industry, this study explores whether illegal versions are substitutes, complements, or both in influencing brand performance. Although prior research in film piracy has created a substantial pool of research, two limitations persist. The first is that there is no consensus on whether illegal copies hurt or help sales – creating two camps (i.e., cannibalization versus sampling). The second is that prior research has focused on the demand side. By omitting the supply side of the market, results may be biased. As such, this sets up that there are four components to the motion picture market: legal and illegal supply, and legal and illegal demand. As the essay notes, one prior research study has tried to examine the interdependence to all four market components, albeit with strong assumptions and issues with measurement. The data here covers 177 movies released in the U.S. over a sixteen month period, empirically testing the four market components using simultaneous equations. Among the key findings are that, on average, illegal demand (piracy downloads) has a negative effect on film performance in the opening week but no effect in the post-launch weeks. This timing consideration helps to explain why both camps are right: piracy both hurts and does not hurt revenues. Furthermore, piracy supply has a positive, reinforcing, lagged effect on legal supply and is not purely a substitute outlet for the genuine good.

Essay 3 investigates the role that extensions of the brand have on creating loyalty or variety-seeking within the brand. Introducing branded variants is a common practice, particularly in mature categories where other marketing mix tools are either limited or have peaked in effectiveness. As such, new product innovations help the brand ward off private label competitors. Yet, the idea here is whether branded varieties create sibling rivalry, inducing competitive effects within the brand family. While variety-seeking and brand loyalty are substantially researched areas, little research has investigated these effects in the context of the 'branded house' strategy in which the brand portfolio extends the brand name to all its products. Consistent with the concept of brand architecture, the propositions ask whether the lowest level of the branded varieties (or modified brands) exhibit variety-seeking or engender loyalty to particular variety of the brand. Using household level purchase data of two large brands in two related product categories, Markov chain switching finds that loyalty to particular offerings of the brand are relatively high. The volume loyalty is in excess of 90% for the flagship branded offering, but even volume loyalty of 80% or more is observed for most modified brands. While brand managers utilize new flavors or pack sizes to invigorate a mature brand, the essay shows that consumers largely stick to one flavor. Additionally, the effect is more pronounced among its heavier users, who make up a disproportionately large amount of the brand's sales volume.

Chapter 2

Essay 1: Secondary Brand Functional and Emotional Valuations as Moderators of the Effect of the Primary Brand on Co-Brand Sales

2.1 Introduction

Co-branded products are increasingly important to a firm's product portfolio, having recently increased from 3.5% to 6% of all new product launches (Schultz 2014). Under co-branding, the secondary brand brings its brand equity to join that of the primary brand and its brand equity. Different from brand extensions, co-branded products compete in the focal (primary) brand's existing product category. Rather than *exporting* its equity to a new product category, the primary brand *imports* the brand equity of the secondary brand. Further, unlike the inclusion of a brand that acts only as a component or ingredient (i.e., Hemi engines in Dodge trucks; Funfetti sprinkles in Pillsbury baking mixes), a co-branded product features two stand-alone brands. A deeper understanding of co-brand performance can help managers decide which partner brands to consider. Despite the growing importance of co-branding, few studies have examined co-brand performance in the marketplace.

Examined in this article are the effects of consumer valuations of the primary and secondary brands on co-brand performance. Valuations are higher-order, summary judgments of a brand. Consistent with the belief that brands provide two broad types of benefits to consumers – functional and emotional (e.g., Chernev, Hamilton, and Gal 2011; Farris 2015; Gill 2008; Keller 1993; Park, Milberg, and Lawson 1991), overall functional performance (*functional valuation*) and the overall emotional connection with the consumer (*emotional valuation*) are the core attitudinal components that each brand brings to a product (Sheth and Mittal 2004).

In co-branding, the primary brand and secondary brand come together in one product, each bringing their functional and emotional valuations. Prior research is extended on consumer perceptions of brand and product combinations (e.g., Newmeyer, Venkatesh, and Chatterjee 2014; Park, Jun, and Shocker 1996; Swaminathan et al. 2015) to develop a model that describes how primary brand valuations and secondary brand valuations work together to affect co-brand performance. These valuations affect co-brand performance separately and through synergies created by having a product with two brands. There are four interactions. Two interactions describe commonality effects (i.e., the functional valuation of both brands and the emotional valuation of both brands). Two interactions describe complementarity effects (i.e., the functional valuation of the primary brand and the emotional valuation of the secondary brand, and vice versa). The theory posits that the commonality interactions contribute negative synergy, while the complementary interactions contribute positive synergy.

This article is organized as follows: First, prior studies of co-branding and consumer valuations of brands are reviewed. Next, a theoretic model that describes how brand valuations interact in the context of co-brands is presented. We test this theory using a generalized estimation equation that combines brand valuations with observed sales. The results show that the secondary brand's functional and emotional valuations have a positive effect on co-brand sales performance. Yet, the interaction of valuations on common dimensions (for instance, the functional valuation of both the primary and secondary brands) brings negative synergy. That is, it attenuates the effect of the secondary brand. Furthermore, different than findings from experimental studies of consumer perceptions of co-brands, complementary valuations do not have a significant effect on co-brand sales performance. A simulation of these results finds that co-brands perform best when the primary brand selects the "right" partner, rather than the strongest partner on all dimensions. This concludes with a discussion of the empirical findings, implications for marketing academics and for managers, and suggestions for future research.

2.2 Background

Prior research on co-branding has largely focused on examining consumer perceptions of co-branded products with an eye towards understanding brand attitudes and intentions. Of particular interest is how consumers view the relationship between the primary and secondary brands, often as it relates to "fit". A fundamental question of interest is whether brands which are similar versus brands that are different than each other can achieve better fit in the eyes of consumers (e.g., Desai and Keller 2002; Mazodier and Merunka 2014; Park, Jun, and Shocker 1996; Swaminathan et al. 2015; Van der Lans, Van den Bergh, and Dieleman 2014). A challenge for researchers has been how to clearly define and operationalize "fit" (Helmig, Huber, and Leeflang 2008). On one hand, some scholars have argued that the more similar brand partners are, the greater the perceived fit (Simonin and Ruth 1998). On the other hand, brands which complement each other are viewed as having greater perceived fit (Van der Lans, Van den Bergh, and Dieleman 2014).

In summary, the behavioral literature suggests that consumer perceptions of co-brands are influenced by perceptions of the individual brands, but leaves open how the brands fit together. Less examined are field studies of co-brands. There, studies of co-brand sales performance have examined two or three co-brands, finding that co-branding can lead to higher choice share for the primary and secondary brands (Desai, Gauri, and Ma 2014; Swaminathan, Reddy, and Dommer 2012). The goal of this research is to present and test a framework that explains how high-level, overall judgments of brands interact to affect the sales performance of co-branded products. The next section presents the framework and hypothesized effects.

2.3 Theoretical Development

In general, brands provide two types of broad benefits that are similar in concept across authors but whose labels can vary: tangible and intangible (Farris 2015), functional and experiential (Keller 1993), functional and symbolic (Chernev, Hamilton, and Gal 2011), function-oriented and prestige-oriented (Park, Millberg, and Lawson 1991), and utilitarian and hedonic (Gill 2008). Tangible judgments reflect product attributes and key differences that distinguish the brand in its performance in use. Intangible judgments include emotions, personality, and aspirations that the brand evokes. Hereafter, these overall brand evaluations are referred to as *functional valuation* and *emotional valuation*, respectively.

Both the primary brand and the secondary brand bring a functional valuation and an emotional valuation. These interact in a co-branded relationship. The next section develops hypotheses for how these interactions influence co-brand sales performance.

2.3.1 Co-Branding and Secondary Brand Valuations

Co-branded products are one of three types depending on the role of the secondary brand: ingredient, licensing/endorsements, and third-party (Keller 2013). Ingredient co-brands utilize the secondary brand to alter the product's composition, either by adding something new to the primary brand or improving on an existing attribute. For instance, Tide with Downy adds a new feature to Tide detergent (i.e., Downy fabric softener). An example that upgrades an existing ingredient is Betty Crocker brownie mix with Hershey's chocolate, where Hershey's chocolate acts as an upgrade from the existing unbranded chocolate. Licensing and third-party co-brands lend a name, likeness, or reputation to a product (for example, cartoon characters or a trade seal of approval), but do not change the fundamental product composition. These secondary brands do not bring a functional benefit (i.e., cartoon characters generate emotional benefits in consumers, but add no new functionality to a product). The brand manager for Cap'n Crunch breakfast cereal, for example, could weigh strategies of featuring a licensed character on its box (e.g., Superman), to include another brand as an ingredient (e.g., Air Heads candy flavors), or to feature the logo of an endorsement or its rating by a third-party (e.g., certain nutritional or sourcing benchmarks).

In addition to the type of co-brand relationship, managers consider which partner brands to pursue. Prior research has highlighted the risks of a secondary brand that might be weaker or create negative spillover effects (Cunha, Forehand, and Angle 2015;

Geylani, Inman, and Ter Hofstede 2008; Lafferty and Goldsmith 2005; Simonin and Ruth 1998). Even if a secondary brand is perceived positively, there might not be appropriate fit with the primary brand. An additional concern is whether the co-branded product will simply cannibalize sales of the primary brand.

Given these managerial considerations, the secondary brand carries potential benefits to be weighed against the risks. The inclusion of a secondary brand creates a point of differentiation and signals an assurance of the primary brand's quality (Rao, Qu, and Ruekert 1999). The secondary brand provides increased brand equity (Desai and Keller 2002). Furthermore, the co-brand can expand markets by appealing to consumers who normally do not purchase in the product category, as familiarity with the secondary brand may induce consumers to try the co-branded product. By enhancing the value proposition, consumers are more likely to purchase the co-brand, and leading to positive sales performance.

When the co-brand offers added functional (emotional) valuation, consumers should value the co-brand more. As such, the addition of the secondary brand's functional and emotional valuations should have a direct, positive impact on sales performance. All else equal, then, the addition of a secondary brand and its valuations should be associated with higher product performance.

H1a: Higher secondary brand functional valuation is associated with higher co-brand sales performance.

H1b: Higher secondary brand emotional valuation is associated with higher co-brand sales performance.

While the secondary brand adds its functional and emotional valuations separately to the co-brand, it also interacts with the functional and emotional valuations of the primary brand. This leads to four interactions. Two of these interactions involve a common dimension (e.g., the primary brand's functional valuation with the secondary brand's functional valuation). The other two interactions involve complementary dimensions (e.g., the primary brand's functional valuation with the secondary brand's emotional valuation). The following sub-sections describe these interaction effects.

2.3.2 Co-Branding and Commonality Effects

Managers expect brands in a co-branding relationship to achieve some degree of fit, realizing positive synergy between the combination (i.e., a positive coefficient reflecting super-additivity of the secondary brand: Davis and Thomas 1993). Since fit can explain when brands are more similar (Simonin and Ruth 1998), a commonality strategy is when two brands have a congruent or similar association. Because each brand in a co-branded relationship has its own functional and emotional valuations, commonality effects describe the interaction of the functional valuations of both brands and the emotional valuations of both brands.

Commonality effects might not yield expected gains. A congruent association between brands, such as a hedonic brand like Apple's iPod with a hedonic service like SiriusXM satellite radio, will be subject to diminishing utility returns (Gill 2008). Related to this are potential ceiling effects: if both brands already provide functional (emotional) valuations, there may be a natural ceiling to just how much extra valuation could be gained. Products approaching the end of an attribute spectrum (such as a ceiling effect) can be seen as more extreme options. Extremeness aversion (Simonson and

Tversky 1992) suggests consumers will prefer choices that are balanced rather than options at the far ends of the spectrum.

Commonality also potentially reduces differentiation, which has an adverse impact on the ability to charge a price premium or enhance revenues (Desai et al. 2001). If the primary and secondary brands have similar valuations, the co-branded product may be seen as too similar to the existing brands. For example, Betty Crocker baking mix with Hershey's chocolate could be viewed as very similar to just Betty Crocker baking mix with unbranded chocolate. This similarity effect (Huber, Payne, and Puto 1982) suggests that a product offering that is viewed as too similar to other offerings does not distinguish itself, and is instead grouped with its like offerings. This enlarges the consideration set, decreasing the likelihood of purchase. Given this consumer research, brands will find it difficult to achieve synergy from similar valuations.

H2a: As the secondary brand's functional valuation increases, there is a weaker relationship between the primary brand's functional valuation and co-brand sales performance.

H2b: As the secondary brand's emotional valuation increases, there is a weaker relationship between the primary brand's emotional valuation and co-brand sales performance.

2.3.3 Co-Branding and Complementarity Effects

Unlike commonality effects, a complementarity strategy suggests two brands combine dissimilar items, usually as a means to 'fill in' what the other may be missing. Along these lines, functional and emotional valuations could also be complementary while not necessarily trading off one for the other. Complementary brands are viewed more favorably than brands that are not complementary, such as pairing the perceived richness of Godiva chocolates with the nutritional value of Slim-Fast (Park, Jun, and Shocker 1996).

As a contrast to extremeness aversion, where consumers shy away from extreme options, an attribute-balance approach suggests consumers prefer a balancing of features (Chernev 2004; Dhar and Simonson 1999). If competing choices have shared features, consumers will ignore the shared features and focus on the differences (Dhar and Sherman 1996). For co-brands, each brand has both a functional and emotional valuation, which are not entirely trade-offs (i.e., a brand can be perceived as doing well on both, one, or neither dimension). An example that highlights complementary effects would be the functional valuation of Klondike frozen novelties with the emotional valuation of Oreo cookies (and vice versa). Nevertheless, the interaction is highly complementary when each brand scores above average in complementary dimensions. For example, Eggo's high functional valuation combined with Oreo's high emotional valuation would be highly complementary. In contrast, the preceding example of Klondike with Oreo would be moderately complementary since Klondike's functional valuation is weaker.

In consideration of these effects, consumers should view complementary associations positively. Hence, functional and emotional valuations interacting together should amplify co-brand sales performance.

H3a: As the secondary brand's functional valuation increases, there is a stronger relationship between the primary brand's emotional valuation and co-brand sales performance.

H3b: As the secondary brand's emotional valuation increases, there is a stronger relationship between the primary brand's functional valuation and co-brand sales performance.

2.4 Methodology

The model development begins by detailing the data, then describing the model, a generalized estimation equation (GEE). Our framework of co-brand performance is consistent with other brand sales performance frameworks (e.g., Ailawadi, Lehmann, and Neslin 2003), in which sales are driven by brand factors, product category factors, and macroeconomic factors. Central to our framework is that the primary brand valuations and secondary brand valuations affect co-brand sales performance. Figure 1 presents this framework, focusing on the primary brand and secondary brand valuations (as both main effects and interactions).

2.4.1 Co-Brand Performance Data

To test the hypotheses of commonality and complementarity effects, the context of consumer-packaged goods (CPG) is examined. Brand and product performance data are from the *Marketing Fact Book*, distributed by IRI through its Builders Suite program. The annual data are category, category type, and product level aggregate measures from a panel of approximately 60,000 U.S. households. This presents aggregate actual prices paid in approximately 300 product categories across multiple types of shopping outlets (i.e., grocery stores, drug stores, convenience stores, etc.). Products purchased by at least

0.5% of households are published by IRI. The data presents single-point measures of average consumer activity during the course of the calendar year.

Two considerations guided the inclusion of products into the data set. First, the brand had to exist as both a co-brand and solo-branded offering (i.e., as a stand-alone product). Some brands only exist as co-branded product. For example, Citrus World sells frozen orange juice concentrate under the name ‘Citrus World Donald Duck’, co-branded with the Disney character Donald Duck. However, there are no observations for just Citrus World in the IRI data. As such, instances of operating only as a co-branded product are excluded. Second, the primary and secondary brands are brands at the product level. By this, the co-branded relationship works where the consumer associates the brand with the product, and not the corporate brand (Smith and Park 1992). A consumer shopping for breakfast cereal, for example, is looking for a particular product brand of cereal, such as Special K or Froot Loops, and not General Mills or Kellogg’s. Instances where only a corporate brand appears as a co-brand are excluded. Product categories were defined by IRI.

The data set covers a fourteen year period of annual data, from 1998-2011, the most recent year of the IRI data. A total of 126 ingredient co-branded products were identified. This comprised 60 primary brands; including secondary brands, this tallied 134 unique brands. These 126 co-branded products encompassed 49 product categories, generating 490 observations (product-category-years). If a brand is sold in multiple categories, it is examined within each category separately. For example, Betty Crocker makes fruit snacks and baking mixes, so it may have category specific brand valuations. To validate the data, two judges were given the same random sample of 20% of the IRI data to determine whether an entry should be classified as a co-brand or not. The inter-coder reliability was 99%, with the difference resolved through discussion.

2.4.2 Consumer Mindset Data

To measure brand valuations, surveys were administered to an online pool of U.S. consumers. The survey was pilot tested four times with consumer focus groups for understandability and instrument selection, with the final survey instrument administered to 542 consumers (526 usable responses after the attention check). Each respondent evaluated 8 different brands. A sample question from the survey instrument is shown in Appendix 1. Survey questions were based on instruments from prior consumer research (Lai 1995; Keller 2013; Park et al. 2010). Following Bergkvist and Rossiter (2007), single-item measures were used to assess functional and emotional valuations of individual brands. A single-measure can capture a multitude of emotions in one higher-order scale, such as the PANAS scale for positive activation or negative activation (Watson et al. 1999). This interpretation facilitates reward seeking or avoidance (Fowles 1994) – analogously used here whether consumers are attracted to a brand, repelled by it, or somewhere in between.

To illustrate how brands vary in their perceived functional valuations and emotional valuations, Figure 2 plots these standardized brand valuations. For example, brands that scored well among consumers on both functional and emotional valuations were Crest toothpaste and Tollhouse cookie dough. Brands that did not fare well on either valuation include Heath candy bars and Farley’s fruit snacks. Some brands fared well on one valuation but not the other. For instance, Klondike frozen novelties and Pez candy scored well on emotional valuation but not functional valuation. On the other side are brands with high functional valuations but not emotional valuations, such as Purex laundry detergent and Fiber One snacks.

One concern for longitudinal brand research is how the brand might change over time. While brand perceptions could in theory be measured over time, practically this could be done only for a select few brands (Petersen et al. 2015). Brand attitude measures over time collected by firms like Millward Brown or BAV do not contain all the brands of interest to this study.

That said, "perceptions and attitudes toward established brands tend to be very stable" (Aaker 1996), particularly for mature products like consumer packaged goods. If brand perceptions are largely stable, then the effects can be treated as time-invariant, allowing for single-point estimates. To test this assumption, Millward Brown's BrandZ list, an annual report of top global brands based on the financial value of the brand, is examined. A key component is Brand Contribution, which measures the closeness of the brand's bond with its customers and is rooted in consumer perceptions of the brand. Using all publicly available years (2006-2015) and all brands that had nine or ten of the available data points, 93 brands were identified. These brands were tested twice for stability in its Brand Contribution. This included an Augmented Dickey-Fuller test to determine the presence of a unit-root (non-stationary) and a Durbin-Watson measure of one period positive autocorrelation. From this, 86 brands (92.5%) were marginally significant ($p < .10$) for either measure; a more stringent test ($p < .05$) found 67 brands (72.0%) were significant for either measure. This lends support to the belief that brand perceptions are relatively stable over time, allowing for single-point measures to be used.

2.4.3 Controls

Inherent product category traits may affect co-brand sales performance, and thus are controlled for. Using existing survey instruments, the first survey asked respondents about the quality of the private label offering (Hoch and Banerji 1993) on a five-point scale. The initial sample of 234 online consumers was reduced to 228 respondents after the attention check. The second survey measured the degree to which consumers viewed the product category as stockpileable, an impulse purchase, and hedonic (enjoyable and appeals to the senses) using seven-point scales (Ma, Ailawadi, and Grewal 2015; Narasimhan, Neslin, and Sen 1996). The initial sample of 223 online consumers was reduced to 217 after the attention check.

Two secondary data controls are also accounted for: advertising and economic conditions. The first is advertising by the primary brand. Since advertising expenditures should impact performance, this is collected from Kantar Media's Ad$pender program. Prior to Ad$pender, the data comes from the *Ad $ Summary* books published annually (1998-2006). Second, the economic cycle is considered, as private label offerings erode brand performance during economic downturns (Lamey et al. 2007). This is measured as U.S. GDP growth from the U.S. Bureau of Economic Analysis.

2.4.4 Model

To assess the market outcomes of co-brands, a generalized estimation equation (GEE) tests the association between sales performance (co-brand market share and revenue) and consumer mindset:

(1) $\text{logit(Share)}_{cit} = \beta_0 + \beta_1\text{FunctionalP}_{ci} + \beta_2\text{EmotionalP}_{ci} + \beta_3\text{FunctionalS}_{ci} +$

$\beta_4\text{EmotionalS}_{ci} + \beta_5\text{FunctionalP}_{ci}*\text{FunctionalS}_{ci} +$

$\beta_6\text{EmotionalP}_{ci}*\text{EmotionalS}_{ci} + \beta_7\text{FunctionalP}_{ci}*\text{EmotionalS}_{ci} +$

$$\beta_8 EmotionalP_{ci}*FunctionalS_{ci} + \beta_9 TypePurCycle_{it} +$$

$$\beta_{10} AnyDealIndex_{cit} + \beta_{11} Stockpile_i + \beta_{12} Hedonic_i + \beta_{13} Impulse_i +$$

$$\beta_{14} PLQuality_i + \beta_{15} AdPercent_{bit} + \beta_{16} PriceIndex_{cit} + \beta_{17} GDP_t +$$

$$\beta_{18} Parent_c + u_{cit}$$

(2) $\ln(Revenue)_{cit} = \beta_0 + \beta_1 FunctionalP_{ci} + \beta_2 EmotionalP_{ci} + \beta_3 FunctionalS_{ci} +$

$$\beta_4 EmotionalS_{ci} + \beta_5 FunctionalP_{ci}*FunctionalS_{ci} +$$

$$\beta_6 EmotionalP_{ci}*EmotionalS_{ci} + \beta_7 FunctionalP_{ci}*EmotionalS_{ci} +$$

$$\beta_8 EmotionalP_{ci}*FunctionalS_{ci} + \beta_9 TypePurCycle_{it} +$$

$$\beta_{10} AnyDealIndex_{cit} + \beta_{11} Stockpile_i + \beta_{12} Hedonic_i + \beta_{13} Impulse_i +$$

$$\beta_{14} PLQuality_i + \beta_{15} AdPercent_{bit} + \beta_{16} TypeRev_{ci} + \beta_{17} GDP_t +$$

$$\beta_{18} Parent_c + u_{cit}$$

The subscripts denote co-branded product *c* in category *i* in year *t*. The $FunctionalP_{ci}$ and $EmotionalP_{ci}$ measure the functional valuations and emotional valuations, respectively, of the primary brand. $FunctionalS_{ci}$ and $EmotionalS_{ci}$ measure the functional valuations and emotional valuations, respectively, of the secondary brand. For each co-brand *c*, the measures are the functional and emotional valuations for both the primary brand *p* and secondary brand *s*. Table 1 presents the constructs and measures used in the analysis.

The GEE model uses a working covariance structure with a Hubert sandwich estimator (White 1980) that is robust to heteroskedasticity and serially correlated errors. The model also accommodates varying error structures, relaxing assumptions that errors be independent. This matters since observations are likely correlated, both across years and within the primary brand (for example, Klondike with Oreo and Klondike with Reese’s likely have shared channels of distribution). As such, an unstructured correlation matrix for co-branded products *c* and *d* within the brand allows for off-diagonal elements α to vary together:

$$(3)\quad Corr(u_{cit}, u_{dit}) = \begin{Bmatrix} 1 & if\ c = d \\ \alpha_{cd} & if\ c \neq d \end{Bmatrix}$$

The control variables account for category effects, brand effects, and macroeconomic conditions. Category effects include how frequently the category is purchased (*TypePurCycle*), whether consumers think the category is stockpileable (*Stockpile)*, hedonic in nature (*Hedonic)*, an impulse buy (*Impulse)*, or the private label quality is high (*PLQuality)*. The brand's percent of category advertising dollars (*AdPercent*) matters since more spending should increase brand performance, but not if competitors are keeping pace in their advertising effort. The promotion impact of the co-brand relative to the category (*AnyDealIndex*) should be positive, as greater promotional efforts should be associated with increased purchases. The price of the co-brand relative to the category average (*PriceIndex)* should be negatively related with market shares. The size of the category type in which the co-brand competes (*TypeRev*) should be positively associated with revenues. Annual economic growth rate, a proxy for the health of the economy (*GDP*), should be positively associated with sales performance of co-brands. Finally, a dummy variable captures whether both brands in the co-branded product are owned by the same parent company (*Parent*). While equations (1) and (2) both take into account brand perceptions and controls, the only difference is price (in the market share model) and market size (revenue model). Table 2 presents descriptive statistics for the consumer mindset measures and control variables.

Market shares are logit transformed in order to map percentages to the real number line, while revenues are log-transformed to account for skewness. Average volume market share was 1.56%, with a range of .03% to 28.45%. Revenues of co-branded products ranged from $5 to $1,025 per 1,000 households, with a mean average of $120 and standard deviation of $202.

The functional valuations (Mean = 4.59, SD = .88 for primary brand; Mean = 4.68, SD = .77 for secondary brand) were higher, on average, than the emotional valuations (Mean = 2.93, SD = .66 for primary brand; Mean = 3.22, SD = .64 for secondary brand). This is not unexpected, as consumer packaged goods are products with high brand recognition but often low purchase involvement (Kotler and Keller 2012). Although not reported as a descriptive statistic, the number of co-brand relationships are still of interest. Instances in which the parent company owns both the primary and secondary brands (e.g., Procter & Gamble's Tide with Febreze) last a little longer on average (3.46 years) than ingredient co-brands overall (3.33 years). A total of 232 observations (47.3% of the sample ingredient co-brands) are instances where both brands are owned by the same parent company. Furthermore, the average primary brand had 3.22 co-branded relationships. The median was one partner, indicating that most primary brands were 'monogamous' with one secondary brand. Secondary brands had, on average, 1.89 relationships with partner brands, but this was also skewed towards one partner being most common.

Table 3 presents the correlations among the valuations. Within brands, the correlation between functional and emotional valuations of the primary brand (.15) and secondary brand (-.35) was not pronounced. The functional and emotional valuations had a modest correlation with market share (-.10 to .26) and revenues (.00 to .33).

2.5 Results

Table 4 presents the two-tailed test results for the market share and revenue models. All the survey variables have been standardized. The reported results are log-odds coefficient estimates for market share and log-level coefficient estimates for revenues. Model fit diagnostics indicate that the full models provide better fit than intercept-only models using the quasi-likelihood information criterion (QIC), a modified Akaike information criterion (AIC) for GEE models (576.89 versus 1,178.01 in the market share model; 575.23 versus 1,131.16 in the revenue model). The generalized R^2 indicates that the variables explain 72.8% of the variation in the market share model and 70.1% of the variation in the revenue model.

All else equal, secondary brand functional valuation and emotional valuation each has a positive main effect on co-brand sales performance. The coefficient for the functional valuation of the secondary brand is $\beta = 1.14$ ($p < .01$) in the market share model and $\beta = 2.24$ ($p < .01$) in the revenue model. The coefficient for the emotional valuation of the secondary brand is $\beta = 2.66$ ($p < .01$) in the market share model and $\beta = 2.99$ ($p < .01$) in the revenue model. Thus, both H1a and H1b are supported; the functional and emotional valuations of the secondary brand have positive, additive effects for co-brand sales performance.

Regarding the commonality effects, which combine the valuations of the primary brand and secondary brand along a common dimension, the coefficients are negative and significant. The coefficient of the interaction of the functional valuation of the primary brand and the functional valuation of the secondary brand is $\beta = -4.98$ ($p < .01$) for the market share model and $\beta = -1.81$ ($p < .10$) for the revenue model. Similarly, the interaction of the emotional valuation of the primary brand and the emotional valuation of the secondary brand is $\beta = -3.50$ ($p < .01$) for the market share model and $\beta = -2.84$ ($p < .01$) for the revenue model. These findings support our notion that commonality effects attenuate the positive, additive effect of the secondary brand's functional and emotional valuations on co-brand sales performance. Thus, both H2a and H2b are supported; on average, the interaction of valuations along a common dimension creates negative synergy between the primary brand and secondary brand.

For complementary effects, the proposed interaction of the functional valuation of the primary (secondary) brand with the emotional valuation of the secondary (primary) brand would create positive synergy. The coefficients are not statistically significant. The coefficient of the interaction of the primary brand's functional valuation and the secondary brand's emotional valuation is $\beta = -.74$ ($p > .22$) for the market share model and $\beta = -.75$ ($p > .21$) for the revenue model. Likewise, the interaction of the primary brand's emotional valuation and the secondary brand's functional valuation is $\beta = .34$ ($p > .69$) for the market share model and $\beta = -.57$ ($p > .45$) for the revenue model. Based on these findings, when brand valuations complement each other along different dimensions, no evidence is found that this creates a positive synergy for co-brand sales performance. As such, H3a and H3b are not supported.

Given that there is little empirical research examining the sales performance of co-brands, several control variables are worth noting. All things equal, co-brand market shares tend to be higher in categories with longer inter-purchase times ($\beta = .03$, $p < .01$) and lower for categories hedonic in nature ($\beta = -.40$, $p < .06$). Prices also work in the expected direction: higher priced co-brands see less market share (β = -1.02, p < .01). In the revenue model, hedonic products were also negatively associated with co-brand performance (β = -.78, p < .01). Categories perceived as more stockpileable were associated with lower co-brand revenues (β = -.30, p < .01), but categories which were seen as more of an impulse purchase had higher co-brand revenues (β = .35, p < .02). As private label perceived quality increases, co-brand revenue decreases (β = -.23, p < .06). Market size (dollars spent per thousand households in the category type) had no significant effect on co-brand revenues (β = .00, p > .13). Variables statistically not significant in either model included, selling more volume on promotion (*TypePurCycle*), share of the category advertising dollars (*AdPercent*), macroeconomic conditions (*GDP*), and when both the primary and secondary brands are owned by the same parent company (*Parent*).

Several robustness checks were performed. First, to assess whether the results were driven by extreme value, models were re-estimated dropping the top and bottom 5% of observations. The substantive conclusions do not change. Second, nonlinear relationships were examined (e.g., log transformations) for some of the explanatory variables, as well as revenues without log transformation. The substantive conclusions do not change. Third, the IRI data is annualized. Thus, during years a co-brand enters or exits cannot be determined if the observation was a full calendar year of sales or not. Models were re-estimated using only observations that were 'book-ended' between observations, ensuring full calendar year duration (n = 239, or 48.8% of the observations). The results were consistent with those reported in Table 4. Finally, the decision by the primary brand to co-brand presents possible self-selection concerns. This is addressed by a two-stage Heckman (1979) process, which finds selection bias is not a significant concern. This is further explained in Appendix 2.

To demonstrate the managerial relevance of the results, a simulation was conducted using the market share results from Table 4. First, each variable was set at its mean value to calculate the mean predicted market share. This became the 'base case'. From this base case, market share was changed by altering the variable describing the functional and emotional valuations ±1 standard deviations from their means. Table 5 presents the market shares for co-branded products when the valuations of the primary brand and secondary brand are simulated. For example, consider a primary brand with functional valuation one standard deviation above the mean and an emotional valuation one standard deviation below the mean. If a secondary brand with functional valuation at the mean and emotional valuation one standard deviation below the mean is paired with this primary brand, the expected market share of the co-branded product is .5%.

The base case is .9% market share when all functional and emotional valuations are set to their mean values. The table shows that interactions among primary and secondary brands that are strong on common valuations (top right area) diminish market share. However, the commonality effects are mitigated when one brand is relatively strong and the other relatively weak (upper left and lower right areas), resulting in greater expected market share. At the same time, weak brands do not achieve positive synergy (lower left area). This highlights that it is not necessarily desirable to partner with a secondary brand that performs well on the same valuation dimension (i.e., a primary brand with a strong functional valuation and a secondary brand with a strong functional valuation). Brand managers of primary brands should consider both the valuations of the primary brand as well as the valuations of a potential secondary brand prior to co-branding; stronger is not always better.

2.6 Discussion

Co-brands represent a growing strategy employed by brand managers. Drawing on ideas developed using experimental studies, a theory is developed for co-brand sales performance based on the notion that brands have overall functional and emotional valuations. When two brands come together in a co-brand, these valuations interact to create brand synergies. In doing so, this links consumer perceptions of both the primary and secondary brands and how these translate into co-brand sales performance. In the context of consumer-packaged goods, the results support the theory that consumer valuations of the primary brand and secondary brand have positive, additive effects on co-brand performance. However, when these valuations interact, on average there is a significant negative interaction for common valuations (e.g., the functional valuations of both the primary brand and secondary brand), but no significant effect when the valuations are complementary (e.g., the functional valuation of the primary brand and the emotional valuation of the secondary brand).

Several implications for marketing theory arise. This study supports prior research on the consumer mindset and the role that functional valuations and emotional valuations play in the success of co-branded products. This addresses whether consumers prefer items that share common valuations or complementary valuations. Second, this study addresses why some co-brands have higher sales performance than other co-brands.

Intuitively, two brands, each with a positive overall impression, should work together to enhance the co-branded product. To the contrary, our theory of commonality indicates that the interaction of valuations on the same dimension (e.g., the functional valuation of the primary brand and the functional valuation of the secondary brand) do not create additional synergies. This is consistent with prior research that consumers do not prefer too much emphasis on one single dimension (Dhar and Simonson 1999). This presents a new perspective on how synergistic relationships might (or might not) work, not just in products, but other brand alliance contexts based on perceptions of partners.

For managers, this research presents an empirical test of drivers of co-brand sales performance. For brand managers, one solution to combat private label growth has been to offer variations that private labels do not (Gielens 2012) and co-branding is one such strategy. Managers ask themselves, "Who should we co-brand with?" Our findings indicate brand managers should pursue co-brand partners that are not too common in their valuations (e.g., a primary brand with a strong functional valuation should not partner with a secondary brand that also has a strong functional valuation). For managers, this presents the counter-intuitive idea that prospective partners should not necessarily be the strongest brands. Rather, primary brands should seek out secondary brands with different valuations, even if these valuations are weaker than its own (e.g., a primary brand with a strong functional valuation is better served partnering with a secondary brand whose functional valuation is not strong).

This research acknowledges several issues that were challenging to address. First, the sample consists of co-brands that have achieved some degree of relevance in the marketplace. It is the hope that this study encourages future research involving new data sets. Second, the advertising data, captured at the brand level, provides little additional breakout to reflect product level activity (i.e., the advertising figure is Klondike ice cream treats, and not separately available for Klondike with Reese's, Klondike with Oreo, etc.). These are natural limitations arising from working with large-scale panel data.

Studying other product categories presents an interesting avenue but has implications for data collection. Co-branding of durable goods (i.e., Dell computers with Windows operating systems; Ford F-150 pickup trucks with the Harley-Davidson package) and services (i.e., the Delta Airlines credit card by American Express) are not uncommon practices. Effects of co-branding here are less known. Furthermore, the long-term effects of co-branding present additional areas of inquiry. Prior research into co-brand sales performance (Desai, Gauri, and Ma 2014; Swaminathan, Reddy, and Dommer 2012) has examined the short-term impact of the co-brand on the primary brand for select co-branded products. Most co-brands are relatively short-lived in the marketplace, but these may have persistent, long-term effects on both the primary brand and secondary brand. Finally, the view from inside the firm would provide a more comprehensive look at co-branding decisions. Not only would investigating profitability be of interest to managers, but also the role of governance (i.e., the costs to create and maintain a co-branded relationship), especially when both the primary and secondary brands are owned by the same parent company.

Chapter 3

Essay 2: Supply of and Demand for Legal and Pirated Information Goods

3.1 Introduction

Brand managers are not always concerned with just direct competitors, but also threats that can arise from illegal or unauthorized variants. Examples include versions passed off as the genuine good (counterfeits), copies made directly from the genuine good (piracy), and unauthorized channels for the genuine goods (gray markets). The impact these unauthorized versions have is not trivial, with annual direct counterfeit costs to hard goods producers like U.S. motor and equipment makers estimated to be $12 billion (MEMA 2010) and $28.5 billion for European fashion designers (OHIM 2015). Piracy costs creators of information goods like motion pictures an estimated $6.1 billion annually (L.E.K. 2006) and business software developers for $9 billion (SBA 2010).

This article studies the impact that pirated supply and pirated demand have on legal supply and legal demand. To date, research on the impact of pirated goods has typically focused on how pirated demand influences legal demand. Relatively unexamined is the role of the supply side, both legal and pirated supply. For instance, legal supply depends on legal demand and possibly also pirated supply. At the same time, legal demand depends on legal supply and possibly also pirated demand, which is driven by both legal and pirated supply. As such, this examines how the four components of legal and illegal supply and demand affect each other as a system.

This study extends prior research on motion picture piracy to develop a model of how the four components of supply and demand influence each other. A theoretical framework is developed that begins with the legal supplier, since pirated goods are derivative products, in the presence of expected legal demand. After that, the four market components simultaneously influence each other. By this, consumers can choose from legal and pirated versions of the product, which affect the supply side (both legal and pirated), which in turn have continuing effects on the demand side. Our theory is that these components influence each other, though the directionality is not always clear. For instance, legal supply and pirated supply could have negative effects on each other as substitutes, or have positive effects as complements in the post-launch period. Part of this could be due to timing effects as the launch and post-launch periods create differential effects of the pirated market.

This article is organized as follows: First, prior piracy research is reviewed and presents a theoretic model of how all four market components influence each other. This further separates out time-specific effects that may occur, namely the launch and post-launch periods. This theory is tested using a system of four simultaneous equations using data from the motion picture industry. This allows for estimating each market component in the presence of each other, using a set of instrumental variables to alleviate endogeneity concerns. The results show that pirated demand (piracy downloads, or *leechers*) has a negative impact on legal demand (revenues) in the opening week of a film's release, but not so in subsequent weeks. Pirated supply (piracy availability, or *seeders*) and legal supply (movie screens) have positive effects on each other post-launch. This suggests the two complement each other, rather than work as substitutes for each other. Legal supply has a positive effect on pirated demand in the launch period, but a negative effect in the post-launch period. The results provide insights into the impact of pirated markets on the legal good, particularly regarding timing. The study concludes with a discussion of the empirical results, implications for managers and marketing academics, and suggestions for further research.

3.2 Theoretical Development

Prior research examining pirated information goods has primarily investigated how piracy demand affects legal demand (e.g., Basuroy and Chatterjee 2008; Chintagunta, Gopinath, and Venkataraman 2010; Elberse and Eliashberg 2003; Henning-Thurau, Houston, and Heitjians 2009; Joshi and Hanssens 2009; Neelamegham and Chintagunta 1999). Piracy demand had no significant effect on the supply of legal music (i.e., comparing the before and after periods of the Napster file sharing program: Waldfogel 2012). Since piracy demand requires a piracy source, the supply side of the piracy market should have implications for the supply and demand of the legal good. However, piracy supply – let alone its effect on the market – remains relatively unexamined. When more piracy supply exists, piracy demand (as downloading behavior) is greater (Bhattacharjee, Gopal, and Sanders 2003).

Research (Smith 1976) has explored the interdependence of the four market components for legal and illegal goods in the context of alcohol wholesalers and state-owned versus private-owned liquor stores. That research examined whether wholesalers under-report sales in order to pay less in state taxes. However, illegal supply and illegal demand are not actually observed, merely inferred from possible under-reporting of sales by wholesalers. The measure of illegal demand is based on consumers living in bordering states who may then drive across state borders to pay less in state alcohol taxation.

Examined here is the piracy of motion pictures where behavior is observed in the illegal market (i.e., counts of the number of downloads and uploads of pirated copies for a particular film). This allows us to see the effects of an illegal supply (rather than inferred tax evasion) with illegal demand as observed incidence (rather than legal purchases where the consumer does not know they are buying an illegal good, and is instead acting on price arbitrage by purchasing the same legal product across state borders). *Prima facie*, each market component has a substitute analog (i.e., illegal supply is a substitute for legal supply). The following subsections describe how all four market components work together. In using motion picture data, the terms legal supply, legal demand, pirated supply, and pirated demand are respectively interchangeable with screens, revenues, seeders, and leechers.

3.2.1 Legal Supply: Screens

The supply of the legal good is a natural starting point for consideration of pirated supply and demand. Exhibitors (i.e., movie theaters) allocate screen space based on expected demand. A film with greater expected demand (and hence greater expected revenues) will be given more screens to increase consumer access to the film (Elberse and Eliashberg 2003).

H1: Higher estimated revenues are associated with greater screens available.

Since pirated goods are derivative products, without a legal supply there would be no pirated supply. In the case of information goods, the pirated supply originates from some legal supply source. While some pirated supply may leak out prior to launch, it is typically minimal. Interviews with executives at a major U.S. movie studio and major U.S. theater chain indicate that the threat from pirated supply in the launch period of a movie is not a concern for screen allocation to a film.

However, once a film has been released, this creates opportunities for pirated copies to be made. Since demand is expected to peak in the opening week, this may deter individuals from creating pirated copies in theaters in the presence of consumers. This may delay the effects of piracy supply (i.e., hypothesizing only post-launch effects). Pirated supply represents a competing source for legal suppliers. A large amount of pirated supply may dissuade legal suppliers from adding additional distribution. In the case of information goods, users who download a pirated copy of a film can become distributors of that pirated copy (seeders). Movie screen availability decreases over time. However, fewer screens mean less accessibility and opportunity to create illegal copies. As a possible substitute, piracy supply should negatively affect movie screen availability.

H2: Increasing seeders in the prior week are associated with fewer screens available.

Although illegal, piracy demand represents underlying consumer interest in the legal good. While this might reflect an unwillingness to pay, an alternative explanation is that when the legal channel is lacking, consumers seek out the pirated copies instead (Danaher et al. 2010). Additionally, piracy demand can also act as a sampling mechanism to give the consumer more information about the product for subsequent purchase of the legal good (Peitz and Waelbroeck 2006). Since piracy demand represents interest in the film, and downloading illegal copies may be the result of reduced screen availability, piracy demand should encourage movie theaters to add more screens.

H3: Increasing leechers in the prior week are associated with greater screens available.

3.2.2 Legal Demand: Revenues

Within motion picture research, observed sales is driven by available legal supply (Basuroy and Chatterjee 2008; Chintagunta, Gopinath, and Venkataraman 2010; Elberse and Eliashberg 2003; Henning-Thurau, Houston, and Heitjians 2009; Joshi and Hanssens 2009; Neelamegham and Chintagunta 1999). Even in the presence of pirated supply and demand, greater screen availability should have a positive effect on revenues.

H4: Increasing available screens are associated with higher revenues.

The supply of piracy represents several possible effects on box office revenues. In one sense, pirated supply reinforces the belief that there is an anticipated demand for the pirated good; individuals who share illegal copies give the impression of being trendy and ‘in the know’ (Ferguson 2008). At the same time, the presence of the illegal supply feeds into illegal demand, which might cannibalize sales. On the other hand, pirated supply has a potential benefit to revenues by creating a sampling mechanism. Consumers may sample when the product is complex, there are heterogeneous tastes, and uncertainty about the product (Peitz and Waelbroeck 2006). Consumers also know that preview versions (i.e., film trailers) are biased and do not represent the entire product (Moul 2005). While pirated supply may directly or indirectly affect revenues by way of pirated demand, the presence of pirated supply indicates an underlying interest in the film, which should have a positive relationship with revenues.

H5: Increasing seeders are associated with higher revenues.

The extant literature has found varying effects of piracy demand on the legal good. Prior research is unsettled whether piracy has a positive impact on the sales of the legitimate good (Givon, Mahajan, and Muller 1995; Fader 2000; Jain 2008), negative impact (Hui and Png 2003; Liebowitz 2008; Rob and Waldfogel 2007), or no impact (Tanaka 2004; Oberholzer-Gee and Strumpf 2007). As a potential substitute, downloads of pirated copies (leeching) represents a possible lost transaction. Leeching is expected to have a negative effect on film revenues.

H6: Increasing leechers are associated with lower revenues.

3.2.3 Pirated Supply: Seeders

Regarding the supply of pirated goods, individuals weigh illegal behavior as the benefits relative to the costs (i.e., the probability of getting caught and the expected penalty: Becker 1974). For information goods, however, the supply of pirated copies is not driven by profit motives, but social motives (Wilcox, Kim, and Sen 2009). Perpetrators perceive the crime as victimless (Peace, Galletta and Thong 2003) or ethically justify it to themselves as 'sharing' (Freestone and Mitchell 2004). While pirated copies of movies can be packaged and sold like a DVD, the focus here is on a contemporaneous legal and illegal channel. Pirated movies sold like a DVD are usually copies of films that are still in theaters and not yet available through the secondary market as a DVD.

When an individual shares pirated copies, two considerations are important for information goods. First, there must be a legal source from which one originates the copy (i.e., in the case of motion picture copies this typically comes from a digital transfer such as a DVD or film reel, or from a video recording made of the film playing in the theater). Second, when the original source has been shared with another user (leecher), that user then has a digital copy that becomes available for further sharing. That is, the leecher then becomes a seeder until they delete the file. Makers of information goods are careful to prevent pirated copies from seeping out prior to launch, but it can leak out through advance copies given to film critics, advertising agencies, or other partners. Pirated copies can also arise if the legal good is released legally in another market earlier. Legal demand is expected to peak in the launch period; with more consumers purchasing the legal good, this can deter individuals from making pirated copies due to the fear of getting caught. Since pirated copies rely on the legal source, in the opening week there should be few pirated copies available to have an effect.

H7a: Increasing screens are associated with lower seeders in the opening week.

H7b: Increasing screens are associated with higher seeders post-launch.

Legal demand should positively influence pirated supply. High revenues reflect high interest in the genuine good. If interest for the film is high and piracy is treated as sharing, a driver for this willingness to share pirated copies is how people want to be perceived. Those who share want to appear trendy and ‘in the know’ (Ferguson 2008). Piracy networks often do not identify the person supplying the pirated good by actual name, but by a user name. For these users, a primary motive is gaining ‘street cred’ or a level of acceptance and respectability by supplying popular goods (Kravets 2012).

H8: Increasing revenues are associated with higher seeders.

An increase in legal demand is believed to have a positive effect on pirated supply. Similarly, pirated demand should have a positive effect on pirated supply. In the case of information goods, however, pirated demand cannot be estimated the way revenues are for allocating screens. Since information goods are relatively costless, and that leechers become seeders after acquiring the pirated copy, this should feed positively reinforce that leechers have a positive relationship with seeding.

H9: Increasing leechers are associated with higher seeders.

3.2.4 Pirated Demand: Leechers

A key premise of pirated demand is that consumers seek out the pirated good due to lack of willingness to pay for the legal good (Sinha and Mandel 2008). Consumers can obtain the product for free (although illegally) versus paying (Conner and Rumelt 1991). Additionally, the "cost" of being caught and facing legal ramifications may be perceived as low enough to justify the risk (Becker 1974; Chellappa and Shivendu 2003), particularly in the sharing of information goods where users can share pirated copies anonymously without meeting face-to-face.

In the case of information goods, consumers have only some knowledge about the good prior to purchase. Consumers may sample if product quality is uncertain (Peitz and Waelbroeck 2006). When a film premieres, few people know how good it really is (i.e., word of mouth from other consumers is limited). As such, the launch period has more availability of the genuine good, which creates more opportunities to learn about the product. In this period, pirated demand may be high since knowledge of the legal good is limited. However, the legal supply of screens should decrease over time while consumers have learned more about the product. Once the legal supply is removed, consumers turn to the pirated supply as a substitute (Danaher et al. 2010). Post-launch, then, screen availability should have a negative association with piracy demand.

H10a: Increasing screens are associated with higher leechers in the opening week.

H10b: Increasing screens are associated with fewer leechers post-launch.

On the surface, the illegal channel operates as a substitute for the legal channel and vice versa. As demand for the legal good increases, this could also reflect consumers who have downloaded a pirated copy for sampling purposes (to get more information about the legal good). An increase in legal demand reflects an overall willingness to pay for the legal good and suggests a higher quality product. As such, higher revenues suggest consumers are willing to pay for the legal good and are less willing to want the pirated good.

H11: Increasing revenues are associated with lower leechers.

If there is no pirated supply, then pirated demand cannot be observed. When the supply of pirated copies is ample, there is more downloading (Bhattacharjee, Gopal, and Sanders 2003). In the case of information goods, since leechers become seeders upon acquiring the pirated copy, this perpetuates its ability to grow the supply side, further encouraging pirated demand.

H12: Increasing seeders are associated with higher leechers.

Figure 3 presents the hypothesized framework of the four market components, and Table 6 summarizes all the hypotheses, predicted directions, and support.

3.3 Methodology

Presented below are the data and measures from the motion picture industry. After this, the model used is described to estimate each of the four components as a system of simultaneous equations, including estimation considerations.

3.3.1 Data Sources

The sample consists of movies released in theaters in the United States over a sixteen month period from September 2013 to December 2014. Films which opened in (or expanded to) at least 200 theaters were tracked for performance and piracy. Expansion means the film had a limited opening and then expanded to more screens in a later week. The sample consisted of 177 films. Data for each film was collected daily until the film's weekend box office revenues were less than 1% of its opening weekend (or expansion) revenues. At this point, the film neared the end of its theatrical run, where further revenues were considered immaterial relative to cumulative revenues. In this manner, the median revenue capture for a film's run was 99.0% of its total U.S. box office revenues.

Our data set comprises six sources. First, a list of upcoming box office releases was gathered each week from Box Office Mojo (boxofficemojo.com), which has revenue and screen data. Films set to open in at least 200 theaters were used in the sample, as there is a clear division between films which opened nationally (usually 2,000 or more theaters) and those that opened in select markets/limited release (often fewer than 50). A film opening in relatively few theaters suggests that either the film was not from a major studio or that it did not have the marketing budget to create national audience awareness. Once a film expanded to at least 200 theaters, it was added to the data set.

Second, the Hollywood Stock Market (hsx.com) prediction market was used to estimate opening week revenues. Buyers and sellers in this market trade "stocks" of

Hollywood films, where the price reflects the estimated box office revenues for the first four weeks of wide release. The film's closing "stock price" was collected during the week prior to release.

Third, film product information was collected daily from the Internet Movie Database (imdb.com) for film features such as production studio, actors, production budget, reviews by film critics, user rating, number of users rating the film, release dates in other markets, buzz generated, genre, and MPAA rating. Production budget data not listed on IMDB was collected from other websites.

Fourth, piracy data was collected daily within a set time interval from Pirate Bay (piratebay.se), the most visited website for pirated content. Search results for the sample films were collected with "video" as the file type to reduce unintended results (video results that were listed as "tv shows", "music", "movie clips", or "other" were removed). The year of the film's release was also included in search results to exclude similar titles or remakes. Although piracy is measured globally (i.e., users can download pirated copies anywhere in the world) and our focus is on U.S. box office revenues, the correlation between U.S. revenues and global revenues for films in the sample is 0.92. Given this high correlation, the impact of piracy to global revenues can be scaled appropriately.

Fifth, advertising expenditures for each film was collected from Kantar Media's Ad$pender. Advertising expense was collected beginning twelve months prior to release.

Sixth, actor/actress star power comes from the 2009 Forbes Star Power Index, the most recent survey available. This index surveys Hollywood agents, producers, and executives to rate which actors and actresses are valuable to a film in terms of box office revenue and name recognition. Since films may take several years in development, production, and post-production before release, this data was still meaningful to films collected in this sample.

3.3.2 Measures

The variables and their operationalization are described in Table 7.

From an *ex ante* perspective, movie theaters must allocate screens to movies before a film opens. One approach to estimating opening weekend revenues for a film is to use the HSX prediction market data, a market sentiment of a film's domestic box office revenues in the first four weeks of release. This is divided by a multiple (2.90) to adjust for the opening week, similar to prior motion picture research (e.g., Elberse and Eliashberg 2003). For example, *Divergent* had a closing HSX price (in H$) of 175.06 on the Wednesday prior to release. Dividing by the 2.90 multiplier yields an estimated opening week of $60,365,517. The observed opening weekend was $68,760,008 for an actual market performance that was 13.9% better than estimated. *REVENUES* and *SCREENS* reflect weekly box office measures for legal sales and distribution, respectively. Because film demand can vary depending on the time of the year (such as during the summer or holidays), *SEASONAL* reflects a percentage difference relative to an average movie week. The seasonality is based on the prior five-year U.S. average, similar to prior movie research on seasonality (e.g. Vogel 2001).

Movie budget (*BUDGET*) and advertising (*AD_EXP*) are measured in dollars. Critical reviews (*CRITIC_REVIEW*) are an average rating by film critics, scaled to a 1-5 continuous rating. Actor star power (*STAR_POWER*) is measured as the sum of actor power for actors listed 'above the line' (i.e., typically on the film poster or opening credits), since some films emphasize ensemble talents rather than one individual actor.

Since the type of studio producing and distributing the film can influence screen allocation (as well as advertising support), *STUDIO_MAJOR* dummy codes whether a film is released by one of the seven biggest film studios (Disney 20th Century Fox, Universal, Paramount, Warner Brothers, Sony/Columbia/Tri-Star, or Lions Gate). The variable *BUZZ* reflects an IMDB proprietary measure of the film's ranking among all film titles based on search popularity. Word of mouth (*WOM*) represents IMDB user sentiment towards the film as rated on a 1-10 scale. Higher-rated films should be more positively perceived and lower-rated films are more negatively perceived by audiences. In addition to this valence measure, volume is measured as the number of IMDB users who have rated the film (*USERS*).

In addition to these drivers of box office performance, competition is also a factor. Competition has two measures in the screens model and one in the revenues model. In order to allocate screen space, theater owners must weigh a focal film against both new releases and ongoing films. The new release measure (*COMP_SCR_NEW)* is the production budget (in $millions) of all new releases that weekend, if available, divided by 10. A higher number represents tougher competition. For competition from ongoing films (*COMP_SCR_ONG)*, the average number of weeks the top 25 films have been in release is used. A higher number represents *weaker* competition for screens, capturing the notion that films collectively coming closer to the end of their theatrical run represent less competition. Revenue competition (*COMP_REV)* is more complex: previous work examined a combination of MPAA rating (i.e., G, PG, PG13, R), genre (action, comedy, western, etc.) and number of weeks in release to capture what a film is competing against in a given week (Elberse and Eliashberg 2003). Here, a film is weighted for each genre assigned by IMDB, as most films span more than one genre. For example, the film *Gravity* is listed on IMDB as three genres: drama, sci-fi, and thriller. Hence, it will have one-third competitive weight against other drama films, one-third competitive weight against other sci-fi films, and one-third competitive weight against other thriller films. While previous work classified films according to five genres, the research here accounts for more genres as well as a film belonging to multiple genres.

Piracy demand reflects the observed incidence of downloaded pirated copies, consistent with prior research (e.g., Oberholzer-Gee and Strumpf 2007; Danaher et al. 2010). The demand side is characterized by the number of users downloading a piracy file. The total number of users downloading a film represents the observed pirated demand (*LEECHERS)*. The total number of users with pirated copies of the film available for download represent the pirated supply (*SEEDERS*). Of the films in the data set, 91% had some piracy incidence during the theatrical run. Since piracy may occur prior to a film's release, the number of days the film has been in release in a major market prior to release in the U.S. is taken into account (*PRIOR_DAYS*).

3.3.3 Opening Week Model

To estimate the model, of interest are the behavioral drivers of exhibitors (theaters), audiences (for both legal and pirated goods), and those sharing pirated copies. Since all four are interdependent, this is treated as a system of four equations. Motion pictures, like other types of information goods, are heavily reliant on the launch period (i.e., opening week of a movie) to set the tone for performance. As such, two sets of equations are estimated: one for the opening week and one for the weeks after the opening week (i.e., post-launch period).

The opening week system of equations consists of Equations (1-4). In each equation, **Y** represents a vector of endogenous variables, **X** represents a vector of time-variant variables set to their week 1 values, and **Z** represents a vector of time-invariant variables.

(1) $\ln(\mathrm{SCREENS}_{i1}) = \beta_0 + \beta_1\ln(\mathrm{Y}_{Si1}) + \beta_2\ln(\mathrm{X}_{Si1}) + \beta_3\ln(\mathrm{Z}_{Si1}) + \varepsilon_{Si1}$

(2) $\ln(\mathrm{REVENUES}_{i1}) = \alpha_0 + \alpha_1\ln(\mathrm{Y}_{Ri1}) + \alpha_2\ln(\mathrm{X}_{Ri1}) + \alpha_3\ln(\mathrm{Z}_{Ri1}) + \varepsilon_{Ri1}$

(3) $\ln(\mathrm{SEEDERS}_{i1}) = \gamma_0 + \gamma_1\ln(\mathrm{Y}_{Pi1}) + \gamma_2\ln(\mathrm{X}_{Pi1}) + \gamma_3\ln(\mathrm{Z}_{Pi1}) + \varepsilon_{Pi1}$

(4) $\ln(\mathrm{LEECHERS}_{i1}) = \delta_0 + \delta_1\ln(\mathrm{Y}_{Li1}) + \delta_2\ln(\mathrm{Z}_{Li1}) + \varepsilon_{Li1}$

Here, $SCREENS_{i1}$ (Equation 1) is the number of screens allocated to film *i* in the opening week. Since legal supply is treated as the starting point for the system of market components and industry practitioners do not consider pirated supply or pirated demand as influential to setting the number of movie screens, the only component of Y_{Si1} is EST_REV_{i1}, the estimated opening week revenue. X_{Si1} is composed of $COMP\_SCR\_NEW_{it}$ and $COMP\_SCR\_ONG_{it}$. Z_{Si1} is made up of $BUDGET_i$, $STAR\_POWER_i$, AD_EXP_i, $CRITIC\_REVIEW_i$, and $STUDIO\_MAJOR_i$ while ε_{Si1} is the error term. Since distribution by a major studio is coded as a dummy variable, it is not log transformed.

$REVENUES_{i1}$ (Equation 2) is the observed total box office revenue for film *i* in its opening week. Y_{Ri1} consists of $SCREENS_{i1}$, $SEEDERS_{i1}$, and $LEECHERS_{i1}$. X_{Ri1} is composed of $COMP\_REV_{it}$ and $SEASONAL_{it}$. Z_{Ri1} contains $STAR\_POWER_i$, AD_EXP_i, and $CRITIC\_REVIEW_i$. ε_{Ri1} is the error term. The seasonality variable is already expressed as a percentage relative to the average week, so it is not log transformed.

$SEEDERS_{i1}$ (Equation 3) is the number of available piracy files for film *i*. Y_{Pi1} is made up of $SCREENS_{i1}$, $REVENUES_{i1}$, and $LEECHERS_{i1}$. X_{Pi1} is composed of $BUZZ_{it}$, the online buzz ranking of the film (which is not log transformed). Z_{Pi1} is made up of similar product features in the decision to supply the legal good, $BUDGET_i$, $STAR\_POWER_i$, AD_EXP_i, and $CRITIC\_REVIEW_i$. This also includes $PRIOR\_DAYS_i$, as the number of days a film has been in legal release can affect piracy supply, which is not log transformed. Finally, ε_{Pi1} is the error term.

$LEECHERS_{i1}$ (Equation 4) is the number of user downloads of pirated copies of film *i*. Y_{Li1} is made up of $SCREENS_{i1}$, $REVENUES_{i1}$, and $SEEDERS_{i1}$. Z_{Li1} reflects product traits similar to the legal demand model: $STAR\_POWER_i$, AD_EXP_i, and $CRITIC\_REVIEW_i$. ε_{Li1} is the error term. Word of mouth considerations would appear in X_{Li1}; however, consumers are wary of trusting early reviews due to potential bias in the product launch period (Li and Hitt 2008), some of which remains from firms manipulating online reviews (Dellarocas 2006).

3.3.4 Post-Launch Model

The post-launch system of equations consists of Equations (5-8),where t > 1.

(5) $\ln(\mathrm{SCREENS}_{it}) = \beta_0 + \beta_1\ln(Y_{Sit}) + \beta_2\ln(X_{Sit}) + D_{Sit} + \varepsilon_{Sit}$

(6) $\ln(\mathrm{REVENUES}_{it}) = \alpha_0 + \alpha_1\ln(Y_{Rit}) + \alpha_2\ln(X_{Rit}) + D_{Rit} + \varepsilon_{Rit}$

(7) $\ln(\mathrm{SEEDERS}_{it}) = \gamma_0 + \gamma_1\ln(Y_{Pit}) + \gamma_2\ln(X_{Pit}) + D_{Pit} + \varepsilon_{Pit}$

(8) $\ln(\mathrm{LEECHERS}_{it}) = \delta_0 + \delta_1\ln(Y_{Lit}) + \delta_2\ln(X_{Lit}) + D_{Lit} + \varepsilon_{Lit}$

This system of equations is similar to that of the opening week system with a few key differences. First, D_{it} represents time dummy variables for the week to account for time-specific fixed effects in each equation. Second, the Y_{Sit} term includes lagged effects from seeders and leechers ($SEEDERS\_LW_{it}$ and $LEECHERS\_LW_{it}$, respectively). X_{Sit} and X_{Rit} now include word of mouth (WOM_{it}). X_{Pit} now includes $USERS_{it}$ as a measure of online interest. X_{Lit} also includes WOM_{it} as well as a squared term to account for curvilinear effects.

3.3.5 Estimation

Estimation of the system consists of several steps. First, revenues are estimated (for the screen allocation equation). Second, the opening week equations are estimated as a system. Third, revenue estimates are updated using observed prior data. Fourth, the post-launch equations are estimated as a system.

Using legal supply as the starting point, exhibitors allocate movie screens based on expected revenues. The number of screens allocated in the opening week depends on the estimated revenue that theater owners anticipate a film will earn as a function of the HSX closing price prior to release.

The opening week system of equations is estimated (Equations 1-4) using a three-stage least-squares (3SLS) procedure. This is preferred to an ordinary least-squares (OLS) procedure, which produces inconsistent estimates due to the endogenous regressors (i.e., *SCREENS, REVENUES, SEEDERS, LEECHERS*) being contemporaneously correlated with the error terms in each equation. The 3SLS allows the error terms to correlate across equations (i.e., items not specified by the model that appear in the error can correlate across equations, such as a film being nominated for an Academy Award) and is more efficient than a two-stage least squares (2SLS) approach (Zellner and Theil 1962).

After launch revenues are observed, theater owners update revenue estimates given film revenues in prior weeks. The *ex ante* approach is extended for estimating revenue in each week (i.e. week 5 revenues for each film are based on actual and predicted values from weeks 1 through 4). Since two time periods are required for the smoothing parameters, week 2 is estimated by multiplying the average of opening week actual and estimated revenues by .70 (assuming an average drop-off in revenues from opening week to second week of 30%). Starting in week 3, estimation uses a double exponential smoothing model (Holt-Winters method) to forecast revenues based on two parameters: one to smooth and the other to account for the trend (i.e., movies typically decrease in revenues over time, but each film has its own rate of decline). This estimation procedure is consistent with prior movie screen and revenue research (e.g., Elberse and Eliashberg 2003) and is further detailed in Appendix 3.

The post-launch system of equations (Equations 5-8) is similar to that of the opening week. The estimation excludes lagged endogenous variables (i.e., seeders and leechers in the prior week for the screens model) as possible instruments due to possible autocorrelation concerns (Greene 2008). In each model with endogenous variables, a Basmann (1960) test of excluded variables for instruments finds that at least some of the instruments are suitable ($p > .10$ in each equation). Panel data estimation usually calls for accounting of unobserved effects or time effects. In the spirit of other motion picture research (e.g., Elberse and Eliashberg 2003), accounting for unobserved individual-specific (i.e., film) effects is not necessary; time-specific effects are accounted for by including a *t-1* dummy variables for each week of a film's run.

A key consideration here is whether each system of simultaneous equations is identified, as by the rank and order conditions. The necessary order condition requires each equation to exclude at least as many system exogenous variables (less those in the equation) as the number of endogenous variables less one (Wooldridge 2009). There are 11 exogenous variables in the opening week system. The post-launch system has 8 exogenous variables (not including lagged seeders or lagged leechers). Each equation in both models has more excluded variables than endogenous, meeting the order condition. The rank condition is discussed at the end of the Results section.

For exposition, Figure 4 presents all four market components plus the estimated revenues for the film *Divergent*. Typical for information goods, all four market components decrease over time. Estimated revenues in the opening week were $60.4M, but actual revenues were $68.8M. Post-launch, the smoothing procedure takes into account prior observations and trend to 'lock on' to forecasts. The film opened to 7,600 screens. Also, the decay for seeders is less steep than leechers, consistent with the belief that users slowly delete files after downloading.

3.4 Results

Table 8 presents descriptive statistics for the variables of interest to both the opening week and post-launch models. The following sub-sections describe the coefficient estimates for each model.

3.4.1 Opening Week Results

Since some films do not have available production budgets, the opening week estimation uses 165 films. Table 9 shows the coefficient estimates for the variables in each equation of the opening week system of equations. The Adjusted R^2 values suggest reasonable explanation of the variance: .88 for the screens model, .64 for the revenues model, .69 for the seeders model, and .66 for the leechers model.

In the legal supply model, estimated revenues ($\beta = .36$, $p < .01$), production budget ($\beta = .21$, $p < .01$), advertising ($\beta = .20$, $p < .01$), and competition from new films ($\beta = -.13$, $p < .01$) are significant and in the hypothesized direction. However, star power ($\beta = -.07$, $p < .02$) and critical reviews ($\beta = -.38$, $p < .01$) are in the direction contrary to conventional belief. Prior research also found critical reviews to be negative (Elberse and Eliashberg 2003). Two explanations for this are that low quality movies push for a larger opening week before word of mouth spreads, or high critical reviews are used to build word of mouth from a limited release. Former producer and editor of industry trade *Variety*, Peter Bart (2001) suggested that the movie star as a driver of revenues may be extinct and that audiences do not respond to actors the way they previously did. Competition for screens from ongoing releases ($\beta = -.00$, $p > .99$) and distribution by a major film studio ($\beta = .05$, $p > .39$) are not significant.

Regarding legal demand, screens ($\beta = 1.41$, $p < .01$), leechers ($\beta = -.86$, $p < .02$), seeders ($\beta = .69$, $p < .04$), and critical reviews are significant and in the hypothesized directions. As expected, pirated demand has a negative effect on the legal demand. Additionally, pirated supply has a positive effect on legal demand. This highlights the interdependence that has been unexplored in prior research: pirated supply is not entirely a threat to the legal good, as prior research has also treated piracy demand as a sampling mechanism. Star power (β = -.02, $p > .76$), advertising (β = .01, $p > .92$), competition for revenues (β = -.07, $p > .45$), and weekly seasonality (β = .04, $p > .84$) are not significant.

As for pirated supply, the key endogenous variables are significant and in the hypothesized directions: screens (β = -1.80, $p < .03$), revenues (β = .85, $p < .05$), and leechers (β = 1.18, $p < .01$). Production budget (β = .32, $p < .04$) has a significantly positive effect on piracy supply. Interestingly, the number of days prior to U.S. release (β = -.03, $p < .01$) is significant, but not in the expected direction that longer lead time leads to more supplied piracy. One possible explanation is that supply is limited early for a film's release. If there is a long time lapse between first release and the U.S. release, interest may not have peaked yet, prompting pirated supply originators to wait until a U.S. release legitimizes the film's demand (and hence demand for sharing). Star power (β = -.15, $p > .11$), advertising (β = .13, $p > .44$), critical reviews (β = -.21, $p > .66$), and buzz ranking (β = -.00, $p > .69$) have no significant effect on seeding.

Lastly, pirated demand is significantly influenced by screens (β = 1.56, $p < .01$), seeders (β = .78, $p < .01$), and revenue (β = -1.04, $p < .01$) in the expected directions. Critical reviews have a marginally positive effect on pirated demand (β = .66, $p < .08$). However, star power (β = -.02, $p > .82$) and advertising (β = -.02, $p > .89$) have no effect on leeching.

3.4.2 Post-Launch Results

In the post-launch period, 1,204 film-week observations are used in the estimation. Table 10 shows the coefficient estimates for the variables used in each equation of the post-launch system of equations. Adjusted R^2 values are higher than the opening week for all equations except screens: .77 for the screens model, .80 for the revenues model, .77 for the seeders model, and .78 for the leechers model. The time-specific dummy variables are largely significant and in the expected direction but are not shown.

Unlike the opening week model, the legal supply now includes effects of the piracy market. Estimated revenue is still significant and in the hypothesized direction ($\beta = .57$, $p < .01$). Prior week seeders are positively significant rather than negative ($\beta = .10$, $p < .01$). One possible explanation is that theaters do not consider pirated supply a threat. As the example of *Divergent* in Figure 4 illustrated, pirated supply and legal supply have similar diffusion patterns which might not be entirely in opposition to each other. Leeching in the prior week had no impact on the supply of movie screens ($\beta = .01$, $p > .88$). Competition for screens from new releases ($\beta = -.06$, $p < .07$) and ongoing releases ($\beta = .042$, $p < .01$) are also significant and in the appropriate direction. Also, user reviews as a measure for word-of-mouth also has a positive effect on screen allocation ($\beta = .23$, $p < .05$).

On the legal demand side, screen availability again has a positive and significant effect on revenues ($\beta = .96$, $p < .01$). Unlike the launch period, the effects of seeding ($\beta = .51$, $p > .62$) and leeching ($\beta = -.47$, $p > .72$) are not significant after the film's release. This decomposition of launch and post-launch periods helps to explain some tension in previous piracy literature as to whether piracy hurts sales or not since support is found for both sides. Competitive effects are not significant ($\beta = -.03$, $p < .01$). As expected, weekly seasonality ($\beta = .57$, $p < .01$) and word-of-mouth ($\beta = 1.47$, $p < .01$) have significantly positive effects on revenues.

Post-launch, legal supply should positively influence the pirated supply since legal supply diffusion in the market creates opportunities for copies to be made.

Additionally, as Figure 4 showed, legal and pirated supply may have similar patterns of availability. This was supported in the estimation by screens having a positive effect (β = .30, $p < .06$). Leeching again has a positive influence (β = 1.40, $p < .01$), but revenues of the film have no effect (β = -.13, $p > .26$) on seeding. Two additional controls of interest, number of users (β = -.11, $p < .05$) and buzz ranking (β = .00, $p < .01$), have a significant effect on seeding but in a direction contrary to theory. An increase in the number of users rating a film, as a proxy for online interest in the film, should be associated with an increase in pirated supply. One possible explanation is that the number of users rating the film online reflects consumers who have seen the film through the legal channel, reflecting only legal demand and not interest on the piracy side of the market.

Finally, pirated demand in the post-launch period is negatively influenced by screen availability (β = -.30, $p < .01$) but positively influenced by seeders (β = .87, $p < .01$). The hypotheses suggest that a reduction in the legal channel would prompt consumers to seek a pirated means for the good by way of a pirated supply. Revenues have no significant impact (β = .13, $p > .13$). Theorized quadratic effects are supported here: word-of-mouth has a positive effect on pirated demand for the good (β = 2.52, $p < .01$), but beyond a point, piracy demand wanes (β = -.03, $p < .01$) with the belief that consumers will pursue the full theatrical experience if perceived quality of the film (as suggested by word-of-mouth) is sufficiently high.

Returning to the issue of identification, the sufficient rank condition requires that if the coefficient estimates are treating as a matrix, there is at least one non-zero determinant of the sub-matrices of the excluded variables. Significant variables in each model would prevent the equations from collapsing into linear dependence. The findings from Tables 9 and 10 indicate that the launch and post-launch models are linearly independent, satisfying the rank condition.

3.5 Discussion

Illegal markets, consisting of both illegal supply and illegal demand, represent a threat to the efforts of brand managers in the legal market. Drawing on prior research of how legal and pirated demand for information goods interact, a theoretical framework is developed for how the supply side interacts. At face value, the prevailing belief is that the alternate counterpart (i.e., pirated demand for legal demand) is a substitute. In the opening week, legal demand and pirated demand each have negative effects on the other, but legal supply *and* pirated supply have positive effects on both of these. Post-launch, however, substitutable effects are not significant on the demand side, while the supply side (both legal and pirated) has positive reinforcing effects. This is the first research to estimate the effects of all four market components acting interdependently. It also resolves prior tension in the piracy literature as to whether pirated copies hurt sales or not; both sides are right.

Several implications for marketing theory arise. This study supports prior research on film piracy that pirated demand has a negative effect on legal demand. However, it also supports prior research that there is no effect. This is due to timing differences in the release of information goods, which often rely on the initial launch period to set the tone for its performance run. The role of the supply side of the market is addressed and how legal supply and pirated supply influence legal demand and pirated demand. Pirated supply and pirated demand positively reinforce each other (Bhattacharjee, Gopal, and Sanders 2003). Furthermore, pirated supply is negatively affected by legal supply in the launch period but positively in the post-launch period. In practice, legal supply and pirated supply are not purely simultaneous, since the illegal supply needs an origination from the legal supply. This presents a new perspective on how pirated goods reach markets and is also indicative of timing effects.

For managers, this research examines the effect that the pirated side of the market has on legal supply and legal demand for information goods. With respect to legal demand, a 1% increase in downloading pirated copies has a -.86% effect on revenues. But this effect is not significant post-launch. This reinforces the prevailing belief among practitioners that the opening week of a film's release is critical to box office success. While exhibitors are currently not concerned about piracy supply, the pirated side of the market has no direct negative effects as to how many screens a film should be allocated post-launch.

Several issues create challenges in conducting this research. First, the piracy data is measured daily, with number of downloads at one point in time, averaged for the weekly data point. The actual number of downloads is unknown, but prior research has used similar estimation measures. Second, the piracy data reflects global downloads from one (albeit the most popular) piracy website. While the effects are examined on just the U.S. box office, the U.S. box office highly correlates with global box office revenues, as weekly revenues by specific market are not readily available.

Studying other types of products presents an interesting avenue but has implications for data collection. For one, observing pirated demand and pirated supply is challenging due to the need for gathering data from an illegal activity. Although previously researched from the demand side, examining the supply side of pirated luxury goods and electronics presents an interesting area. Since the pirated demand side of information goods is treated as having no price involved, and motion pictures are treated as having uniform pricing, pricing effects present an additional complication for how legal suppliers (and pirated suppliers) price their products. A final consideration is that all pirated demand might not be equal. That is, copies that are of higher quality (i.e., direct film reel transfers) may have different effects on legal demand and supply.

Chapter 4

Essay 3: Brand Loyalty and Variety-Seeking Within a Branded House

4.1 Introduction

A much discussed area of marketing that is particularly relevant to managers is how to grow the brand. Particularly for mature categories, this often means introducing new branded variants to either maintain overall share for the brand or to possibly create a new product category. By differentiating within the brand, this has the added effect of warding off competitors, including private label offerings (Gielens 2012). This presents unique or exclusive varieties while maintaining the consumer connection to the brand. Unlike 'fighter brands' (Ritson 2009), which are differently branded products with similar features designed to appeal to more price sensitive consumers, branded variants are designed to maintain the existing brand equity while still retaining the consumer base of the brand. This represents a 'branded house' strategy in which the product portfolio retains the focal brand name. Consistent with the notion of brand architecture (Aaker 1996), this research examines the switching behaviors of households at the lowest line extension level, or the modified brand (e.g., Cherry Coke, Pepsi Max, etc.).

Two areas highlight competing perspectives about consumers' reaction to branded variants. On one hand, consumers are at times variety-seeking, gaining utility through stimulation of something different (McAlister and Pessemier 1982), by alleviating boredom from repeat purchasing (Howard and Sheth 1969; Van Trijp, Hoyer, Inman

1996), or reducing risk (Simonson 1990). On the other hand, consumers are seen as brand loyal, repurchasing the same brand within a product category because of the inherent value of the brand. This also reduces search and switching costs (Howard and Sheth 1969; Wernerfelt 1991) and minimizes risk through brand trust (Chaudhuri and Holbrook 2001).

While this appears to help the brand retain customers *and* offers variations of the brand to alleviate variety-seeking, little research exists on the brand loyalty and variety-seeking effects of this strategy. Do variations of a brand create variety-seeking *within* a brand? Or do the variations create their own loyalty (for instance, do Diet Cherry Coke users buy only Diet Cherry Coke and not the other varieties)?

To address these questions, theoretical explanations explore brand loyalty and habit formation. Propositions are examined through empirical evidence of consumer household panel purchases of two distinct but related product categories using Markov chain switching probabilities. Several key findings emerge. First, the master modified brands (i.e., the flagship brand most associated with the product) have the largest consumer base for the brand relative to other modified brands. Second, rather than variety-seek within the brand's offerings, most households (close to 95%) that primarily purchase the master modified brand (i.e., Regular Coke, Diet Coke, Regular Pepsi, and Diet Pepsi) continue to do so in subsequent quarters. Third, the other modified brands (e.g., Coke Zero, Caffeine-Free Diet Pepsi) continue to purchase majorities of their volume of the same variety (approximately 90%). The exception was mostly for cherry flavored Coke or Pepsi, which still had majority repurchases of the variety, but at lower rates than the other modified brands. Finally, households switching from these brand varieties do so primarily towards the master modified brand (for example, Cherry Coke households who do switch will do so to Regular Coke), although some asymmetric switching takes place between varieties. To the author's knowledge, this is the first study that examines switching behavior within the brand. A key implication is that variety-seeking is not common within the brand, and that brand loyalty applies not only to the master brand level, but at the brand level of the variety as well. While modified brands develop a following of their own, the master modified brand dominates sales and exhibits the highest loyalty.

The remainder of this research article is organized as follows. First, strategies by brand managers are examined, particularly as brand extensions through brand architecture. The context of the Cola Wars illustrates this. Then, propositions are developed as to whether this brand architecture encourages loyalty or variety-seeking within the brand. Following this, the panel data and Markov chain switching probabilities are discussed. Third, the results of the switching probabilities and the implications for marketing academics and managers are elaborated. Finally, this research concludes with limitations and future research directions.

4.2 Theoretical Development

Growing the brand in a mature product category presents a difficult challenge for managers. Marketing mix tools that were useful earlier in the category lifecycle now have less of an impact. Indeed, long-term effects show that elasticities are higher for product and distribution than advertising or promotions (Ataman, Van Heerde, and Mela

2010). That is, strategies for the product line and distribution have greater returns to sales. Managers are wary of competing on price since price wars can decimate industry profits without altering market shares (e.g., U.S. airlines in the early 1990s, Cola Wars of the late 1970s). Advertising effects are also lower in the mature stage than growth stage (Sethuraman, Tellis, and Briesch 2011), as consumers are well aware of the brand and its benefits. Distribution, by this point in the category lifecycle, has likely peaked as the brand has found ways to reach the consumer; brands should even cut back unprofitable outlets (Kotler and Keller 2012). This leaves the product line as an area of most interest to the brand manager.

Extending the brand to new categories (brand extension) or within the existing category (line extension) carries risks and rewards for the manager. On the positive side, line extensions can attract customers who might not normally purchase the brand. By offering innovations and varieties that private labels cannot match, this stabilizes aggregate market share for national brands (Gielens 2012). A potential downside is that an underperforming extension can perceivably hurt brand equity. Furthermore, a moderately successful extension might cannibalize sales of the brand.

Because of these risks, managers are careful about the brand architecture strategy used to extend the brand. This spectrum (Aaker 1996) uses the name of the brand at one end (i.e., a branded house strategy where products carry a common brand name, such as BMW and Virgin) and a ‘house of brands’ strategy at the other (where brands are independent of each other, such as that used by Proctor & Gamble). In between these two strategies are combinations of the two to endorse or sub-brand the line extension (e.g., Courtyard by Marriott, McDonald’s McMuffin).

In light of these considerations, the focus becomes how to grow the brand without compromising the brand to loyal consumers. Unlike growing categories, in which unattached customers can be acquired, the prevailing view is that growing the brand at this stage involves stealing market share (customers) from competitors. An additional view is that growth can be achieved through current customers increasing their purchasing and consumption.

The loyalty perspective faces two challenges. The first is that consumers have already learned much about the brands and the product category over time; if brands are consistent in meeting consumers' needs, then consumers become attached to a brand through trust and brand affect, resulting in brand loyalty (Chaudhuri and Holbrook 2001). This aids the brand in keeping loyal customers, but also makes converting customers from competing brands a difficult endeavor. The second is that as customers become more knowledgeable about a category, they perceive the brands as less differentiated, resembling commodities (Rangan, Moriarty, and Swartz 1992). This prompts brands to compete on price rather than differentiation. It is not surprising, then, that loyal customers are more price sensitive (Krishnamurthi and Raj 1991).

By offering varieties of the brand, the brand manager hopes to have the best of both worlds. Extending the brand name creates consumer associations of trust with the brand and what it means in terms of delivering quality to the new product. This reduces search and switching costs (Wernerfelt 1991) and minimizes risk through trust in the brand (Chaudhuri and Holbrook 2001). Additionally, the new brand variation allows consumers to variety-seek, gaining utility through stimulation of something different

(McAlister and Pessemier 1982), by alleviating boredom from repeat purchasing (Howard and Sheth 1969; Van Trijp, Hoyer, Inman 1996).

What is unknown is whether these branded variants serve supporting roles by alleviating consumer boredom and providing new stimuli, or instead carve out sub-markets with their own loyalty. Consistent with prior definitions (Keller 2013), the umbrella or *family brand* is the highest brand level, which may be used in more than one product category (e.g., Dell , Coke). The family brand is sub-divided into *individual brands*, which are restricted to just one product category (e.g., Dell Latitude laptops, Diet Coke). The individual brand contains *modified brands*, which specify a particular configuration of the product such as a model, version, or flavor (e.g., Dell Latitude E6410, Diet Coke with Lime).

Amid the modified brands, there is likely a dominant or flagship brand within the category. This ‘master’ brand is so entrenched in consumers’ minds that it “owns” the brand’s association to the category (Farquhar et al. 1992). This is likely attributed to the original offering of the brand, serving as an archetype for the category. For example, when consumers think of Coca-Cola, most would associate the name with its regular cola offering rather than Vanilla Coke or Cherry Coke). In the spirit of Farquhar et al. (1992), this is denoted as the *master modified brand*. Figure 5 presents an example of Coke’s brand architecture. The next sub-section further explores whether these modified brands induce variety-seeking within the brand or create sub-loyalties.

A key premise of introducing line extensions is to uncover new consumer segments. However, frequent purchased products, such as consumer packaged goods, should have higher rates of variety-seeking (Zhang, Krishna, and Dhar 2000) as consumers look for new stimuli, reducing loyalty. While this strategy may keep consumers variety-seeking within the individual brand (and sustain overall market share for the individual brand), it also suggests loyalty to any particular modified brand may be low. An unintended consequence, though, is that more offerings by the brand can lead to more options for the consumer, which leads to variety-seeking (Kahn 1998). Too many options create conflict for consumers, hindering any purchase at all in the category (Iyengar and Lepper 2000).

At the same time, frequently purchased categories may lead consumers to develop habits in order to economize decision making. This aligns with the notion that brand repurchases are attitudinal (i.e., the consumer loves the brand) or habitual in nature (e.g., Chaudhuri and Holbrook 2001; Dekimpe et al. 1997; Howard and Sheth 1969). While variety-seeking may serve to break habits, an alternative view is that consumers may switch to a new modified brand, but this may create a new habit entirely. Since modified brands seek to meet consumer needs, these modified brands should resonate with select consumer segments, leading to trial and adoption. As such, modified brands should develop their own followings and create loyal sub-segments of consumers.

P1: Loyalty rates are high for modified brands.

If loyalty at the modified brand is high, in accord with Proposition 1, this further begs the question of which modified brands have the highest loyalty. While the modified brand should create a loyal sub-segment of consumers, it is expected that some group of consumers loyal to the master modified brand will try a different variety from their usual modified brand (e.g., a household that normally purchases just Diet Coke may purchase Diet Coke Vanilla, either in place of Diet Coke, or as an addition to its Diet Coke purchase). Consumers attached to the master modified brand have likely developed purchasing habits that are not easily disrupted by other variations of the brand. As the modified brand that has typically existed longest in the marketplace, and is the brand from which other modified brands emerged from, the master modified brand should exhibit higher rates of loyalty than other modified brands in the family.

P2: The master modified brand has higher loyalty than other modified brands.

Since the belief is that the master modified brand has greater loyalty than other modified brands, a natural consideration is which direction incurs the most switching between modified brands. For instance, if the master modified brand has higher loyalty than other varieties, according to Proposition 2, then it will have fewer consumers switching to the other modified brands. Consumers loyal to the other modified brands who do switch have a choice of what to pursue: the master modified brand or another modified brand. Since the master modified brand has been in the marketplace the longest and is more familiar to consumers, consumers will switch more to the master modified brand than to other modified brands.

P3: The master modified brand attracts more switchers than other modified brands.

The next section elaborates on the data and methodology to examine whether there is empirical support for loyalty to modified brands.

4.3 Methodology

To investigate the propositions into whether varieties of a brand (the modified brand level) create variety-seeking within the brand or create loyalties within the brand, data comes from a mature product category with two brands that use a branded house strategy. The data and model used are described below.

4.3.1 Data

Of particular interest for examining product brand loyalty is a product category where the family brand has been extended into product sub-categories, then further varied by creating modified brands. Carbonated beverages fit these criteria. Coca-Cola and Pepsi are also highly visible family brands, ranking as the 3rd and 22nd best global brands (Interbrand 2013). Both regular and low calorie (diet) soft drinks are examined. Only the cola varieties for both Coca-Cola and Pepsi are analyzed. The Coca-Cola company, for example, also owns other soda brands such as Sprite, Fanta, Pibb, and Mello Yello, which are not considered as part of the brand loyalty analysis.

Consumer shopping history comes from the Consumer Panel Data set, a joint panel database from the James M. Kilts Center for Marketing at the University of Chicago and the Nielsen Company. Available to academic researchers, the representative panel contains information on approximately 1.4 million UPC bar codes, as well as purchase location, household demographics, and product information. The data covers calendar year 2011, tracking purchases of consumer packaged goods for 62,092 participating households across the United States. Hereafter, consumer and household are used interchangeably, as well as soda in place of carbonated beverages, and diet for low calorie sodas. ‘Coke’ and ‘Pepsi’ refer to the family brand, specifying Coke and Pepsi products at the modified brand level.

Examining household purchase data of regular and diet sodas presents some desirable features. In addition to two well-known brands that use a branded house strategy, it allows for controls of marketing mix factors. For instance, Coke and Pepsi compete between each other similarly in terms of pricing, distribution, and advertising. Within the brand, these controls are also reasonably similar: within Coke (or Pepsi), the brand uses line pricing across its modified brands (i.e., when Coke is on sale, all flavor varieties of Coke are the same sale price – pricing differs only by pack size), distribution is similar for modified brands, and advertising and promotions apply across modified brands.

To illustrate market performance of Coke and Pepsi modified brands, Figure 6 presents total volume for these brands in the first quarter of 2011 from the household panel data. Both regular and low calorie sodas are similar in offerings for both brands (the master modified brand, caffeine-free, and cherry flavor), although the diet soda category also includes a uniquely segmented diet offering (Coke Zero and Pepsi Max). The figure shows that across the four individual brands, the master modified brand (e.g., Regular Coke, Diet Coke, Regular Pepsi, and Diet Pepsi) make up the largest amount of volume. This is anticipated, as these are the incarnations of the brands that have been around the longest, and from which other modified brands emerge. The figure also illustrates that diet soda sales are greater for Coke and Pepsi than their regular soda offerings. Caffeine-free modified brands also perform better among diet sodas than regular. The ‘other’ represents modified brands that collectively garner a fraction of the sales volume. This is 1.3% in Regular Coke (namely Coke C2 and Vanilla Coke), 0.0% in Regular Pepsi (namely Pepsi Vanilla and Pepsi Edge), 1.2% in Diet Coke (Diet Coke

Plus, Diet Coke Vanilla), and 4.6% in Diet Pepsi (chiefly Diet Pepsi One, Diet Pepsi Lime, Diet Pepsi Vanilla, Diet Pepsi Twist, and Diet Pepsi Jazz).

The data set includes purchase histories of 50,338 households that purchased made any sodas during 2011. From these households, a two-step filtering criteria is used to decide which households to include for analysis. First, a household needs to purchase a majority of its volume within a family brand. For example, a household that purchased 60% of its regular soda volume as Coca-Cola products would be a 'Coke' household. This same approach was applied at the individual brand level (i.e., regular versus diet soda), and at the modified brand level (i.e. of 'Coke' households, one would be classified as a Diet Coke, Caffeine-Free Diet Coke, Coke Zero, or Diet Cherry Coke household). Households that had no majority, such as 50/50 volume splits or a plurality of purchase volume, or were loyal to one of the 'other' modified brands are excluded from analysis. The belief that most households have a preferred modified brand bears out in model-free evidence, described below.

Second, households in the upper half of volume were further retained for analysis. Continuing with the example, only 50% of 'Coke' households (or regular soda households or Coke Zero households, depending on the level of analysis) are assessed. This 50% threshold, in accordance with the 'heavy half' theory (e.g., Frank, Massy, and Boyd 1967; Morrison 1968; Twedt 1964), advocates that the upper median of a firm's consumers constitute a much greater proportion of purchase volume. To show the effect that the heavy half has on the category, consider Figure 7. Of all household soda purchases in the first quarter, the volume skews heavily towards the left portion of the curve, since household volume is sorted in descending order. At the far left end, the maximum purchased by any one household was more than 45,000 ounces of soda. At the other extreme end are households that only purchased one 20 ounce single-serving soda. The dashed vertical line represents the median.

Focusing on the heavy half serves two purposes. First, casual users of the category do not reflect true brand loyalty. This also eliminates small sizes (i.e., a household with one purchase is by definition 100% loyal), and creates a natural demarcation rather than an arbitrary volume amount. Second, heavy users matter more to the firm because they constitute the bulk of purchase volume. As a percent of volume in the first quarter, Coke's heavy half households were 86.0% of its total volume and Pepsi's heavy half households made up 85.5% of its total volume.

The number of households from both steps for analysis is 3,168 for Regular Coke, 2,395 for Regular Pepsi, 4,238 for Diet Coke, and 2,721 for Diet Pepsi. Of the households analyzed, percentages are small for the number that do not have a majority volume preference for a modified brand (or were majority for an 'other' modified brand): 2.1% of Regular Coke households, 0.3% of Regular Pepsi households, 4.3% of Diet Coke households, and 7.1% of Diet Pepsi households.

4.3.2 Model

Probabilistic brand switching is treated as the proportion of households that match in majority modified brand purchase volume between quarters. The proportion of brand switching outcomes between the first quarter and subsequent quarters represents a Markov chain, classifying the probability of switching from one state (i.e., modified brand) to another in the subsequent time period (e.g., Ehrenberg 1965; Lattin and McAlister 1985; Poulsen 1990; Styan and Smith 1964). Here, household purchases are aggregated across each quarter of 2011, using the first quarter as the base period. A time period this long will allow for variety-seeking while too short a timeline will not establish enough purchases for brand loyalty (Sharp 2010). Households in the first quarter were examined in the second, third, and fourth quarter for volume switching.

One of the concerns with modeling variety-seeking behavior is that traditional choice models do not account for multi-item choice (Harlam and Lodish 1995). Typical logit models are restricted by the assumption of single unit purchases (Dubé 2004), making total volume purchased instead the preferred metric. Volume purchased is the appropriate measure as number of shopping trips does not account for units and unit sizes (carbonated beverages are frequently purchased as several units within a shopping trip, as well as mix-and-matching of pack sizes).

After assignment to a master brand, product category, or product brand based on first quarter volume, the household is checked against its majority purchase volume classification in subsequent quarters. The switching matrix represents the percentage of households that matched first quarter and subsequent quarter majority volume purchased by modified brand. Not all households have data or sub-brand majorities in subsequent quarters.

4.4 Results

Additional model-free evidence is presented in Figure 8, which also highlights the threshold definitions used in the analysis. Here, the figure shows heavy half households for the fourteen modified brands (seven each for Coke, as black lines, and Pepsi, as gray lines). Solid lines represent regular soda and dashed lines represent diet soda. The square markers are for master modified brands, triangles for caffeine-free, circles for cherry, and cross-hairs for Coke Zero and Pepsi Max. For example, of the heavy half households that were designated Regular Coke households in the first quarter (the black solid line with squares, where more than 50% of their Coke volume was regular soda at the master modified brand level), 97.2% of these households purchased at least 70% of their volume from this modified brand. At a purchase threshold of 90% of household volume, this describes 91.6% of households in the first quarter. Finally, using a 100% threshold level, fully 88.1% of these households made Regular Coke its only Coke purchase in the first quarter.

This evidence suggests that most households have fairly high repurchase rates of a particular modified brand. To examine the subsequent switching over time for households, three volume thresholds are used: 50%, 70%, and 90%. These are outlines for each of the four individual brands in the following sub-sections.

4.4.1 Regular Coke

Table 11 presents the probability of Regular Coke households in their modified brand purchasing from the first quarter into the second, third, and fourth quarters. Within this individual brand, the master modified brand (i.e., just Regular Coke) has the greatest number of households with a majority purchase (n = 2,465). Much smaller in number are the Caffeine-Free Coke households (n = 124) and Cherry Coke households (n = 79).

The 50% threshold (left columns) indicates the percent of Regular Coke households that purchased at least half their Regular Coke volume of a particular modified brand in the subsequent quarter. At this 50% threshold, the retention rate for the master modified brand is between 97.4% and 98.6%. This indicates that very few households which make Regular Coke its primary purchase end up switching to the caffeine-free or cherry varieties. This also holds at the 70% threshold (middle columns: 98.2% to 99.0% of households) and 90% threshold (right columns: 98.5% to 99.1%).

For the non-master modified brands, repurchase rates were also high, but not as high as that of Regular Coke. Caffeine-Free Coke partitions the market on a product function as not having caffeine (unlike Regular Coke or Cherry Coke). Its retention rate is 72.9% to 79.0% (50% threshold), 77.4% to 80.2% (70% threshold), and 71.4% to 78.3% (90% threshold). Cherry Coke, on the other hand, operates as a more hedonic flavor differentiator. Its retention rate was for the most part slightly less than that of Caffeine-Free Coke: 66.7% to 74.0% (50% threshold), 68.3% to 73.0% (70% threshold), and 70.2% to 77.8% (90% threshold). In support of Proposition 3, households which do switch a majority of their purchasing to another modified brand do so to Regular Coke.

4.4.2 Regular Pepsi

Similar to Regular Coke, Table 12 presents the probabilities of Regular Pepsi households that make a majority of their modified brand purchases. Here as well, the master modified brand has the greatest number of households (n = 1,885), which is less than Coke. However, it has more caffeine-free households (n = 173) and fewer cherry households (n = 63).

Regular Pepsi’s loyalty rate ranges from 97.6% to 98.0% (50% threshold), a very high rate similar to that of Regular Coke. The rate remains strong at higher thresholds: 98.2% to 98.6% (70% threshold) and 98.8% to 99.1% (90% threshold). In short, very few Regular Pepsi households switch to Caffeine-Free Pepsi or Cherry Pepsi.

As to Caffeine-Free Pepsi, it exhibits higher loyalty rates than that of its Coke counterpart: 81.5% to 86.6% (50% threshold), 87.2% to 90.7% (70% threshold), and 88.2% to 92.5% (90% threshold). However, Cherry Pepsi has more switching than Coke: 64.3% to 69.4% (50% threshold), 66.7% to 68.1% (70% threshold), and 65.8% to 69.2% (90% threshold). Like Coke, most switching to another modified brand that does occur happens overwhelmingly for Regular Pepsi.

4.4.3 Diet Coke

Unlike the regular soda market, the diet soda market is bifurcated with two similar master modified brands. That is, Coke Zero is very similar to Diet Coke; the former was launched with the perception that Diet Coke appealed to women. Diet Coke still dominates the category space in number of households (n = 2,153) and Caffeine-Free Diet Coke (n = 760) makes up a larger share of households here than in the regular soda category. Coke Zero (n = 613) has developed its own following, but Diet Cherry Coke still remains a niche variety (n = 130). Table 13 presents the retention rates.

The master modified brand of particular interest, Diet Coke, exhibits high loyalty rates. This ranges are from 92.2% to 93.6% (50% threshold), 94.0% to 96.0% (70% threshold), and 95.4% to 96.8% (90% threshold). Although not as high as Regular Coke, one speculation is that this might be higher if not for Coke Zero's presence in the category.

Both Caffeine-Free Diet Coke and Coke Zero display similar switching rates, albeit less than that of Diet Coke. For Caffeine-Free Diet Coke this is 83.5% to 87.6% (50% threshold), 86.4% to 91.4% (70% threshold), and 87.8% to 91.7% (90% threshold). Coke Zero is 84.6% to 87.9% (50% threshold), 87.0% to 92.8% (70% threshold), and

87.8% to 93.4% (90% threshold). Diet Cherry Coke, like its regular variant, has the lowest loyalty levels among the modified brands of Diet Coke: 67.6% to 70.7% (50% threshold), 70.3% to 72.6% (70% threshold), and 66.3% to 73.6% (90% threshold).

Diet Coke households that do switch are almost twice as likely to switch to Caffeine-Free Diet Coke rather than Coke Zero. This holds relationship is even stronger the other way: Caffeine-Free Diet Coke households who do switch go to Diet Coke at almost five times the rate than that of Coke Zero. Yet, Coke Zero households are most likely to switch to Diet Coke first, Diet Cherry Coke second, and Caffeine-Free Diet Coke last. Diet Cherry Coke households persist as a niche modified brand – households that do switch prefer Diet Coke, followed by Coke Zero.

4.4.4 Diet Pepsi

Pepsi has a similar strategy as Coke in the diet soda space, with two seemingly master modified brands. Table 14 shows Diet Pepsi households (n = 1,389) still make up the largest component, followed by Caffeine-Free Diet Pepsi (n = 451), then Pepsi Max (n = 224). All modified brands are fewer in number here than comparable Diet Coke offerings, although Diet Cherry Pepsi has more households (n = 137) than Diet Cherry Coke.

The master modified brand displays loyalty rates almost as high as that of Diet Coke: 91.8% to 94.7% (50% threshold), 93.7% to 96.1% (70% threshold), and 95.4% to 97.1% (90% threshold). Caffeine-Free Diet Pepsi has slightly less loyalty (but slightly more loyalty than Caffeine-Free Diet Coke): 85.3% to 90.0% (50% threshold), 87.1% to 93.2% (70% threshold), and 86.9% to 94.0% (90% threshold). The effect is similar for Pepsi Max: 87.5% to 91.1% (50% threshold), 89.8% to 93.8% (70% threshold), and

92.4% to 94.6% (90% threshold). In some cases performing even better than Pepsi Max, Diet Cherry Pepsi experiences greater loyalty than Diet Cherry Coke. Diet Cherry Pepsi's loyalty rate range is 96.9% to 90.0% (50% threshold), 90.4% to 92.5% (70% threshold), and 92.7% to 95.3% (90% threshold).

An asymmetrical relationship appears for the switching between modified brands. Here, Diet Pepsi households are almost equally likely to switch to Caffeine-Free Diet Pepsi as Pepsi Max. However, Caffeine-Free Diet Pepsi households are much more likely (about eight or nine times more likely) to switch to Diet Pepsi than Pepsi Max. Diet Cherry Pepsi households are most likely to switch to Diet Pepsi, with Caffeine-Free Diet Pepsi and Pepsi Max varying for the next most switched to modified brand depending on the quarter and threshold.

4.5 Discussion

This research has examined a new level of brand loyalty, that of whether consumers switch *within* the brand through the varieties the brand offers. This is driven by the notion that for mature brands to compete, product innovation as brand line extensions represent one of the few strategies available to the brand manager. Consistent with the definitions from prior literature, the brand architecture dictates that extension strategies follow those that use the brand (i.e., branded house) versus those that do not (i.e., house of brands), or somewhere in between. By extending the brand, managers risk inducing variety-seeking within the branded house. However, consumers develop habits which are shown here through the loyalty of many households to one modified brand.

This study gives rise to several implications for marketing theory. Little research has examined loyalty within brand architecture, especially for mature brands. By creating new variations of the brand, the brand creates variety-seeking within its brand architecture. Three propositions cover effects of variety-seeking within the branded house. The first is that loyalty is high for each modified brand. The second is that the master modified brand has the highest loyalty rates of all variations. The third is households that do switch are more likely to switch to the master modified brand. In a sense, the modified brands are experiencing internal ‘double jeopardy’ (e.g., Ehrenberg, Goodhardt, and Barwise 1990) – unless the modified brand is able to carve out its own identity, it has a base of fewer customers and is purchased less often.

For managers, this research demonstrates that loyalty rates are quite high for specific variations of the brand. Among heavy usage households that purchase Coke or Pepsi soda, these rates can hover around 95% or higher for most modified brands. However, a niche modified brand, such as the cherry flavored Coke or Pepsi, typically has much lower loyalty. Households loyal to the caffeine-free and cherry varieties are also most likely to switch towards the master modified brand. By working with heavy usage households (the upper median of which make up about 86% of Coke and Pepsi’s sales volume), the focus stays on consumers of most interest to the manager. Additionally, substantial numbers of these households are 100% loyal, monogamous to one specific modified brand

Several challenges persist in conducting this research. This research analyzes loyalty for two well-known brands in two related product categories of fast-moving consumer packaged goods. In looking at the switching at the lowest level of the brand architecture, most marketing mix tools of price, advertising, and distribution are not distinctly different (except in the case of Coke Zero and Pepsi Max to their diet brands). Product categories in which individual brands market their modified brands differently may see different loyalty behaviors. A second consideration is that this study has focused on brands using the branded house strategy. This should be different for the house of brands strategy, where different marketing resources and tactics are allocated to different consumer segments. For instance, 'fighter brands' (Ritson 2009) are differently branded products sold by the individual brand within the same category, usually as a means to lower-priced competitors. Finally, this paper examines mature brands in mature product categories. For growing product categories as well as new brands, the goal may be to expand the market first by growing the master modified brand and then introducing additional modified brands. As such, pre- and post-launch measurement of a modified brand may interesting in its effect on the master modified brand, as well as how long it takes for customer loyalty to develop.

Several possible research directions emerge. Durable goods and services may exhibit different loyalty within line extensions. Product upgrades may keep consumers buying newer versions of products (example: Apple iPod or Apple MacBook and MacBook Pro laptops). Durables often have aspirational elements: price points and product feature differences help to segment the market but also create a natural direction for 'moving up' (Bhat and Reddy 1998). Services also present research opportunities for line extension loyalty; banks offer varying types of savings and checking accounts, for example, to appeal to different consumers. High switching costs makes it unlikely that customers change accounts frequently. A third area of future research may be to look at business relationships (B2B). Stable relationships and partnerships allow for efficient business and reduced searching and switching costs. Still, switching rates of 3-5% (Sharp 2010) indicate some switching takes place. Switching within an existing relationship (for example, to account managers) presents an additional opportunity.

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Table 1: Constructs, Variables, and Definitions for Co-Brand Performance

Construct	Variable	Definition	Exp. Sign	Source
Revenues	Ln(Revenue)	Revenue (per 1,000 households) of product i in category type c in year t (log-transform)	NA	IRI
Market share	Logit(Share)	Volume share of product i in category type c in year t (logit-transform)	NA	IRI
Functional valuation	FunctionalP	Perceived functional valuation of primary brand p	+	Survey
Functional valuation	FunctionalS	Perceived functional valuation of secondary brand s	+	Survey
Emotional valuation	EmotionalP	Perceived emotional valuation of primary brand p	+	Survey
Emotional valuation	EmotionalS	Perceived emotional valuation of secondary brand s	+	Survey
Purchase frequency	TypePurCycle	Average time, in days, between purchases of product i in category type c in year t	+/-	IRI
Promotions	AnyDealIndex	Ratio of product p volume sold on any trade deal divided by category type c volume sold on any trade deal in year t	+	IRI
Stockpileable	Stockpile	Perceived stockpileability of category c*	+	Survey[a,b]
Enjoyableness	Hedonic	Perceived extent that category c* appeals to the senses	+	Survey[b]
Impulsiveness	Impulse	Perceived impulse buying of category c*	+	Survey[a,b]
Unbranded competition	PLQuality	Quality of private label product in category c*	-	Survey[c]
Advertising	AdPercent	Percent of category advertising dollars for brand p in year t**	+	Kantar
Price	PriceIndex	Average selling price of product i divided by average selling price of category type c in year t	-	IRI
Market size	TypeRev	Revenues (per 1,000 households) of category type c in year t	+	IRI
Economic growth	GDP	U.S. annual GDP growth rate in year t	+	U.S. Bureau of Economic Analysis
Intra-firm ownership	Parent	Indicator if both primary and secondary brands are owned by the same parent company	+	Brand websites

Note: * Survey item which asks respondents at the higher level category rather than category type

** Advertising data at the product level, or even category type level, is seldom broken out by Kantar. Instead, the brand level spending at the higher-level of the category is used

[a] adapted from Narasimhan, Neslin, and Sen (1996)

[b] adapted from Ma, Ailawadi, and Grewal (2015)

[c] adapted from Hoch and Banerji (1993)

Table 2: Co-Brand Performance Descriptive Statistics

Variable	Mean	Std Dev	Min	Max	Median
Revenue	$120	$202	$5	$1,025	$40
Market Share	1.56%	2.48%	.03%	28.45%	.72%
FunctionalP	4.59	.88	3.18	6.28	4.43
EmotionalP	2.93	.66	1.61	4.06	2.92
FunctionalS	4.68	.77	3.15	6.21	4.50
EmotionalS	3.22	.64	1.73	4.75	3.15
FunctionalP*FunctionalS	21.94	7.28	11.72	38.23	19.89
EmotionalP*EmotionalS	9.48	3.06	4.32	17.78	9.79
FunctionalP*EmotionalS	14.54	3.03	7.36	23.55	14.08
EmotionalP*FunctionalS	13.74	4.12	6.94	23.37	12.83
TypePurCycle	71.58	20.43	15.48	118.42	69.67
AnyDealIndex	1.01	.51	.01	3.00	1.04
Stockpile	5.17	.68	3.40	6.41	5.31
Hedonic	3.84	1.22	1.30	6.08	4.05
Impulse	2.96	.68	1.60	4.51	2.96
PLQuality	3.77	.26	3.20	4.30	3.77
AdPercent	1.48%	2.97%	.00%	15.56%	.16%
PriceIndex	1.28	.50	.13	3.41	1.18
TypeRev	$10,992	$13,165	$97	$75,763	$6,301
GDP	3.86%	2.40%	-.92%	6.52%	4.40%

Table 3: Correlations of the Functional and Emotional Valuations

	Revenue	Market Share	FunctionalP	EmotionalP	FunctionalS	EmotionalS	FunctionalP*FunctionalS	FunctionalP*EmotionalS	EmotionalP*FunctionalS
Market Share	**.24**								
FunctionalP	**.33**	**.26**							
EmotionalP	**.19**	-.03	**.15**						
FunctionalS	.02	**.24**	**.67**	.08					
EmotionalS	.00	**-.10**	**-.40**	**.16**	**-.35**				
FunctionalP*FunctionalS	**.19**	**.27**	**.92**	**.13**	**.90**	**-.42**			
FunctionalP*EmotionalS	**.32**	**.13**	**.53**	**.28**	**.25**	**.56**	**.42**		
EmotionalP*FunctionalS	**.17**	**.09**	**.49**	**.82**	**.62**	-.07	**.61**	**.36**	
EmotionalP*EmotionalS	**.10**	-.09	**-.15**	**.77**	**-.16**	**.74**	**-.17**	**.54**	**.51**

Note: Items in **bold** significant at $p < .05$

Table 4: Co-Brand Volume Share and Revenue Share Estimation Results

	Exp.		DV: logit(Share)			DV: ln(Revenue)		
Hyp.	Sign	Variable	Estimate	SE		Estimate	SE	
		Intercept	-6.06	.59	***	3.98	.58	***
		FunctionalP	3.52	1.20	***	1.71	.94	*
		EmotionalP	2.28	.81	***	2.65	.74	***
1a	(+)	FunctionalS	2.24	.52	***	1.14	.40	***
1b	(+)	EmotionalS	2.99	.54	***	2.66	.54	***
2a	(-)	FunctionalP*FunctionalS	-4.98	1.40	***	-1.81	1.09	*
2b	(-)	EmotionalP*EmotionalS	-3.50	.53	***	-2.84	.47	***
3a	(+)	FunctionalP*EmotionalS	-.74	.61		-.75	.61	
3b	(+)	EmotionalP*FunctionalS	.34	.88		-.57	.77	
		TypePurCycle	.03	.01	***	-.01	.01	
		AnyDealIndex	.04	.11		-.04	.10	
		Stockpile	.05	.15		-.30	.12	***
		Hedonic	-.40	.21	*	-.78	.17	***
		Impulse	.23	.15		.35	.15	**
		PLQuality	.18	.12		-.23	.12	*
		AdPercent	-1.12	2.84		1.86	2.77	
		PriceIndex	-1.02	.16	***			
		TypeRev				.00	.00	
		GDP	.84	2.08		.07	1.88	
		Parent	.01	.24		.11	.19	
		QIC	576.89			575.23		
		Generalized R^2	.728			.701		
		n	490			490		

* $p < .10$

** $p < .05$

*** $p < .01$

Note: Consumer survey variables are standardized

Table 5: Simulated Brand Pairing Effects on Co-Brand Market Share

Primary Brand *Functional*	Primary Brand Emotional	Secondary Brand *Functional* -1 SD / Emotional -1 SD	-1 SD / Mean	-1 SD / +1 SD	Mean / -1 SD	Mean / Mean	Mean / +1 SD	+1 SD / -1 SD	+1 SD / Mean	+1 SD / +1 SD
+1 SD	+1 SD	2.6%	1.6%	1.0%	1.6%	1.0%	.6%	1.0%	.6%	.4%
+1 SD	Mean	1.5%	1.5%	1.5%	.9%	.9%	.9%	.5%	.5%	.5%
+1 SD	-1 SD	.9%	1.4%	2.3%	.5%	.8%	1.3%	.3%	.5%	.7%
Mean	+1 SD	1.3%	.9%	.7%	1.4%	1.0%	.7%	1.5%	1.0%	.7%
Mean	Mean	.8%	.9%	1.0%	.8%	.9%	1.0%	.8%	.9%	1.0%
Mean	-1 SD	.4%	.8%	1.6%	.4%	.8%	1.5%	.4%	.8%	1.4%
-1 SD	+1 SD	.7%	.6%	.5%	1.2%	1.0%	.8%	2.2%	1.8%	1.4%
-1 SD	Mean	.4%	.5%	.7%	.7%	.9%	1.2%	1.1%	1.5%	2.0%
-1 SD	-1 SD	.2%	.5%	1.1%	.4%	.8%	1.7%	.6%	1.3%	2.8%

Table 6: Hypotheses and Predicted Directions of Piracy and Box Office

Construct	DV	Predictor	Hypothesis	Direction	Support
Legal supply	Screens	Revenues	H1	+	Yes
		Seeders	H2	-	No
		Leechers	H3	+	No
Legal demand	Revenues	Screens	H4	+	Yes
		Seeders	H5	+	Partial
		Leechers	H6	-	Partial
Pirated supply	Seeders	Screens	H7a	-	Yes
		Screens	H7b	+	Yes
		Revenues	H8	+	Partial
		Leechers	H9	+	Yes
Pirated demand	Leechers	Screens	H10a	+	Yes
		Screens	H10b	-	Yes
		Revenues	H11	-	Partial
		Seeders	H12	+	Yes

Table 7: Motion Picture Variables, Descriptions, and Measures

Variable	Description	Measure	Source
$REVENUE_{it}$	Weekly revenues	Weekly box office, in $(000)	Boxoffficemojo
$SCREENS_{it}$	Weekly number of screens	Weekly number of screens	Boxoffficemojo
EST_REV_{it}	Expected weekly revenues	Launch: HSX stock price two days before opening, divided by HSX multiplier, multiplied by 000,000; Post-Launch: double exponential smoothing	HSX, Boxofficemojo
$BUDGET_{i}$	Production budget	in $(000)	IMDB, Wikipedia
$STAR\_POWER_{i}^{a}$	Actor star power	Sum of actor power in a film	Forbes Star Power
AD_EXP_{i}	Advertising expense	Total advertising expense prior to and including launch, in $(000)	Kantar
$CRITIC\_REVIEW_{i}$	Reviews from film critics	Metacritic rating from 1-100, divided by 5 (to get to 1-5 scale)	IMDB
$COMP\_SCR\_NEW_{it}^{a,b}$	Competition for screens from new releases	New releases, weighted by production budget, for every $10 million each week	Boxoffficemojo
$COMP\_SCR\_ONG_{it}^{c}$	Competition for screens from ongoing films	Average age, in weeks, of ongoing films of the top 25 films in the prior week	Boxoffficemojo
$COMP\_REV_{it}$	Competition for audience revenues from other films	Competitive similarity of other films based on MPAA rating and genre, weighted by week	Boxoffficemojo
WOM_{it}	Word of mouth	User rating	IMDB
$LEECHERS_{it}^{a}$	Leechers	Number of leechers, as a weekly average	PirateBay
$SEEDERS_{it}^{a}$	Seeders	Number of seeders, as a weekly average	PirateBay
$SEASONAL_{t}$	Demand seasonality	Weekly U.S. total cinema revenues relative to the average U.S. week, based on prior 5 year average	Boxofficemojo

$USERS_{it}$	Online users who rated the film	Number of online users rating the film, as a weekly average	IMDB
$BUZZ_{it}$	Broad interest	IMDB ranking of the film based on user search and interest	IMDB
$STUDIO\_MAJOR_{i}$	Distribution by a major U.S. film studio	Dummy coded if the film was released by Lions Gate, Warner Brothers, Universal, Sony/Columbia/TriStar, Fox, Paramount, or Disney	IMDB
$PRIOR\_DAYS_{i}$	Days of prior market release	Number of days the film was released in another market prior to the U.S.	IMDB

Notes:

[a] Variable had 1 added to it, so that the log transformation was not undefined.

[b] In a given week, if movie X faces two new releases, movie Y with a budget of $50 million and movie Z with a budget of $115 million, movie X is assigned a score of 5 + 11.5 = 16.5

[c] A higher number represents older (and presumably *weaker*) competition.

[d] Since many films have multiple genre and sub-genre appeal, a weighting system was used for each film. For example, *21 Jump Street* is listed as 3 genres: action, comedy, and crime. Its genre is then .33 for each, where all competing films in the top 25 that week that have any of those genre components are also weighted. When *21 Jump Street* (rated R) was in week 10 of release and *Dark Shadows* (rated PG-13) was in week 2 of release, *Dark Shadows* is .5 comedy and .5 fantasy, so only the .5 comedy part competes with *21 Jump Street*, so the competition score is genre/weeks (or .5 / 2) for .25. When *21 Jump Street* in week 10 was screening opposite week 6 of *The Cabin in the Woods* (rated R), which had genres of .33 each for Thriller, Horror, and Mystery genres (so no overlap in genre with *21 Jump Street*), but the MPAA rating was the same (R), then the value here is 1/6 (1 for matching genre, divided by its age, 6). Both genre and MPAA ratings were added together to get a total competition score.

Table 8A: Motion Picture Descriptive Statistics (Opening Week)

Variable	Mean	Median	SD	Min	Max
SCREENS	3,610	3,200	2,723	210	12,600
REVENUES	26,509,792	14,366,966	33,143,103	289,613	222,116,056
SEEDERS	215	10	329	0	1,796
LEECHERS	147	30	238	0	1,468
BUDGET	47.69	28.00	52.27	1.00	255.00
STAR_POWER	15.47	13.45	12.89	0	77.08
AD_EXP	13,274.80	12,355.85	9,692.61	0.32	37,901.70
CRITIC_REVIEW	2.53	2.48	0.84	0.68	4.85
COMP_REV	3.38	3.17	1.50	0.30	9.32
COMP_SCR_NEW	10.34	8.80	7.95	0	41.00
COMP_SCR_ONG	5.61	5.56	0.94	3.60	8.20
SEASONAL	0.98	0.90	0.30	0.56	1.82
BUZZ	402	50	968	1	5,000
PRIOR_DAYS	7	2	19	0	223
STUDIO_MAJOR	0.57	1.00	0.50	0	1.00

Table 8B: Motion Picture Descriptive Statistics (Post-Launch)

Variable	Mean	Median	SD	Min	Max
SCREENS	1,543	775	1,807	5	11,500
REVENUES	4,694,452	1,263,796	8,877,058	4,426	87,548,900
SEEDERS	261	226	252	0	3,125
LEECHERS	88	55	123	0	1,481
COMP_REV	3.71	3.49	2.20	0.11	56.00
COMP_SCR_NEW	14.23	13.70	8.51	0.50	41.00
COMP_SCR_ONG	5.57	5.36	1.03	3.60	8.20
USERS	30,259	9,479	46,010	108	297,048
WOM	6.89	7.00	1.18	1.46	8.90
SEASONAL	0.97	0.90	0.28	0.56	1.82
BUZZ	560	55	1,255	1	5,000

Table 9: Opening Week Piracy and Motion Picture Estimates

DV: Screens

	Estimate	**SE**	
INTERCEPT	1.26	0.35	***
ln(EST_REV)	0.36	0.04	***
ln(BUDGET)	0.21	0.03	***
ln(STAR_POWER)	-0.07	0.03	**
ln(AD_EXP)	0.20	0.03	***
ln(CRITIC_REVIEW)	-0.38	0.07	***
ln(COMP_SCR_NEW)	-0.13	0.03	***
ln(COMP_SCR_ONG)	0.00	0.15	
STUDIO_MAJOR	0.05	0.06	
Adj.R^2	0.88		

DV: Revenues

	Estimate	**SE**	
INTERCEPT	-1.62	1.78	
ln(SCREENS)	1.41	0.38	***
ln(LEECHERS)	-0.86	0.36	**
ln(SEEDERS)	0.69	0.33	**
ln(STAR_POWER)	-0.02	0.07	
ln(AD_EXP)	0.01	0.15	
ln(CRITIC_REVIEW)	0.60	0.29	**
ln(COMP_REV)	-0.07	0.09	
SEASONAL	0.04	0.18	
Adj.R^2	0.64		

DV: Seeders

	Estimate	**SE**	
INTERCEPT	1.87	2.33	
ln(SCREENS)	-1.80	0.80	**
ln(LEECHERS)	1.18	0.18	***
ln(REVENUE)	0.85	0.42	**
ln(BUDGET)	0.32	0.15	**
ln(STAR_POWER)	-0.15	0.10	
ln(AD_EXP)	0.13	0.17	
ln(CRITIC_REVIEW)	-0.21	0.48	
PRIOR_DAYS	-0.03	0.00	***
BUZZ	0.00	0.00	
Adj. R^2	0.69		

DV: Leechers

	Estimate	**SE**	
INTERCEPT	-2.14	1.99	
ln(SCREENS)	1.56	0.53	***
ln(SEEDERS)	0.78	0.14	***
ln(REVENUE)	-1.04	0.23	***
ln(STAR_POWER)	-0.02	0.08	
ln(AD_EXP)	-0.02	0.16	
ln(CRITIC_REVIEW)	0.66	0.36	*
Adj. R^2	0.66		

N = 165

* $p < .10$
** $p < .05$
*** $p < .01$

Table 10: Post-Launch Piracy and Motion Picture Estimates

	DV: Screens				**DV: Revenues**		
	Estimate	**SE**			**Estimate**	**SE**	
INTERCEPT	1.32	0.29	***	INTERCEPT	-2.32	0.45	***
ln(EST_REV)	0.57	0.01	***	ln(SCREENS)	0.96	0.12	***
ln(SEEDERS_LW)	0.10	0.03	***	ln(LEECHERS)	-0.47	1.35	
ln(LEECHERS_LW)	0.01	0.04		ln(SEEDERS)	0.51	1.04	
ln(COMP_SCR_NEW)	-0.06	0.03	*	ln(COMP_REV)	-0.05	0.06	
ln(COMP_SCR_ONG)	0.42	0.11	***	ln(WOM)	1.47	0.42	***
ln(WOM)	0.23	0.11	**	SEASONAL	0.57	0.13	***
Adj. R^2	0.77			Adj. R^2	0.80		

	DV: Seeders				**DV: Leechers**		
	Estimate	**SE**			**Estimate**	**SE**	
INTERCEPT	-1.30	0.40	***	INTERCEPT	-2.04	0.33	***
ln(SCREENS)	0.30	0.16	*	ln(SEEDERS)	0.87	0.04	***
ln(LEECHERS)	1.40	0.07	***	ln(SCREENS)	-0.30	0.11	***
ln(REVENUE)	-0.13	0.12		ln(REVENUE)	0.13	0.09	
ln(USERS)	-0.11	0.05	**	ln(WOM)	2.52	0.18	***
BUZZ	0.00	0.00	***	WOM^2	-0.03	0.00	***
Adj. R^2	0.77			Adj. R^2	0.78		

N = 1,204

* $p < .10$
** $p < .05$
*** $p < .01$

Table 11: Switching Probabilities of Regular Coke Heavy Half Households

	Modified Brand > 50%				Modified Brand > 70%				Modified Brand > 90%			
time t+1 (Q2)	n	Coke	Caffeine-Free Coke	Cherry Coke	n	Coke	Caffeine-Free Coke	Cherry Coke	n	Coke	Caffeine-Free Coke	Cherry Coke
Coke	2,465	97.8%	0.8%	1.4%	2,396	98.8%	0.3%	0.9%	2,286	98.9%	0.2%	0.8%
Caffeine-Free Coke	124	19.4%	79.0%	1.6%	111	18.0%	80.2%	1.8%	85	20.0%	77.6%	2.4%
Cherry Coke	79	26.0%	0.0%	74.0%	65	27.0%	0.0%	73.0%	55	22.2%	0.0%	77.8%
time t+2 (Q3)	n				n				n			
Coke	2,350	98.6%	0.9%	0.6%	2,292	99.0%	0.6%	0.4%	2,213	99.1%	0.5%	0.4%
Caffeine-Free Coke	117	23.9%	73.5%	2.6%	106	21.7%	77.4%	0.9%	83	21.7%	78.3%	0.0%
Cherry Coke	66	30.8%	0.0%	69.2%	58	29.3%	0.0%	70.7%	47	29.8%	0.0%	70.2%
time t+3 (Q4)	n				n				n			
Coke	2,359	97.4%	1.0%	1.6%	2,293	98.2%	0.7%	1.0%	2,218	98.5%	0.6%	0.9%
Caffeine-Free Coke	119	24.6%	72.9%	2.5%	103	21.6%	77.5%	1.0%	78	27.3%	71.4%	1.3%
Cherry Coke	70	33.3%	0.0%	66.7%	63	31.7%	0.0%	68.3%	49	24.5%	0.0%	75.5%

Table 12: Switching Probabilities of Regular Pepsi Heavy Half Households

	Modified Brand > 50%				Modified Brand > 70%				Modified Brand > 90%			
time t+1 (Q2)	n	Pepsi	Caffeine-Free Pepsi	Cherry Pepsi	n	Pepsi	Caffeine-Free Pepsi	Cherry Pepsi	n	Pepsi	Caffeine-Free Pepsi	Cherry Pepsi
Pepsi	1,885	97.9%	1.0%	1.2%	1,844	98.6%	0.8%	0.7%	1,770	98.9%	0.7%	0.5%
Caffeine-Free Pepsi	173	14.5%	82.7%	2.9%	149	12.1%	87.2%	0.7%	127	11.8%	88.2%	0.0%
Cherry Pepsi	63	28.6%	3.2%	68.3%	56	30.4%	1.8%	67.9%	41	31.7%	2.4%	65.9%
time t+2 (Q3)	n				n				n			
Pepsi	1,792	97.6%	0.8%	1.6%	1,750	98.2%	0.6%	1.2%	1,678	98.8%	0.4%	0.8%
Caffeine-Free Pepsi	149	10.1%	86.6%	3.4%	129	7.0%	90.7%	2.3%	107	6.5%	92.5%	0.9%
Cherry Pepsi	62	27.4%	3.2%	69.4%	47	27.7%	4.3%	68.1%	39	28.2%	2.6%	69.2%
time t+3 (Q4)	n				n				n			
Pepsi	1,743	98.0%	0.8%	1.1%	1,711	98.6%	0.6%	0.8%	1,656	99.1%	0.5%	0.4%
Caffeine-Free Pepsi	151	13.9%	81.5%	4.6%	125	10.4%	88.0%	1.6%	108	10.2%	88.9%	0.9%
Cherry Pepsi	56	33.9%	1.8%	64.3%	45	31.1%	2.2%	66.7%	38	31.6%	2.6%	65.8%

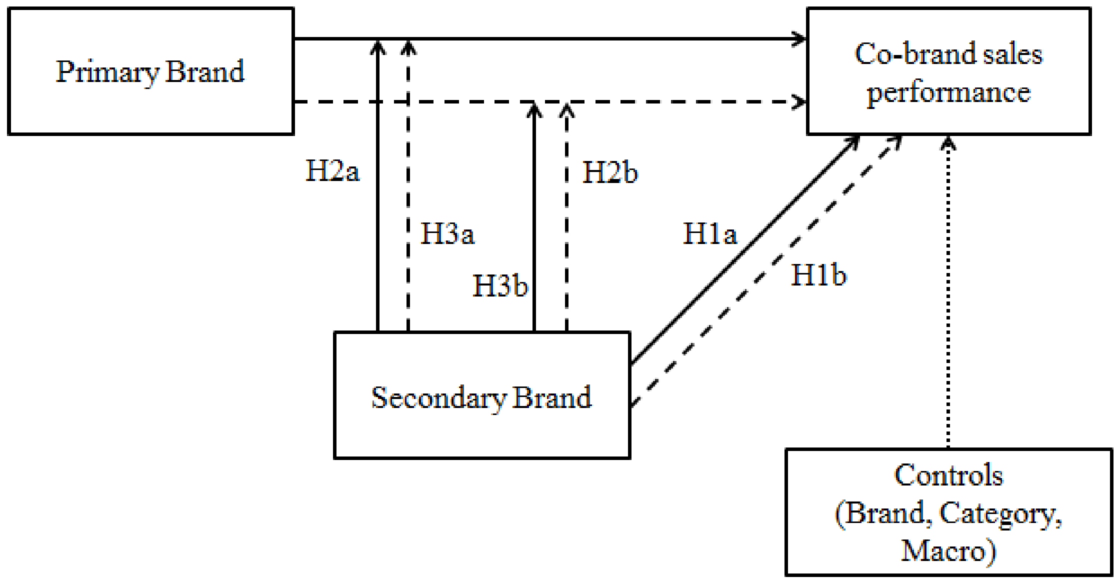
Table 13: Switching Probabilities of Diet Coke Heavy Half Households

	Modified Brand > 50%					Modified Brand > 70%					Modified Brand > 90%				
time t+1 (Q2)	n	Diet Coke	Caffeine-Free Diet Coke	Coke Zero	Diet Cherry Coke	n	Diet Coke	Caffeine-Free Diet Coke	Coke Zero	Diet Cherry Coke	n	Diet Coke	Caffeine-Free Diet Coke	Coke Zero	Diet Cherry Coke
Diet Coke	2,153	93.6%	3.9%	1.7%	0.8%	1,976	96.0%	2.4%	1.2%	0.5%	1,776	96.8%	1.7%	1.0%	0.4%
Caffeine-Free Diet Coke	760	10.5%	87.6%	1.3%	0.5%	650	7.2%	91.4%	1.1%	0.3%	516	6.8%	91.7%	1.2%	0.4%
Coke Zero	613	8.6%	0.7%	87.9%	2.8%	527	5.3%	0.4%	92.8%	1.5%	458	5.0%	0.4%	93.4%	1.1%
Diet Cherry Coke	130	18.5%	4.6%	10.0%	66.9%	108	18.5%	4.6%	6.5%	70.4%	83	20.5%	4.8%	8.4%	66.3%
time t+2 (Q3)	n					n					n				
Diet Coke	2,041	92.9%	4.4%	2.2%	0.5%	1,910	94.9%	3.0%	1.8%	0.3%	1,711	95.9%	2.5%	1.4%	0.3%
Caffeine-Free Diet Coke	722	11.6%	85.0%	2.8%	0.6%	625	9.4%	87.8%	2.1%	0.6%	502	7.8%	89.4%	2.0%	0.8%
Coke Zero	590	9.3%	1.7%	86.4%	2.5%	527	8.3%	1.3%	88.2%	2.1%	443	7.7%	0.9%	89.6%	1.8%
Diet Cherry Coke	116	14.7%	3.4%	11.2%	70.7%	95	13.7%	2.1%	11.6%	72.6%	72	13.9%	1.4%	11.1%	73.6%
time t+3 (Q4)	n					n					n				
Diet Coke	2,041	92.2%	4.7%	2.6%	0.6%	1,904	94.0%	3.2%	2.4%	0.4%	1,704	95.4%	2.5%	1.8%	0.3%
Caffeine-Free Diet Coke	709	13.7%	83.5%	2.3%	0.6%	604	11.6%	86.4%	1.8%	0.2%	483	10.4%	87.8%	1.7%	0.2%
Coke Zero	577	9.9%	2.9%	84.6%	2.6%	516	9.1%	2.3%	87.0%	1.6%	433	8.5%	2.1%	87.8%	1.6%
Diet Cherry Coke	111	16.2%	3.6%	12.6%	67.6%	91	15.4%	4.4%	9.9%	70.3%	76	17.1%	2.6%	9.2%	71.1%

Table 14: Switching Probabilities of Diet Pepsi Heavy Half Households

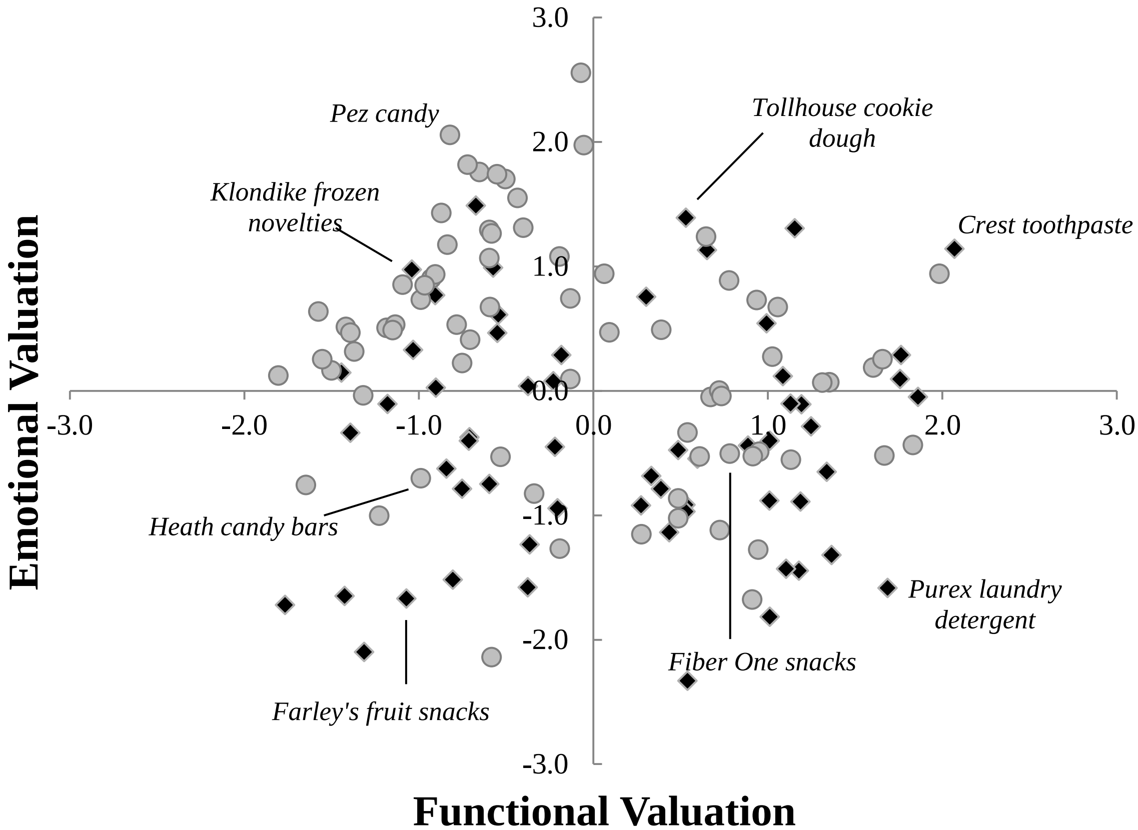
	Modified Brand > 50%					Modified Brand > 70%					Modified Brand > 90%				
time t+1 (Q2)	n	Diet Pepsi	Caffeine-Free Diet Pepsi	Pepsi Max	Diet Cherry Pepsi	n	Diet Pepsi	Caffeine-Free Diet Pepsi	Pepsi Max	Diet Cherry Pepsi	n	Diet Pepsi	Caffeine-Free Diet Pepsi	Pepsi Max	Diet Cherry Pepsi
Diet Pepsi	1,389	94.7%	2.7%	2.3%	0.3%	1,291	96.1%	1.9%	1.7%	0.2%	1,155	97.1%	1.4%	1.3%	0.3%
Caffeine-Free Diet Pepsi	451	8.0%	90.0%	1.1%	0.9%	399	5.5%	93.2%	0.5%	0.8%	336	4.5%	94.0%	0.6%	0.9%
Pepsi Max	224	4.9%	3.1%	91.1%	0.9%	194	4.1%	2.1%	93.8%	0.0%	166	3.6%	1.8%	94.6%	0.0%
Diet Cherry Pepsi	137	8.0%	3.6%	1.5%	86.9%	115	7.8%	1.7%	0.0%	90.4%	96	6.3%	1.0%	0.0%	92.7%
time t+2 (Q3)	n					n					n				
Diet Pepsi	1,347	92.4%	3.9%	2.4%	1.4%	1,268	94.7%	2.9%	1.5%	0.9%	1,121	96.3%	2.0%	1.2%	0.6%
Caffeine-Free Diet Pepsi	428	11.9%	85.3%	1.6%	1.2%	378	10.1%	87.6%	1.6%	0.8%	314	8.9%	89.2%	1.3%	0.6%
Pepsi Max	224	7.6%	2.2%	87.5%	2.7%	205	6.8%	1.5%	89.8%	2.0%	170	4.7%	1.2%	92.4%	1.8%
Diet Cherry Pepsi	129	7.8%	2.3%	2.3%	87.6%	106	4.7%	0.9%	1.9%	92.5%	86	2.3%	1.2%	1.2%	95.3%
time t+3 (Q4)	n					n					n				
Diet Pepsi	1,306	91.8%	3.8%	2.7%	1.8%	1,217	93.7%	2.6%	2.6%	1.1%	1,106	95.4%	2.1%	1.7%	0.8%
Caffeine-Free Diet Pepsi	437	12.4%	85.4%	1.6%	0.7%	389	10.8%	87.1%	1.5%	0.5%	336	11.3%	86.9%	1.2%	0.6%
Pepsi Max	204	8.3%	1.5%	88.7%	1.5%	180	5.6%	1.1%	92.8%	0.6%	159	4.4%	1.3%	93.7%	0.6%
Diet Cherry Pepsi	130	6.2%	0.8%	3.1%	90.0%	122	5.7%	0.8%	1.6%	91.8%	89	3.4%	1.1%	1.1%	94.4%

Figure 1: Framework of Commonality and Complementary Pairings



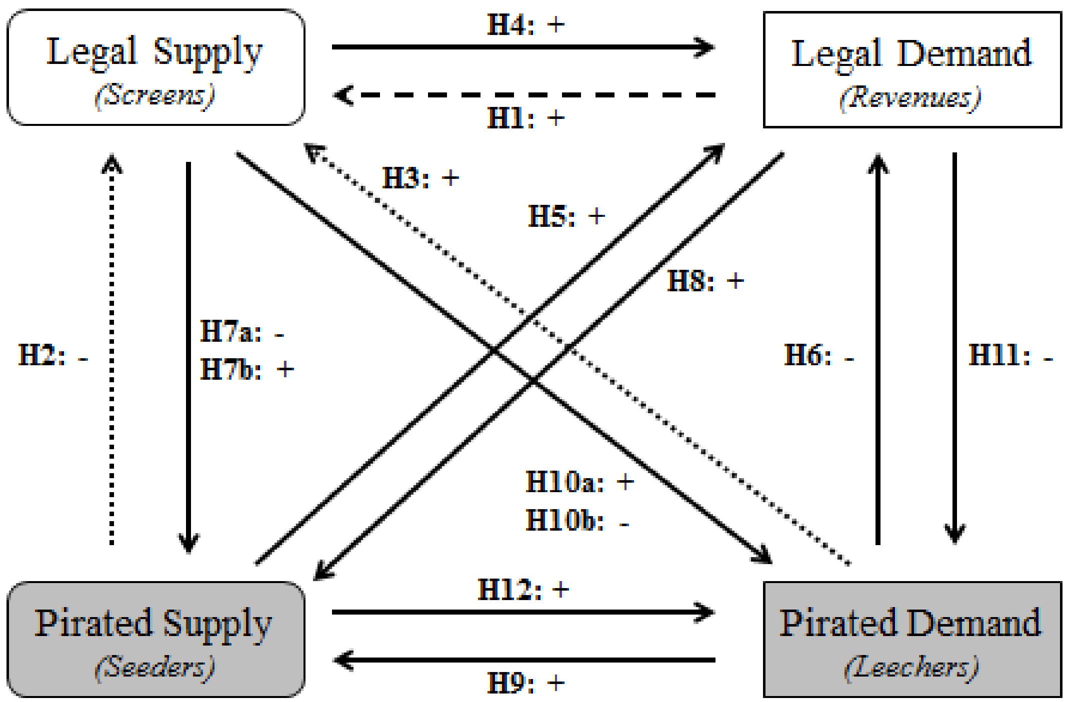
Note: Solid lines represent perceived functional valuations and dashed lines represent perceived emotional valuations. The dotted line represents additional brand, category, and macro-environment controls.

Figure 2: Functional and Emotional Valuations for Primary and Secondary Brands



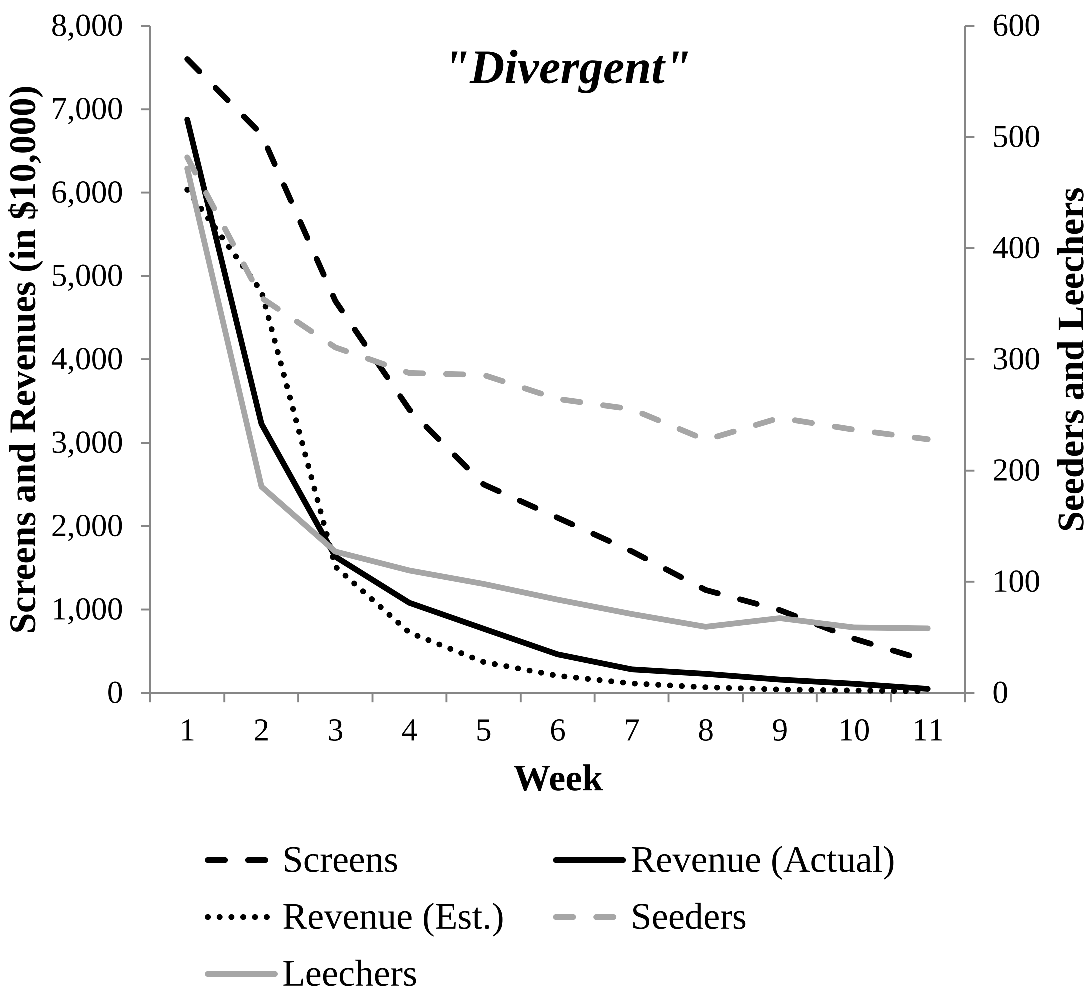
Note: Black diamonds represent primary brands and gray circles represent secondary brands. Some brands appeared as both primary and secondary brands, but are designated as primary brands here. The functional valuations and emotional valuations are standardized. Data point labels highlight representative brands.

Figure 3: Conceptual Framework of Motion Picture Piracy



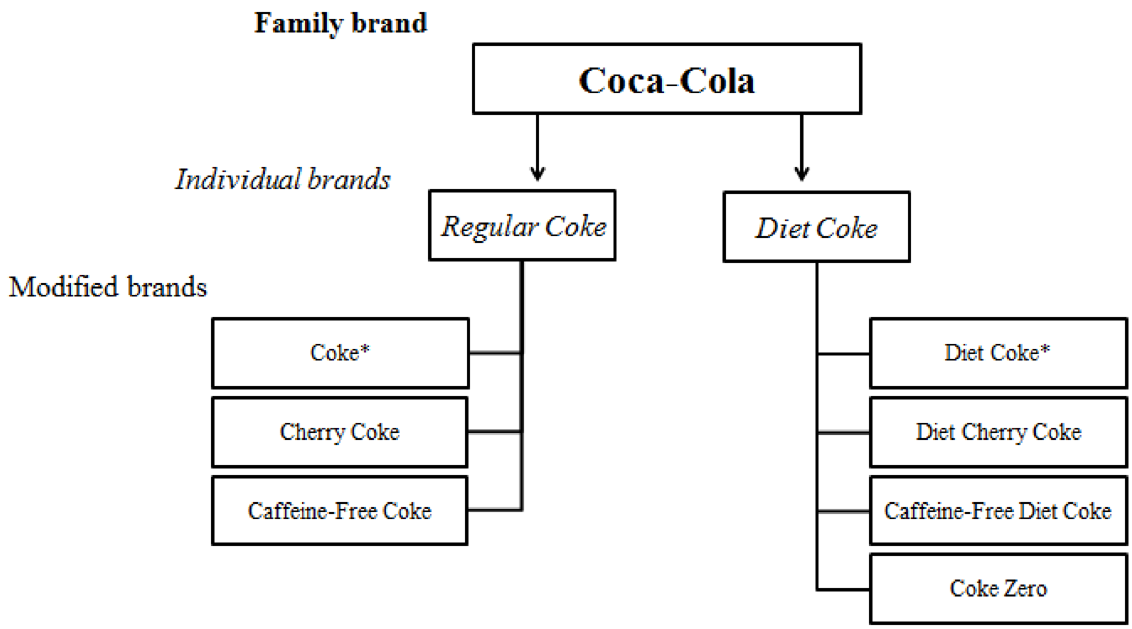
Note: White boxes represent the legal market components while gray boxes represent the pirated market components. Boxes with rounded corners represent the supply side and boxes with square corners represent the demand side. The dashed line represents a forecast estimate, and dotted lines represent lagged measures

Figure 4: Example of Legal and Pirated Supply and Demand



Note: Black lines represent legal market components and gray lines represent pirated market components. Solid lines reflect demand side and dashed lines reflect supply side.

Figure 5: Brand Architecture Example: Coca-Cola



Note: * indicates master modified brand

Figure 6: Soda Volume in Ounces Across Coke and Pepsi Modified Brands in Q1

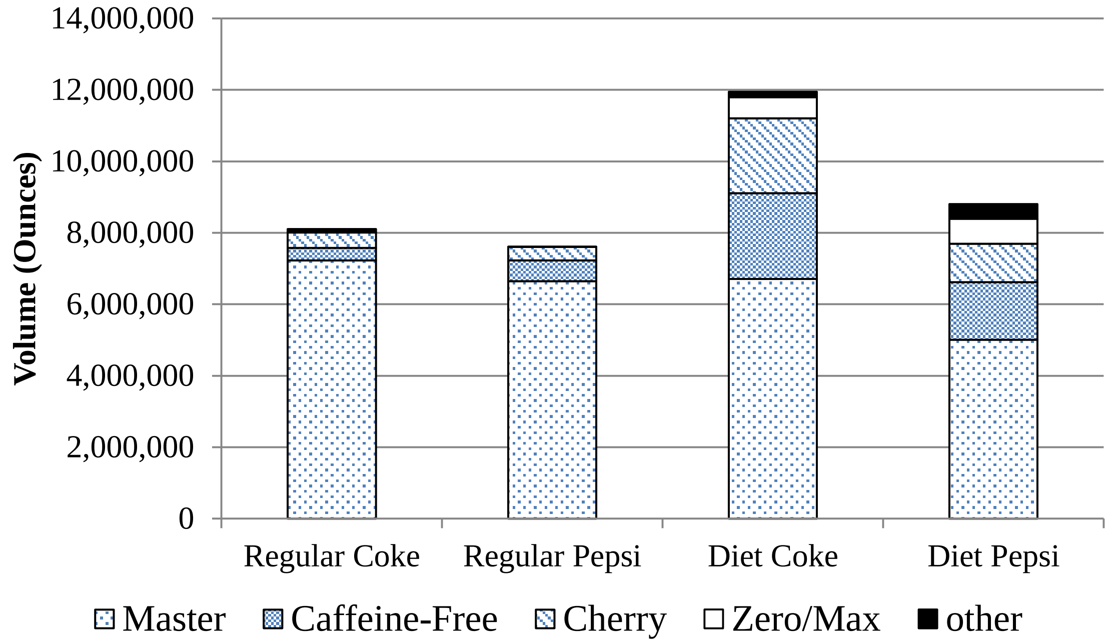


Figure 7: Distribution of Household Total Soda Volume in Ounces Purchased in Q1

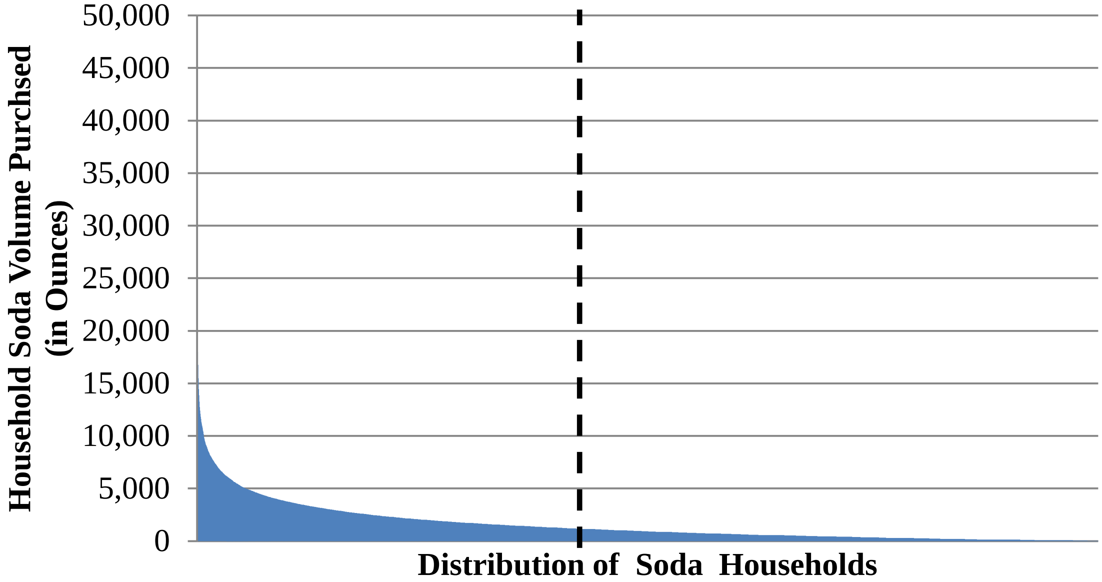
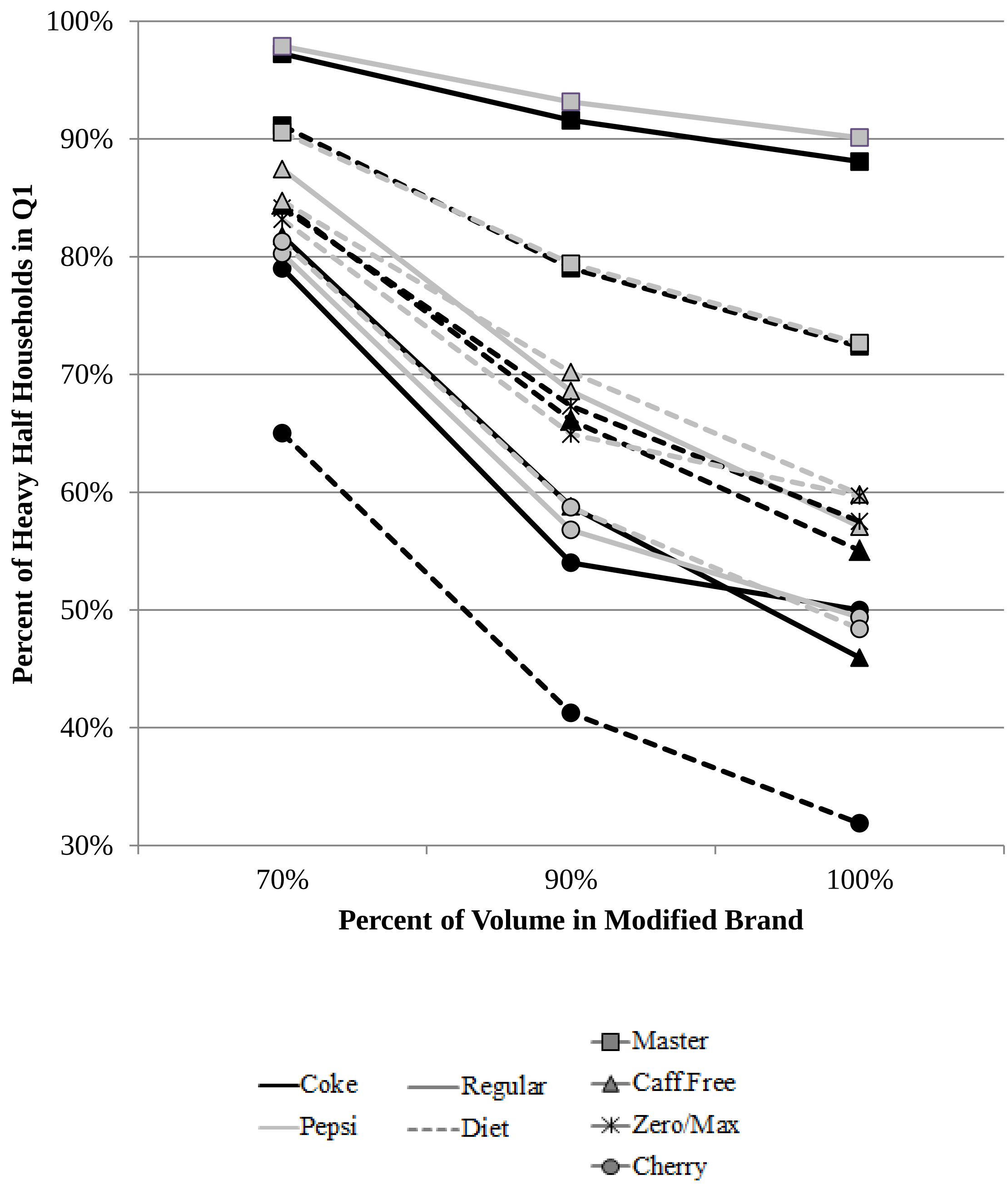


Figure 8: Heavy Half Coke and Pepsi Household Purchase Thresholds in Q1



Appendix 1: Co-Brand Consumer Survey Instrument Example: Bounce

1. I believe BOUNCE brand DRYER SHEETS provide functional benefits.

[Functional benefit refers to a product's capacity for functional, utilitarian, or physical performance. Functional benefits are derived from the tangible/concrete attributes that a consumer may directly experience when using/consuming the product]

Scale 1-7 (from Strongly Disagree to Strongly Agree)

2. I feel an emotional bond towards BOUNCE brand DRYER SHEETS.

Scale 1-7 (from Strongly Disagree to Strongly Agree)

Appendix 2: Heckman Correction for Co-Brand Self-Selection Bias

One consideration in co-branded relationships is that it is not a random process; brands choose to enter the relationship. As such, the IRI data reflects these self-selected relationships. It is possible that brands which perform well in the market feel less need to seek co-branded partnerships in order to differentiate their products. Another possibility is that in a crowded product space, with many different brands and products for the consumer to choose from, the brand may feel the need to co-brand in order to better differentiate itself. Still another scenario could be where there is a strong private label; here, the brand may co-brand as a way to position itself as offering additional value to the consumer.

To address this concern of observing only when brands enter the co-branded relationship, a Heckman two-stage correction method is used (Heckman 1979). The first stage presents a 'co-brand or not' stage to include observations of non-co-branded products, such that:

(A1) $P(y = 1|\mathbf{x}) = \Phi(\mathbf{z}\boldsymbol{\beta})$

In this first stage of equation (A1), *y* is a binary response taking on the value 1 when a co-brand occurs and 0 otherwise, **z** is a vector of explanatory variables, **β** is vector of parameters, and Φ is a standard normal cumulative distribution function. Since the decision is whether to co-brand or not in a given year, the observations of the non-co-branded products from the existing brand set are used. This becomes n = 3,036 observations. The vector **z** includes the same variables in the second stage estimation, which is the same as equation (1) but also must include key variables that might influence the decision to co-brand. This includes number of products competing in the category, market share of the private label in the category type, and market share of the solo-brand (non-co-branded) in the prior year.

Since the decision is *when* to co-brand rather than *who* to co-brand with, the secondary brand's functional and emotional valuations have been excluded from **z**. Estimation of the first and second stage Heckman correction produces an Inverse Mills Ratio that is not statistically significant ($\lambda = -.72$, SE = .64, $p > .26$), indicating sample selection is not a concern.

Appendix 3: Estimation of Revenues Used in the Movie Screens Equation

Using the *ex ante* perspective that movie theaters decide how many screens to allocate to a film for the coming weekend, managers anticipate what demand (revenues) might be, and adjust the number of screens accordingly. The number of screens allocated in the opening week depends on the estimated revenue that theater owners anticipate a film will earn, as a function of the HSX closing price prior to release. After launch (or expansion) revenues are observed, theater owners update revenue estimates for week 2. Since two time periods are required for the smoothing parameters, week 2 is estimated by multiplying the average of opening week actual and estimated revenues by .70 (presuming an average drop-off in revenues from opening week to second week of 30%). This is estimated with single exponential smoothing, where the prior week expected revenues are updated by part of the prediction error (Elberse and Eliashberg, 2003):

(A1) $EST\_REV^*_{it} = EST\_REV^*_{i,t-1} + \lambda_{i,t}(REVENUE_{i,t-1} - EST\_REV^*_{i,t-1})$ for t>2

Here, λ is the smoothing parameter, varying between 0 and 1, and $EST\_REV^*_{it}$ is the expected revenues from simple smoothing. Since movie revenues typically decline over time, a double exponential smoothing procedure is applied with a trend, T_{it}, and a second smoothing parameter, π_{it} in Equation A2. For weeks 3 and on, the sum of squared differences between actual and expected revenues is minimized to update the smoothing parameters. Note, $T_{i1} = 0$, since no trend has formed yet.

(A2) $T_{it} = \pi_{i,t}(REV\_EST^*_{it} - REV\_EST^*_{i,t-1}) + (1- \pi_{i,t})T_{i,t-1}$ for t>2

The EST_REV_{it} used in the model comes from the double smoothing process in Equation A3:

(A3) $EST\_REV_{it} = EST\_REV^*_{it} + T_{it}(1- \pi_{i,t})/ \pi_{i,t}$ for t>2