ABSTRACT

Title of Document: **ESSAYS ON STRATEGIC MARKETING**

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Essay 1 focuses on purchasing behavior in the video game market, which can be conceptualized as a two-stage process where users first purchase a console and then purchase content for that console. Prior research on platform-mediated markets, which are defined by this interdependence in platform and content sales, has highlighted the relationship between installed base size (i.e. the total number of console adopters) and content sales. We extend this research by examining how two characteristics of installed bases, unrelated to size, affect content sales. First, we investigate the effect of installed base innovativeness, defined as the proportion of total adopters from early in the platform product's lifecycle, on content sales. Next, we evaluate the effect of installed base recency, defined as the proportion of total adopters that recently adopted the platform product. We find that more innovative or recently adopted installed bases purchase more content on a per user basis. These results suggest that content sales depend on more than just installed base size,

providing an opportunity to increase content sales through the identification of installed bases high in either innovativeness or recency.

In Essay 2, we examine how media exposures from sponsorship can impact a firm's financial performance. The extant literature has typically used aggregate expenditures as a proxy to study the financial effect of paid marketing communications. However, prior research has demonstrated that expenditures might not be an appropriate proxy for the overall effect of these marketing communications. We, therefore, study how exposures impact firm financial performance independently of firm expenditures used to obtain those exposures. Using a unique context (stadium naming rights agreements), in which the firm receives a random number of exposures, and leveraging the temporal nature of paid promotion in this context, we separately identify the effects of exposures from expenditures. In three analyses, we find that exposures increase firm stock returns and lower firm systematic risk, while promotional expenditures decrease firm stock returns and raise firm systematic risk. These results begin to bridge the gap in how promotional communications are measured between the marketing/finance interface literature and the broader literature on marketing effectiveness.

ESSAYS IN STRATEGIC MARKETING

By

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Table of Contents

This Table of Contents is automatically generated by MS Word, linked to the Heading formats used within the Chapter text.

List of Tables

List of Figures

Chapter 1: The Effects of Platform and Consumer Lifecycles on Content Sales in a Platform-Mediated Market

Introduction

The video game market is one of the fastest growing and largest entertainment markets, with an estimated $93 billion in worldwide sales in 2013.[1] According to recent estimates, 59% of all Americans play video games, with 51% of US households owning at least one dedicated game console.[2] This market has grown at an annualized rate of approximately 6% since 2000 and is projected to grow at over 12% per year from 2012-2015. The growth of this entertainment market has led game developers to allocate greater resources to the development of these games, often matching the development budgets of blockbuster movies. For example, Grand Theft Auto Five cost Rockstar Games $266 million to develop.[3] As games become more expensive, the risk of a poorly selling game increases substantially for the game developer. As such, it is important to better understand how end consumers purchase games.

In the video game market, consumer buying behavior is defined by a two-stage process. In the first stage, consumers need to purchase a console, which is a durable electronic product that serves to allow end users to play games. After console

[1] Source: Gartner, Inc.
[2] Source: Entertainment Software Association
[3] Source: Fast Company

purchase, in order to generate utility, consumers then purchase content (games) for the console. This structure is defined as a platform-mediated market, in which a platform product (e.g., the gaming console) serves to link end consumers and content developers. Platform-mediated markets are traditional in some entertainment industries (i.e. video games and home video) and are expanding into other markets due to technological innovation (i.e. smartphones, digital music players, and e-readers). As such, it is critical to develop a more thorough understanding of how the characteristics of the platform's installed base of users affect content sales.

Prior research related to platform-mediated markets has focused on the relationship between installed base size, which is the total number of prior platform product adopters, and content sales. This research has found that a larger installed base, which indicates a larger potential market for content, leads to an increase in content sales (Schilling 2002; Gallaugher and Wang 2002). This relationship is especially crucial in entertainment content markets, such as the market for video games, because product sales in these markets are characterized by rapid early sales immediately after content release followed by an exponential decline in sales as the content ages (Sawhney and Eliashberg 1996; Moe and Fader 2001; Calantone et al 2010). Therefore, it is crucial for entertainment content, such as games, to be released with a relatively large existing installed base. However, in this type of market, the availability of content is also a crucial determinant of the installed base's size, since consumers generate utility based on the availability of content (Binken and Stremersch 2009; Lee 2013; Anderson et al. 2014), which will only be developed if content sales are anticipated. This cyclical relationship between the development of an installed base and content sales poses a dilemma for content developers. Certain content developers, especially platform firms, which are major content developers in the video game industry (Marchand and Hennig-Thurau 2013), are dependent on the development of a particular installed base. As such, if the content developer only considers the effect of the size of the installed base, these firms need to tradeoff higher content sales and the development of a larger installed base when releasing content.

We explore the possibility that installed base size fails to entirely capture the content purchasing potential of an installed base. Indeed, prior literature has shown that the consumers that compose an installed base can change over time (Batislam et al. 2007). These systematic changes in the installed base over time could potentially change the nature of the relationship between the installed base and content sales.

Therefore, in this paper, we, study how an installed base evolves over time in its content purchasing behavior. Building on prior research from the broader marketing literature, we identify two potential sources of installed base dynamics: (1) the innovativeness and (2) the recency of the installed base.

First, we examine the innovativeness of the installed base by classifying users as "innovative" based on adoption timing within the console's product lifecycle. Building on the extant literature (Ram and Jung 1994; Gandal 1999), we classify earlier adopters of the console as "innovative" when compared to later adopters. We characterize the innovativeness of the installed base using a variety of measures derived from the product lifecycle literature (Rogers 1962; Chandrasekaran and Tellis 2011; Gretz and Basuroy 2013). Using these measures, we study how an installed base composed of a higher proportion of early console adopters differ from an installed base with a higher proportion of later adopters.

Second, we examine how the recency of the installed base affects content sales. We characterize the recency of an installed base by measuring the proportion of console users who recently purchased the platform versus previously existing platform users. We also test the potential that innovativeness and recency may interact, suggesting that the effects of platform adoption recency might change over the platform product's lifecycle.

In order to study the effects of the innovativeness and recency of a platform's installed base on content sales, we gather a variety of data from the video game market. Specifically, we collect weekly sales data for the three major gaming consoles in the seventh technological generation of the video game market along with data on the total weekly content sales. We use the console sales data to construct a variety of metrics that characterize innovativeness and recency and examine how content sales respond to these metrics. We collect total content sales associated with each console as well as sales for 98 specific games released on all three focal consoles at a title-console level (i.e. Call of Duty 3 for the PlayStation 3).

Using this data, we model how installed base recency and innovativeness affects the total sales of content per user on a console system, while controlling for seasonality and console-specific effects. In order to do so, we evaluate the effects of recency and innovativeness on the total sales of content on a per user basis, which controls for the effects of the size of the installed base on content sales.

We find that an installed base with either higher innovativeness or recency purchases more content on a per user basis than an installed base with a lower proportion of innovative or recent consumers. We also provide evidence that these effects interact negatively, suggesting that later adopters of the platform product cease their purchasing behavior more rapidly than earlier adopters, strengthening the relationship between installed base recency and content sales for less innovative installed bases.

Additionally, we also model the effect of installed base recency and innovativeness on individual title sales. The goal of this analysis is to study the effect of installed base recency and innovativeness on content sales while controlling for content quality. In order to do so, we analyze the sales of a specific content title on a per user basis for titles that have been released on each of the three console systems. As such, this analysis controls for content quality, since content quality should not vary for the same title across consoles, while still allowing for the study of installed base innovativeness and recency, as the staggered console release dates in our data provide variance in installed base innovativeness and recency across consoles in the same week.

Our analysis at the content title level again shows that installed base innovativeness and recency are associated with higher content sales per installed user. We again estimate a significant and negative interaction effect of these metrics, which suggests that the effect of recently adopted consumers in an installed base is larger for an installed base with a lower proportion of "innovative" consumers. These results provide evidence that installed base recency and innovativeness effects are not due to systematic differences in content quality released to different installed bases.

These findings provide important insights for content managers in many platform-mediated markets. Our results suggest that the likelihood of content purchase for an installed base on a per user basis declines over time, as the proportion of "innovative" or "recent" consumers in an installed base decreases over time. This effect serves to somewhat ameliorate the effect of installed base size, which increases over time, on content sales. Based on these findings, content firms should seek to release content when installed bases have relatively high numbers of recent adopters of the platform product and should balance the competing effects of installed base size and the proportion of "innovative" consumers in the installed base.

The remainder of this paper is organized as follows: first, we establish a deeper theoretical development and our formal hypotheses. Then, we describe our dataset for the empirical analysis. Third, we provide an overview of our analyses and our empirical results. Finally, we outline some managerial insights provided by our results and conclude.

Theoretical Development

In this section, we briefly discuss some relevant research related to platform-mediated markets. We then develop the two constructs of interest for this paper: the innovativeness and recency of an installed base and propose hypotheses for how these constructs affect content sales.

Installed Bases within Platform-Mediated Markets

Prior research in platform-mediated markets has shown the importance of developing a large installed base of platform users (Schilling 2002; Gallaugher and Wang 2002) for content developers as it increases the potential market size for their products. However, relatively limited research has looked at the impact of installed base characteristics other than size. One exception is Shankar and Bayus (2003) who examine the role of installed base size and strength on content sales and show how under some circumstances, a small installed base can prevail over a larger installed base if the former has higher network strength. In a related paper on platform-mediated markets, Lee (2013) considers the role of content availability and demonstrates how the availability of exclusive software impacts the industry structure. However, Lee's (2013) research focuses on how exclusivity can impact the sales of consoles and content in the video game market. In this paper, we focus on how the qualities of the console's installed base, based on adoption timing, affect content sales. We extend the research proposed by Shankar and Bayus (2003) and continue to explore non-size characteristics of the installed base, but rather than focusing on network strength, we consider the innovativeness and the recency of the console's installed base.

Installed Base Innovativeness and Platform Lifecycles

The extant marketing literature has developed the concept of product lifecycles to describe the process by which a durable product diffuses through the market over time. Researchers have commonly described product lifecycles as consisting of a series of stages, generally composed of either four stages starting with the introduction stage followed by the growth, maturity and decline stages (Cox 1967; Golder and Tellis 2004) or five stages (Rogers 1962).

Prior research has established that the customer base evolves over the lifecycle of the product, with each stage of the lifecycle attracting new adopters with distinct characteristics (Rogers 1962; Ram and Jung 1994). For example, Rogers (1962) classifies new adopters into five groups, each of which first adopts the product at a different stage of the product lifecycle. In the first stage, consumers consist of innovators which make up the first 2.5% of adopters. The next 13.5% of adopters are described as early adopters, and the remaining customers are described as the early majority (34%), the late majority (34%) and laggards (16%).

Other researchers have characterized adopters simply as innovators or imitators (van den Bulte and Joshi 2007) where innovators are driven more by an inherent desire for the product and imitators are more influenced by word-of-mouth effects. This framing has been applied to the video game context by Gretz and Basuroy (2013) who classify the early stage of the platform lifecycle as the "Introduction" phase and suggest systematic differences between those who adopt in the Introduction phase versus those who adopt later.

Some recent research on new product takeoffs has attributed product success on the ability of new products to cross over from the innovator population to the imitator population (Chandrasekaran and Tellis 2011). What is particularly interesting in this stream of research is that in many cases, the takeoff is preceded by a dip in sales, referred to as a saddle. This saddle has been interpreted as the point in time where the adopter profile shifts from that of an innovator to that of an imitator. This typically occurs when approximately 30% of consumers have adopted the durable product.

Overall, the above research argues that notable differences exist between customers who adopt a new product early versus later in the product lifecycle. Primarily, the innovativeness of the customer varies (Ram and Jung 1994, Schreier et al. 2007). From this, we argue that a customer base comprised of a high proportion of early adopters is more innovative than one that includes many late adopters. Because researchers have shown that these more innovative early adopters also display a higher involvement with the product and are more risk tolerant and thus more willing to try new things (Ram and Jung 1994, Steenkamp et al. 1999), we hypothesize that the innovativeness of the installed base is also related to content purchasing behavior. Namely, a more innovative installed base (as measured by adoption timing of the users in the installed base) will generate more content sales on a per user basis.

H1: More “innovative” installed bases (i.e., those composed of a higher proportion of adopters from early in the platform product lifecycle) purchase more content per installed base member than less “innovative installed bases (i.e., those composed of a higher proportion of later adopters).

Installed Base Recency and Individual Consumer Lifecycles

Prior research has shown how consumers' buying behavior changes over his or her own consumption lifecycle (Sismeiro et al. 2012). In other words, consumers who are new to the market may behave differently from those who entered the market earlier and are now long established members of the installed base. Applied to the video game market, consumers who just bought the gaming console may differ from those who are already established gamers on a particular console. Of interest to us is whether these differences affect how much content users buy. In order to examine this issue, we draw on prior consumer-level theory that suggests ways in which consumers may evolve in their content purchasing behavior based on how long they have been members of the installed base.

Hauser and Urban (1986) discuss the role of consumer budgets in purchasing behavior and propose a system in which consumers list purchases in order of preference and then buy the products until a budget threshold (or a threshold in which the product is no longer worth the price paid for the product) is reached. In our context, this behavior would result in a large number of game purchases early in the consumer's lifecycle as this is when the budget is at its largest. However, as purchases are accrued over time, not only do budget constraints become more salient but the games with the highest utility for the user have already been purchased. This leaves the user facing the decision of whether or not to buy a less desirable game with his/her shrinking budget. This dynamic over time would lead to a glut of content purchases early in the customer lifecycle and more limited content purchases later.

In addition to budget considerations, the user is also trying to build a library of games. The value of the gaming system to the user increases as more content is available. Lee (2013) shows, at the market level, how content developers can increase the value of a gaming system by creating content for it. However, at the level of the individual user, the value of the gaming system increases only if the user's own library of games increases. Thus, early in the consumer's lifecycle, there is a need to purchase a lot of content to build the user's library of games. A large library provides higher utility for the user by offering a variety of gaming option (McAlister 1982; Kahn and Lehmann 1991). Later in the consumer lifecycle, fewer purchases are needed to provide variety and thus content purchasing should slow.

Finally, we theorize that a potentially reverse causal relationship, in which consumers actually purchase the console in order to consume some form of content immediately, could also result in significant dynamics in an individual consumer's content purchasing behavior. For example, Binken and Stremersch (2009) have shown a "superstar software" effect for the video game platform market in which platform product purchase is driven by the desire to purchase certain "superstar" content titles. If individual consumer's console purchase is motivated specifically by the desire to purchase certain "superstar" content titles, we would see a very high amount of content purchasing associated with the console purchase itself, as consumers will want to obtain the utility generating component of the platform market, specifically content, rapidly and will then slow in their content purchasing behavior after obtaining the "superstar software."

Based on these three effects (budgetary constraints, consumer variety seeking, and "superstar software" effects), we theorize that content sales will decline for each consumer as they progress to later periods in their individual consumer lifecycle. In order to aggregate these individual level effects into installed base-level content purchasing behavior, we propose the concept of installed base recency. We define and measure installed base recency as the proportion of the total installed base that are recent adopters of the platform product (and thus are early in their individual consumer lifecycle). Later in this paper, we will describe how we empirically specify recency and test the sensitivity of our results to different specifications. However, overall, we expect that a more recent installed based will be associated with greater content sales per user.

H2: An installed base that is high in recency, a measure of the proportion of the installed base that recently adopted the console, will purchase more content on a per user basis than an installed base that is lower in recency.

Interaction between Installed Base Innovativeness and Recency

We also test whether installed base recency and innovativeness interact. Again, this effect is theoretically based on individual level behaviors aggregated into installed base level effects. An interaction between recency and innovativeness would suggest that recently adopted consumers act in a different manner depending on how early in the platform lifecycle those consumers adopt. So, for example, if we see a negative interaction, that would mean that later adopters purchase whatever content they will obtain more quickly than earlier adopters.

Prior theory suggests that we will observe this negative interaction term. Specifically, the extant literature has found that early adopters use the product less than later adopters immediately following adoption (Prins et al. 2009). However, these early adopters increase their usage later in the product's lifecycle. In our context, this would suggest that more innovative consumers will purchase less content immediately following console adoption, but will continue to purchase content for a long time after adoption. In comparison, later adopters will purchase their content rapidly, and then purchase less content later in their product lifecycle.

Therefore, we propose that, at an installed base level, installed base recency will negatively interact with installed base innovativeness. This finding suggests that the effect of having a recently installed base on content sales will be higher when an installed base's innovativeness is low, often towards the end of the platform lifecycle.

H3: Installed base recency and innovativeness negatively interact, suggesting that the effect of being a higher recency installed base will increase content sales by more when the innovativeness of the installed base is lower.

<u>Data</u>

Our empirical data are drawn from the video game market, which is a platform-mediated market characterized by a series of technological generations. The platform firm in this market is the console producer, who manufactures the hardware used to consume content. Each firm that chooses to participate in this market as a platform firm produces a new console each technological generation to compete with other platform firms. A set of firms produce content for these consoles. End users in this market purchase both a console and content in order to gain utility from the system. A consumer needs to purchase a console each technological generation to utilize new content due to a lack of forward compatibility.

Our data are drawn from the 7th technological generation of the video game market, which consists of three stationary consoles: the Microsoft Xbox360, Sony PlayStation3, and the Nintendo Wii. We restrict our analysis to these directly competitive consoles. We exclude portable consoles due to the limited amount of content released on both portable and stationary consoles, which is an especially crucial consideration for our data on individual content title sales.

These data are collected from vgchartz.com, which reports weekly sales pertaining to video game consoles and content (games). Vgchartz.com collects and publishes this sales data by using a variety of methods including resale prices and the polling of end consumers, retailers, video game publishers, and video game developers to calculate the weekly sales of both video game consoles and content. Due to differences between regions in content and console release timing, we limit our data to the North American sales.

Our data window spans an over 4 year period for each console starting with console launch. Given the different launch dates of each console system, we left align our data windows and include the first 230 weeks of sales data for each console system. For the Nintendo Wii system, these data range from the week of November 19, 2006 until the week of April 10, 2011. Our data for the Sony PlayStation 3 system span from the week of November 12, 2006 to April 3, 2011. Finally, our Microsoft Xbox 360 data window is from the week of November 20, 2005 to the week of April 11, 2010. We also collect the total sales for each console prior to October 2014, to evaluate when certain sales thresholds were met.

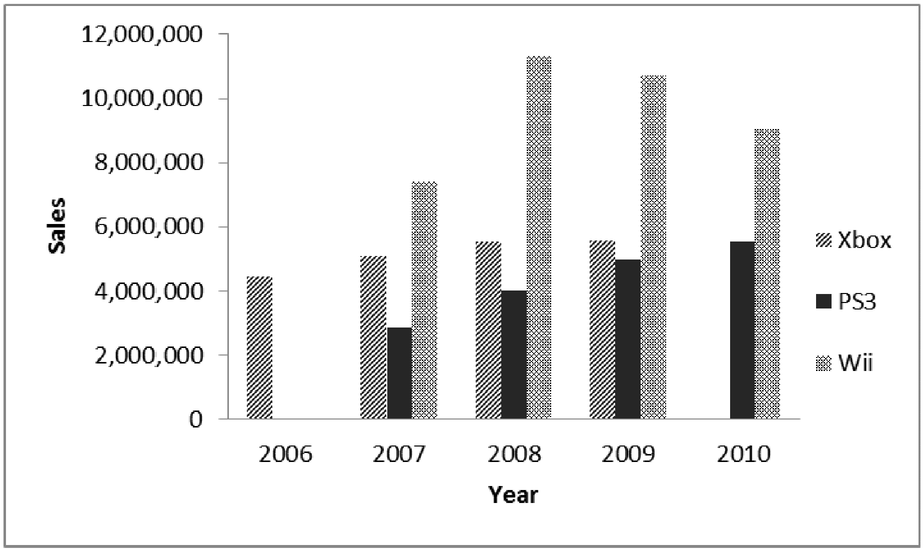
We divide our data into three separate datasets: (1) console sales data, (2) total content sales, and (3) individual content title sales data. Each of these datasets will be combined to test our hypotheses in our statistical analyses.

Console Sales Data

Our console sales data report the cumulative console sales for a particular console prior to an observation week, which represents the size of a console's installed base in each week. We collect 230 observations of weekly sales data for each console, for a total of 690 console sales observations. These data allow us to both measure the relative innovativeness and recency of an installed base and provide an installed base size that serves to transform content sales into a per user measure.

Figure i plots the total annual sales for each console during our analysis period. As can be seen in this figure, the product launches are staggered, with the Xbox360 being released a year earlier than either the PlayStation3 or the Wii. In other words, the Xbox360 is often in a more advanced stage of the platform lifecycle than either the PS3 or the Wii, resulting in substantially different values for installed base innovativeness for the three console systems during the same week.

Figure i: Annual North American Console Sales



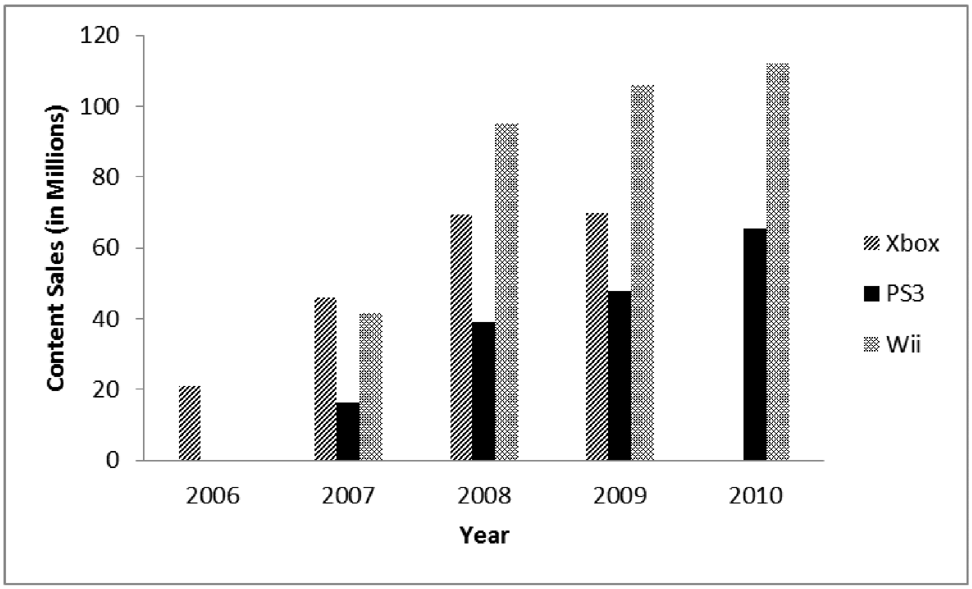
* Partial years not displayed.

Total Content Sales Data

For each console, we collect the weekly total content sales, which are the sales of all content titles on a particular console system in the focal week. Matching our console sales data, we collect 230 observations of total content sales for each console system, resulting in 690 total observations across the three console systems. These data are used to evaluate the effects of both installed base recency and innovativeness.

Figure ii provides the annual total content sales for each console system. As with console sales, total content sales increase throughout the lifecycle of the platform product. The console systems with the largest installed bases also have the highest total content sales in each year. This provides model-free evidence of the effect of installed base size on content sales in the video game market.

Figure ii: Total Content Sales by Year



Individual Title Sales Data

Finally, we collect the sales of individual content titles. These data contain the sales of 98 titles that were released on all three consoles during our data window. We gather the weekly sales of each individual content title for each of the three focal consoles.

Individual title sales patterns for content in the video game market match that of other entertainment content markets such as music and movies. Each of these markets is characterized by high initial product sales followed by an exponential decline in sales over time. Figures iii and iv are representative examples of this sales pattern with high initial sales followed by exponential declines. In Figure iii, we show the weekly sales for "Call of Duty: World at War" on the Sony PlayStation 3. Figure iv shows the weekly sales for "Ghostbusters: The Video Game" on the Nintendo Wii.

Figure iii: Sales of "Call of Duty: World at War"

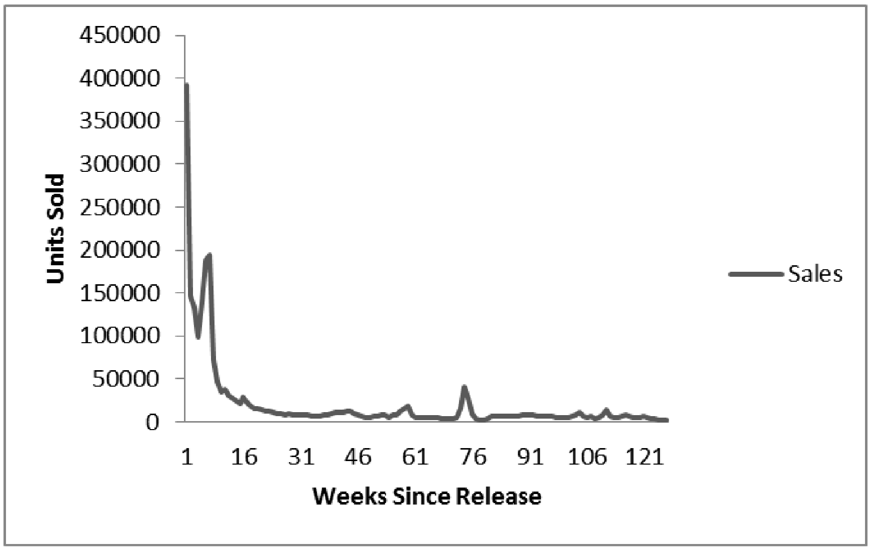
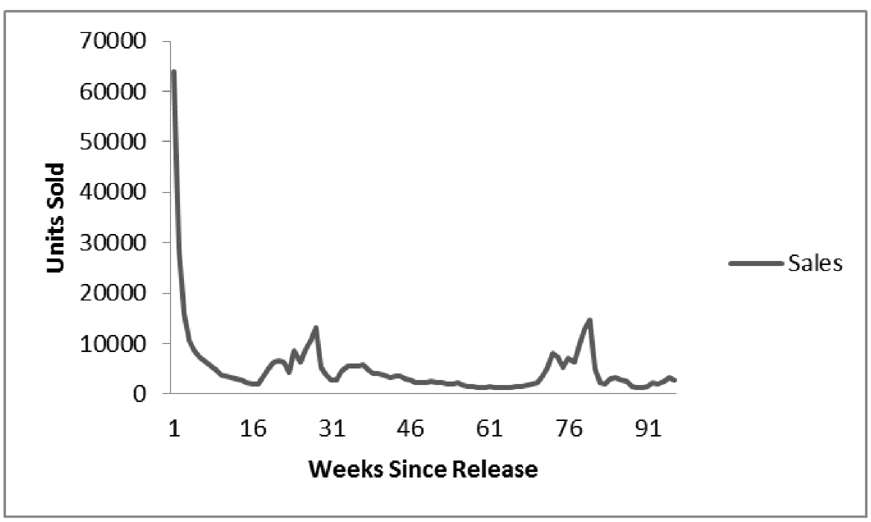


Figure iv: Sales of "Ghostbusters: The Video Game"



This sales pattern results in a high proportion of total sales for a content title occurring in the first ten weeks after product release. We provide further evidence of this in Table i, which describes the sales of individual content titles in each of the first ten weeks after the content titles are released. Content title sales decline rapidly in the first ten weeks, with the mean sales of an individual content title in week 10 only constituting 17% of the mean sales of titles in the first week that the content is available for purchase.

Table i: Individual Title Sales Data Description by Week

Week	Title Sales Mean	Title Sales Range
1	58,081.89	152-889,647
2	25,856.99	122-388,081
3	19,035.94	117-320,217
4	16,600.83	203-233,183
5	16,913.00	151-324,287
6	17,296.83	125-404,077
7	15,523.46	111-325,954
8	13,474.66	93-258,874
9	11,544.99	85-196,634
10	9,672.74	71-84,185

Models and Results

Total Content Sales Model

In order to evaluate the effects of installed base recency and innovativeness, we first design a model that accounts for the effects of both focal installed base characteristics.

$$(1)\quad \ln\left(\frac{content_{jt}}{IB_{jt}}\right) = \alpha + \gamma_1(Xbox_j) + \gamma_2(PS3_j) + \beta_1(Innov_{jt}) + \beta_2(Recency_{jt}) + \beta_3 Innov_{jt} * Recency_{jt} + \beta_4(Seas_t) + \varepsilon$$

Our dependent variable for this analysis is the total sales of content per installed base user. The use of a per user transformation allows us to identify the effects of installed base recency and innovativeness separated from the effects of installed base size. We operationalize this measure as the log transformed total content sales ($content_{jt}$) divided by the size of the installed base (IB_{jt}) for console j in week t. We model this measure as a function of installed base innovativeness ($Innov_{jt}$), recency ($Recency_{jt}$), and their interaction effect. We also include indicator variables to control for the console ($Xbox_j$ and $PS3_j$) as well as seasonality ($Seas_t$). In the North American video game market, from which our data sample is drawn, sales increase in the last week in November and the first four weeks of December. $Seas_t$ is an indicator variable for an observation week being within those five weeks.

In order to measure installed base innovativeness, we consider a number of specifications for $Innov_{jt}$. This allows us to test the robustness of our findings to different definitions of innovativeness.

1. Rogers' (1962) "Innovators": We define all console adopters from Rogers' Innovators phase in the product lifecycle, which is defined as the first 2.5% of adopters, as innovative consumers. In order to determine the number of consumers found in the first 2.5% of all adopters, we find the total market size as of October of 2014, which is well after the beginning of the eighth technological generation in the video game market. We then compute the percentage of the overall installed base for console j in week t (IB_{jt}) that is classified as innovative as our measure of $Innov_{jt}$.

2. Rogers' (1962) "Early Adopters": This specification is identical to the Rogers' (1962) "Innovators" specification proposed above, except that rather than classifying only the first 2.5% of adopters as innovative, we consider the first 15% of adopters (innovators and early adopters) as innovative.

3. Chandrasekaran and Tellis' (2011) Saddle: Conceptually, this specification classifies all consumers that adopt prior to the "saddle" as innovative. The extant research shows that, on average, saddles are observed after 30% of the market adopts. Thus, we define the first 30% of adopters as innovative consumers. The determination of the final market size and the computation of $Innov_{jt}$ after innovative consumers are identified are similar to methods (1) and (2) above.

4. Gretz and Basuroy's (2013) "Introduction" Phase: We classify all consumers who adopt during the "Introduction" phase, which occurs for at least the first six months after product release and until the product experiences a 20% change in the monthly moving average of sales, as innovative. Installed base innovativeness is found by dividing the number of adopters from this period by the overall size of the installed base.

5. Fixed Four Million: We classify the first four million adopters of a console as innovative consumers. We calculate the installed base innovativeness by finding what percent of the total installed base adopted as one of the first four million adopters of a console.

6. Fixed Eight Million: We classify the first eight million adopters of a console as innovative consumers. We again calculate the installed base innovativeness by finding what percent of the total installed base adopted as one of the first four million adopters of a console.

To operationalize the recency of an installed base, we need to determine how to define "recent" adopters separately from less recent adopters within the end user installed. However, prior literature provides limited guidance for how to define individual consumers as "recent" within this particular platform product context. As such, we define a series of relatively short time windows during which a consumer will be considered to have adopted recently. Again, this allows us to test the robustness of our findings to different definitions and specifications of recency.

Specifically, we define five distinct thresholds for characterizing a consumer as "recently" adopted using one to five week long time windows. We, therefore, calculate how many adopters have adopted the platform in the prior *l* weeks, in which *l* is the number of weeks for which a console adopter is considered a "recent" adopter. We then divide the total number of "recent" adopters by the size of the installed base in week t for console j in order to measure installed base recency.

Total Content Sales Results

We first examine how installed base innovativeness and recency impact the overall sales of content for a platform system. This model is estimated using ordinary least squares with robust standard errors. We report the results for two definitions of installed base innovativeness, Rogers' (1962) "Early Adopters" and Gretz and

Basuroy's (2013) "Introduction" phase, in Table ii. We find that these two thresholds provide representative results. Results for all other definitions of installed base innovativeness are reported in Appendix A.

We find that, regardless of the definition of innovativeness, a more innovative installed base results in higher content sales per user. The estimated value of β_1 in which $Innov_{jt}$ is defined by Rogers' (1962) "Early Adopter" innovative threshold ranges from 1.27-1.43 ($p < 0.01$), while the estimate for β_1 in which $Innov_{jt}$ is operationalized by the Gretz and Basuroy (2013) "Introduction" phase threshold ranges from 0.96-1.11 ($p < 0.01$). These results provide support for H1, which is that more innovative installed bases purchase more content per user than less innovative installed bases.

We also find that, regardless of the definition of installed base recency, a more recent installed base, in which there is a higher proportion of recent console adopters, purchases more content per user than an installed base with lower recency. The estimated value of β_1 ranges from 8.39 - 41.24 ($p < 0.01$). These results provide support for H2. We also find that the stricter definitions of installed base recency, the classifications in which adopters from a shorter period of time before the observation week are used to calculate recency, have larger effect sizes than the less strict definitions of recency, suggesting that the effect of installed base recency decays rapidly.

Finally, we estimate a significant and negative interaction term between installed base innovativeness and recency. The estimated value of β_3 ranges from -7.11 to -38.66 (p-value < 0.01). This finding provides empirical evidence to support

H3. In our context, this result suggests that, on an individual level, recent non-innovative adopters of the platform product purchase a greater amount of their content immediately after console purchase, while early adopters continue to purchase content well after adoption. On an aggregate level, this finding shows that the effect of installed base recency is stronger when an installed base has lower innovativeness, which often occurs later in the platform product lifecycle.

Table ii: Results for Content Sales Per Member of the Installed Base

Innovator Definition	Rogers' (1962) "Early Adopters"					Gretz and Basuroy's (2013) "Introduction" Phase				
New Definition	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks
Intercept	-3.62***	-3.64***	-3.63***	-3.61***	-3.59***	-3.32***	-3.32***	-3.30***	-3.28***	-3.26***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Innovativeness	1.42***	1.39***	1.34***	1.30***	1.27***	1.11***	1.05***	1.00***	0.96***	0.96***
	(0.06)	(0.06)	(0.06)	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.08)
Recency	41.24***	29.11***	21.53***	16.51***	12.91***	30.41***	20.65***	14.81***	11.04***	8.39***
	(0.32)	(1.73)	(1.27)	(1.03)	(0.84)	(2.07)	(1.50)	(1.18)	(0.95)	(0.76)
Interaction	-38.66***	-26.95***	-19.66***	-14.87***	-11.50***	-27.91***	-18.55***	-13.01***	-9.50***	-7.11***
	(2.73)	(1.67)	(1.22)	(0.98)	(0.81)	(1.99)	(1.43)	(1.11)	(0.88)	(0.72)
Xbox360	-0.05	-0.04	-0.03	-0.03	-0.04	0.07**	0.07**	0.07**	0.07*	0.06
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
PS3	0.05	0.06*	0.06**	0.07**	0.07**	0.12***	0.12***	0.13***	0.13***	0.13***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Seasonality	0.45***	0.43***	0.48***	0.55***	0.67***	0.27***	0.29***	0.37***	0.49***	0.63***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
R^2	0.75	0.75	0.74	0.72	0.71	0.75	0.74	0.72	0.70	0.69

* Significant at 90%
** Significant at 95%
*** Significant at 99%

Individual Title Sales Analysis

One issue with our results for the effects of installed base innovativeness and recency on total content sales is that they do not control for content quality. Since, in a platform-mediated market, content quality is a function of the installed base, it is possible that the differences in sales could be due to differences in content quality. Content sales could, therefore, be due to higher quality content rather than directly due to the characteristics of the installed base.

To address these potential issues, we estimate a model where the dependent variable is content sales at the title-console level. We include only titles that were released on all three consoles, thereby controlling for content quality and its effects on console systems while allowing the installed base characteristics of innovativeness and recency to vary as content release dates fall on different points of the console lifecycle.

We estimate a model similar to the model with which we tested total content sales. The dependent variable for this analysis is the sales of individual games by console ($titlesales_{ijt}$) where i indexes the specific game, j indexes the console, and t indexes calendar time.

(2) $$\ln\left(\frac{titlesales_{\ ijt}}{IB_{jt}}\right) = \alpha_i + \gamma_1(Xbox) + \gamma_2(PS3) + \beta_1\left(Innov_{jt}\right) + \beta_2\left(Recency_{jt}\right) + \beta_3 Innov_{jt} * Recency_{jt} + \beta_4(Seas_t) + \sum_{m=1}^{9}\lambda_m\,(Week_m) + \varepsilon$$

The variables included in this equation match the variables from our total content analysis (Equation 1) with a few exceptions. First, we include title-specific fixed effects (α_i) to capture for the variance across titles. Second, we control for the number of weeks since the title was released ($Week_m$), due to the fact that content sales in this market typically diffuse very rapidly over time and exhibit an exponential decline that may mask the effects of other factors if we do not control for the title-specific time dynamics. Specifically, $Week_m$ are a series of indicator variables that represent each week after release for the titles in these data.

We limit our analysis to only the first ten weeks after the game's release to ensure that our results are not biased by titles released toward the beginning of the platform product lifecycle. The sales of these titles are typically characterized by many low sales weeks during the later weeks of the platform product lifecycle, at which time installed base innovativeness will be low. Given the high proportion of sales that occur in the first few weeks after title release, and the importance of these weeks for content developers, this limitation is unlikely to bias our results.

We report representative results for two definitions of installed base innovativeness, based on Rogers' (1962) Early Adopters (first 15% of sales) and adopters during Gretz and Basuroy's (2013) "Introduction" phase, in Table iii. We also provide results for each of the other definitions of innovativeness in Appendix B.[4]

We again find that installed base innovativeness increases content sales per person. β_1 ranges from 1.16 to 1.69 ($p < 0.01$) when innovativeness is defined by adoptions during Rogers' (1962) "Early Adopter" stage and from 1.34 to 1.64 ($p < 0.01$) when innovativeness is defined by adoptions during Gretz and Basuroy's (2013)

[4] We do not run this model with the Rogers' (1962) Innovators operationalization of innovativeness due to limited variability in installed base innovativeness for this threshold.

"Introduction" phase. More innovative installed bases purchase more copies of the specific content titles per installed base member. These results provide further evidence to support H1.

Table iii: Results for Title-Specific Analysis

Innovator Definition	Rogers' (1962) "Early Adopters"					Gretz and Basuroy's (2013) "Introduction" Phase				
New Definition	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks
Intercept	-8.95***	-9.82***	-9.98***	-10.12***	-10.19***	-9.33***	-9.48***	-9.58***	-9.67***	-9.70***
	(0.11)	(0.14)	(0.14)	(0.15)	(0.16)	(0.10)	(0.11)	(0.11)	(0.11)	(0.12)
Innovativeness	1.16***	1.39***	1.53***	1.64***	1.69***	1.34***	1.47***	1.56***	1.61***	1.64***
	(0.19)	(0.19)	(0.19)	(0.19)	(0.20)	(0.18)	(0.19)	(0.19)	(0.19)	(0.19)
Recency	19.38***	16.36***	13.91***	12.18***	10.50***	12.86***	10.73***	9.07***	7.77***	6.45***
	(2.27)	(1.62)	(1.30)	(1.13)	(1.01)	(1.51)	(1.07)	(0.86)	(0.73)	(0.65)
Interaction	-18.67***	-15.67***	-13.21***	-11.48***	-9.92***	-12.32***	-10.19***	-8.52***	-7.24***	-6.04***
	(3.14)	(1.59)	(1.28)	(1.11)	(1.00)	(1.46)	(1.03)	(0.82)	(0.71)	(0.63)
Week 1	1.49***	1.50***	1.53***	1.56***	1.59***	1.48***	1.50***	1.53***	1.57***	1.59***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Week 2	0.96***	0.97***	0.99***	1.03***	1.05***	0.95***	0.97***	0.99***	1.03***	1.05***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 3	0.72***	0.73***	0.75***	0.78***	0.80***	0.71***	0.73***	0.75***	0.78***	0.80***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 4	0.60***	0.60***	0.61***	0.64***	0.66***	0.59***	0.60***	0.61***	0.64***	0.66***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 5	0.50***	0.51***	0.51***	0.53***	0.55***	0.49***	0.51***	0.52***	0.54***	0.55***
	(0.05)	(0.05)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 6	0.41***	0.40***	0.42***	0.43***	0.45***	0.41***	0.41***	0.42***	0.44***	0.45***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 7	0.30***	0.29***	0.29***	0.31***	0.32***	0.29***	0.29***	0.29***	0.31***	0.32***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 8	0.19***	0.17***	0.16***	0.17***	0.18***	0.18***	0.16***	0.16***	0.17***	0.18***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 9	0.09*	0.08*	0.07	0.07	0.08*	0.08*	0.08*	0.07	0.08	0.08*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Xbox360	0.18***	0.20***	0.21***	0.22***	0.22***	0.28***	0.30***	0.32***	0.34***	0.33***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
PS3	0.50***	0.49***	0.48***	0.48***	0.47***	0.57***	0.57***	0.58***	0.58***	0.58***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Seasonality	0.49***	0.49***	0.50***	0.53***	0.60***	0.47***	0.46***	0.48***	0.52***	0.59***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)	(0.05)	(0.04)	(0.04)	(0.04)
R^2	0.87	0.87	0.88	0.88	0.88	0.87	0.87	0.88	0.88	0.88

* Significant at 90%
*** Significant at 99%

In addition, we find that higher installed base recency leads to higher content title sales per installed base member, in support of H2. The estimated value of β_2 ranges from 6.45 to 19.38 ($p < 0.01$). The effect size for installed base recency declines significantly in many cases between more restrictive and less restrictive definitions of recency, suggesting, again, that the effect of installed base recency declines rapidly.

Finally, these results show a significant and negative interaction effect between installed base innovativeness and recency on individual content title sales (β_3 ranges from -6.04 to -18.67; p-value < 0.01 for all estimates). These findings provide further support for H3, showing that the effect of installed base recency is stronger when installed base innovativeness is relatively low, which is often later in the platform product's lifecycle. .

The results of the individual title analysis, therefore, provide further evidence to support our earlier results in the total content sales analysis. Our findings in this analysis suggest that those results were not due to potential issues with the content firm's decision making process in relation to content release timing and quality but were instead based on installed base dynamics.

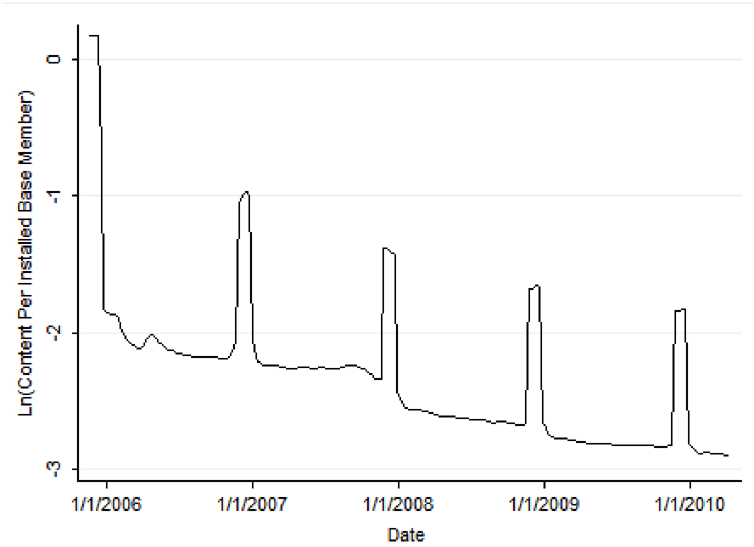
Discussion

These findings have important implications for both our theoretical understanding of the relationship between installed bases and content sales and to managers in platform-mediated markets, especially those for content producers. A better understanding of the relationship between installed bases and content sales is especially crucial for the entertainment industry going forward, as many forms of entertainment are moving to a platform-mediated structure. While we provide our results from the video game industry, a sector of the wider entertainment industry that has traditionally exhibited a platform-mediated market structure, many additional sectors of the entertainment industry, such as the music industry, have recently developed this structure. Therefore, as platform-mediated markets become more prevalent in new forms of entertainment, managers in the entertainment industry need to develop a thorough understanding of the nature of installed bases, the importance of their composition between different types of consumers, and how installed bases can evolve over time.

From a theoretical perspective, we show that the likelihood of an installed base in a platform-mediated market to purchase content is dynamic based on at least two effects, innovativeness and recency, which are both defined by the nature of individual consumer adoption timing. It is important to consider these characteristics of installed bases, and not just the size of the installed base, when evaluating an installed base from the perspective of the content producing firm.

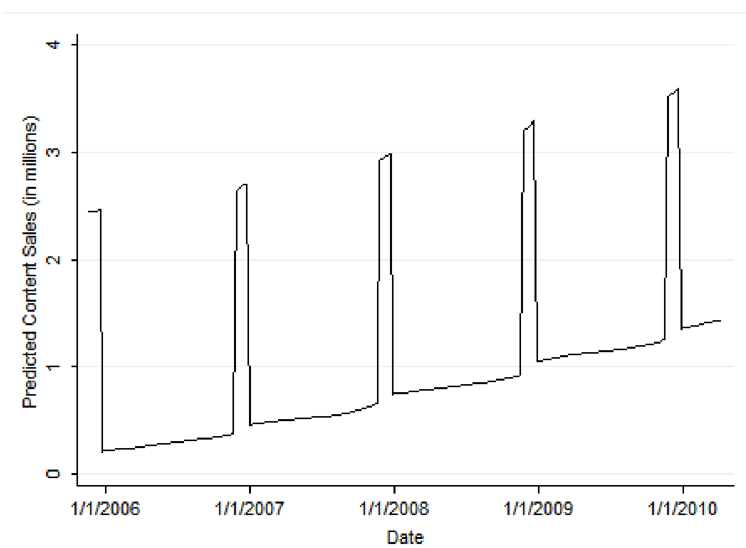
Our findings suggest that the value of the installed base on a per user basis to the content firm, as defined by content sold per installed base member, decreases over the platform product's lifecycle due to declining installed base recency and innovativeness. For example, in Figure v, we show how the predicted content purchases per member of the installed base changes over the lifecycle of the Xbox360, using an "Early Adopter" definition of innovativeness and a 3 week definition of recency. This graph shows a substantial decrease in the content purchasing behavior of the members of an installed base over the platform's lifecycle.

Figure v: Predicted Content Sales per Installed Base Member



In contrast, a model that predicts total content sales using only the control variables from our models and the overall size of the installed base, as defined by the total number of prior console adopters, finds an increase in the predicted content sales over the platform product's lifecycle (Figure vi).

Figure vi: Content Sales Predicted by Installed Base Size



These findings, therefore, show conflicting evidence as to how purchasing behavior will evolve during the platform product's lifecycle. While installed base size, which serves as a measure of potential market size for content in a platform-mediated market, increases over the platform product's lifecycle and thus increases predicted content sales, the likelihood of content purchase for each member of that installed base decreases over time, somewhat ameliorating the effects of installed base size. Therefore, our results show why it is necessary to evaluate installed bases at a deeper level than just examining the impact of installed base size.

These findings also offer important insights for managers in platform-mediated markets. Specifically, our results help inform managers in their content release timing decisions. Content firms need to consider the dynamic components of installed base recency and innovativeness when releasing content. The evaluation of how likely each member of an installed base is to purchase content could result in firms making the decision to release content earlier in the platform lifecycle. Specifically, the firm could try to take advantage of higher installed base innovativeness and recency rather than waiting for a larger installed base size.

For managers in platform firms, these results provide important knowledge about the nature of installed bases. Specifically, our findings further inform these firms about the relationship between end users and content providers. Platform firms often subsidize one side of their market to develop a large installed base that can be used to help sell the platform to the other side of the market (Parker and Van Alstyne 2005). Given that the size of the installed base does not appear to be the only component of an installed base that may be of value to content producers in a platform-mediated market, platform firms should consider how to appropriately attract consumers who might purchase more content to the platform system. Within our results, this means that platform firms should heavily subsidize “innovative” users to ensure as many of these users as possible in the platform system.

While these findings provide important insights on both a theoretical and managerial level, they also provide an opportunity for further research. While we study two sources of installed base dynamics, innovativeness and recency, other characteristics of an installed base could also impact the amount of content purchased per user in an installed base. Further study is needed to theoretically establish and empirically test these potential effects.

Future research could also further study how the dynamic nature of installed bases might result in differences in installed base preferences for certain types of content. In the video game context used in this research, it is possible that installed base innovativeness and recency is related to demand for different genres of games. For example, an installed base high in recency but lower in innovativeness might comparatively demand more children’s games, while a highly innovative installed base might prefer more sports games. A better understanding of the relationships between installed base recency and innovativeness and genres of content will provide further insights on how to time content releases in platform-mediated markets.

Conclusion

We show that installed bases in platform-mediated markets display dynamic characteristics that affect content purchasing behavior. We find that more innovative installed bases purchase more content per person than less innovative installed bases. Our results also show that higher recency installed bases, which on average adopted the platform product more recently, purchase more content than installed bases with a lower recency. Finally, our results show a significant interaction effect between installed base innovativeness and recency, suggesting that the effect of installed base recency on content sales is larger for installed bases with lower innovativeness.

These results are crucially important for managers of content firms in platform-mediated markets. This is a common and expanding market structure within many entertainment industries, where content is now often distributed through platform products. As platform markets expand further in the entertainment industry, it will be crucial to better understand how installed bases purchase content. These results provide insights for content managers in their content release timing decisions. Specifically, managers need to consider installed base innovativeness and recency in addition to installed base size when determining the timing of content releases.

Chapter 2: Financial Value of Sponsorship and Associated Media Exposures

Introduction

The extant literature on the effectiveness of promotional communications has been characterized by a divide in how these promotional communications are measured to evaluate their effects. One set of research, which examines the impact of advertising, the most commonly studied form of paid promotional communication, on consumer behavior or firm outcomes such as sales or profits, has developed with a rich set of measures. This literature has specifically examined a variety of different drivers of advertising effectiveness, including exposures (Batra and Ray 1986, Pechmann and Stewart 1988, and Tellis 1988), creative characteristics (Till and Baack 2005, Dahlen et al. 2008, Smith et al. 2008, and Bertrand et al. 2010), targeting (Esteban et al. 2003, Iyer et al. 2005, Bergemann and Bonatti 2011, and Goldfarb and Tucker 2011), and fit with the product (Kamins and Gupta 1994, McDaniel 1999, and Till and Busler 2000). Another stream of research examines the impact of promotional communications, typically advertising, on firm financial performance (Erickson and Jacobson 1992, Conchar et al. 2005, Singh et al. 2005, McAlister et al. 2007, Srinivasan et al. 2009, Joshi and Hanssens 2010, and Luo and de Jong 2012). This research has exclusively measured the effect of these promotions using the aggregate expenditures on adevertising at the firm level.

There are two primary reasons for the divergent use of predictor variables in these two streams of research. First, these two literatures have divergent goals and desired managerial implications. Research focused on the financial effect of advertising often seeks to determine the effect of firm marketing allocation decisions on firm financial performance. Advertising spending is the most appropriate independent variable for evaluating this research question. In contrast, the wider advertising effectiveness literature has developed with a wider variety of research goals, such as linking different advertising measures and components to either firm outcomes, like sales, or to consumer behaviors or attitudes, including purchasing behavior or brand preference. This set of varied goals requires varied measures of advertising.

In addition to the theoretical differences between these two literatures, the use of spending as a predictor variable serves a practical purpose in the estimation of the effects of paid promotional communications on firm financial performance. The aggregate nature of studying these marketing communications at a firm level neccesssitates either the simultaneous analysis of many variables that each could impact the effectiveness of the marketing communication or, alternatively, the use of a single proxy that theoretically should capture all of these effects. Therefore, prior research on the topic of the financial effects of advertising uses advertising spending as an implicit proxy for the overall effect of advertising on the firm, based on the link between expenditures and a variety of other measures of advertising, including exposures, creative elements, and appropriate targetting.

However, we ask whether spending is actually an appropriate proxy for the total effect of paid promotional communications. In considering this question, we first provide an illustrative example that shows how expenditures may not completely capture the total effect of paid marketing communications. In the 2012 Presidential campaign, both the Barack Obama and Mitt Romney campaigns purchased a television advertisement for the same “daypart,” that is to say the same time, day, program, and television channel. Both campaigns purchased a 30-second advertisement placed on “Wheel of Fortune” in Columbus, Ohio. However, due to a variety of factors in how the advertisements were purchased, the Obama campaign only paid $500 for this advertisement, while the Romney campaign paid $2,800 for their advertisement. If we were to perform an econometric analysis in which we use advertising spending as a proxy for the overall effect of advertising, the model would predict that the advertising for Romney’s campaign would have more of an impact than the Obama campaign’s advertisement. However, setting aside the creative component of advertising, a prediction that Romney’s campaign would receive significantly more of an effect from what was essentially the same exposure seems unlikely.

Generalizing this example, the extant literature has found that this imperfect link between advertising exposures and expenditures exists across advertisers, with a correlation between exposures and expenditures of between 0.39 and 0.62 (Chang and Kinnucan 1992; Chung and Kaiser 1999). These findings suggests that we need to examine other measures of paid marketing communications in econometric models in order to test the overall financial effect of these communications.

We, therefore, begin to bridge the gap between the literature studying the financial effect of paid promotional communications and the wider marketing communication effectiveness literature by examining the independent effects of exposures and expenditures on firm financial performance. This is a challenge in most contexts, such as in most advertising contexts, due to the direct tie between spending and exposures, in which exposures are directly purchased by the firm, resulting in the continued relationship, however imperfect, between exposures and expenditures. We, therefore, seek a context in which exposures occur outside of the direct control of the firm. While unusual within an advertising context, this will allow the independent estimation of exposures and expenditures, providing a better understanding of how marketing communications affect a firm's financial performance. We also seek a context in which some of the other drivers of the effectiveness of these communications, such as creative elements, are relatively less important in order to more thoroughly isolate the effects of exposures and expenditures.

The context we use in this study is stadium naming rights. Stadium naming rights agreements are sponsorship agreements in which firms get to name sports venues after one of their brands or the firm itself. The goal of these agreements is to generate media mentions of the firm, which are indirectly purchased through the purchase of the stadium’s name. Specifically, every time the stadium is mentioned in a media source, the firm or brand's name is also mentioned. These mentions serve as exposures in this context. Firms pay for this sponsorship agreement with a set fee established at the signing of the naming rights agreement. This fee does not vary with the number of mentions the firm actually receives. The expenditures are, therefore, independent of the actual media mentions of the stadium and firm/brand name. In addition, the shallow nature and lack of firm control over the exposures results in a relatively clean test of the effect of exposures, mostly separated from other drivers of communication effectiveness, such as creative capability.

This unique context, which allows for the study of how financial markets react to media exposures, serves, from a theoretical perspective, as a transitional form of communication between advertising and earned media or publicity. Eisend and Küster (2011) define advertising as “paid communication that identifies the message sponsor” while defining publicity as “communication that secures editorial space in media for promotion purposes and does not have an identifiable sponsor.” Stadium naming rights agreements provide exposures through editoral space in media. This would suggest that advertising could be considered publicity, as the firm seeks exposures in a media source that is not directly controlled by the firm. However, the sponsor is clearly identified in these exposures, as the firm or brand name is the basis of the exposure itself. Therefore, while stadium naming rights as a form of sponsorship may not qualify directly as advertising, the unique nature of this form of marketing communication is such that our results may have implications for how advertising can impact a firm’s financial performance.

Using this unique context, we study how media exposures can affect a firm's stock returns and systematic risk. The extant literature has found relatively heterogeneous results for the effects of advertising on firm stock returns (Erickson and Jacobson 1992, Conchar et al. 2005, Srinivasan et al. 2009, Joshi and Hanssens 2010, and Luo and de Jong 2012). These results suggest that firm marketing communications might have a small and positive effect on firm stock price, but that the identification of this effect is difficult when only using spending as a proxy for the total effect of the communications. In contrast, prior models have consistently shown that increases in advertising spending lower a firm's systematic risk (Singh et al. 2005; McAlister et al. 2007). However, these models have been unable to demonstrate the mechanism by which this form of marketing communication lowers systematic risk. Prior theory suggests that this effect could occur either due to the expanding of the consumer base through increased marketing communications or through signaling that a firm is safer due to an increase in marketing spending. By separating exposures from expenditures, while limiting the effects of other components of the marketing communication, we seek to better understand one mechanism by which paid promotional communications affect financial performance.

Based on the nature of stock return measurement as established by the extant asset pricing literature, we conduct two separate analyses to evaluate the effects of exposures and expenditures on stock returns. The use of separate tests is necessitated by the temporal nature of this context. Prior financial theory has suggested that stock markets only react to new information. The stadium naming rights context is characterized by a variable number of exposures over time and a fixed expenditure, announced at the beginning of the agreement. The temporal nature of this context allows us to independently identify the effects of expenditures and exposures. However, it does necessitate the use of two separate analyses, each uniquely designed to capture the effects of these two measures on stock returns over their unique time windows.

We design a stock market return model to capture the effect of unexpected media exposures on stock returns. This model implictely controls for the stadium naming rights expenditures due to the aforementioned temporal nature of these expenditures in this context, in which the expenditures have been announced prior to the measurement of the media exposures on a monthly basis over the length of the naming rights agreement. Therefore, theoretically, the stock market should fully account for the effect of stadium naming rights expenditures by the time of exposure observation.

Next, due to the nature of stadium naming rights expenditures, which are announced upon agreement signing, we conduct an event study based on the signing of new stadium naming rights agreements. This analysis will first inform us if financial markets on average reward the firm for signing a naming rights agreement. More importantly for our research question, we can then use the individual lifts in stock prices for each firm as a dependent variable in a model that determines whether other variables, including stadium naming rights expenditures, affect the stock market reaction to newly signed stadium naming rights agreements.

Finally, we test the effect that expenditures and exposures have on firm systematic risk. Unlike in our analyses for stock returns, we can measure the effects of both spending and exposures on systematic risk over time in our stadium naming rights agreement context. We test the annual effect of both variables on systematic risk using a variety of different specifications representing differing sets of modeling assumptions.

The monthly stock returns model provides evidence that unexpected media exposures increase firm stock returns, suggesting that the financial markets reward firms for experiencing unexpected exposures. This effect is implicitly separated from a variety of other drivers of the effect of marketing communications. Expenditures are controlled by the temportal nature of stadium naming rights agreements. In addition, the randomness of exposures, lack of firm influence over when the exposures occur, and the relatively shallow nature of this form of promotion, in which only the brand or firm name is mentioned, control for firm strategy and the creative quality of the promotion. These controls lead to an evaluation of exposures that is relatively isolated from other relevant effects. We also show that additional exposures lead to lower firm systematic risk, when controlling for the effects of expenditures, regardless of the modeling assumptions and specification. These results suggest that financial markets react positively to increased exposures controlling for these other drivers of the effectiveness of marketing communications.

Our second analysis provides evidence that, holding other factors of marketing effectiveness constant, agreements with higher expenditures result in decreased stock returns relative to lower cost agreements. In the systematic risk model, we find inconsistent evidence that suggests that expenditures might increase firm systematic risks, holding media exposures constant. This set of results for expenditures suggests that financial markets react negatively to higher cost agreements by lowering stock returns and by potentially increasing firm risk.

These results underline the importance of considering additional measures when attempting to estimate the overall effect of promotional communications, such as advertising, on firm financial performance. Specifically, we find that independently identifying the effects of exposures and expenditures in a sponsorship context results in competing effects between these two measures of the promotional campaign. While exposures improve firm financial performance, expenditures have potentially detrimental effects on financial performance. As such, our analysis suggests that in order to gain a richer understanding of the often studied link between paid marketing communications and firm financial performance, researchers should consider how to identify different measures and components of this communication in a manner that is independent from spending.

The paper is organized as follows. We first review the prior literature on the financial impact of marketing in general and marketing communications, primarily advertising, specifically. We then describe our data and present each of our analyses and their findings. Finally, we conclude with a discussion of the implications of our findings.

Asset Pricing Models in Marketing Contexts

We use asset pricing models to study how media exposures and associated promotional expenditures affect firm performance in a stadium naming rights context. A variety of research has tied marketing activities to firm stock market performance using asset pricing theory. For example, the extant literature has examined the effects of product quality (Aaker and Jacobson 1994), brand attitude (Aaker and Jacobson 2001), marketing strategy (Mizik and Jacobson 2003), product innovations (Srinivasan et al. 2009), and aggregate advertising expenditures (Erickson and Jacobson 1992, Joshi and Hanssens 2010, Srinivasan et al. 2009, and McAlister et. al 2007) on firm stock market performance.

The advantage of this approach compared with other performance metrics, such as firm sales or profits, is the long time horizon of financial metrics. A firm's stock price, theoretically, is the present value of all future cash flows for the firm. Many firm performance metrics, such as profitability and sales, are limited in the scope of their analysis. These metrics restrict our ability to judge the effectiveness of a marketing strategy for the firm, since marketing programs are often designed to improve firm sales and profits over the long-term.

Given the long-term nature of the effect of advertising investments, in which firms invest in advertising that often does not lead to immediate sales or profits, prior research has extensively analyzed the effect of advertising expenditures on firm financial performance (Erickson and Jacobson 1992, Conchar et al. 2005, Singh et al. 2005, McAlister et al. 2007, Srinivasan et al. 2009, Joshi and Hanssens 2010, and Luo and de Jong 2012). Erickson and Jacobson (1992) find that by controlling for unobserved heterogeneity, advertising expenditures result in limited additional stock returns for the firm. This result refutes earlier findings, which had not accounted for unobserved variables and had shown positive financial effects from investments in advertising (Connolly and Hirschey 1984). Erickson and Jacobson (1992) also determine that spending on advertising was not necessarily viewed favorably by the markets but was rather seen as an expense that reduced firm profitability. In contrast, Srinivasan et al. (2009) and Joshi and Hanssens (2010) find that markets react well (through increased firm stock returns) to advertising support for a firm's products and towards advertising expenditures in general. A meta-analysis of this literature (Conchar et al. 2005) finds that while prior analyses on this topic have, as a whole, shown some positive effect of advertising expenditures on firm value, this effect is very sensitive to how firm value changes are modeled. Effect sizes in this literature have a relatively high variation depending on modeling assumptions. This may potentially be due to the inability to separate the effects of advertising expenditures from that of advertising exposures. Since the correlation between these two drivers of advertising's financial effect would be expected to vary across contexts, the use of aggregate advertising spending as a proxy for the overall effect of advertising may explain the heterogeneous results reported in the literature.

In contrast to these varying findings on the effect of advertising on firm stock returns, prior research suggests a more definitive relationship between firm advertising spending and risk. Specifically, the extant literature suggests that advertising lowers firm systematic risk (Singh et al. 2005 and McAlister et al. 2007), which is a measure of the firm's exposure to changes in the overall returns of the stock market. Firms seek to lower their systematic risk in order to lower their cost of capital (Lubatkin and O'Neill 1987). A lower cost of capital allows the firm to engage in additional investments which have a positive net present value (NPV) that previously would have had a lower, and potentially negative, NPV. In addition, firm-specific assets, such as employees, are cheaper to acquire for firms with lower risk, holding other factors constant (Lim and Wang 2007). This literature, therefore, finds that lower risk results in financial benefits for the firm, specifically by potentially increasing the long-term financial returns of the firm by lowering the future cost of capital.

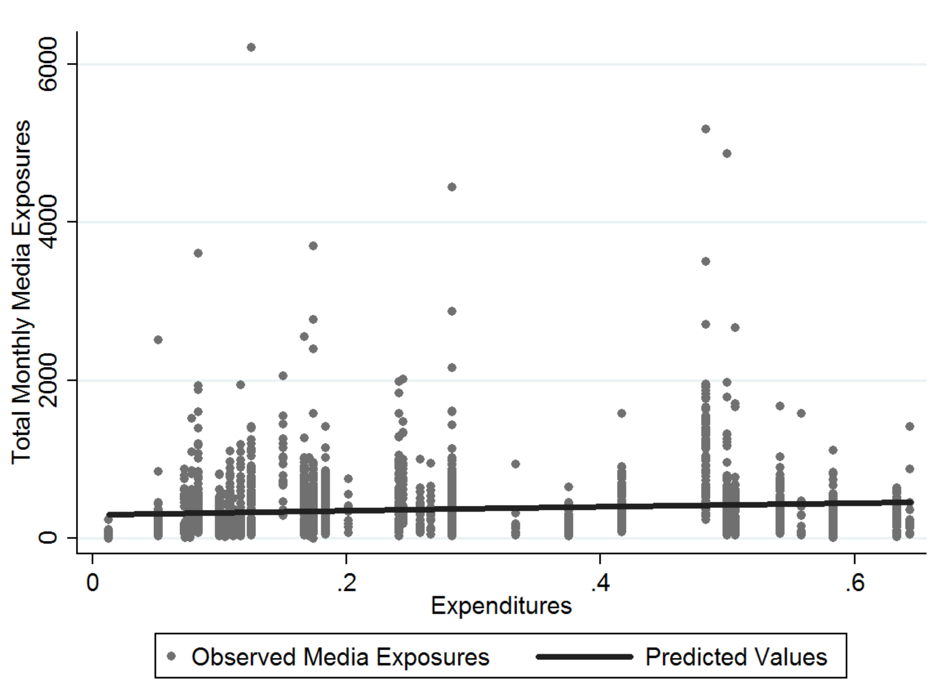
We expand on these previous findings by examining the disparate effects of media exposures and their associated expenditures in a stadium naming rights context on firm financial performance. While our context differs from traditional advertising contexts in the fact that the firm does not pay the publication medium directly for the exposure, enough similarities exist to suggest that promotion in this context will be similar to promotion in an advertising context, as the firm purchases the right to promotional content in which the sponsor is identified in each context. As such, we expand on the prior literature studying the effect of advertising on firm financial performance. Specifically, we provide results suggesting *how* different components of marketing communications impact the firm's stock returns and systematic risk. These results provide a richer understanding of the relationship between paid promotional communications and firm financial performance than found in prior analyses on this topic.

Data

The context for our study is stadium naming rights agreements, which is a form of paid promotion through corporate sponsorship. The firm agrees to pay a certain amount per year for a stadium naming rights agreement, regardless of the number of exposures of the firm's name. Rather than the traditional tie between expenditures and exposures, this results in the firm paying a flat rate for what is effectively a random set of exposures. These agreements often range in length from 10-25 years. Firms typically announce the total expenditures and contract length as part of the initial signing of the agreement, providing the financial markets with certainty with respect to the agreement's parameters. However, the actual number of exposures on a monthly level contain a random component that can't be completely predicted by either the firm or the financial markets.

In Figure vii, we plot exposures versus expenditures in the stadium naming rights context. The lack of a clear relationship is obvious. This figure shows that this form of sponsorship is a natural platform in which to separately study the effects of media exposures and associated expenditures, as the correlation between expenditures and exposures is only 0.10 in this context.

Figure vii: Predicted and Observed Mentions and Expenditures[5]



Our dataset consists of naming rights agreements for stadiums with sports franchise tenants competing in the major sports leagues in the United States and Canada: the National Football League (NFL), Major League Baseball (MLB), the

[5] Citi Field excluded from graph and p-value due to scale issue.

National Basketball Association (NBA), the National Hockey League (NHL), Major League Soccer (MLS), and major college football (Division I Bowl Subdivision) and college basketball (Division I). Each stadium has at least one sports organization from one of these leagues as a tenant. We only analyze stadium naming rights agreements involving public firms, due to our use of stock market data. In addition, inclusion of a stadium naming rights agreement in the dataset is determined by the release of information on the firm's expenditure and the length of the contract for the stadium naming rights agreement.

We collect data on the number of media exposures for each stadium from the News Library database (http://nl.newsbank.com). This database contains media articles from 4,597 publications across the United States. Exposures are defined as the number of articles that mention the complete stadium name. The inclusion of only complete stadium names ensures that we do not capture extraneous brand mentions in the media sources. For example, we only collect mentions of "Bank of America Stadium" so as not to include unconnected business articles discussing Bank of America's finances, allowing us to isolate the effects of this specific form of marketing communications. These data are collected at the monthly level.

In order to ensure that our results are not due to issues with the composition of the database, which does not contain a complete census of media sources, we augment our dataset for any metropolitan areas in which the largest daily newspaper was not included in this dataset. Major local daily newspapers have a disproportionate impact on the total number of media mentions for a stadium, necessitating that each metropolitan area be represented by at least one major newspaper. These additional data were collected from either the Factiva database, when the local major daily newspaper was available, or from the website of the newspaper itself, when the major newspaper was unavailable in both databases.[6]

Each of our three analyses requires a distinct dataset with different included variables, time windows, and requirements for the calculation of firm financial performance. As such, we provide a more detailed description of the dataset used for each analysis while outlining each methodology.

Effect of Media Exposures on Firm Stock Returns

We build our model on extant asset pricing theory, which is based on the Capital Asset Pricing Model (CAPM) (Sharpe 1964 and Lintner 1965). This model specifies a firm's returns adjusted for the returns of risk-free assets based on several components: market returns, the returns of a risk-free asset, a firm's idiosyncratic risk, and the firm's estimated systematic risk. The CAPM captures the relationship between market returns and firm stock returns. Other researchers (Fama and French 1993 and Carhart 1997) have augmented this model with effects that account for firm size (SMB), book-to-market ratio (HML), and momentum (UMD), forming the "four-factor model" (1).

(1) $$(R_{it}-R_{rft})=\alpha+\beta_1(R_{mt}-R_{rft})+\beta_2 SMB_t+\beta_3 HML_t+\beta_4 UMD_t+\varepsilon$$

[6] Phoenix and Nashville are the only two metropolitan areas that require direct data collection from the newspaper's website.

As is standard in this form of analysis, our dependent variable is formed by subtracting the risk free asset return rate at time t (R_{rft}) from firm i's stock returns at time t (R_{it}). The firm's systematic risk is the coefficient (β_1) describing the effect of market returns (R_{mt}), adjusted for the risk free return rate, on firm stock returns. The CAPM states that in order to increase the predicted stock returns on a portfolio of assets, an investor must increase the systematic (or non-diversifiable) risk of the portfolio. Firms with a higher systematic risk are more sensitive to macroeconomic shocks than firms with a comparatively lower systematic risk. The remaining coefficients control for whether the firm tends to change in value similarly to smaller or larger firms (β_2), high or low book-to-market firms (β_3), and firms that previously increased in value or those that previously decreased in value (β_4). This model also includes an intercept (α) which captures any structural differences between a portfolio or firm's return and the market's return. The error term captures what is often called a firm's idiosyncratic risk. This model is a standard, accepted methodology for studying the effect of marketing on firm financial performance (Srinivasan and Hanssens 2009).

For this analysis, we use a panel of 49 stadium naming rights agreements from 2001-2010, collected at the monthly level. The agreements and time windows for each agreement were selected based upon the focal firm's status as a public firm that reports advertising expenditures, the expenditures on the stadium naming rights agreement, and the time period in which the agreement remains active. These data consist of 2,576 observations. We calculate a firm's monthly stock returns, adjusted for dividends and any changes in the number of shares outstanding, using data from the Center for Research in Security Prices (CRSP).

In order to test the effect of media exposures, we extend the four-factor model (1) to include lagged media exposures adjusted for the number of events in the stadium in the observation month and controls for observed firm characteristics (2).

$$(2) \qquad (R_{it} - R_{rft}) = a_i + \beta_1(R_{mt} - R_{rft}) + \beta_2 SMB_t + \beta_3 HML_t + \beta_4 UMD_t + \beta_5\left(\frac{Totalmedia\ \ exposures_{\ it-1}}{Totalgames_{\ it-1}+1}\right) + \varepsilon$$

This approach – including as an additional regressor our variable of interest – is a standard method for testing the effect of firm activities on stock returns, conditional on the characteristics of the overall financial market. The values for the four market-level factors are collected from Kenneth French's Data Library.[7] The variable *Totalmediaexposures* is the (lagged) number of media exposures for each month t for stadium i.

As all sports franchises operate on predictable event schedules, in which each sport is "in season" (holding events/games) during a specific period of time, it is also crucial to control for the seasonality and market expectations of media exposures. However, traditional controls for seasonality, such as indicator variables for each month, are inappropriate here as each stadium will experience seasonality in a different manner depending on the sports played in the stadium. For example, Safeco Field, the baseball stadium in Seattle, is active between the months of April and October, while CenturyLink Field, the football stadium in Seattle, is active between

[7] Kenneth French's Data library can be found at:
http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

the months of August and January. In addition, even within a season, certain months will be more active than other months, based upon both a random component of scheduling and differences within seasons for each sport. For example, in November 2011, the Seattle Seahawks played 4 games, while they only played 3 games in November 2012. As schedules are announced well prior to the start of the active "season," this seasonality is already accounted in the market expectation for the number of media mentions. More active months will have higher market expectations for exposures, necessitating the use of a control for the number of games played by the tenants of a stadium in each month.

The unique nature of seasonality in this context necessitates the use of a unique control for market expectation. We control for market expectations based on seasonality by dividing the total number of media exposures by the total games played by all sports franchise tenants of that stadium in the observation month.[8] More traditional methods for determining market expectations, such as the use of a simple autoregressive model, are inappropriate in this case. Specifically, an autoregressive model, which sets market expectations based on the prior month would not account for the stadium specific seasonality issues.[9]

We include descriptive statistics and correlations for each of the variables studied within our model in Tables iv and v.

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[8] We add 1 to this total due to the prevalence of months without events within our data.

[9] We do test the robustness of our results to alternative specifications of market expectations, including the use of a model in which monthly exposure expectations are a function of total events in a month and the number of exposures in the same month 1 year prior to the observation month. Our results are robust to this specification of exposure expectations.

Table iv: Descriptive Statistics

	Mean	Median	St. Dev.	Min	Max
$R_{it} - R_{rft}$	0.81	0.39	15.13	-83.66	394.14
$R_{mt} - R_{rft}$	0.35	0.94	5.07	-18.55	11.04
SMB	0.43	0.09	2.55	-6.53	6.83
HML	0.25	0.17	2.89	-9.93	13.88
UMD	-0.19	0.39	6.12	-34.75	12.56
$\frac{Totalmediaexposures_{it-1}}{Totalgames_{it-1}+1}$	108.88	52	229.21	0	5170

Table v: Correlations

	Returns	Mkt. Ret.	SMB	HML	UMD	Exposures
Returns	1					
Mkt. Ret.	0.35	1				
SMB	0.14	0.37	1			
HML	0.19	0.27	0.17	1		
UMD	-0.25	-0.48	-0.16	-0.23	1	
Exposures	7.33E-3	-0.04	-9.17E-3	0.04	-8.62E-3	1

In estimating Model (2), we also include agreement-level fixed effects to control for unobserved heterogeneity. It's worth noting that the inclusion of these variables is contrary to finance theory, which suggests that, after controlling for the four-factors, firms should not systematically demonstrate differences in α, which would be captured by fixed effects. However, in our context, these fixed effects are crucial to control for time-invariant, agreement-level effects. Notably, these effects provide controls for market expectations for per-game exposures based on between-stadium differences, other promotional components of stadium naming rights agreements (e.g. signage), and time-invariant sports franchise and metropolitan area characteristics. The fixed effects, therefore, allow for the separation of the effects of expected media exposures from the effects of random and unexpected brand exposures. Due to this potential conflict between financial theory and our approach, we estimate this model both with and without the fixed effects included to evaluate the robustness of our results.

A Breusch-Pagan test on (2) indicates significant heteroskedasticity at the stadium naming rights agreement level. Thus, we estimate these models using Feasible Generalized Least Squares (FGLS),[10] which is more efficient than Maximum Likelihood estimation with robust standard errors in the presence of heteroskedasticity (Carroll and Ruppert 1982). We estimate this model with a heteroskedastic error structure for each of the models. Table vi presents our main results.

Table vi: FGLS Results

	(1)	(2)	(3)	(4)
	Four-Factor Model	No Media Exposures	No Fixed Effects	Full Model
Constant	0.18		0.05	
	(0.13)		(0.15)	
Market Returns	0.76***	0.76***	0.76***	0.76***
	(0.03)	(0.03)	(0.03)	(0.03)
SMB	-0.07	-0.07	-0.07	-0.07
	(0.06)	(0.06)	(0.06)	(0.06)
HML	0.15***	0.15***	0.14***	0.14***
	(0.05)	(0.05)	(0.05)	(0.05)
UMD	-0.07***	-0.07***	-0.07***	-0.07***
	(0.03)	(0.03)	(0.03)	(0.03)
Lagged Total Exposures			1.10E-3**	1.13E-3**
			(5.68E-4)	(5.91E-4)
Fixed Effects	No	Yes	No	Yes
N	2576	2576	2576	2576
LL	-9147.34	-9129.31	-9145.55	-9127.59

** Significant at 95% Level
*** Significant at 99% Level

[10] FGLS estimators are asymptotically efficient and represent the minimum variance linear unbiased estimator in the generalized regression model.

As shown in Model specifications (3) and (4), we find that total media exposures per event is significantly and positively related to firm stock returns at the 95% level.[11] Moreover, our results are robust to the inclusion or exclusion of fixed effects in the model. These results imply that financial markets react to an increase in exposures directly rather than simply reacting to expenditures, a correlated variable that has been the proxy used in prior analyses of the effect of paid marketing communications on firm value.

One concern in our results is that they could be due to the time window in which the observations were taken (2001-2010) and the inclusion of many firms in the financial industry. Specifically, this time period includes a major recession in the United States that heavily impacted the financial sector. We test the robustness of our results to the inclusion of indicator variables for financial firms and whether the observation month occurs in the years 2008-2009. We find that our results are robust to the inclusion of these terms, suggesting that our results are neither driven by industry- or time-specific concerns in relation to the macroeconomic environment.

Effect of Promotional Expenditures on Firm Stock Returns

In Model (2), we find a positive effect of *exposures* on firm stock returns, holding constant the expenditures based on the nature of stock returns models. Expenditures are announced at agreement signing, which occurs prior to the realization of these media exposures. Therefore, we need to analyze the effect of

[11] In order to ensure that our results are not due to influential datapoints, we also run this analysis eliminating all points found to be influential through high Cook's Distance values. Our results are robust to the elimination of these datapoints.

expenditures using a model designed to capture the stock market's reaction to the initial signing of the naming rights agreement.

A positive relationship between promotional expenditures and returns could occur either directly, in which spending serves as a signal of firm quality to the financial market, or indirectly by signaling product quality to consumers (Nelson 1974, Kihlstrom and Riordan 1984, and Milgrom and Roberts 1986) and increasing firm sales. However, prior research has also suggested that financial markets might punish firms for promotional expenditures that do not yield sufficient short-term ROI (Erickson and Jacobson 1992). Therefore, while we have shown that some of the positive financial effects within a sponsorship context are driven by the effect of exposures, the extant literature suggests that we could see either a positive or negative effect of the associated expenditures, conditional on the number of exposures expected by the financial markets.

Due to the temporal nature of the stadium naming rights context, in which expenditures are time-invariant and announced at agreement signing, we analyze the stock price impact of promotional expenditures using an event study. The focal event for this event study is the signing of the stadium naming rights agreement. This methodology will allow us to analyze the impact of *expenditures* while controlling for the market's expectations for exposures.

We employ a cumulative abnormal returns model (CAR), a common financial event study methodology previously employed in a marketing context by Gielens et al. (2008). This approach compares the firm's observed stock returns, which includs the effect of the event, and its expected returns without the event. The difference between observed and expected returns without the event is an estimate of the effect of the event. The use of cumulative abnormal returns is the preferred method for identifying the impact on firm stock price of a discrete event over a short time horizon (Gielens et al. 2008; Srinivasan and Hanssens 2009).

We collect daily stock returns data for 89 firms with stadium naming rights agreements from CRSP. These data consist of all agreements signed by public firms with an announced expenditure and agreement length for the focal major sports leagues. We divide the data into two time windows relative to the agreement announcement date (the "event date"). The first window consists of financial data for each of the firms for approximately 4 weeks before and after the event date. This is henceforth referred to as the "event window." The second data window runs for approximately 35 weeks prior to the beginning of the "event window." This window is used to establish a financial baseline by estimating firm-specific coefficients for each of our firms, and is thus referred to as the "estimation window."

In order to establish these baseline financial coefficients for each firm, we estimate a series of firm-specific Capital Asset Pricing Models (CAPM) using OLS (3).[12] This set of analyses is conducted on the data from the estimation window.

$$(R_{i\tau} - R_{rf\tau}) = \alpha_i + \beta_{1i}(R_{m\tau} - R_{rf\tau}) + \varepsilon \quad (3)$$

In this equation, we use the firm's returns (R_i), the risk-free asset return (R_{rf}), and the market return (R_m) on estimation window day τ to estimate a firm-specific value for α, which captures structural differences between firm and market returns,

[12] We use a CAPM instead of a Four-Factor Model in keeping with the Patell (1976) adjustment, which is designed for a CAPM, described in subsequent paragraphs

and β_{1i}, which is the firm's sensitivity to changes in market returns (also known as systematic risk).

Each firm's baseline characteristics are then used to define an expected return value for each firm on each day within the "event window" (4). This expected return value is the counterfactual stock return that would be expected to exist in the absence of the event on each day *t* during the "event window."

(4) $$E(R_{it}-R_{rft}) \equiv \alpha_i + \beta_{1i}(R_{mt}-R_{rft})$$

Following the standard CAR event study approach, we subtract the expected stock returns for each day in the event window from the observed firm stock returns on that day. The difference between the observed and expected stock returns is used as an estimate of the financial market reaction to the event (the signing of the naming rights agreement). We classify each day in the event window by their relationship to the event date for the appropriate firm. For example, for each firm, the day before the announcement of the naming rights agreement is classified as Day -1, while the day after the announcement is classified as Day 1. This results in 89 observations for each day relative to the event date within the event window.

The difference between the predicted and observed stock returns is adjusted according to the procedure proposed by Patell (1976). This adjustment is commonly used within the finance event-study literature (see, e.g., Brown and Warner 1985, Seiler 2000, Gielens et al. 2008, and Corrado 2011) and serves two purposes. First, it accounts for differences in variance between observed and expected stock returns due to the use of a separate estimation dataset, which, theoretically, could increase variance as firms might change characteristics between the estimation and event windows. This method also mitigates the influence of particularly high-variance observations in the calculation of aggregated stock returns due to the event. The adjustment, therefore, helps ensure that our results are not simply driven by a small number of agreements but rather due to changes seen across the broader set of firms within our database.

In order to perform this adjustment on the raw returns, we first calculate a measure designated as C_{it}, which accounts for the increase in variance due to the use of a separate estimation dataset outside of the estimation period (5). This term is specific for each firm i and each day within the event window t. All notation matches Patell (1976).

(5) $$C_{it} = 1 + \frac{1}{T} + \frac{(R_{mt} - \bar{R}_m)^2}{\sum_{t=1}^{T}(R_{m\tau} - \bar{R}_m)^2}$$

In this equation, T is equal to the number of days in the estimation period, R_{mt} is the return of the market at time t during the event window, $R_{m\tau}$ is the return of the market at time τ during the estimation window, and $\bar{R}_m$ is the mean of market returns during the estimation period as defined by Equation 6.

(6) $$\bar{R}_m = \frac{1}{T}\sum_{\tau=1}^{T} R_{m\tau}$$

We also calculate the variance during the estimation window and the corresponding predicted values of the firm-specific CAPM (7).

(7) $$s_i^2 = \frac{\sum_{t=1}^{T}\hat{\varepsilon}_{i\tau}^2}{T-2}$$

Finally, we adjust the firm's stock returns using each of these terms (8). In this equation, L represents the number of days within the event window under examination. For example, if we want to find the returns of the firm over the day of the event and the day immediately before the event, L would be equal to two. Expected returns are calculated as in (6), in which each coefficient is estimated by the firm-specific estimation of the CAPM using the estimation dataset.

$$Adjret_{lit} = \sum_{l=1}^{L} \frac{\left(R_{it} - R_{rft}\right) - E\left(R_{it} - R_{rft}\right)}{s_i\sqrt{L(C_{it})}} \tag{8}$$

We use the adjusted returns from this equation to empirically estimate both the length and valence of the event's impact on firm financial performance. This empirical estimation ensures that we accurately account for both "leakage," which is the dissemination of information on the event prior to the official announcement, and for potential issues with slow dissemination of information after the event has been officially announced. The amount of leakage and the speed of information dissemination are typically handled empirically for financial event studies (Gielens et al. 2008).

We do not find a period in which there is a significant lift in firm stock returns due to the implementation of a new stadium naming rights agreement, using a Z-Statistic methodology proposed by Patell (1976).[13] The relatively small size of market reaction to the overall naming rights agreement suggests an important result. As these agreements are negotiated between a seller (typically the sports franchise or a local municipality) and a buyer (the advertiser), the negotiations produce efficient results. The seller is able to extract enough from the buyer that they do not, on average, gain excess stock returns due to the signing of the agreement. While interesting, the goal

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[13] The Z-score for the two-day window is approximately 0.01, which is the highest value for any tested window, which included a variety of one-, two-, five-, and seven-day windows.

of this research is not to determine the average impact of a naming rights agreement on the firm's stock returns. We seek to determine whether expenditures, which potentially moderate the effect of the event on stock market returns, have a significant effect on the stock price lift experienced by the firm due to the signing of the agreement. We, therefore, need to select a window in which to analyze moderating variables that might affect the lift a stock receives based on the report of a stadium naming rights agreement.

The signing of naming rights agreements are often accompanied by press conferences involving sports franchise representatives, municipal leaders, and C-suite executives from the firm. Based on this characteristic of the event, we theorize that there is likely a small amount of information leakage prior to the announcement due to the pre-announcement of this press conference. The high visibility of the event should theoretically result in rapid information dissemination to the financial markets that the agreement has been signed on the day of the anouncement of the agreement. Therefore, we select a 2-day window, defined as the day before the public announcement and the day of the public announcement, for analysis.[14]

We estimate a regression model to test the impact of annual expenditures on the stock market returns due to the naming rights agreement signing (9). We use $Adjret_{lit}$ as the dependent variable in our analysis. $Adjret_{lit}$ represents the change in firm i's returns due to the event compared to expected firm returns without the event over window l. Using this measure, we test the moderating effect of a variety of variables on the lift in firm returns caused by the event. This methodology is

[14] Our results are robust to the use of an alternative time windows, including a shorter event window.

consistent with Gielens et al. (2008), who tested the effects of moderating variables on the stock market lift due to a discrete event.

$$Adjret_{lit} = \alpha + \beta_1(Expenditure_i) + \sum_{m=2}^{M} \beta_m(X_{im}) + \varepsilon \tag{9}$$

We estimate this model including a variety of control variables (X_{im}). First, we control for expected exposures. This measure is calculated by finding the total number of media exposures for the stadium's sports franchise tenants in the year prior to the beginning of the event dataset. This control ensures that our estimates for the effect of expenditures is independent of the market's expectations for exposures that will be accounted for by the financial markets at the signing of the naming rights agreement.

In our full model, we account for a variety of other variables that could impact how the firm's stock price reacts to the signing of the naming rights agreement. We include controls for the population of the metropolitan area and the growth of the metropolitan area. These data are collected from the Texas A&M Real Estate Center population database (http://recenter.tamu.edu/data/pop/) and from the Canadian census. The population of the metropolitan area is likely related with positive affect for the affiliated sports franchise and with the overall influence of the franchise. We also include controls for whether or not the stadium is located in New York City, which allows us to capture any non-linear effects for the purchase of stadium naming rights in the largest market in our dataset. Finally, we include a variety of other control variables, including whether the stadium is located in the same metropolitan area as the firm's headquarters (fit between stadium and firm), the winning percentage of the tenant sports organization, total attendance for the teams in the prior season, and indicator variables for expansion or college teams. These data are collected from a variety of online datasets.[15] Summary statistics for each of these variables are found in Table vii. We also provide correlations for each of these variables (Table viii).

Table vii: Descriptive Statistics

	Mean	Median	St. Dev.	Min	Max
Adjusted Returns	0.10	0.03	0.98	-1.92	5.04
Expenditure	3.36	2.1	3.42	0.15	20
Expected Exposures	8,341.64	6,719	9,963.16	0	58,540
Population	4,305,752	3,019,651	4,109,622	246,865	18,568,830
Change in Population	41,298.08	27,356	44,725.09	-56,212	144,777
Winning Pct.	0.53	0.52	0.13	0.24	0.85
Total Attendance	907,523.6	601,969	775,792.2	17,838	3,379,535

Table viii: Correlations

	Adj. Returns	Expenditures	Exposures	Pop.	Change in Pop.	Attendance
Adj. Returns	1					
Expenditures	-0.22	1				
Expected Exposures	-0.12	0.34	1			
Pop.	-0.03	0.51	0.25	1		
Change in Pop.	0.20	0.08	0.08	0.13	1	
Attendance	-0.02	0.16	0.56	0.14	0.16	1

These correlations suggest that expenditures, expected exposures, metropolitan area population, and annual attendance are potentially related variables. Therefore, it is important to ensure that our results for the effect of expenditures on firm stock returns are robust to the inclusion of these variables in the analysis.

We estimate three models for the two-day event windows: a model without any of the control variables, a model including only the expected media exposures control variable, and a model with the full set of control variables. All of our models

[15] Most records were found from the online sports-reference database (http://www.sports-reference.com/) and the ballparks.com database (http://www.ballparks.com/). Team and NCAA records were used for college and MLS teams.

are estimated using Maximum Likelihood with a sample of 89 stadium naming rights agreements (Table ix).

Table ix: Stock Market Reaction to Expenditures

	No Controls	Expected Exposures	Full Set of Controls
Intercept	0.32**	0.34**	0.42
	(0.15)	(0.16)	(0.77)
Expenditures	-0.06***	-0.06**	-0.10**
	(0.03)	(0.02)	(0.04)
Expected Exposures		-5.26E-6	-3.56E-6
		(7.47E-6)	(9.31E-6)
Population			8.66E-9
			(2.52E-8)
Population Growth			5.59E-6***
			(1.88E-6)
New York City			1.01
			(0.94)
Hometown			0.31
			(0.22)
Winning Pct.			-0.71
			(1.11)
Total Attendance			-6.48E-8
			(1.70E-7)
College			0.09
			(0.33)
Expansion Team			0.24
			(0.33)
N	89	89	89
AIC	2.79	2.81	2.88
BIC	-309.59	-305.32	-277.77
Log Pseudolikelihood	-122.05	-121.93	-117.07

** Significant at 95%
*** Significant at 99%

Additional expenditures on stadium naming rights have a significant negative effect on stock returns following the announcement of the agreement. This effect is robust to the inclusion of both expected mentions and the full set of control variables to the model. This result suggests that additional expenditures lead to lower stock returns upon stock market announcement of the naming rights agreement.[16]

Only one of the other included variables, the growth of the city's population, has a significant effect on the lift caused by the signing of the naming rights agreement, suggesting that most variables are captured efficiently in the negotiation between the naming rights firm and stadium owners, leading to a lack of excess returns for the naming rights firm.

Due to the lack of significance for many of the other included variables, the more parsimonious models perform better than the model containing all of the control variables according to both AIC and BIC measures. Combined, then, the results of this section and the previous section suggest that financial markets punish the firm for promotional expenditures, except insofar as they lead to increased unexpected exposures of the firm or brand name.

Effect of Media Exposures and Expenditures on Firm Systematic Risk

Based on our finding that media exposures and expenditures each affect firm stock returns in a distinct manner as well as on prior findings suggesting that advertising spending has a significant and negative effect on firm systematic risk (Singh et al. 2005 and McAlister et al. 2007), we investigate the effects of both media exposures and expenditures on systematic risk. Systematic risk is the firm's exposure to macroeconomic risk that can't be eliminated by investors through portfolio

[16] We again conduct a robustness check to ensure that our results are not due to a few influential datapoints. Our results in the full model are robust to the exclusion of datapoints with a high Cook's Distance from the dataset.

diversification. Lowering this risk can lead to a lower cost of capital for the firm, potentially increasing future firm profitability (Lubatkin and O'Neill 1987). While prior research has found that advertising lowers a firm's systematic risk, the extant literature has been unable to independently identify the effects of advertising exposures from advertising expenditures on this form of firm risk. We evaluate how both exposures and expenditures can seperately affect a firm's systematic risk in the stadium naming rights context. Again, the nature of this context suggests that our results may inform us as to the nature of exposures and expenditures in other promotional communication contexts, such as advertising.

We test these effects on firm systematic risk using data for North American major sports affiliated stadium naming rights agreements from 2001-2012. We collect the daily stock price, number of shares outstanding and dividends from CRSP for each firm for all years in which the stadium naming rights agreement is active and in which the firm reports financial results and advertising expenditures. In addition, we collect the annual firm sales, net income, and advertising expenditures from each firm's annual reports for the years in which they report each of these metrics and have an active naming rights agreement. Finally, we collect the annual mentions of the stadium for each year within our analysis from the News Library database, augmented as in prior analyses for metropolitan areas without a major daily newspaper in this database.

Using the daily financial data, we estimate the annual systematic risk for each firm in a standard manner consistent with McAlister et al. (2007). In order to find the annual systematic risk for the firm, which is defined as the coefficient describing the relationship between market returns and firm returns, we estimate a CAPM for each firm-year pair (10). The value of the β_{1ij} coefficient is found for each firm i in year j. This model is estimated using OLS and is conducted using each day t during year j.

$$(10) \qquad (R_{ijt} - R_{rft}) = \alpha_{ij} + \beta_{1ij}(R_{mt} - R_{rft}) + \varepsilon$$

With this model, we calculate the systematic risk for 320 firm-years over 53 firms. We use this set of estimated systematic risk values ("betas") to independently study the effects of media exposures and expenditures. We estimate a variety of models in order to evaluate the robustness of our results to different modeling decisions and specifications. The simplest of these models involves no control for unobserved heterogeneity (11). We estimate this model with both a linear and a loglinear specification.

$$(11) \quad \beta_{1ij} = \alpha + \varphi_1(\beta_{1ij-1}) + \varphi_2(Expenditures_i) + \varphi_3(MediaExposures_{ij-1}) + \sum_{k=1}^{11} \zeta_k(Year_k) + \varepsilon$$

This model includes a lagged endogenous term controlling for firm systematic risk in the prior year. Prior empirical research on systematic risk suggests the use of this term to account for the slow rate of change in firm systematic risk (Chan and Chen 1991, Jostova and Philipov 2005, Gysels and Jacquier 2006, Ang and Chen 2007, and Adrian and Franzoni 2009). We also include a set of indicator variables for the year of the observation (designated as year k) to control for any differences over time in our sample's exposure to risk. Finally, we analyze both media exposures of the stadium name in the previous year and the annual expenditures on the stadium naming rights agreement.

Due to the presence of heteroskedasticity, we estimate this model using OLS with robust standard errors and with FGLS, which is more efficient in the presence of heteroskedasticity than Maximum Likelihood estimation with robust standard errors (Carroll and Ruppert 1982). Using a Wooldridge test (Wooldridge 2002), which tests for autocorrelation in panel data, we find significant evidence for autocorrelation at the 90% level (p-value = 0.07). We account for autocorrelation by estimating the FGLS model using a panel-specific AR(1) model. Due to the nature of this model, we conduct this analysis only on observed stadiums with more than 2 observation years. Our sample size for this model is, therefore, smaller (287) than for the other specifications.

We also estimate a pair of models controlling for unobserved heterogeneity using random effects (12). A significant value for the Breusch-Pagan Lagrange multiplier test on our empirical estimates suggests the importance of including controls for unobserved heterogeneity in the estimation of our model. A Hausman specification test indicates that the more efficient random effects method is most appropriate for dealing withunobserved heterogeneity in this instance. The standard random-effects model is estimated using GLS.

$$\beta_{1ij} = (\alpha + u_i) + \varphi_1\left(\beta_{1ij-1}\right) + \varphi_5(Expenditures_i) + \varphi_6\left(MediaExposures_{ij-1}\right) + \sum_{k=1}^{11} \zeta_k (Year_k) + \varepsilon \qquad (12)$$

However, the standard random effects model is unable to test the effect of annual expenditures on the naming rights agreement, as these are time invariant within our context. Hausman and Taylor (1981) propose a manner to measure time invariant variables while still controlling for unobserved heterogeneity through the use of random effects. Specifically, they introduce an instrumental variable approach in which the assumption of exogeneity between the random effects and regressors is relaxed. This method, therefore, allows us to simultaneously deal with unobserved heterogeneity, time-invariant effects, and lagged endogenous terms within a single model.

The empirical results for each of these estimated models are presented in Table x.[17]

Table x: Systematic Risk Results

	Linear- No Unobserved Heterogeneity	Loglinear- No Unobserved Heterogeneity	FGLS- Heteroskedastic and Panel-Specific AR(1)	Random Effects	Hausman-Taylor
Intercept	0.29***	0.64***	0.76***	1.18***	0.81***
	(0.11)	(0.19)	(0.10)	(0.10)	(0.15)
Lagged β_1	0.71***	0.68***			0.30***
	(0.06)	(0.05)			(0.06)
Lagged Media	-2.80E-5***	-0.09***	-1.33E-5***	-3.30E-5***	-3.56E-5***
Exposures	(8.36E-6)	(0.02)	(4.24E-6)	(1.00E-5)	(1.32E-5)
Expenditures	1.85E-2	0.05*	0.04***		3.01E-2*
	(1.43E-2)	(0.03)	(0.01)		(1.78E-2)
Year Indicators	Yes	Yes	Yes	Yes	Yes
N	294	294	287	294	294
Wald Chi^2			140.80	39.25	86.31
R^2 (total or within-panel)	0.60	0.59		0.16	

* Significant at 90%
*** Significant at 99%

We find that regardless of model specification and estimation procedures, the number of media exposures for the firm lowers the firm's systematic risk in

[17] As a robustness check, we also calculated a Fixed Effects and Arellano-Bond estimator, finding that both methods provide negative and significant values for the effect of lagged media exposures on systematic risk. In addition, we test the robustness of our results to the inclusion of firm financial data, such as firm sales, net income, and advertising spending. Our results are robust to the inclusion of these terms.

subsequent years. The results for expenditures are somewhat inconsistent across different specifications. We find significant and positive effects of expenditures on firm systematic risk at the 99% level for the FGLS model accounting for heteroskedasticity between panels using an AR(1) specification for autocorrelation. We also show marginally significant increases in risk due to higher expenditures with the loglinear model and with the Hausman-Taylor estimate.[18]

Discussion

Our findings begin to bridge the gap between the financial/marketing interface literature and the broader marketing literature on how the effectiveness of paid marketing communications are measured. While prior marketing/finance interface research has focused exclusively on the effects of spending, which serves as a proxy for the overall effects of these paid communications, we more closely link this research to the broarder marketing literature, which focuses on a variety of measures and components of marketing communications.

Based on our findings in a sponsorship context, media exposures drive positive financial effects for the firm, both increasing firm stock returns and decreasing firm risk. In contrast, promotional expenditures, when controlling for media exposures, lead to negative financial results, specifically decreasing stock returns and weakly increase firm systematic risk. These findings provide us with a richer understanding of *how* paid marketing communications impact a firm's financial performance, increasing our theoretical understanding of the role of these

[18] We also test that our results are not driven by the recession that occurred in our data window, which disproportionately affected some of the firms in our sample, especially those in the banking industry. We find that our results are robust to the inclusion of indicator variables for the worst recession years and for the finance industry.

communications and their effects for the firm. Our results underline the importance of actively managing a firm's marketing communication strategy in order to maximize the number of exposures per dollar of expenditure.

In addition, our results provide evidence of the importance of exposures for managing firm systematic risk. We find that exposures consistently lower a firm's systematic risk, regardless of the modeling assumptions or included variables. In comparison, expenditures on these communications potentially increase a firm's systematic risk depending on the modeling specification. These results suggest that the firm may actually lower the effectiveness of *future* marketing investments (as well as other investments) through the implementation of an inefficient (low number of exposures per dollar of expenditure) present communication strategy. This inefficient campaign leads to a higher cost of capital in the future, raisng the cost to the firm of future campaigns. These results serve to further highlight the importance of effective media planning as ineffective planning can hurt the firm's financial performance over both the short- and long-term.

This study contains several limitations that provide ample opportunities for future research. First, we only examine the effect of one form of promotion (stadium naming rights agreements). It is possible that with other forms of marketing communications, such as advertising, consumers or financial markets react to exposures and expenditures in a different manner. For example, exposures within the stadium naming rights context are relatively coarse, containing only the name and information about the association with the sports franchise and city. Other contexts, which contain richer information as part of the exposure, provide an interesting opportunity to further study how the information conveyed in marketing communications can directly impact a firm's financial performance.

In addition, our findings do not demonstrate the effects of either exposures or expenditures on firm idiosyncratic risk, which is the risk that is potentially diversified away by investors. As with systematic risk, firms prefer a lower idiosyncratic risk, due to cost of capital concerns. This offers a future research opportunity to study how different different measures of a paid marketing communication campaign can affect firm idiosyncratic risk.

These results also don't offer insights into whether exposures or expenditures affect a firm's stock returns directly or indirectly through increases in firm sales as described by Joshi and Hanssens (2010). This potential extension would provide greater insight into how consumers receive information from paid marketing communications and how that information is incorporated into firm financial performance.

Finally, this study only analyzes the financial effect of one driver of paid marketing communication's effect, exposures, while attempting to limit the effects of other components, such as creative aspects. Future research is needed to continue to bridge the gap between the marketing/finance interface literature and the wider marketing literature in regards to how marketing communications can impact a firm's performance.

Conclusion

Through the use of the unique stadium naming rights agreement context, we are able to answer the question of how media exposures and associated expenditures can independently affect a firm's financial performance. In doing so, we overcome the limitations that have previously plagued analyses on the financial effects of these paid marketing communication, which had not been able to clearly delineate the effects of exposures and expenditures due to the implicit relationship between these two variables.

We find that the financial markets increase firm stock returns and lower firm systematic risk in response to an increase in exposures, while decreasing firm stock returns and weakly raising firm systematic risk in response to an increase in associated expenditures. These results suggest that financial markets reward the firm based on the number of exposures received rather than increasing firm value based solely on the increased allocation of assets to the firm's budget for paid marketing communications.

This study uses a unique context that allows for the isolation of exposures from expenditures to begin to bridge the gap between the marketing/finance interface literature and the broader marketing literature studying the effect of maketing communications. As such, our findings provide a richer understanding of *how* firm marketing communications can affect a firm's financial performance. In the future, further research should develop our understanding of the financial impact of other drivers and measures of the effectiveness of marketing communications. It is important to continue to develop a richer understanding of how these communications can impact a firm's financial value.

Appendices

__Appendix A__

Appendix A: Results for Content Sales Per Member of the Installed Base

Innovator Definition	Rogers' (1962) "Innovators"				Chandrasekaran and Tellis' (2011) "Saddle"				
New Definition	1 Week	2 Weeks	3 Weeks	4 Weeks	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks
Intercept	-3.11***	-3.12***	-3.11***	-3.10***	-4.15***	-4.18***	-4.18***	-4.17***	-4.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)	(0.06)	(0.06)	(0.07)
Innovativeness	0.96***	0.86***	0.81***	0.81***	1.89***	1.89***	1.85***	1.81***	1.77***
	(0.09)	(0.11)	(0.13)	(0.15)	(0.08)	(0.08)	(0.08)	(0.08)	(0.09)
Recency	19.91***	13.71***	10.12***	7.72***	51.25***	37.38***	28.52***	22.56***	18.13***
	(1.43)	(1.06)	(0.85)	(0.70)	(4.15)	(2.45)	(1.80)	(1.51)	(1.29)
Interaction	-17.74***	-11.88***	-8.53***	-6.38***	-48.54***	-35.11***	-26.52***	-20.75***	-16.52***
	(1.34)	(0.96)	(0.75)	(0.60)	(1.49)	(2.42)	(1.78)	(1.49)	(1.29)
Xbox360	0.09**	0.10**	0.11**	0.10**	-0.17***	-0.16***	-0.15***	-0.15***	-0.15***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
PS3	0.15***	0.15***	0.15***	0.15***	-0.04	-0.03	-0.02	-0.02	-0.02
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Seasonality	0.44***	0.45***	0.51***	0.60***	0.69***	0.64***	0.64***	0.67***	0.75***
	(0.06)	(0.07)	(0.08)	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
R^2	0.73	0.72	0.70	0.68	0.70	0.70	0.70	0.70	0.69

* Significant at 90%
** Significant at 95%
*** Significant at 99%

Appendix A: Results for Content Sales Per Member of the Installed Base

Innovator Definition	Fixed Four Million					Fixed Eight Million				
New Definition	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks
Intercept	-3.45***	-3.45***	-3.45***	-3.43***	-3.40***	-3.75***	-3.77***	-3.77***	-3.75***	-3.73***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
Innovativeness	1.28***	1.24***	1.19***	1.15***	1.13***	1.57***	1.55***	1.51***	1.47***	1.44***
	(0.05)	(0.06)	(0.06)	(0.06)	(0.07)	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
Recency	34.81***	24.16***	17.83***	13.55***	10.49***	42.52***	30.31***	22.77***	17.75***	14.11***
	(2.35)	(1.51)	(1.12)	(0.89)	(0.73)	(2.93)	(1.75)	(1.28)	(1.05)	(0.87)
Interaction	-32.32***	-22.11***	-16.05***	-12.00***	-9.18***	-39.94***	-28.16***	-20.90***	-16.08***	-12.66***
	(2.28)	(1.45)	(1.06)	(0.84)	(0.71)	(2.88)	(1.72)	(1.24)	(1.02)	(0.86)
Xbox360	0.04	0.05	0.05	0.04	0.03	-0.09**	-0.07**	-0.07*	-0.06*	-0.07*
	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
PS3	0.03	0.04	0.05	0.05	-0.04	-0.12***	-0.10***	-0.09**	-0.08**	-0.08**
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Seasonality	0.38***	0.39***	0.43***	0.52***	0.65***	0.58***	0.54***	0.57***	0.62***	0.71***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
R^2	0.77	0.76	0.74	0.73	0.71	0.74	0.74	0.73	0.72	0.71

** Significant at 95%
*** Significant at 99%

Appendix B

Appendix B: Results for Title-Specific Analysis

Innovator Definition	Fixed Four Million					Fixed Eight Million				
New Definition	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks
Intercept	-9.37***	-9.53***	-9.90***	-9.91***	-9.89***	-9.32***	-9.48***	-9.59***	-9.69***	-9.73***
	(0.11)	(0.11)	(0.10)	(0.10)	(0.10)	(0.13)	(0.13)	(0.13)	(0.14)	(0.09)
Innovativeness	1.12***	1.28***	1.41***	1.47***	1.48***	0.51***	0.64***	0.71***	0.77***	0.24*
	(0.15)	(0.15)	(0.15)	(0.16)	(0.16)	(0.13)	(0.14)	(0.14)	(0.14)	(0.14)
Recency	14.31***	12.02***	10.40***	9.00***	7.57***	18.71***	15.18***	12.71***	11.12***	1.60***
	(1.70)	(1.21)	(0.97)	(0.84)	(0.74)	(2.29)	(1.62)	(1.29)	(1.11)	(0.35)
Interaction	-13.61***	-11.33***	-9.66***	-8.26***	-6.94***	-18.02***	-14.48***	-11.99***	-10.38***	-0.76***
	(1.66)	(1.18)	(0.95)	(0.82)	(0.73)	(2.26)	(1.60)	(1.27)	(1.10)	(0.23)
Week 1	1.49***	1.50***	1.52***	1.56***	1.58***	1.53***	1.54***	1.55***	1.58***	1.55***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Week 2	0.95***	0.97***	0.99***	1.02***	1.04***	0.99***	1.00***	1.01***	1.04***	1.00***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 3	0.72***	0.72***	0.74***	0.77***	0.79***	0.75***	0.75***	0.77***	0.79***	0.76***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 4	0.60***	0.60***	0.61***	0.64***	0.65***	0.62***	0.63***	0.63***	0.65***	0.62***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 5	0.50***	0.50***	0.51***	0.53***	0.55***	0.52***	0.53***	0.53***	0.55***	0.53***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 6	0.41***	0.41***	0.42***	0.44***	0.44***	0.43***	0.43***	0.43***	0.45***	0.44***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 7	0.30***	0.29***	0.29***	0.31***	0.32***	0.32***	0.31***	0.31***	0.33***	0.34***
	(0.05)	(0.09)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 8	0.18***	0.16***	0.16***	0.17***	0.18***	0.20***	0.18***	0.17***	0.18***	0.20***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)	(0.05)
Week 9	0.08*	0.08*	0.07	0.08	0.08*	0.09*	0.09*	0.08	0.08*	0.09*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Xbox360	0.23***	0.26***	0.28***	0.29***	0.29***	0.21***	0.22***	0.24***	0.25***	0.10***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)
PS3	0.40***	0.39***	0.38***	0.37***	0.37***	0.58***	0.58***	0.57***	0.57***	0.41***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.09)
Seasonality	0.50***	0.50***	0.50***	0.53***	0.59***	0.57***	0.57***	0.58***	0.60***	0.71***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
R^2	0.87	0.87	0.87	0.88	0.87	0.87	0.87	0.87	0.87	0.87

* Significant at 90%

*** Significant at 99%

Appendix B: Results for Title-Specific Analysis

Innovator Definition	Chandrasekaran and Tellis' (2011) "Saddle"				
New Definition	1 Week	2 Weeks	3 Weeks	4 Weeks	5 Weeks
Intercept	-9.58***	-9.76***	-9.89***	-10.02***	-10.11***
	(0.18)	(0.19)	(0.19)	(0.20)	(0.21)
Innovativeness	0.80***	0.96***	1.05***	1.14***	1.20***
	(0.19)	(0.20)	(0.20)	(0.21)	(0.21)
Recency	29.46***	23.15***	18.98***	16.49***	14.58***
	(3.71)	(2.67)	(2.15)	(1.88)	(1.70)
Interaction	-28.79***	-22.49***	-18.30***	-15.79***	-13.98***
	(3.70)	(2.67)	(2.14)	(1.88)	(1.70)
Week 1	1.53***	1.54***	1.55***	1.57***	1.59***
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
Week 2	0.99***	1.00***	1.01***	1.03***	1.05***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 3	0.76***	0.76***	0.77***	0.78***	0.80***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 4	0.63***	0.63***	0.63***	0.65***	0.66***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 5	0.52***	0.53***	0.53***	0.54***	0.55***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 6	0.43***	0.43***	0.43***	0.45***	0.45***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 7	0.32***	0.32***	0.32***	0.33***	0.34***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 8	0.20***	0.19***	0.18***	0.19***	0.20***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Week 9	0.09*	0.09*	0.08*	0.08*	0.09*
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
Xbox360	0.18***	0.18***	0.19***	0.19***	0.19***
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
PS3	0.57***	0.57***	0.56***	0.56***	0.56
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
Seasonality	0.61***	0.61***	0.63***	0.64***	0.67***
	(0.04)	(0.04)	(0.05)	(0.04)	(0.03)
R^2	0.87	0.87	0.87	0.87	0.87

* Significant at 90%
*** Significant at 99%

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