ONLINE CUSTOMER ENGAGEMENT, ONLINE COMMUNITIES, AND POST PURCHASE PRODUCT OUTCOMES

by

KEITH MARION SMITH

(Under the Direction of John Hulland)

ABSTRACT

The recent growth of online customer communication and digital product development and adoption has begun to transform the world economy, as computer technology is increasingly adopted and implemented in households around the globe. Entire industries have been disrupted by the transition to digital goods (and away from physical goods), including books (Kindle, Nook), music (iTunes, Spotify), movies (Netflix, Hulu), software (Apple App Store, Windows Store), and games (Steam, EA Origin). The trend towards digital products and online communication is expected to further accelerate in the future. However, very little is currently understand about how customers consume digital products following purchase, and how they interact with other customers in online venues established to discuss these products. Utilizing online data collection techniques, across a collection of three essays, consumer involvement in the consumption, modification, and promotion of digital products following purchase is investigated. Essay 1 examines digital product consumption, online communities, and digital product features to gain insights on the potential for digital product design to influence post-purchase consumption through social interaction and online community participation. Essay 2 examines digital product post-purchase co-creation to reveal the presence of three different categories of co-creation, as well the factors that differentially affect each group. Finally, Essay 3 examines online community leadership and identifies those customers most likely to introduce new ideas and concepts to the community.

INDEX WORDS: online customer engagement, online communities, post purchase, product design, product co-creation, community leadership

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A Dissertation Submitted to the Graduate Faculty of The University of Georgia in Partial Fulfillment of the Requirements for the Degree

DOCTOR OF PHILOSOPHY

ATHENS, GEORGIA

2016

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May 2016

DEDICATION

To Becky, for developing in me courage, patience, and dedication. Without your support, and endless patience over the years I would not be half of the person I am today. I am endlessly lucky and thankful to have you in my life. I love you for your intellectual curiosity, and I know that we will help each other keep our curiosity alive, today and into the future.

To my parents, Linda and Darrell, for instilling in me a love of knowledge, creativity, and curiosity. Mom, your love of education and knowledge are invaluable gifts I cherish, and which live on. Dad, your lessons in dedication and determination have provided the foundation to achieve my dreams.

ACKNOWLEDGEMENTS

Over the last five years a great number of people have provided support and encouragement during the doctoral process. My advisor, John Hulland, has provided immeasurable guidance and advice throughout the process, and I wish to thank him for that. Between countless research ideas, complaints and frustrations, and the often hockey discussion, John has been a mentor, colleague, and friend.

I also wish to express my deep thanks to Scott Thompson. Scott has provided the encouragement and confidence to pursue research in online communities, and the technical skills to collect and analyze that data. His advice and support have been valuable and welcome and I am lucky to call him a friend.

Charlotte Mason, Andrew Stephen, and the other faculty at UGA have provided constant support and guidance throughout and for that I am grateful.

My fellow grad students at UGA have provided a community of shared experiences that will connect us far into the future. I am grateful for their daily support and only hope my support has made their own path a bit easier.

Thanks to family and friends who understood the chaos of a doctoral student and were supportive and forgiving of the result of that chaos.

Much of my work conducted at UGA would not be possible without the financial and research support of the Marketing Science Institute.

Finally, thanks to Wade Fields, my IT enabler and friendly ear. Without your help I would still be plugging parts and installing software.

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CHAPTER 1

INTRODUCTION AND LITERATURE REVIEW

The recent growth of online customer communication and digital product development and adoption has begun to transform the world economy, as computer technology is increasingly adopted and implemented in households around the globe. Entire industries have been disrupted by the transition to digital goods (and away from physical goods), including books (Kindle, Nook), music (iTunes, Spotify), movies (Netflix, Hulu), software (Apple App Store, Windows Store), and games (Steam, EA Origin).

At the same time, the interactive nature of online communication has accorded the customer with an enhanced level of post-purchase control over a firm's marketing actions. Consumers can now play a more direct role in marketing communication and product development than in any other period in modern business history. Consumers directly design products, craft marketing messages, target unique consumers, and create relationships with consumers. In some cases these actions are taken in partnership with the firm, though in others consumers act independently.

The trend towards digital products and online communication is expected to further accelerate in the future. However, very little is currently understand about how customers consume digital products following purchase, and how they interact with other customers in online venues established to discuss these products. Given the increasing level of control consumers hold on marketing, it is critical that consumer involvement in the consumption, modification, and promotion of digital products following purchase, and the online communication that precedes and follows that purchase is understood. The following three dimensions of consumer experience and marketing management guide investigation into these phenomenon.

Digital Product Post-Purchase Engagement

Digital products are becoming a pervasive part of the economy, increasingly replacing physical products as customers become more comfortable with digital distribution. Yet digital products possess unique characteristics, unstudied in the literature, that make post-purchase product consumption an important consideration for firms managing costs, revenues, and profitability. Digital goods are both imperishable and inherently social in nature due to their online distribution. These characteristics have the potential to influence post-purchase social engagement and consumption, yet these outcomes have rarely been studied in the literature.

Post-purchase Customer Control of Marketing

Traditionally, marketers have viewed customers as buyers and consumers of the products they develop and sell. However, increasingly customers have greater control over the product's marketing following purchase, from post-purchase word-of-mouth, through online community discussions, to post-purchase product modification. The following essays attempt to better understand how customers engage in marketing activities following purchase, and how customer post-purchase actions can influence outcomes of interest to the firm.

Online Behavior

Consumption of digital products requires computer technology, and detailed records of consumption are often automatically logged by those computer devices. These records present opportunities to digitally observe consumer post-purchase behavior for digital products; opportunities that do not exist for packaged goods. Rather than simply capturing behavioral intentions, real behavioral actions can be captured through these online contexts. Consumer purchase behavior, consumption behavior, and word of mouth behavior for millions of consumers can be observed in online venues and forums. Utilizing custom online data collection technology, all three essays capture real digital product consumption behavior from public online venues, providing a window into consumer patterns of digital product use and customer interaction.

Essay 1 (Chapter 2)

Game On: Aggregate Digital Consumption, Digital Product Design, and Social Interaction

Digital products are becoming a pervasive part of the economy as customers become more comfortable with digital distribution. Yet digital products possess unique characteristics that make post-purchase product consumption an important consideration for firms managing costs, revenues, and profitability. The relationship between digital product consumption, product design, and social interaction is unclear, and thus is ripe for investigation. Product features can influence digital product consumption by providing social benefits, facilitating group consumption, and impacting related online communities. These relationships are tested using automated data collection techniques to capture 6.8 million hours of digital product consumption and 450,000 instances of online community activity in the computer game market. The results reveal that product features that communicate social setting and social status information increase digital product consumption, as do online community size and concentration. Further, online community concentration mediates the relationship between social product features and digital product consumption in different ways. Concentration decreases as social setting features increases, which in turn decreases digital product consumption. However, more social status features increases online community concentration, increasing digital product consumption.

Essay 2 (Chapter 3)

Post-Purchase Co-Creation: Consumer Segmentation in Consumer-Driven Collaborative Product Design

Product co-creation, or collaborative product development in which customers actively contribute and/or select the content of a new product, has become an increasingly interesting trend for both marketing academics and practitioners. Product co-creation during pre-release or pre-purchase contexts has been studied and embraced by some firms across a varied group of industries. Yet few firms have explored post-purchase co-creation and the marketing literature is absent of any systematic investigation of the phenomenon. Utilizing automated online data collection techniques real product co-creation activities were captured from co-creation efforts developed for traditionally firm created products. Through latent class cluster and panel regression techniques, three distinct and different segments of co-creation participants are identified: Co-creation Creators, Co-creation Consumers, and Core Product Users. Consumer's engagement with co-creation, community levels of co-creation engagement, and strategic marketing actions reveal an interesting and complex set of relationships on product consumption between the different segments.

Essay 3 (Chapter 4)

Coaches and Cheerleaders: Leaders and Followers in Online Brand Communities

Increasingly, marketers desire to engage in product or communication seeding, an attempt to identify influential consumers and utilize those consumer's connections to spread marketing communication and influence. Often this practice attempts to identify leaders and followers of brand community discussion as prime targets for seeding. Yet relying on traditional metrics of online discussion leadership might lead marketers to focus on the most vocal or most active consumers. Drawing on concepts from social identity theory, it is proposed that these individuals resemble followers of brand community discussion, and that an entirely different set of consumers may be more appropriate targets for product or communication seeding, depending on the goals of the firm. Utilizing a dataset collected from online brand communities comprising over 874,000 messages collected from more than 30,000 unique users across a 60 month period, an investigation into leadership and followership is conducted. Results support the concept that brand community conversation leaders participate across a wider range of communities, and at an earlier period than traditionally defined brand community leaders. The data further suggest that community leaders defined by volume of activity may actually be members of the rival brand community who enter the preferred brand community in order to evangelize and recruit to the rival brand community.

CHAPTER 2

GAME ON: AGGREGATE DIGITAL CONSUMPTION, DIGITAL PRODUCT DESIGN, AND SOCIAL INTERACTION[1]

[1] Smith, Keith Marion, Scott A. Thompson, and John Hulland. To be submitted to *Journal of Interactive Marketing.*

Abstract

Digital products are becoming a pervasive part of the economy as customers become more comfortable with digital distribution. Yet digital products possess unique characteristics that make post-purchase product consumption an important consideration for firms managing costs, revenues, and profitability. The relationship between digital product consumption, product design, and social interaction is unclear, and thus is ripe for investigation. Product features can influence digital product consumption by providing social benefits, facilitating group consumption, and impacting related online communities. These relationships are tested using automated data collection techniques to capture 6.8 million hours of digital product consumption and 450,000 instances of online community activity in the computer game market. The results reveal that product features that communicate social setting and social status information increase digital product consumption, as do online community size and concentration. Further, online community concentration mediates the relationship between social product features and digital product consumption in different ways. Concentration decreases as social setting features increases, which in turn decreases digital product consumption. However, more social status features increases online community concentration, increasing digital product consumption.

Product purchase has often been the focal outcome in studies of product adoption rates, (e.g., Jacobson and Aaker 1987; Tellis, Yin and Niraj 2009), with the implicit assumption that product purchase is synonymous with consumption. For many physical products, this assumption reflects the fact that the product is used up, and must be repurchased for continued consumption. In contrast, many digital products are not used up during consumption, and can be consumed repeatedly without exhausting or degrading the product, and without requiring product repurchase. For example, a customer may purchase a digital product such as a song, download it to a digital device, and not use it at all without fear of the product deteriorating over time as can happen with physical products such as CDs. Even were the digital device to degrade, the song could be downloaded again from a remote server (e.g. the "cloud") to a new device, all without repurchase.

Purchase and consumption have been established as different phases of a product's life in the literature (Holbrook and Hirschman 1982), a distinction that is especially relevant for digital products. Previous research has supported the distinction between purchase and consumption by demonstrating that different advertising strategies may differentially influence product purchase versus consumption rates (Zhu, Billeter and Inman 2012), and that products can generate satisfaction in purchase, but not in consumption or vice versa (Heitmann, Lehmann and Hermann 2007). Consumption has been established as a distinct product phase, however, aggregate product consumption has not been studied in the literature, and very little is known about what factors drive it. Furthermore, it has not been studied in the digital context.

Product purchase has tended to dominate the marketing literature because of a focus on revenue generation that for most physical goods is only realized at purchase. However, post-purchase consumption of a digital product has important implications for firm profitability above and beyond purchase. Digital product consumption can generate additional revenue through increased customer loyalty to the product and to the firm. While not all digital products generate revenue through consumption, opportunities for revenue generation exist that scale directly with consumption depending upon a firm's business model. For example, *Farmville*, a *Facebook* digital game, generates revenue by selling virtual currency that is consumed each time a customer plays the game. *Google* generates ad revenue every time a customer conducts a search. By creating additional touch points between the firm and the customer during consumption, digital products increase customer-firm interaction, and generate revenue as an outcome of customer consumption of the product, above and beyond the revenues obtained at the time of product purchase.

Furthermore, digital products differ from physical products in that they can also generate costs for the firm, beyond product development costs, that escalate with consumption. For example, *Amazon* allows consumers to purchase digital copies of movies, but *Amazon* additionally must bear the costs of the streaming of that movie any time a customer choses to consume it, an event that can occur many times over the life of the product for each customer. *Farmville* must support the server, bandwidth, and maintenance costs that allow their customers to access the game, costs which increase the more the product is consumed. Therefore, understanding the drivers of digital consumption is important to forecast and manage costs as well as to identify revenue generation opportunities.

In this paper, automated online data collection techniques are used in order to better understand the impact that product features and online social interactions have on digital product consumption. Collecting over 6.8 million hours of digital product consumption across 129 different digital products, it is possible to observe actual digital product usage, and identify the product factors that contribute to that consumption. Automated collection of over 450,000 instances of online community activity across all 129 products further provides insight into the role that social interaction plays in digital product consumption, and how product design decisions can influence that social interaction.

The literature on product development (Green and Srinivasan 1990; Thompson and Norton 2011; Thompson, Hamilton and Rust 2005) and online communities (Algesheimer et al. 2010; Gruner, Homburg and Lukas 2014; Thompson and Sinha 2008) is extended by identifying the factors important to post-purchase digital product consumption. By developing an understanding of how digital product consumption is affected by product and social factors, I hope to arm marketing managers with knowledge regarding how their product design and community management decisions could create unanticipated costs and/or could generate a newfound source of revenue for the firm.

Background

Digital Products

Until recently, digital products were not widespread, mostly constrained to high tech fields. However, digital products are now not only commonplace, but product categories previously dominated by discrete packaged products are being replaced by digital products. Movies, music recordings, books, software, tablet and smartphone apps, and games have all made the shift to digital markets, and demand for their physical counterparts have been consistently shrinking. Firms like *Blockbuster Video* and *Borders Books* can attribute their deaths at least in part to a lack of foresight regarding the rise of digital products. Digital distribution and sales have increased as customers become more comfortable with digital distribution of software and entertainment media for smartphones, tablets, and computers. Digital products have even invaded the B2B space as business software has increasingly shifted towards an online distributed product model, where business software is hosted on remote servers and business users log in to access functionality.

Digital products now cross a wide range of product categories that were once sold exclusively as packaged physical goods, and are expected to continue to grow as the technical infrastructure to support them becomes more widespread. For example, digital products now account for almost 60% of US computer and video game sales in 2013, representing revenues of over $9 billion (Nayak and Baker 2012). The *Apple App Store*, an entirely digital marketplace that provides digital software for *Apple* computer, tablet, and smartphone devices, generated over $10 billion in global annual revenue in 2013 (Apple 2014). Industry groups for movies/television and music report that US digital product revenues for 2013 accounted for 6.5 billion (Digital Entertainment Group 2014) and 5.9 billion (International Federation of the Phonographic Industry 2014) dollars respectively. In every case, digital formats for these products have been growing year over year, while physical formats have continued to shrink. Digital products in 2013 comprise 39% of global music revenues (International Federation of the Phonographic Industry 2014), 35% of US home television and movie revenues (Digital Entertainment Group 2014), and 100% of global tablet and smartphone app revenues.

Digital Product Consumption

Because physical goods are frequently "used up" during consumption, marketing managers and marketing researchers have placed primary emphasis on the traditional revenue generation of product purchase. Consumer packaged goods like toothpaste and toilet paper are eliminated or "used up" as they are consumed, and even durable goods like refrigerators or automobiles are "used up" over a longer product lifespan. In such a product paradigm, focusing on purchase over consumption was beneficial because product consumption could be implicitly assumed through repeat purchases, and the act of consumption did not generate additional revenue opportunities for the firm separate from purchase.

Digital goods, however, have unique properties that make consumption a critical and important stage in a product's life beyond purchase. First, digital goods are not "used up" during consumption. A movie, song, or game is not diminished or eliminated upon consumption, and can be consumed many times with no product degradation. This characteristic results in a separation of purchase and consumption, that introduces unexpected costs because the product must be supported beyond the repeat purchase period associated with most physical products.

Another important property of digital goods is the seamless social integration possible as a result of the online networked nature of these products. Digital goods are sold through online digital distribution platforms like *Steam*, the market leading digital game distribution platform, and *Amazon's* digital movie distribution platform, that expose the pool of platform users to product designers. Product designers can choose to integrate features that connect product customers to each other, enabling social interaction through shared consumption of the product. Products can be designed to encourage customers to interact and to provide consumption-based social status markers. Products designed with social integration can impact support costs and revenue generation by establishing consumption as a vehicle for social interaction. The separation of purchase and consumption for digital goods creates potentially escalating consumption that is no longer tied to purchase, but instead to the benefit of socially consuming the product with others.

Given the size and growth of the digital product market, and the role that consumption plays in the profitability of digital products, understanding how digital product design can uniquely influence consumption is critical. The design decision to add features to a product that can facilitate or inhibit social interaction around the product can have a lasting impact on the resulting consumption and hence profitability of the product. Despite the importance of this issue, however, no previous research has investigated the drivers of digital product consumption. In the following sections, I consider digital product features and other factors that may influence digital product consumption to develop my hypotheses.

Product Features

Functional features. Product features have been identified as a key driver of new product purchase, with much of the existing literature focused on creating an optimal product design based on tangible product features that result in products with increasing functional utility (e.g., Green and Srinivasan 1978, 1990; Nowlis and Simonson 1996;

Srinivasan, Lovejoy and Beach 1997; Thompson and Norton 2011). Each tangible feature increases the product's utility, signaling a product capable of performing better, though at extreme levels feature overload may diminish performance (Thompson, Hamilton, and Rust 2005).

I define functional features as digital product attributes that provide tangible benefits, drawn from the implied definition in the product development literature (Green and Srinivasan 1978, 1990). Where the presence of tangible functional features increases utility and is associated with higher purchase rates, it follows that those same features may provide enhanced utility following purchase (Thompson and Norton 2011; Thompson, Hamilton and Rust 2005). Consistent with this past work, I expect aggregate digital product consumption to be higher for products with a higher level of functional product features.

Social setting and social status features. Product features that provide more intangible benefits, or whose benefits take longer to realize (e.g., aesthetics, emotional appeal, usability, social value) can increase product utility, but have been difficult to capture in traditional product development models (Srinivasan, Lovejoy and Beach 1997). Such intangible characteristics have been shown to affect product consumption rates but rarely influence product purchase rates (Thompson, Hamilton and Rust 2005). Features that enable shared or group consumption reinforce social interaction and group engagement. Similarly, social groups can assign status to the ownership of certain features (Thompson and Norton 2011), especially when those product features communicate and reinforce group values.

Two different types of social product features can play important roles in digital product success: social setting features and social status features. Social setting features are defined as digital product attributes that enable shared group consumption. These features facilitate social interaction through product consumption and provide more delayed intangible social benefits through consumption with others. Examples include features that provide the ability to share music playlists through iTunes, or the ability to play video games together. These features enable the diffusion of product consumption group values and expected consumption patterns (Hogg and Terry 2000), effectively establishing rules for a social setting of group consumption. These groups, by nature of their consumption focus, reinforce shared product consumption. Thus products with a higher level of social setting features are likely to have higher levels of consumption as associated consumption groups reinforce expected consumption patterns.

A second class of intangible social product features is social status features, defined as digital product attributes that enable social comparison within groups. These features facilitate group rank structures, and provide both an aspirational goal and a marker of group status, an important contributor to group membership (Grier and Deshpandé 2001). Examples include features that display how many 'liked' an iTunes playlist, or product performance tracking systems like video game 'win/loss records' that display how effective an individual is at product usage. Thus, products with a higher level of these features will be consumed more as group members actively engage in consumption to increase performance and product mastery, and thus increase status within the group (Hogg and Terry 2000). Based on the preceding discussion, I offer the following hypothesis:

H1: Digital products that include a higher (lower) level of a) functional features, b) social setting features, and c) social status features will be associated with higher (lower) levels of aggregate product consumption.

Online Consumption Communities

The literature on brand communities and consumption communities has highlighted the important role that social interaction plays in consumption. Research on brand communities, defined as "communities based on a structured set of social relationships among admirers of a brand" (Muniz, Jr. and O'Guinn 2001), has revealed that social interactions around a brand can create product benefits beyond a product's tangible benefits alone. In particular, participation in brand and consumption communities can influence a number of important purchase outcomes, including product adoption (Gruner, Homburg and Lukas 2014; Thompson and Sinha 2008), brand loyalty (Adjei, Noble and Noble 2010), and product risk (Algesheimer et al. 2010; Zhu et al. 2012). Notably, the literature on brand and consumption communities has focused on communities primarily based on physical products such as cars, packaged consumer goods, and computer hardware (e.g., Algesheimer et al. 2010; Muniz, Jr. and O'Guinn 2001; Thompson and Sinha 2008). However, communities are not limited to physical goods.

The influence of brand and consumption communities takes time to develop, as the social group evolves and expands. As a consequence, community influences are more pronounced in digital consumption settings where the likelihood of interaction increases as the product is used over a wider range of consumption settings (McAlexander, Schouten and Koenig 2002; Thompson and Sinha 2008). The electronic and online nature of many digital products further shifts the focus of brand communities to the online space.

Online community influences during product adoption and purchase are typically limited to group opinion collection of product experiences and product benefits. However, following purchase, digital products are frequently consumed with others, highlighting the influence these online communities of like-minded consumers can have during consumption (Bagozzi and Dholakia 2006; Muniz, Jr. and O'Guinn 2001). A larger, more active online consumption community generates more opportunities for shared consumption among fellow admirers of the product, and more opportunities for a range of social benefits associated with the product (Schau, Muñiz Jr and Arnould 2009). Frequent community interaction can increase the likelihood of community membership (Bagozzi and Dholakia 2006; Muniz, Jr. and O'Guinn 2001), and increase the frequency of group product consumption in order to reinforce online community membership.

Despite the group level focus of the brand community literature, existing research has overwhelmingly investigated individual behavior within the online community (Bagozzi and Dholakia 1999, 2006; Muniz, Jr. and O'Guinn 2001) rather than investigate the impact that a community as a whole can have on overall product consumption. Yet, managerial interest in communities is derived from their aggregate impact on products. Aggregate community influences on products are not well understood, and it is these aggregate group-level characteristics that gain focus in this study. The brand community and customer leadership literature suggests that three different group-level characteristics of product-related online communities have the potential to influence aggregate product consumption: community size, community vitality, and community concentration.

Community size. I define community size as the volume of active participation in the online community drawn from the implied definition in the community practices literature (Schau, Muñiz, Jr and Arnould 2009). Larger online communities provide a greater opportunity for increased activity, as both a larger number and a more diverse set of group members are available as potential interaction and consumption partners. As the community size grows, the group's potential for social interconnectedness increases, and the opportunities for social benefits increase (Schau, Muñiz, Jr and Arnould 2009). Given the group focus around shared consumption of the product, a larger group size should increase the aggregate consumption of that product.

Community vitality. Schau, Muñiz, Jr, and Arnould (2009) note that while measures of community size and volume may provide evidence of community interest, they do not necessarily assess the vitality of a community. Defined as the amount of interaction between online community members, community vitality captures the depth of interaction rather than the breadth of interaction within the group. More vital online communities exhibit a greater number of community practices (Schau, Muñiz, Jr and Arnould 2009), including product community rules, knowledge, and engagement. Online communities with a high level of vitality are characterized by lengthy and frequent interactions between group members. These communities provide a more supportive and rewarding group membership (Ellemers, Spears and Doosje 2002), and reinforce the perception of a strong support network (Zhu et al. 2012). Products associated with a vital online community are more likely to be consumed together in order to maintain and strengthen the community bond. These products function as the mechanism to enhance and deepen group relationships, and to facilitate new member initiation. Again, given the group focus around shared consumption of the product, a higher level of group vitality will directly increase the aggregate consumption of the product. Thus, products with a more vital online community should be consumed more than those with less vital communities.

Community concentration. Defined as the amount of active participation accounted for by the most active online community participants, community concentration plays an important role in community formation and maintenance. Community participants reinforce and communicate group consumption norms and expectations. Online communities settle on accepted rituals and traditions centered on shared consumption experiences (Muniz, Jr. and O'Guinn 2001), and these more active group members reinforce and encourage those community norms. The sense of moral responsibility shared by the group is an important marker of community (Muniz, Jr. and O'Guinn 2001), and it is these more active group members that most frequently provide help and support to the group. The influence of a concentrated segment of involved leaders is not new to the product purchase and adoption literature. Opinion leaders and market mavens (Feick and Price 1987; Kozinets et al. 2010) actively acquire and share product or market expertise with community members, and are often looked upon by the community as important sources of knowledge.

Online communities with high levels of concentration are more likely to exhibit a strong set of common consumption rituals and traditions, and to exhibit clear processes for group initiation, helping, and consumption. Digital products associated with these communities will have higher levels of consumption because of the shared understanding of the role consumption plays in community initiation and status (McAlexander, Schouten, and Koenig 2002; Palmatier, Scheer, and Steenkamp 2007). In contrast, less concentrated online communities are plagued by a more diverse and conflicting set of active participants and corresponding beliefs about community practices, which leads to lower levels of activities (e.g. consumption) associated with group membership (Gaertner and Schopler 1998; Lickel et al. 2000). Group-wide expectations of community interaction and consumption activities are more obscured by the increasing noise from diversity, and therefore group members are both more ignorant of preferred consumption activity, and less motivated to engage in consumption to solidify group membership. Therefore digital products associated with communities with lower levels of concentration should have lower levels of consumption. Based on the above:

H2: Digital products associated with an online community with higher (lower) levels of a) community size, b) community vitality, and c) community concentration will be associated with higher (lower) levels of aggregate product consumption.

Mediating Effects

Given the established importance of brand communities to product purchase (Muniz, Jr. and O'Guinn 2001; Schau, Muñiz Jr, and Arnould 2009), it is worthwhile to consider how some digital products may come to be associated with large, vital, concentrated online communities, while other digital products are associated with smaller, less vital, more diffuse online communities. Specifically, certain characteristics of the digital product itself possess the potential to influence the processes involved in the development and life of online communities. An examination of commonly established online community processes suggests that social identity is the key building block of communities (Bagozzi and Dholakia 2002, 2006).

Group social identity plays a driving role in many of the mechanisms used to explain the influences of consumer communities. A shared group identity built around common consumption interests develops as consumers interact with each other (Muniz, Jr. and O'Guinn 2001). This shared group identity provides cues that guide group behavior based on a consensus set of consumption patterns and product beliefs (Hogg and Abrams 2003). The group identity further provides guidelines for initiation of new group members and membership maintenance for existing members. Finally, the group social identity is developed and maintained over time by group social interaction and social status management within the group (Hogg and Terry 2000; Turner et al. 1987). Certain types of product features are capable of reinforcing the development and maintenance of these group social identities.

Much of the research on social identity in the community literature has emphasized individual behaviors and has generated insight into why individuals choose to engage with certain groups with which they share common product values and preferences. However, social identity theory was originally developed to make predictions and generate insights into group level attitudes and actions (Ellemers, Spears, and Doosje 2002; Gaertner et al. 1993; Tajfel 1970). Reexamining online communities with a group level social identity lens suggests that certain digital product features may facilitate group social identities, and thus can generate larger, more vital, more concentrated online communities.

Social setting product features. Digital products with a high level of social setting features provide a path of expected consumption, and a motivation to interact with other product owners. These digital products reinforce social consumption of the product, and both introduce and reinforce the group social identity through fellow product consumers. The strong group identity, generated and reinforced by shared social consumption, leads to increased community size and vitality, which in turn generates increased consumption. Thus, digital products with a higher level of social setting features are associated with higher levels of consumption through the complementary mediation of online community size and vitality. These digital products are associated with higher levels of consumption at least partially because of the influence these social setting features have on increased community size and vitality.

However, digital products with these social setting features also introduce a wider variety of consumers to the online community. A strong concentrated community is likely to have a strong group social identity as a result of the smaller proportion of leadership voices disagreeing about expected consumption patterns and product beliefs. Alternatively, products with high levels of social setting features introduce more frequent challenges to the group social identity as the more heterogeneous set of consumers naturally introduce ideas counter to the existing group. These disparate voices decrease the concentration of leadership, and weaken the group social identity. Thus, digital products with a higher level of social setting features may be associated with lower levels of consumption through the competitive mediation of online community concentration. These digital products may be associated with lower levels of consumption at least partially because of the influence these social setting features have on decreased community concentration. While these online community characteristics are unlikely to exclusively explain the relationship between social setting features and consumption, they are expected to play at least a partial role.

Social status product features. Digital products with a high level of social status features provide objective markers of a clear group rank structure. By providing both an aspirational goal and a marker of high status traits, these features clearly communicate the commonly accepted group social identity. These features provide a flagpole around which the group can strengthen the social identity. Group members clearly identify high status activities, and engage in social consumption of the product to pursue those activities. The strong group identity leads to increased community size, vitality, and concentration, which in turn generates increased consumption. Thus, digital products with a higher level of social status features are associated with higher levels of consumption through the complementary mediation of online community size, vitality, and concentration. These digital products are associated with higher levels of consumption at least partially because of the influence these social setting features have on increased community size, vitality, and concentration.

It is worth noting that community concentration is not expected to have the same competitive mediation effect on social status features as it has on social setting features. Social status features, rather than encouraging a more diverse group, actually facilitate a narrower group social identity. Digital products with these features provide a more explicit and easily identified group identity for each member to adopt. Thus, rather than increasing the diversity of the group, they actually decrease diversity by encouraging and rewarding group members who more closely match the group identity. Again, while these online community characteristics are unlikely to exclusively explain the relationship between social setting features and consumption, they are expected to play at least a partial role. Figure 2.1 illustrates the resulting conceptual model.

H3: The relationship between a digital product's social setting features and its aggregate level of consumption will be a) positively mediated by community size b) positively mediated by community vitality and c) negatively mediated by community concentration.

H4: The relationship between a digital product's social status features and its aggregate level of consumption will be a) positively mediated by community size b) positively mediated by community vitality and c) positively mediated by community concentration.

Study Context

To assess the role of digital product features and online communities in digital product consumption, I chose a study context that provides a rich source of data on online interactions and consumption activities: digital computer games. The computer and video game industry has undergone explosive growth in the past ten years, with reported global revenues of $78 billion in 2012 (Nayak and Baker 2012). By comparison, the global computer and video game market is roughly equivalent to the movie industry, which earned $126 billion in 2012 (IBISWorld 2013). In the U.S. market alone, 2012 computer and video game revenues of $20.8 billion were twice that reported by the movie industry at just over $10.8 billion (Entertainment Software Association 2013). Further, over 60% of all US computer and video games sold in 2013 were delivered as digital products rather than discrete packaged goods (i.e. distributed as downloaded software across the internet, without physical media), compared to 40% in 2012 and 20% in 2009 (Entertainment Software Association 2014), reflecting the increasing shift towards digital products. A wide range of digital products, including motion pictures, music recordings, television, business software, and smartphone applications, all share the key focal characteristics of my study context: digital post-purchase consumption that can vary independent of purchase, product features that can facilitate social interaction, and a community of consumers around the products. Finally, computer and video games have a rich history of social product features and large online communities, and have provided a study context for some recent studies in marketing (e.g., Liu 2010; Zhu and Zhang 2010).

The market leader for the distribution of digital game products is *Steam*, which controls roughly 50-70% of market sales (Chiang 2011). With over 65 million active accounts in 2013, and over 7 million concurrent users, the *Steam* online digital storefront exceeds even Microsoft's *Xbox Live* customer base (Chacos 2013). In addition to providing a digital storefront and distribution platform, *Steam* provides a game management interface and community tools that make it an ideal platform to investigate the impact of social product features and online communities on digital product consumption. Each game sold by *Steam* has a dedicated message board that facilitates interaction and communication between consumers of the game. These game-specific communities facilitate social interaction among admirers and consumers of a specific game product, and provide a venue for members of each game's community of users to interact.

Empirical Study

Since the purpose of the study is to examine the drivers of aggregate consumption, the focal unit of analysis for this study is the firm-developed product (game), rather than individual customers. This approach allows us to examine the impact of product-level features and product community characteristics on the aggregate level of consumption of the game.

Sample

I collected product, community, and aggregate digital consumption data in three separate phases from November 2011 to May 2012 (see Figure 2.2). The first phase was comprised of digital product feature data collection, and occurred in November 2011. The second phase was comprised of online community activity data collection, and occurred from December 2011 to February 2012. The final third phase was comprised of aggregate digital consumption data collection and occurred from March 2012 to May 2012. None of the three phases overlapped in time. This procedure of discretely separating each phase was done to ensure that digital consumption had no reverse effect on community activity in my tested model.

Both phases 2 and 3 were comprised of separate 85 day observation windows. Since the social phenomena in the hypotheses require time to develop, an 85 day window was selected to provide the time required for the social phenomenon under investigation to develop. Phase 2 (online community activity) was collected with custom web crawler software that captured all community posting activity over the entire observed 85 day time window. Phase 3 (aggregate digital consumption) was also collected with custom web crawler software that captured product consumption in fifteen minute increments over a separate observed 85 day time window. The resulting 8,160 (96 fifteen minute windows per day x 85 days) digital consumption observations for each product were then combined to obtain the aggregate measure of digital product consumption.

Digital Product Features

Each game in *Steam's* online digital storefront has a dedicated webpage. This webpage includes a detailed description of the product, images and videos that depict the product, a list of product feature tags that identify specific product features present in the product, and the game genres into which the product is categorized. The product feature literature suggests that product features are multi-dimensional (Green and Srinivasan 1990), and include both functional and social aspects that may influence consumption differently (Thompson and Norton 2011). Product features that support multiplayer gameplay (i.e. shared product consumption with others) or single player gameplay (i.e. solitary product consumption) communicate the expected setting for consumption, whether with a group or alone. Game leaderboards, statistics, and achievements (a list of in-game performance goals) facilitate social group rank structures by providing a visible objective measure of product performance efficiency (i.e. kill/death ratio) or group contribution (i.e. damage done or damage per second) that provide both an aspirational goal and a marker of social group status within the consumption community.

In order to classify these different types of product features, I conducted an exploratory factor analysis on the product feature tags from the *Steam* storefront page. Principal components factor analysis with varimax rotation for the full set of 322 games resulted in three orthogonal factors (see Table 2.1).[2] These three factors support my hypothesized set of feature categories: functional features, social setting features, and

[2] I used the full set of games for which information was available to avoid concerns about "cherry picking".

social status features. While these key features are not exhaustive of all possible product features, these features are utilized by marketing managers to promote and market these products on the *Steam* storefront, and thus are utilized by customers to make purchase and consumption decisions. These three factors together explain 69% of the variance in the original feature information for the digital products.

Functional features that signal a premium digital product, including audio captions, high definition graphics, commentary, and product source code load highly on the functional feature factor (e_1=3.08). Multiplayer only gameplay, free-to-play features, and single player gameplay all load highly on the social setting feature factor (e_2=2.49). Leaderboards, achievements, stats, and controller support all load highly on the social status feature factor (e_3=2.05). In the analysis that follows, I use game-specific factors scores based on this factor structure.

Online Community Measures

A number of different online community activity measures have been employed in the literature. In order to capture the multi-dimensional nature of the online community, measures of different characteristics of the social group were collected. Message board post and thread counts were collected, consistent with previous community research (e.g., Adjei, Noble and Noble 2010; Thompson and Sinha 2008; Zhu et al. 2012). Average posts per thread, an alternative measure of online community activity proposed in past work (Adjei, Noble and Noble 2010) was also collected. Forum user counts and average posts per user capture aggregate level online community activity and were additionally collected. Capturing online community concentration is accomplished by measuring the percent of posts by the top ten percent of users. Top ten percent was selected to reflect online community activity patterns that are often more heavily concentrated towards community leaders, experienced members, and enthusiast contributors compared to traditional users (Kozinets, Hemetsberger, and Schau 2008; McAlexander, Schouten, and Koenig 2002; Ouwersloot and Odekerken-Schröder 2008).

Each of these measures capture different elements of online community activity (Schau, Muñiz, Jr and Arnould 2009) that taken together provide an overall perspective of the health of the online community. The above online community measures were collected for the entirety of the 85 day Phase 2 observation window, and preceded the temporally distinct 85 day Phase 3 digital consumption observation window. Principal components factor analysis with varimax rotation was conducted on these measures, resulting in three orthogonal factors. These three factors represent three distinct characteristics of the online community, and together account for 90% of the variance in the original items. The first factor was comprised of total counts of posts, threads, and users, and captures the size of the online community (e_1=2.62). The second factor contained posts per thread and posts per user, and captures the amount of interaction between members of the group, reflecting online community vitality (e_2=1.88). Finally, the third factor, with percent of posts by the top ten percent of users, captures online community activity concentration and reflects the role of online community leadership in reinforcing common consumption rituals and traditions, and in communicating clear processes for group initiation, helping, and consumption (e_3=0.88). A scree plot of the online community factors further supported a three factor solution. I retained the third factor despite an $e_i < 1$ because of the established importance of community and customer leadership from past literature, and because of its theoretical importance in understanding the role of online community beyond simple measures. Factor loadings associated with the online community can be found in Table 2.2.

Dependent Variable: Aggregate Digital Product Consumption

Steam provides a constantly updated list of the top 100 games based on aggregate digital consumption (i.e. the total number of consumers currently playing the game). This list provides an instantaneous snapshot of each digital product's aggregate level of consumption at any point in time. Collecting this data continually over the Phase 3 (aggregate digital consumption) 85 day observation window, and transforming it to average daily digital consumption, I captured a total measure of how many hours a specific digital product was consumed across all customers of *Steam* for an average day. Similar to a project man hour measure in an organizational context, a game hour captures the equivalent of one hour's worth of digital consumption for a specific digital product. This approach captures each digital product's aggregate level of consumption directly, and contrasts with consumption measures based solely on sales, which only indirectly capture consumption by virtue of the inseparability of purchase and consumption present for the majority of physical goods. For a more detailed explanation of how the digital consumption measure was calculated, see the Appendix.

Because *Steam* lists the top 100 games being played at any particular point in time, less popular games only occasionally made this list during the 85 day observation window. Games that appeared five or fewer days were eliminated from the dataset, along with unreleased games still in a beta testing (i.e., not formally released to the public) state, or that did not have quality ratings (see below) available, resulting in the final dataset of 129 commercially released games. Robustness checks were performed using alternative elimination screens, but did not result in substantively different findings.

Controls

Based on the prior literature, a number of covariates were collected to address alternative explanations and minimize bias, including digital product quality ratings, time on market, and game genres. Product quality has been demonstrated to have an important influence on product adoption in the context of community influences (Tellis, Yin and Niraj 2009), and was included as a potential covariate. Over time, higher quality products are adopted at a greater rate (Tellis, Yin and Niraj 2009), suggesting that quality plays an important role in both product popularity and adoption. As a consequence, product quality may also influence overall post purchase consumption. Product quality was measured through the use of aggregated critic product ratings collected from *Metacritic*, an online aggregation service that generates a single review score for each game product based on the average of all credible critic reviews available. *Metacritic* ratings have become a standard measure of quality in media industries such as music, movies, and video games. This measure captures a wide range of critic reviews, and is similar to quality measures used in existing research (Tellis,Yin and Niraj 2009).

Time on market for each game was collected to ensure the findings were not influenced by simple time factors. More active online communities may be associated with more recently released games, and newer games may be played more as a result of their novelty. Time on market was collected as the number of days since release as measured at the beginning of the 85 day digital consumption observation window.

Product popularity could provide an alternative explanation for both online community activity and digital product consumption. More popular games may generate a larger, more vital, more concentrated community, as well as higher levels of aggregate digital consumption. In order to address these possibilities, a collection of game category dummies were coded based on the genre categories used by *Steam* to group and display games for consumers. Certain genre categories in the computer game market are far more popular than others, and thus generate greater sales and revenue. Based on the Entertainment Software Association's Sales, Demographic, and Usage Report for 2012 and 2013 (Entertainment Software Association 2013, 2014), I included two genre categories consistently listed high in popularity: Strategy and Casual, and two consistently listed low in popularity: Action and Racing.

This set of four genre controls capture differences that may be due to high or low popularity games, as reflected by the most and least popular game genre categories. In the absence of individual digital product sales data, these controls allow us to address product popularity as an alternative explanation. Genre categories were not mutually exclusive, and cross-genre games could be categorized in more than one category. Table 2.3 provides descriptive statistics and a correlation matrix for all variables (other than the genre category variables as they constitute dummy variables).

Analysis

I used multiple regression analysis to test the direct effects of digital product features and online community interaction on digital product consumption. Two direct effect models were estimated with ordinary least squares regression. Model 1 tests the direct influence of digital product features on digital product consumption (H1) and excludes the community variables. Model 2, the full model, tests the influence of both digital product features and online community activity on digital product consumption (H2). Equation 1 describes this full model (for game *i*):

$$\text{(1)} \quad \text{Aggregate Digital Consumption}_i = \beta_0 + \beta_1\text{Functional Features}_i + \beta_2\text{Social Setting Features}_i + \beta_3\text{Social Status Features}_i + \beta_4\text{Community Size}_i + \beta_5\text{Community Vitality}_i + \beta_6\text{Community Concentration}_i + \beta_7\text{Days on Market}_i + \beta_8\text{Quality}_i + \beta_9\text{Strategy Genre}_i + \beta_{10}\text{Casual Genre}_i + \beta_{11}\text{Action Genre}_i + \beta_{12}\text{Racing Genre}_i + \varepsilon_i$$

In order to test the mediated influence of social setting features and social status features on digital product consumption through online communities (H3-H5), Preacher and Hayes (2004) bootstrap mediation was conducted. Bias-corrected bootstrap confidence intervals for the indirect effects were estimated, based on 1,000 bootstrap samples with replacement[3] (Preacher and Hayes 2004; Zhao, Lynch, Jr and Chen 2010). All three characteristics of online community were simultaneously tested as mediators[4].

Results

Direct Effect Analysis

Table 2.4 reports the results of both direct effect models for digital consumption. The VIF scores are all less than 2, indicating no serious problems with multicollinearity (Hair et al. 2010). The reduced digital consumption Model 1 is significant ($F(9, 119) = 3.40$, $p < .01$), and indicates that social setting features ($\beta = .295$, $p < .01$) and social status features ($\beta = .346$, $p < .01$) both significantly influence digital product

[3] I reran the mediation models with a higher number of bootstrap samples (10,000) in order to narrow the sampling distribution of the standard error of the indirect effects. These tests resulted in virtually identical results.

[4] While the indirect influence of all three product features could not be tested simultaneously, each mediation model was estimated with the two non-focal product features as covariates, in addition to the control covariates included in the direct models.

consumption, whereas functional features have a marginally significant influence on digital consumption ($\beta = .177$, $p < .1$), all in support of H1.

Looking at the controls, consistent with the previous literature on quality (Tellis, Yin and Niraj 2009) product quality ("quality rating") significantly influences digital product consumption. Products with a higher critic quality rating are associated with a higher level of aggregate digital consumption ($\beta = .340$, $p < .01$). On the other hand, the amount of time a product has been on the market and most of the genre category dummies have no influence on digital product consumption.

The full digital consumption Model 2 is also significant ($F(12, 116) = 8.35$, $p < .01$). Further, a comparison between this model and the previous one indicates that the full model with online community variables included provides a significantly better fit to the data than the reduced model ($F=18.66$, $p < .01$). The estimated coefficients in this full model indicate that social setting features ($\beta = .345$, $p < .01$) and social status features ($\beta = .248$, $p < .05$) continue to have a significant influence on digital product consumption in support of H1b and H1c, but the influence of functional features is no longer significant. Online community size ($\beta = .520$, $p < .01$) and community concentration ($\beta = .516$, $p < .01$) significantly influence digital product consumption, while community vitality has no apparent effect on digital consumption, providing support for H2a and H2c, but failing to support H2b. The control variable effect of quality is diminished when online community activity factors are added to the model ($\beta = .181$, $p < .1$). The amount of time a product has been on the market continues to have no influence on digital product consumption, and the genre dummies are all non-significant.

Mediation Analysis

Mediation analysis of the digital product consumption effects reveals that the social setting features' and social status features' influence on digital consumption is partially mediated through online community concentration (see Table 2.5, top panel). A higher level of social setting features is directly associated with a higher level of digital product consumption ($\beta = .345$, $p < .01$). However, social setting features exert a significant negative indirect influence on digital consumption through online community concentration ($\beta = -.123$, $p < .01$), in support of H5a.[5] Online community concentration competitively mediates the influence of social setting features on aggregate digital product consumption (Zhao, Lynch, Jr and Chen 2010). However, an examination of the total effect of social setting features on digital consumption reveals a net positive significant influence ($\beta = .295$, $p < .01$), suggesting that the positive direct influence outweighs the negative impact through reduced online community concentration. Complete results for all initial mediation tests can be found in the top panel of Table 2.5.

Social status features also have a direct positive influence on digital product consumption ($\beta =.248$, $p < .05$). In contrast to social setting features, social status features have a significant positive influence on digital consumption through online community concentration ($\beta =.066$, $p < .05$), in support of H5b.[6] In addition, community concentration acts as a complementary mediator on the influence of social status features on digital product consumption (Zhao, Lynch, Jr and Chen 2010). An examination of the total effect reveals a positive significant influence ($\beta = .347$, $p < .01$). Mediation analysis for online community size and online community intensity was non-significant, failing to

[5] A bias-corrected bootstrap 99% confidence interval for the indirect effect of social setting features on digital consumption through online community concentration (-.237/-.022) was entirely below zero.
[6] A bias-corrected bootstrap 95% confidence interval for the indirect effect of social status features on digital product consumption through online community concentration (.002/.184) was entirely above zero.

provide support for H3 and H4. Robustness checks for mediation utilizing an alternate construction of consumption (discussed below) and utilizing Heteroscedasticity-Consistent Standard Errors (Hayes and Cai 2007) were conducted, leading to the results reported in the lower panels of Table 2.5. They produce substantively similar results.

Robustness Tests

While multiple regression models provide results that are simple and easy to understand, they are subject to a number of potential biases that can lead to erroneous results and interpretation. Therefore, I conducted a number of robustness tests to rule out alternative explanations and address potential biases in the analyses. Details of all robustness checks conducted can be found in Table 2.6.

Our construction of the aggregate digital consumption variable substituted half the minimum consumption value of each observation window for games with missing values (as described in the Appendix). I recognize that this approach may overestimate the daily digital consumption values for less popular games. To evaluate whether this biased the results, I created an alternate digital consumption variable that did not substitute half the minimum value of consumption for missing observations, but instead used a value of zero whenever a game fell off of the *Steam* top 100 list (which underestimates aggregate consumption). Multiple regression and mediation analyses using this alternate aggregate digital consumption variable yielded substantively equivalent results to those reported above, suggesting that the results are robust to the construction of the consumption variable.

Online community concentration was operationalized as the percentage of posts by the top ten percent of the online community based on the common nature of these community distributions. However, alternate constructions of online community concentration are possible. One such construction could utilize an “80/20” rule and examine the percentage of posts by the top twenty percent of the online community. A revised analysis utilizing a 20% concentration measure was conducted and produced results substantively similar to the original digital product consumption models and mediation analyses.

Since the digital consumption measure was non-normal, it is possible that the results may have been influenced by a number of extreme values. While the influence of the extreme values themselves were corrected by transforming the data, the heteroskedastic nature of the errors may not have been corrected with the transformation. Results from a Breusch-Pagan test (Breusch and Pagan 1979) indicated the need for robust standard errors. A multiple regression model utilizing Huber-White robust standard errors (White 1980) produced results substantively identical to the original digital product consumption model.

The focal sample analyzed in the reported multiple regression models and corresponding robustness analyses was based on digital products that appeared in the *Steam* Top 100 list at least 5 days in the observation window. However, games that do not appear with frequency in the Top 100 list are likely different than those that do, raising concerns about the prospect of selection biases. In an effort to address this potential selection bias, a two-step Heckman Selection model was estimated. Utilizing all 322 games used for the construction of factor scores, a selection model was first estimated. The residual from that model was then transformed into an Inverse Mills Ratio and entered into the main models to account for the potential selection bias. Again, the findings were not substantively different from those obtained using the original models.

Discussion

The results of this study provide new insights into the features and factors that drive aggregate consumption of digital products. Digital products incorporating features that communicate the social consumption setting result in higher aggregate digital consumption. Similarly, digital products with a large number of features that communicate social status result in higher aggregate digital consumption. Both of these types of digital product features result in increased aggregate digital consumption independent of the online community. In contrast, functional product features appear to have little impact on aggregate digital consumption, a somewhat surprising finding considering the focus on functional features common in the product purchase literature. This suggests that while functional product features may play an important role in product purchase, they appear to have less influence on how much a digital product is consumed post-purchase.

Consumer community research is just beginning to explore the different characteristics of consumer communities and their corresponding outcomes. In the case of digital consumption, online community size and concentration play important and complementary roles. Both lead to increases in aggregate digital consumption. Yet a tension exists between the two online community characteristics illustrated in their mediating influences of different types of digital product features.

Digital products with stronger social setting features are associated with an increase in the size of the online community. This may be because digital products with these features more effectively communicate an expectation of shared group consumption, and connect customers to the community through consumption. Yet those same social setting features also dilute the concentration of the online community as the group grows more diverse from the influx of new community participants. In my study, the total positive influence of online community size on aggregate digital consumption overwhelmed the negative impact of reduced concentration. However, digital products with extremely high concentration (tight-knit) communities may actually generate greater consumption from limiting group growth so as to maintain high group cohesion.

In contrast, digital products with stronger social status features are associated with an increase in both the size of the online community and online community concentration, and thus an increase in aggregate digital consumption. If a digital product is designed to capture additional revenue from consumption, integrating social status features will result in a larger, more concentrated online consumer community, higher aggregate product consumption, and therefore increased revenue generation. However, in those cases where higher post purchase aggregate consumption imposes costs on the firm, designing digital products with social status features may lead to higher than anticipated aggregate consumption and thereby erode profits.

Managerial Implications

Traditional product design strategies emphasize integration of product features to encourage product purchase. However, my findings suggest that designing digital products exclusively for adoption ignores the critical phase of post-purchase consumption. Managers who design digital products without focusing attention on consumption will at the least fail to leverage potentially significant sources of revenue, and at the worst, introduce crippling product costs that could escalate as their product is consumed more. A better understanding of the impact of product design decisions is therefore necessary for firm success in the digital product age.

For example, for digital products with significant variable after-market costs, integrating social product features could generate unexpected and undesired outcomes. My findings suggest that the heavy use of social features in a product's design can drive aggregate digital consumption beyond traditionally expected levels, and correspondingly increase the costs of product maintenance and support. Attempts to rectify this problem after release, such as cutting product support, risks not only discouraging new digital product sales, but also might generate negative word of mouth for the product as previously faithful customers are alienated and communicate their displeasure to others. As a consequence, it is vital that managers understand and consider the impact of features on digital consumption during product development.

Alternatively, digital products with social features could strengthen the product brand, by turning casual customers into loyal product evangelists through extended digital product consumption. A stronger product brand makes line extensions and complementary products more attractive, influences future purchases, and could increase the reputation of the firm. Thus, these digital product social features enhance online community participation and consumption. However, they can also create a potential "threat to a marketer should a community collectively reject marketing efforts or product change, and then use communal communications channels to disseminate the rejection" (Muniz, Jr. and O'Guinn 2001, p 427).

Despite these potential negative outcomes of increased digital product consumption, the potential positive impact on revenue from increased consumption is considerable. In the context of my study, digital line extensions and digital complementary goods have the potential to generate significant revenues. Video game downloadable content (DLC - additional content released after the core product release) was expected to generate over $1billion in revenue in 2012 (EEDAR 2011). Recently released games have reported earnings of over $60 million on downloadable content in just the first quarter following product release (Dring 2014). When firms design digital products to generate revenue directly from consumption, the revenue opportunities are even larger, as evidenced by *Zynga* (makers of *Farmville*) which generated over $750 million from online games in 2013 (Zynga 2014).

Our findings also provide insights into online community management. Traditional managerial metrics of online communities focus primarily on community size and volume. However, my results suggest that managers that desire strong product communities should consider community concentration as an important alternate measure. Managers may benefit from building online communities with a clear common set of expectations and behaviors, reinforced by community and product leaders in order to increase community concentration. Further, community vitality, while an interesting measure of group activity, may not be as important as concentration for managers focused on product consumption. Managers should be careful what community metrics they manage to, depending on their desired outcomes.

Limitations and Further Research

There are limitations to the investigation that should be kept in mind. I focused my analysis on the consumption of digital computer and video game products. While they share many features with other digital products, integrating social product features may be easier for these products than for other types. Nonetheless, social integration in digital products is becoming more commonplace as more customers are interconnected through online networks. At a minimum, most digital products provide a mechanism to share their experiences with the product on a number of social media platforms such as *Facebook*. Other non-game digital products such as smartphone apps and digital music have integrated social product features in the form of crowd-sourcing and product gamification, and frequently have vibrant online communities. I would expect, then, that similar results would be found in other digital product categories. Future research might investigate whether differences in types of social integration features across digital product categories moderate the relationship with consumption.

Also, I chose to focus my analysis on aggregate product consumption, advancing the literature past the product purchase stage. However, additional product outcomes such as word of mouth, product loyalty, and brand value may be similarly affected by digital product features and online communities. Future research could investigate these additional outcomes and examine the role that social product features and online communities play in influencing them.

Conclusions

Understanding the relationships between features, communities, and aggregate consumption is essential for researchers and managers studying digital products. Digital products, by virtue of their distribution through the Internet, innately lend themselves to social influences. The results of my study suggest that social product features and online consumption communities play important roles in the aggregate post-purchase consumption of digital products. Digital products with social product features are associated with increased aggregate digital consumption directly and indirectly through online community concentration. Further, online community size and concentration are both associated with aggregate digital consumption. However, the relationships between social product features and online communities in digital products are complex and interesting, as reflected by the competitive and complementary mediation through community concentration. By contributing to an understanding of these relationships, this study provides new insights into the drivers of digital product consumption.

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TABLE 2.1
PRODUCT FEATURE PRINCIPLE COMPONENTS
FACTOR ANALYSIS RESULTS

	F_1 - Functional	**F_2 - Social Setting**	**F_3 - Social Status**
Audio Captions	.894	.019	.119
High Definition Graphics	.867	.063	.137
Commentary	.844	.016	.124
Source Code	.792	.004	.083
Multiplayer Only	.037	.965	-.020
Free-to-play	.010	.767	.016
Singleplayer	-.037	-.965	.020
Leaderboard	-.169	-.023	.807
Achievements	.130	-.045	.746
Controller	.264	-.081	.670
Stats	.273	.156	.580
Eigenvalue	3.08	2.49	2.05
Proportion Variance	.28	.23	.18

TABLE 2.2
ONLINE COMMUNITY PRINCIPLE COMPONENTS
FACTOR ANALYSIS RESULTS

	F_1 - Size	**F_2 - Vitality**	**F_3 - Concentration**
# Threads	.914	.273	.289
# Posts	.872	.361	.126
# Users	.843	.352	.362
Users per Thread	.395	.881	.213
Posts per Thread	.329	.844	.402
Percent of Posts by Top Ten Percent of Posters	.225	.254	.666
Eigenvalue	2.62	1.88	0.88
Proportion Variance	.44	.31	.15

TABLE 2.3
DESCRIPTIVE STATISTICS AND CORRELATION MATRIX

		Mean	Std Dev	1	2	3	4	5	6	7	8	9
1	**Functional Features**	.022	1.085	1								
2	**Social Setting Features**	.051	1.032	.03	1							
3	**Social Status Features**	.105	.936	.07	-.12	1						
4	**Community Size**	.026	.987	.16†	.09	.06	1					
5	**Community Vitality**	-.060	.907	.19*	.11	.23**	.03	1				
6	**Community Concentration**	.087	.896	.16†	-.26**	.12	.03	.13	1			
7	**Days on Market**	850	903	.20*	.02	-.37**	-.07	-.18*	.04	1		
8	**Quality Rating**	81.09	8.416	.33**	-.26**	-.18*	.14	-.03	.21*	.35**	1	
9	**Daily Consumption Game Hours**	52,892	146,778	.26**	.21*	.04	.65**	.13	.24**	.19*	.22*	1
10	**Daily Consumption ln(Game Hours)**	9.630	1.265	.26**	.15†	.21*	.48**	.15†	.36**	-.02	.18*	.77**

†p<.1 *p<.05 **p<.01

TABLE 2.4
DIRECT CONSUMPTION MODELS

		Consumption ln(Game Hours)	
		Model 1	Model 2
	Constant	9.616**	9.482**
Product Features	**Functional Features**	.177†	.095
	Social Setting Features	.295**	.345**
	Social Status Features	.346**	.248*
Community	**Community Size**		.520**
	Community Vitality		.027
	Community Concentration		.516**
Controls	**Days on Market**	-9.212×10^{-5}	-2.089×10^{-5}
	Quality Rating	.340**	.181†
	Strategy Genre	.126	.354
	Casual Genre	-1.488†	-.761
	Action Genre	.064	-.013
	Racing Genre	-.761	-.573
Model Fit	**R2**	.205	.464
	Adj R2	.144	.408
	F Test	3.40 (9,119)**	8.35 (12,116)**
	F Change		18.66 (3,116)**

†p<.1 *p<.05 **p<.01

TABLE 2.5

MEDIATION MODELS – CONSUMPTION LN(GAME HOURS)

	Direct	**Indirect Size**	**Indirect Vitality**	**Indirect Concentr.**	**Total**
Functional Features	.095	.059	.004	.019	.177†
Social Setting Features	.345**	.069	.003	-.123**	.295**
Social Status Features	.248*	.029	.003	.066*	.347**
Alternate Consumption Model (Zero Minimum)					
Functional Features	.235	.066	.003	.027	.331†
Social Setting Features	.586**	.077	.002	-.178**	.487*
Social Status Features	.498*	.032	.003	.096*	.628**
Heteroskedastic Model					
Functional Features	.095	.059	.004	.019	.177
Social Setting Features	.345**	.069	.003	-.123**	.295*
Social Status Features	.248*	.029	.003	.066†	.347**
Alternate Concentration Model (Top 20%)					
Functional Features	.095	.060	.001	.021	.177†
Social Setting Features	.346**	.068	.001	-.120**	.295**
Social Status Features	.250*	.031	.001	.065†	.347**

†p<.1 *p<.05 **p<.01

TABLE 2.6

ROBUSTNESS CHECKS

	Alternate Consumption Models		Heteroskedastic Models		Heckman Selection Models		Alternate Concentration Model	
Constant	9.159**	8.997**	9.616**	9.482**	10.202**	10.055**	9.616**	9.476**
Functional Features	.331†	.235	.177	.095	.167	.085	.177†	.095
Social Setting Features	.487*	.586**	.295*	.345**	.292**	.342**	.295**	.346**
Social Status Features	.628**	.498*	.346**	.248*	.359**	.260**	.346**	.250*
Community Size		.576**		.520**		.520**		.530**
Community Vitality		.022		.027		.028		.006
Community Concentration		.750**		.516**		.514**		.503**
Days on Market	-4.647×10^{-4}*	$3.924 \times 10^{-4\dagger}$	-9.21×10^{-5}	-2.09×10^{-5}	-7.86×10^{-4}	-8.08×10^{-6}	-9.21×10^{-5}	-2.38×10^{-5}
Quality Rating	.467*	.270	.340*	.181	.415**	.224†	.340**	.185†

TABLE 2.6 CONT.

ROBUSTNESS CHECKS

Strategy Genre	.251	.579	.126	.354	.123	.350	.126	.363
Casual Genre	-5.614**	-4.566**	-1.488**	-.761†	-1.453†	-.731	-1.488†	-.755
Action Genre	-.010	-.126	.064	-.013	.092	.013	.064	-.001
Racing Genre	-1.462	-1.208	-.761**	-.573**	-.699	-.515	-.761	-.574
Inverse Mills Ratio					-.763	-.708		
R2	.264	.390	.205	.464			.205	.464
Adj R2	.203	.326					.144	.408
Fit Test	F=4.74 (9,119)**	F=6.17 (12,116)**	F=11.47 (9,119)**	F=14.97 (12,116)**	χ^2=31.53 (df=9)*	χ^2=108.42 (df=12)**	F=3.40 (9,119)**	F=8.36 (12,116)**
Breusch-Pagan			χ^2=4.87*	χ^2=5.91*			9.616**	9.476**

†p<.1 *p<.05 **p<.01

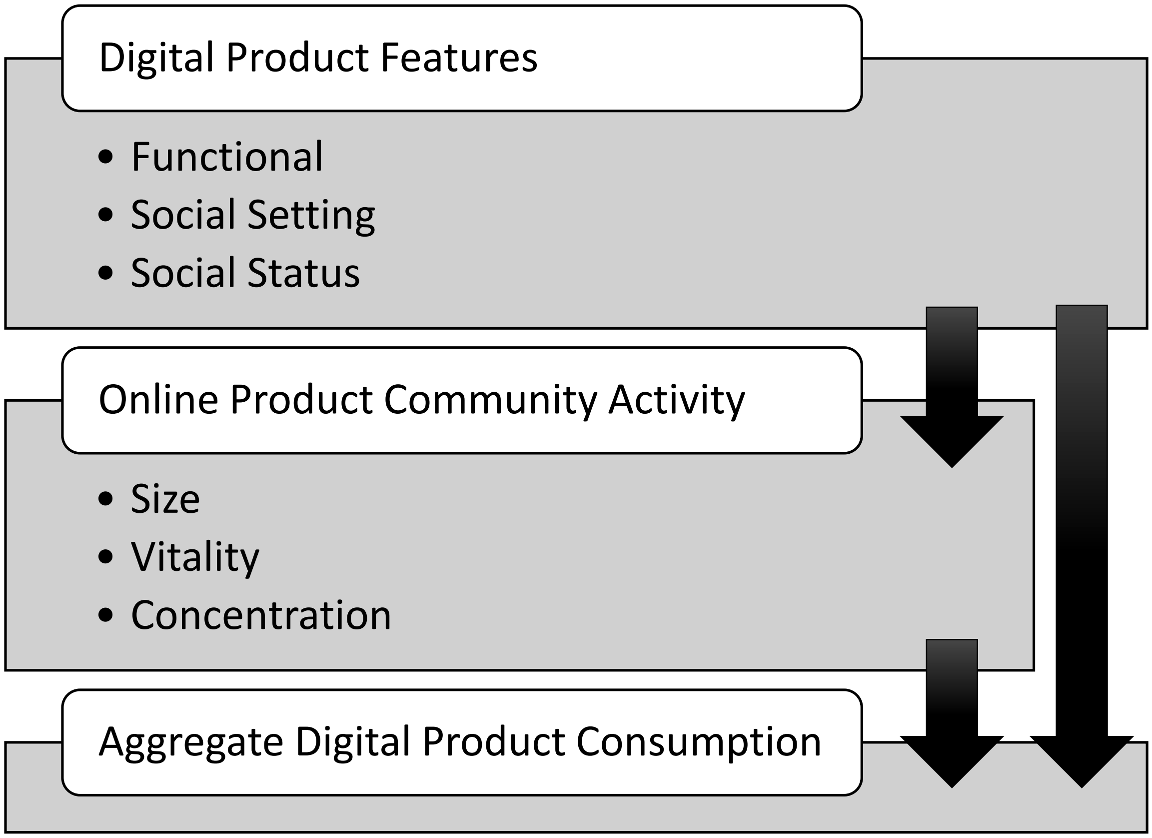

FIGURE 2.1
CONCEPTUAL MODEL

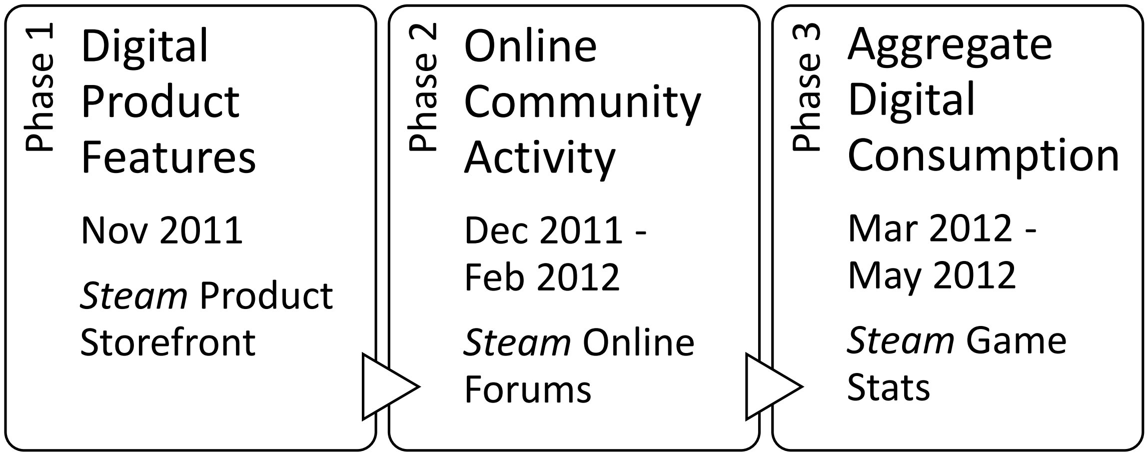

FIGURE 2.2
DATA COLLECTION PHASES

Appendix – Calculation of Consumption Variable

Consumption for a game was measured as average daily consumption based on the total hours of gameplay for each game, accumulated across all users of *Steam*. Data was collected every fifteen minutes in order to account for fluctuations in consumption patterns throughout the day and summed to the daily level. Fifteen minute increments were used in order to capture short-term changes in consumption, but without overwhelming the capabilities of the data collection hardware that would have occurred with smaller observation windows.

In order to account for weekly and monthly patterns in leisure game consumption, daily total consumption was collected for an 85 day window. The mean of that 85 day sample was then used as my measure of product consumption, average daily consumption. Initial analysis revealed that the distribution of product consumption was not normal. Thus, the natural log of the final measure of product consumption was taken and utilized in model building.

(1) $$\text{Consumption}_i = \ln \{\text{mean}\ (\text{Consumption}_{it})\}$$

where i indexes the game, t indexes the day.

Due to fluctuations in consumption over time, while the most popular games remained in *Steam's* top 100 at all times, less popular games moved in and out of the top 100 list throughout a day. *Steam's* Top 100 list only permitted collection of consumption data for the top 100 games. Thus, games that fell out of the top 100 for any period were likely to be consumed in some quantity, but be missing from the dataset during this period. In order to eliminate bias associated with this missing consumption, the total consumption of the 100th game for every 15 minute period was captured, and half that value was assigned to those games with missing data points in order to estimate the cyclic nature of games falling in and out of the top 100.

CHAPTER 3

POST-PURCHASE CO-CREATION: CONSUMER SEGMENTATION IN CONSUMER-DRIVEN COLLABORATIVE PRODUCT DESIGN[7]

[7] Smith, Keith Marion, John Hulland, and Andrew Stephen. To be submitted to *Journal of Marketing Research*.

Abstract

Product co-creation, or collaborative product development in which customers actively contribute and/or select the content of a new product, has become an increasingly interesting trend for both marketing academics and practitioners. Product co-creation during pre-release or pre-purchase contexts has been studied and embraced by some firms across a varied group of industries. Yet few firms have explored post-purchase co-creation and the marketing literature is absent of any systematic investigation of the phenomenon. Utilizing automated online data collection techniques real product co-creation activities were captured from co-creation efforts developed for traditionally firm created products. Through latent class cluster and panel regression techniques, three distinct and different segments of co-creation participants are identified: Co-creation Creators, Co-creation Consumers, and Core Product Users. Consumer's engagement with co-creation, community levels of co-creation engagement, and strategic marketing actions reveal an interesting and complex set of relationships on product consumption between the different segments.

Academics have long advocated integrating external sources of innovation into the product development process (Chesbrough 2003; von Hippel 1988; Stephen, Zubcsek, and Goldenberg 2013; Toubia 2006). Integrating customers in an otherwise firm-controlled product management process, often called *co-creation*, can provide benefits to the firm. O'Hern and Rindfleisch (2010, p 86) define co-creation as "a collaborative new product development activity in which customers actively contribute and/or select the content of a new product offering."

Co-creation can enhance the speed and effectiveness of product development. Transferring the iterative process of design-prototype-test to customers, who are more intimately aware of their product needs (Thomke and von Hippel 2002), increases the likelihood that development addresses specific customer needs, and reduces the time associated with need assessment and communication between the customer and the firm. It can satisfy a wider range of customer demands, increasing sales and better educating the firm regarding their customer's needs for future product design (Prahalad and Ramaswamy 2000; Ramaswamy 2008). Finally, co-creation, when paired with traditional marketing activities, can enhance communication with customers, influence the customer's product experience, and decrease the cost and risk associated with marketing communication (Ramaswamy 2008; Thomke and von Hippel 2002).

Integrating consumers into the design and development processes can be done in many ways (O'Hern and Rindfleisch 2010), depending on the degree to which the activity is led by the firm or customer, the degree to which the activity is open or restricted, and the marketing goals of the firm. Despite this diversity, however, existing marketing literature has focused almost exclusively on consumer selection of firm-created designs (Bendapudi and Leone 2003; Troye and Supphellen 2011), and pre-release collaboration in either open source product contexts (Grewal, Lilien, and Mallapragada 2006; Mallapragada, Grewal, and Lilien 2012) or user generated content (Albuquerque et al. 2012; Ransbotham, Kane, and Lurie 2012). Relatively little attention has been paid to post-purchase or post-release co-creation (Jeppesen and Molin 2003). This type of co-creation is often found in the software, video game, and music industries, where firms provide consumers with opportunities to modify their products, post-purchase, to best satisfy their own unique preferences. These markets represent significant potential value,; for example the published software market alone generated over 192 billion dollars in sales in the United States in 2015 (Blau 2015). While not every piece of published software currently has an active co-creation community, the possibility exists for this type of customer co-creation engagement in these product markets. Further, post-release co-creation has a wider potential reach since every consumer who purchases the product is a potential co-creation participant. Pre-release software co-creation in contrast has rarely been adopted by end-users and has been restricted to low level software development of back-end systems ("The 2015 Analytics Software Market" n.d.).

Different types of consumers appear to engage in co-creation for different reasons, including empowerment (Fuchs, Prandelli, and Schreier 2010), self-serving bias (Bendapudi and Leone 2003), and associative self-anchoring (Troye and Supphellen 2011), among others (O'Hern and Rindfleisch 2010). However, much of the empirical literature on co-creation has assumed that each participant in co-creation is essentially similar, or has accounted for heterogeneity by allowing individual level unobserved differences in co-creation participation (Albuquerque et al. 2012; Mallapragada, Grewal, and Lilien 2012; Ransbotham, Kane, and Lurie 2012). The varied motivations identified in the literature suggest that different categories of co-creation participants may exist, and that category membership can influence product purchase and consumption differently. Further, marketing actions taken by the firm may differentially influence these distinct categories.

A small number of studies have identified different types of participants in the co-creation process, including Mallapragada, Grewal & Lilien's (2012) separation of developer and end users in an open source software environment, and Jeppesen & Molin's (2003) identification of different co-creation consumer categories in online computer games. However, existing research on these co-creation categories in a post-purchase co-creation context has been limited to explorative case studies. The post-purchase setting has simply not received attention, despite the greater volume of potential consumer involvement in this stage ("The 2015 Analytics Software Market" n.d.).

The product categories often associated with co-creation (software, music, games) are more accessible to post-purchase co-creation in part due to their digital nature. This same digital characteristic raises the question of consumption separate from purchase. Because these digital products do not degrade over time, repurchase following consumption is not necessary. Thus, beyond the initial purchase, consumption drives many post-purchase marketing processes, including satisfaction, word-of-mouth, loyalty, and lifetime value.

In order to understand the post-purchase co-creation context, and the related influences on product consumption, consumer engagement in online communities of co-creation, and associated product consumption are examined. Since co-creation category membership is unobserved and needs to be inferred, a latent class cluster methodology is utilized that allows categorization of consumers into different customer segments based on their co-creation activity. Combined with time-series panel modeling, an investigation is conducted to understand how co-creation engagement, the co-creation community, and strategic marketing actions influence product consumption over time, across different co-creation customer segments.

Conceptual Background

Product Co-Creation

Interest in customer-created content has grown in recent years, with research investigating both user-generated content (Albuquerque et al. 2012; Moe and Schweidel 2012; Ransbotham, Kane, and Lurie 2012) and the open source software community (Grewal, Lilien, and Mallapragada 2006; Kumar, Gordon, and Srinivasan 2011; Mallapragada, Grewal, and Lilien 2012; Oh and Jeon 2007; Singh, Tan, and Mookerjee 2011). These two forms of customer collaboration and interactivity have provided fertile ground for (O'Hern and Rindfleisch 2010) "collaborative new product development activity in which customers actively contribute and/or select the content of a new product," often termed co-creation. Despite the theoretical work on co-creation driven by firm actions, the majority of empirical work in the area has examined user-generated or open-source projects developed by consumer teams, without the input of a firm, and unaffiliated with any existing market products. How do these co-creation contexts and communities influence consumers when the co-creation is affiliated with existing products post-release, and what is post-purchase or post-release co-creation?

This integration of consumers into the post-purchase design and development process goes beyond traditional product customization offerings that allow consumers to change the color of a product (e.g. Timbuk2 Bags) or pick from a few different options (e.g. Dell) to customize the product they desire during the purchase decision. Instead, co-creation in the post-release stage facilitates fundamental changes in the function and form of the core product, permitting customers to innovate and refine the product to meet their unique and specific needs, and access communities of co-creation to implement other customer's innovations into their own products.

Moreover, post-release co-creation provides customers with opportunities to reconfigure and redefine the original product, increasing the time that they find the product interesting. These co-creation activities have the potential to greatly impact the consumer's product experience following product purchase, and represent a part of the consumer product experience that firms can influence on an on-going basis. However, are these consumers all created equal? Are there different ways that consumers may experience products that support post-purchase co-creation, depending on each consumer's engagement in the co-creation community, and does this engagement influence their consumption of the product? This research aims to investigate these relationships and better understand the role of post-purchase co-creation in consumption.

Types of Co-Creation Customers

Based on a synthesis of the literature, three distinct consumer co-creation segments are expected in a post-purchase context: Co-Creation Creators, Co-Creation Consumers, and Core Consumers. Co-Creation Creators modify existing products and generally share their modifications with the community. Co-Creation Consumers do not themselves create modifications, but rather integrate existing modifications published by Creators into their own products. Finally, Core Consumers are either unaware of or uninterested in co-creation and simply consume the core product as offered by the firm.

This consumer structure arises out of past work that has made a distinction between content creators and content consumers in co-creation contexts. Distinct roles for creators and consumers have been investigated in an open source context (Mallapragada, Grewal, and Lilien 2012), and in a user-generated content context (Zhang et al. 2012), providing support for the idea that different categories of co-creation consumers can contribute different value to the firm. Traditional pre-release co-creation literature has rarely examined non-creators however, and certainly not core consumers uninvolved with co-creation. In contrast, Jeppesen & Molin (2003) distinguish between content creators, content consumers, and core product users in the computer game marketplace for post-purchase product modifications, though they focused their investigation on descriptive differences identified via a qualitative analysis. However, no quantitative empirical study has been conducted to confirm the presence and number of groups that arise out of post-purchase co-creation.

Co-Creation Creators actively create new content and/or make modifications to existing products to satisfy their own unique needs for a different product experience (Jeppesen and Molin 2003), driven by feelings of empowerment (Fuchs, Prandelli, and Schreier 2010). They sometimes participate in a product community to share their co-created products with other consumers. Co-Creation Consumers are interested in consuming modified products to meet their unique product needs, but have no interest in devoting the resources to develop the knowledge to make successful modifications, nor the resources to actually modify the products. An extensive level of product knowledge is required in order to successfully modify most products (Kohler et al. 2011; Nambisan and Baron 2009), and customers interested only in consuming co-created products are not likely to have this knowledge, nor be motivated by feelings of empowerment to develop it. Instead, these modification-adopters are likely to seek revised products already available in the community. Finally, Core Consumers utilize the product as designed by the firm. They have no awareness of or desire to make modifications or adjustments to the product.

Co-Creation Outcomes and Drivers

Much of the co-creation literature has focused predominantly on non-marketing outcomes such as knowledge creation (Kuk 2006), or on pre-purchase open-source outcome measures such as project downloads or project popularity (Mallapragada, Grewal, and Lilien 2012). While these outcomes are themselves important, they fail to examine individual level marketing outcomes of interest to firm managers. Product consumption comprises a unique and separate phase of the individual consumer experience, and provides a mechanism through which product loyalty, word-of-mouth, and other downstream marketing outcomes are achieved (Holbrook and Hirschman 1982; Schouten and McAlexander 1995). Consumption, like post-purchase co-creation, occurs following purchase, and provides a worthy object of study to understand individual level phenomenon in post-purchase co-creation.

Turning to the identified drivers of co-creation, much of the existing literature has focused on social interactions, social structure, and social capital within a network of creators. Increased social capital, measured through network centrality at the individual level, has been shown to influence commercial and technical success (Grewal, Lilien, and Mallapragada 2006), time to product release (Mallapragada, Grewal, and Lilien 2012), and consumption (Ransbotham, Kane, and Lurie 2012). Social cohesion or strong interpersonal connections within a project, measured via repeat ties, has further been linked to technical success (Singh et al. 2011). Finally, imbalances in the structure of a co-creation network have been linked to quality (Ransbotham and Kane 2011) and knowledge creation (Kuk 2006).

Despite the extensive work on social influences in co-creation, almost all of the work explores the structure of the social network. Little is known about how the act of socially interacting influences co-creation and consumption. Furthermore, the majority of the literature has examined the individual within a network, and the connections each individual makes with other co-creators. No work has explored the role that the community has on individual consumers. A rich history of research in brand and online communities (Muniz, Jr. and O'Guinn 2001; Schau, Muñiz Jr, and Arnould 2009) provides a framework to explore social interactions within co-creation communities that extend beyond an individual's structural position within a network of co-creators

Online & Brand Communities

A healthy body of research has explored the value of brand communities both to consumers and to the firm (Muniz, Jr. and O'Guinn 2001), demonstrating a process of value creation from brand communities through a number of social processes, including community engagement, shared brand use, social networking, and impression management (Schau, Muñiz Jr, and Arnould 2009). Much of the brand value creation derived from communities arises following purchase of the product. These post-purchase influences from brand communities suggest that these communities may play an important role in post-purchase co-creation.

Increasingly, a number of studies have leveraged behavioral secondary data to link individual level brand community participation measures to marketing outcomes. Brand community participation has been shown to increase sales and retention (Adjei, Noble, and Noble 2010), increase risky behavior through reliance and trust on community members (Zhu et al. 2012), and increase new product success through dissemination of product information (Gruner, Homburg, and Lukas 2014). Brand community participation has also been linked to faster new product adoption, especially when consumers do not participate in multiple communities, or when brands tied to the community are first to market (Thompson and Sinha 2008).

Many products that offer post-release co-creation opportunities additionally provide consumers with the opportunity to engage in social interaction around the creation process. For example, customers can share their designs (e.g., software modifications) with others, vote on other customers' designs, and interact in online communities or social networks(e.g. Threadless, a fashion company that allows customers to vote on product designs to be manufactured (Ogawa and Piller 2006)). These firms facilitate customer communities by providing members with tools that allow them to interact and take part in co-creation activities.

Both brand communities and co-creation tools introduce a source of extended consumer experience with products, and offer firms the ability to continually engage consumers in product experiences that may build additional product value over time. Therefore, an examination of post-purchase co-creation would benefit from an investigation of brand community's role in co-creation engagement and product consumption, and extend the literature on social interactions in co-creation.

Strategic Marketing Actions

Very little research has explored how marketing managers can influence co-creation environments. Some studies have investigated public relations and price discounts in user-generated content contexts and found that firm-initiated public relations, and creator referrals increase content generation activity, and purchase, while price discounts influence purchase (Albuquerque et al. 2012; Zhang et al. 2012). Investigation of product based elements of the marketing mix in pre-release co-creation have been limited to innovativeness (Fang 2008) and product labeling (Fuchs et al. 2013; Schreier, Fuchs, and Dahl 2012), and have been focused on consumer experimental methodologies.

Ultimately, the same focus on consumer-driven open source contexts that has provided limited insight into post-release co-creation has also made it difficult to understand the tools marketers can leverage to affect co-creation and consumption. Post-purchase or post-release co-creation contexts presents interesting opportunities and challenges to marketers. These products are developed and marketed for the core consumer, and co-creation communities adopt these products that were never intended to be modified, or where those modification opportunities were targeted at a small portion of the customer base. What influence do marketers have on consumption in these contexts then? Further, what distinctions exist between different types of co-creation customers?

Empirical Study

Study Context

Existing literature has explored pre-launch product co-creation activity through online communities of software or knowledge development (e.g. Sourceforge, Wikipedia). These same study communities provide a context to investigate post-launch co-creation. For example, post-launch or post-purchase co-creation in the computer game market occurs frequently when games are modified by customers, and then shared with the rest of the community. Customers may add new graphics, items, or quests to an existing game, or even change entire game systems to create new games. These co-creation projects are typically called 'mods' in the video game marketplace.

Steam is the largest online product storefront and digital distributor of computer games, comprising over sixty percent of the market in 2015. In addition to selling computer game products, *Steam* provides support for post-purchase product co-creation activity through their Workshop initiative. Firms partner with *Steam* to include Workshop features in their products, including product co-creation tool-kits, mod websites and forums, and seamless browsing, installation, and updating of consumer developed product mods. The Steam platform additionally provides systems for customers to connect with other customers, and to join groups of like-minded customers.

Steam's Workshop provides a platform for mod creators to upload their project files for download by others, and provides a communication interface to interact with other consumers. Each project is uploaded to Steam's servers, and the project creators can include a description of the mod, images associated with the project, and different tags used to categorize projects. *Steam's Workshop* further provides a mechanism to interact with project creators through comments associated with each project, facilitating a conversation between interested consumers and the mod creator. Mods uploaded to the *Workshop* can be easily searched by interested consumers, installed into each game with a single button, and those mods are automatically updated as project creators make changes.

Steam's online co-creation Workshop included over 2,250,000 submitted projects for over 300 different games in December of 2015. Users who engage in co-creation through *Steam's Workshop* system have a corresponding account that tracks their game consumption and community interaction activity, in addition to key information regarding their co-creation activities. Purchased games, game consumption times, online forum activity, online co-creation engagement, and networked friends and their corresponding data are all available for all co-creation customers. Consumer data from *Steam* was captured utilizing custom automated online data collection techniques. This data was combined with marketing activity data and media activity data from public sources (described in more detail below).

Sample

Given the focus on co-creation engagement and product consumption by individual consumers, the unit of analysis for the purposes of this study was the individual consumer. Data was collected for one game, Torchlight 2. This focal game was selected for its active but mature consumer market (six months post-release), active co-creation environment, and developer provided co-creation toolkit that facilitated co-creation. Torchlight 2 is a fairly representative game in the marketplace, a sequel with an established fan base, good critical reception (Metacritic scores of 88/100) ("Torchlight II for PC Reviews - Metacritic” 2016), and solid sales figures, with over one million unit sales in the first 10 months (Farokhmanesh 2013), and around three million in unit sales since launch (Kuchera 2015).

Two phases of data collection were conducted. A Subject Selection phase occurred in an initial eight week window (October to December, 2013), wherein any consumer active in at least one mod project or in the product community forum was identified for inclusion. A Subject Activity phase followed over a 32 week window (December 2013 to August 2014), collected very two weeks, wherein product co-creation activity, product consumption activity, and community engagement activity was collected for each individual identified during subject selection. Individuals with no consumption activity during the 32 week Subject Activity phase were eliminated from the sample, resulting in a final sample of 960 consumers.

Measures

The existing literature suggests that different communities may exist for co-creation creators, co-creation consumers, and core product users, reflecting different consumer motivations and community norms. Data was collected to assess this claim and to better understand consumer segmentation in the collected dataset. Five categories of measures were collected, including profiling measures, time-varying individual measures, time-varying community measures, marketing activity measures, and a number of control measures. Detailed descriptions of those categories and the collected measures follow. Measure definitions and overall descriptive statistics can be found in Table 3.1, while correlations can be found in Table 3.2.

Profiling Measures

A set of measures was collected that could potentially separate co-creation creators, co-creation consumers, and core product users. Because co-creation segmentation is expected to be relatively stable within the timeframe under investigation (32 weeks) the following measures represent aggregate measures across the entire study window for each consumer.

Frequency of Authorship Activity. For each period, a dummy measure of authorship activity was collected that identified whether a consumer had uploaded at least one new mod or updated at least one existing mod during that period. These 16 period measures (collected every two weeks) were then summed to obtain a measure of frequency of period authorship activity over the entire 32 week study window, resulting in a measure that ranged from 0-16 across the sample for the entire window. Thus, a consumer who had been active in authoring every period would receive a score of 16 while a consumer that had only been active in authoring for four periods would receive a score of four. Because this measure is summed across the entire study window it provides a time-invariant measure of authorship activity.

Frequency of Commenting Activity. For each period, a dummy measure of commenting activity was collected that identified whether a consumer had commented on at least one mod during that period. These 16 period measures were then summed to obtain a measure of frequency of period commenting activity over the entire 32 week study window, resulting in a measure that ranged from 0-16 across the sample for the entire study window. Because this measure is summed across the entire study window it provides a time-invariant measure of commenting activity.

Time Varying Individual Measures

A set of time-varying individual level measures of consumption and co-creation activity was collected that could explain within-group differences in product consumption. Collected every period over the 16 period window, these measures help explain period to period changes in consumption for each consumer.

Focal Consumption. Consumption was measured as the total number of hours the focal game, *Torchlight 2*, was consumed by each customer over the each two week period. Examination revealed a number of extreme values that could influence model estimation; thus, a log normal transformation was performed to reduce the impact of these extreme values.

Author Activity. Consumer activity in authorship for a specific period was measured as a simple dummy variable. Consumers were counted as active in authorship if they uploaded a new mod for that period, or if they updated an existing mod in the period. These authoring events capture an endpoint of co-creation development activity, as mod projects are only available to the public following an official release or update by the author. These period level, time-varying measures of authorship, when combined across the entire study window, comprise the time-invariant profiling measure of authorship activity noted above.

Comment Activity. Consumer activity in commenting for a specific period was additionally measured as a simple dummy variable. Consumers were counted as active in commenting if they posted a comment on a mod someone else had uploaded. These comments capture engagement in the co-creation community by measuring the degree to which consumers interact with others within the co-creation environment. These period level, time-varying measures of commenting activity, when combined across the entire study window, comprise the time-invariant profiling measure of commenting activity noted above.

Authors who commented on their own uploaded mods were not counted as engaging in commenting activity. Author comments on their own projects were typically responses to other non-author commenters or a part of a discussion with other members of the community related to the development of their own mods. Thus, their own project commenting behavior was characterized as a part of their authorship behavior and not captured in the Commenting Activity measure.

Time-Varying Community Measures

A set of time-varying community level measures of consumption and co-creation activity was collected, to examine community influences on product consumption. Conceptually, the influence from the creator community and consumer community may be different. Thus, these measures were calculated following segmentation of the consumer dataset into creator and consumer clusters (see Latent Class Cluster Model below), by collecting total levels of activity from consumers categorized into the co-creation creator sub-community and the co-creation consumer sub-community.

Creator Community Author Activity. A measure of the level of authorship activity amongst Creators was captured to examine the influence the Creator community has on consumption. A count of the number of total Creators that either uploaded a mod or updated an existing mod in the period was calculated. Corresponding measures of community authorship were not included for either Co-creation Consumers or Core Consumers because of their relative lack of co-creation activity. Measures of these communities would be effectively zero due to a lack of co-creation activity within these consumer segments, and the corresponding variables would be uninterpretable.

Creator Community Comment Activity. Similar to Creator Community Authorship Activity, a count of the number of total Creators who posted a comment to any non-owned mod project for each period was calculated to examine Creator community commenting separate from authoring. As noted above, comments posted to their own mods were excluded as they are more likely to capture co-creation authorship behavior than community commenting behavior.

Consumer Community Comment Activity. A count of the number of total Co-creation Consumers who posted a comment to any mod for each period was calculated to examine Co-creation Consumer community commenting separate from the Creator community. Again, a corresponding measure of community commenting was not included for Core Consumers because of their relative lack of commenting activity. Measures of the Core Consumer communities would be effectively zero due to a lack of co-creation commenting activity within this consumer segments, and the corresponding measure would be uninterpretable.

Controls

A number of controls were collected to rule out alternative explanations or to corroborate prior findings in the co-creation and consumption literatures.

Last Period Focal Consumption. Past levels of the dependent variable were calculated in order to account for unit level effects in the panel dataset, and to control for the influence of past behavior. Like current period consumption, a log normal transformation was performed to reduce the impact of extreme values.

Platform Consumption. In order to account for variation in overall game consumption levels, a measure of product consumption on *Steam* was captured, excluding the focal game for any given period. Like focal consumption, this variable had a log normal transformation applied to reduce the impact of extreme values.

Platform Investment (Platform Products Owned). A measure of how many total games each consumer owns on the *Steam* platform for each period was collected to provide a control for overall platform investment.

Connections. Steam provides a friend connection system that allows an individual to connect and play with others. This same system allows the capture of a measure of how connected a consumer is within the entire *Steam* network, not simply within the network of co-creators.

Marketing Activity Measures

In an attempt to examine the influence of strategic marketing actions in a post-purchase co-creation context, a number of variables were collected from the *Steam* platform and PR measures were collected from the top fourteen most visited video game news websites as identified by *Amazon's Alexa* website ranking service (Alexa 2016), at the first data collection window. While the impact of these factors on sales has been well established and deeply explored, their influence on consumption in a post-purchase setting, and especially on different segments of consumers in a co-creation context, is unknown.

Proportion of Mod Stories in Media. The proportion of media stories about co-creation (mods) in my focal game compared to all stories on the focal game was collected for each period, allowing investigation of the influence of the content of public relations on consumption.

Product Promotion. Steam offers a number of different promotion types on their platform that range from free play weekends, individual product sales, whole publisher catalog sales, and game competition events. A dummy was captured identifying those periods where the firm organized a promotion on the *Steam* platform to investigate the influence of promotions on consumption

Model and Estimation

Exploring individual co-creation behaviors, group level influences, and marketing actions over time, and considering how these factors may influence consumption across different types of consumers presents a number of modeling challenges, including consumer heterogeneity, panel unit effects, and serial correlation.

Consumer Heterogeneity: Latent Class Cluster Model

In order to account for consumer heterogeneity in co-creation engagement and to test for the expected presence of three different categories of co-creation consumers, a latent class cluster model was estimated. By utilizing latent class cluster models that statistically test for the presence of a mixture of multiple distributions within a single distribution of data (Vermunt and Magidson 2002), separate discrete sub-distributions corresponding to Co-Creation Creators, Co-Creation Consumers, and Core Consumers could potentially be identified.

Theoretically, the three clusters under investigation in this study differ primarily in their authorship and commenting behavior. Prior literature in co-creation has established authorship or content creation as the primary outcome of the co-creation process (Goldenberg, Oestreicher-Singer, and Reichman 2012; Grewal, Lilien, and Mallapragada 2006; Mallapragada, Grewal, and Lilien 2012), with a secondary role for communication or interaction within co-creation networks (Albuquerque et al. 2012; Kuk 2006; Ransbotham, Kane, and Lurie 2012). Further, the expected segmentation into Co-Creation Creators, Co-Creation Consumers, and Core Consumers has been previously motivated by the distinctions in authorship and community interaction (Jeppesen and Molin 2003).

Therefore, in support of the previous literature, the latent class cluster model included two variables: Frequency of Authorship Activity, and Frequency of Commenting Activity. Since both of these measures are counts of activity across the entire study window (16 periods), the latent class cluster model was estimated as a multivariate Poisson distribution.[8] The latent model is characterized as follows:

$$f(y_i) = \sum_{x=1}^{K} P(x)\, f\left(\begin{matrix}\text{Frequency of}\\ \text{Authorship Activity}_i\end{matrix}\middle|\, x\right) f\left(\begin{matrix}\text{Frequency of}\\ \text{Commenting Activity}_i\end{matrix}\middle|\, x\right)$$

where i=1,...,n individuals, and x is the latent category variable with *K* classes

Panel Regression Model

Following consumer segmentation into discrete classes, a regression model approach was adopted to examine the influences on product consumption separately for each consumer class. The consumer data contain repeated measures over time for each consumer in the dataset. In order to account for the influence of past levels of consumption, as well as to address unit effects, a lagged value of the dependent variable

[8] It is technically possible for consumers to shift between different latent segments over the sixteen periods. In reality, the data revealed relatively stable levels of both authorship and commenting activity, suggesting that such shifts did not occur within the dataset. This stability is unsurprising given the maturity of the game, and likely well established consumer segments.

is included in the model (Beck and Katz 2011). Inclusion of the lagged dependent variable allows for pooled OLS estimation. A separate model is estimated for each of the three hypothesized groups in order to account for heterogeneous influences on consumption.[9] The three regression models are characterized as follows:

$$\textit{Co-creation Creator Focal Consumption}_{it} = \beta_0 + \beta_1 \textit{ Author Activity}_{it} + \beta_2 \textit{ Creator Community Author Activity}_{it} + \beta_3 \textit{ Comment Activity}_{it} + \beta_4 \textit{ Creator Community Comment Activity}_{it} + \beta_5 \textit{ Consumer Community Comment Activity}_{it} + \beta_6 \textit{ Proportion of Mod Stories}_{it} + \beta_7 \textit{ Product Promotion}_{it} + \beta_8 \textit{ Last Period Focal Consumption}_{it} + \beta_9 \textit{ Platform Consumption}_{it} + \beta_{10} \textit{ Platform Investment}_{it} + \beta_{11} \textit{ Connections}_{it} + \varepsilon_{it}$$

$$\textit{Co-creation Consumer Focal Consumption}_{it} = \beta_0 + \beta_1 \textit{ Creator Community Author Activity}_{it} + \beta_2 \textit{ Comment Activity}_{it} + \beta_3 \textit{ Creator Community Comment Activity}_{it} + \beta_4 \textit{ Consumer Community Comment Activity}_{it} + \beta_5 \textit{ Proportion of Mod Stories}_{it} + \beta_6 \textit{ Product Promotion}_{it} + \beta_7 \textit{ Last Period Focal Consumption}_{it} + \beta_8 \textit{ Platform Consumption}_{it} + \beta_9 \textit{ Platform Investment}_{it} + \beta_{10} \textit{ Connections}_{it} + \varepsilon_{it}$$

$$\textit{Core Consumer Focal Consumption}_{it} = \beta_0 + \beta_1 \textit{ Creator Community Comment Activity}_{it} + \beta_2 \textit{ Consumer Community Comment Activity}_{it} + \beta_3 \textit{ Proportion of Mod Stories}_{it} + \beta_4 \textit{ Product Promotion}_{it} + \beta_5 \textit{ Last Period}$$

[9] Integrating the latent class cluster and the regression into one model, means that community influences would need to calculated in real time as a part of the model estimation, and would result in potentially changing cluster sizes and community measures that would make estimating such a model intractable. As a result, separate regression models have been estimated for each of the consumer clusters.

$$Focal\ Consumption_{it} + \beta_6\ Platform\ Consumption_{it} + \beta_7\ Platform\ Investment_{it} + \beta_8\ Connections_{it} + \varepsilon_{it}$$

where i=1,…,n individuals and t=1,…,16 time periods

As noted previously, variables measuring authorship and commenting would be uninterpretable for segments not engaging in these behaviors. Note that Authorship Activity was included only in the Co-Creator model, and that Commenting Activity was included only in the Co-Creator and Co-Creation Consumer models.

Serial Correlation

In order to address potential serial autocorrelation in the data, a Woolridge Autocorrelation test (Woolrdige 2010) was conducted for all three consumer regression models, Co-Creation Creators, Co-Creation Consumers, and Core Consumers. All three tests indicated that significant autocorrelation was present in the data. Thus panel corrected standard error estimators that assume the errors are both heteroskedastic and autocorrelated were implemented in all models to correct for the autocorrelation (Beck and Katz 2011).

Results

Complete latent class cluster model results and panel regression results are reported below. Briefly, the latent class cluster analysis revealed a four cluster solution to be the best fitting model. Cluster-specific descriptive statistics support the proposed consumer clusters. Panel regression analysis conducted separately for each of the clusters reveal differing results.

Latent Class Cluster Analysis

Latent Class Cluster models with *Frequency of Authorship Activity* and *Frequency of Commenting Activity* as indicators were estimated. Vermunt and Magidson (2013) recommend AIC and CAIC as the most appropriate fit statistics for latent class cluster models. Table 3.3 Panel A provides full latent class cluster model fit statistics. Models ranging from one to five classes included were estimated, and model fit statistics consistently indicate that a four class model is most appropriate (AIC = -1790, CAIC = -2067). The four class model produced the lowest AIC and CAIC values.

Table 3.3 Panel B provides class profile data that helps illustrate specifically how the four classes differ across *Frequency of Authorship Activity* and *Frequency of Commenting Activity.* The four classes, from smallest to largest in size comprise 0.8%, 1.4%, 6.9%, and 91% of consumers. Initial analysis of the four class model might suggest a poor fit with the proposed three class model based on prior literature and the proposed consumer structure. However, upon closer examination of the class profile descriptive data (Table 3.3 Panel B), the picture becomes clearer.

The largest class (.910) comprises the group least involved in either co-creation authorship (.011) or co-creation commenting (.142) behavior. This group corresponds to the Core Consumers. The second largest class (.069) has a relatively higher level of commenting activity (1.508), though again negligible levels of authorship activity (.052). This subgroup corresponds to the Co-Creation Consumer segment.

The remaining two groups share similarities with the Co-Creation Creator group. However, a deeper examination of these two groups reveals an interesting dichotomy. Both groups are relatively small and of equal size. Further, both groups have far higher levels of authorship activity than the Core Consumers or Co-Creation Consumers (at a minimum 30 times the authorship activity, and in some cases over 500 times the authorship activity). One of these Co-Creation Creator groups however has very high levels of authorship activity (5.181) and modest levels of commenting activity (1.069). These consumers are termed Code Creators for their overwhelming focus on the activity of developing mod projects. The alternative Co-Creation Creator group has modest levels of authorship activity (1.801) and very high levels of commenting activity (9.384). These consumers are termed Community Creators for their dual focus on both mod project development and community engagement with other creators.

Table 3.3 Panel C provides the model coefficients and overall model tests. The results from the four class model confirm that both *Frequency of Authorship Activity* and *Frequency of Commenting Activity* play an important role in identifying the multiple unique distributions of consumers within my greater consumer dataset. Overall model fit statistics indicate the model with *Frequency of Authorship Activity* and *Frequency of Commenting Activity* is significantly better than a constants only model ($X^2 = 5621.69$, $p < .001$).

More specifically, high levels of *Frequency of Authorship Activity* are positively associated with being classified as either a Community Creator ($\beta = 1.801$) or a Code Creator ($\beta = 2.996$). Alternatively, high levels of *Frequency of Authorship Activity* are negatively associated with classification into the Co-Creation Consumer ($\beta = -1.600$) or Core Consumer ($\beta = -3.197$) clusters. A Wald test comparing these coefficients indicates that there is a significant difference between the clusters when considering the influence of Frequency of Authorship (Wald = 329.79, $p < .001$). These results indicate that Code

Creators and Community Creators are heavily engaged in product modification behavior and product co-creation, supporting previous evidence that a clear group of creators exist within the co-creation community.

Frequency of Commenting Activity is positively associated with classification into the Co-Creation Consumer ($\beta = .222$) or Community Creator ($\beta = 2.049$) clusters. Alternatively, high levels of Frequency of Commenting Activity are negatively associated with classification into the Code Creator ($\beta = -1.600$) or Core Consumer ($\beta = -1.600$) cluster. A Wald test comparing these coefficients indicates that there is a significant difference between the clusters when considering the influence of Frequency of Commenting (Wald = 543.867, $p < .01$). These results indicate that both Community Creators and Co-Creation Consumers are heavily engaged with the greater community. Previous research in co-creation and online communities has found support for the role of community interaction in creation and consumption.

The dichotomy between different types of creators is interesting and deserving of further exploration. Ideally separate analysis could be conducted on both groups of Creators to better understand these differences. Unfortunately, the small sizes of these groups (.014 and .008 respectively) precludes such an analysis. Thus, for the purposes of this study the two Co-Creation Creator groups were combined into a single group to achieve acceptable sample sizes. Both groups are clearly more engaged in co-creation authorship than the Core Consumers or Co-Creation Consumers.

Cluster-Specific Descriptive Statistics

Cluster-specific descriptive statistics from the three consumer clusters (Co-Creation Creators, Co-Creation Consumers, and Core Consumers) provide a clearer picture of consumer engagement in co-creation and the resulting consumption. One cluster (Co-Creation Creators) is dedicated to the creation of modified products and community engagement around those co-created modifications. One cluster (Co-Creation Consumers) is dedicated to the community engagement around co-created modifications, but does not engage in co-creation modification. The final cluster (Core Consumers) is either unaware or uninterested in the co-creation community, instead focused on overall platform consumption and investment. These three clusters provide a framework to examine how consumer actions, community-level behavior, and marketing strategy can influence product consumption and engagement in co-creation. Complete cluster-specific descriptive statistics can be found in Table 3.4.

The smallest cluster (2.08%) comprises the two combined Creator clusters. This group is characterized by high levels of authorship behavior, both in terms of likelihood of engaging in authorship activity (29.38%), and the average number of mod projects uploaded to the Workshop environment (2.383 projects). Their commenting activity also occurs at a high level, with a high likelihood of posting a comment for any period (25.63%) and a higher average number of comments posted per period (.994 comments). Their consumption patterns reveal relatively high high levels of focal consumption (5.322 hours) and moderate levels of platform consumption on *Steam* (24.070 hours). They further have moderate levels of platform investment (83.703 products). Despite their small size, this segment comprises almost ten percent (9.05%) of the total focal consumption in the dataset, far disproportional to their size.

The second largest cluster comprises the Co-Creation Consumers, characterized by their participation in commenting on mod projects. They exhibit a larger likelihood of commenting (7.58%) compared to the Core Consumers, and have a higher average level of comments per period (.185 comments). Their authorship activity is low, with a low likelihood of authorship activity (.66%) and a low number of published mod projects (.222 projects). Yet when examining their consumption activity, this cluster has far higher levels of focal consumption (5.926 hours) than Core Consumers, and a similar level compared to Co-Creation Creators. Their levels of *Steam* platform consumption are moderate (25.196 hours), though they have a relatively lower level of platform investment (90.891 products) than Core Consumers. This group is relatively small in size (6.88%), though they also comprise a far higher proportion of total consumption activity (33.27%) than would be expected.

Examination of the Core Consumer cluster reveals an essentially zero likelihood of uploading a mod for any single period (.04%), and an essentially zero number of mod projects uploaded on the *Steam* Workshop for any single period (.060 projects). Their likelihood of posting a comment is similarly small with an incredibly low likelihood of posting a comment for any single period (.13%) and an incredibly low number of comments posted for any single period (.002 comments). Turning to their consumption pattern, they have a relatively small amount of focal consumption for any single period (.776 hours), a moderate level of *Steam* platform consumption per period (27.26 hours), and higher levels of platform investment (122.16 products) when compared to the other two consumer clusters. This cluster comprises the largest percentage of consumers (91.04%), however their consumption comprises a much smaller proportional percentage of the overall consumption (57.68%) in the dataset.

Panel Regression Analysis

Three separate panel regression models on the three identified clusters were estimated to understand the influence of consumer co-creation activity, community co-creation activity, and marketing actions on product consumption. Separate analyses were conducted on each cluster to allow for heterogeneous influences across clusters. One model was estimated for Co-Creation Creators, one for Co-Creation Consumers, and one for Core Consumers. Complete panel regression results for all three clusters can be found in Table 3.5.

Co-Creation Creator Panel Analysis

Panel estimation results for Co-Creation Creators reveals an interesting influence from author activity, comment activity, creator community comment activity, product promotion, platform consumption, platform investment, and connections on focal consumption. Model Fit tests indicate the model provides an improvement on a constants only model (Wald = 331.04, $p < .001$). More specifically, author activity has a positive influence on consumption ($\beta = .373$, $p < .001$), comment activity has a positive influence on consumption ($\beta = .278$, $p < .05$), and creator community comment activity has a positive influence on consumption ($\beta = .097$, $p < .001$). Of the strategic marketing measures, product promotion has a positive influence on focal consumption ($\beta = .440$, $p < .01$). Of the platform measures, platform consumption has a positive influence on consumption ($\beta = .186$, $p < .001$), platform investment has a negative influence on consumption ($\beta = -.002$, $p < .001$), and connections has a positive influence on consumption ($\beta = .003$, $p < .001$). Last period focal consumption has a positive influence on focal consumption ($\beta = .063$, $p < .001$).

The influence of authorship activity on consumption provides an interesting extension of the existing literature's focus on co-creation activity. Engagement in co-creation appears to actually influence the consumption of the core product in addition to knowledge creation and other established co-creation outcomes. The influence of creator community commenting behavior further extends the effects demonstrated in the community literature by illustrating that creators are motivated by interaction and communication with likeminded creators, but don't appear to be influenced by other creator's authorship behavior, or by online interaction within the co-creation consumer community (the segment that is essentially the creator's target market).

The positive influence of product promotion provides a surprising result that promotions have an impact beyond product sales. Even for those that own the product, promotions can induce increased consumption. The positive influence of connections provides further support for the connected nature of these types of consumers found in past literature.

Co-Creation Consumer Panel Analysis

Panel estimation results for Co-Creation Consumers reveals an interesting dynamic. Only commenting activity, connections, and last period focal consumption have any influence on current period consumption. Model Fit tests indicate the model provides an improvement on a constants only model (Wald = 400.86, $p < .001$). More specifically, commenting activity has a positive influence on consumption ($\beta = .585$, $p < .001$), connections has a negative influence on consumption (β = -..003, $p < .001$), and last period focal consumption has a positive influence on focal consumption ($\beta = .035$, $p < .001$).

These results seem to indicate a Co-Creation Consumer segment that is self-focused on their own behavior and relatively insensitive to the community. While focused on their own commenting and consumption behavior, it must be noted that their commenting behavior occurs in the context of the co-creation community. While these consumers may not be motivated to consume by others participation in the community, they are motivated by their own participation in the community of co-creation. These results suggest that Co-Creation Consumers are actively invested in their participation in the community and do seek interaction and acceptance amongst the community of co-creators, perhaps aspiring towards creator group membership and attempting to validate that group membership through community engagement. The negative influence of connections is interesting, though may be the result of an increased propensity to engage in shared consumption with a wider variety of products on the platform.

Core Consumer Panel Analysis

Panel estimation results for Core Consumers reveals an interesting set of influences from consumer community comment activity, proportion of mod stories in the media, product promotion, platform consumption, platform investment, connections, and last period focal consumption on focal consumption. Model Fit tests indicate the model provides an improvement on a constants only model (Wald = 246.45, $p < .001$). More specifically, co-creation consumer comment activity has a positive influence on consumption ($\beta = .008$, $p < .001$), the proportion of mod stories in the media has a negative influence on consumption ($\beta = -.075$, $p < .05$), and product promotions have a positive influence on consumption ($\beta = .092$, $p < .001$). Platform consumption has a positive influence on consumption ($\beta = .021$, $p < .001$), platform investment has a negative (though incredibly small) influence on consumption ($\beta = -.00008$, $p < .001$), and last period focal consumption has a positive influence on focal consumption ($\beta = .031$, $p < .001$).

Core Consumers are characterized by their lack of engagement in either authoring or commenting in the co-creation community. This consumer segment is unaccounted for in the co-creation literature because of the focus on pre-purchase co-creation. In a post-purchase co-creation context, this consumer segment is significant in size, though less so in their levels of consumption. Interestingly, this segment does appear to be influenced by consumer community comment activity, suggesting that while they are not actively participating, they are listening to, and responding to, the trends within a part of the community.

Perhaps more interestingly, this group is influenced by marketing actions, despite the fact that all consumers in the dataset have already purchased the product. The negative influence of co-creation stories suggests that the more this consumer segment is reminded that the product has strong support for co-creation, the less likely they are to consume, perhaps reflecting a preference for pure firm-developed products. The positive influence of promotions provides interesting support for the idea that the influence of promotions can extend beyond sales. Promotions may provide top-of-mind effects that motivate consumers to return to the product and consume after a period of reduced consumption.

Finally, the effects of platform consumption and platform investment suggest a consumer segment that more closely resembles serial game consumers. These individuals are more focused on consuming a wider variety of products within the category, and their cluster descriptive statistics support this concept with a much higher level of platform investment on average compared to the other two clusters.

Discussion

While the Co-Creation Creator is the source of collaborative new product development, and has been the target of much of the existing marketing literature and practitioner interest, a number of different consumer segments clearly exist in post-purchase co-creation. Co-Creation Creators and Co-Creation Consumers comprise a disproportional percentage of total consumption based on their representation in the consumer base. These two consumer segments, with their increased consumption, are more likely to develop long term relationships with the brand, and exhibit increased loyalty and increased lifetime value than Core Consumers, demonstrating that in the context of post-purchase co-creation, consumers who engage in collaborative development in some way provide value to the firm.

Despite the small size of the Co-Creation Creator segment, this segment of consumers is critically important to the co-creation process. These individuals develop and disseminate shared knowledge about co-creation, and their influence on fellow creators is manifested through their community interaction. Their influence on Co-Creation Consumers however cannot be understated. Without their product modifications shared with the community, the Co-Creation Consumer would not even exist, and the increased value generated from those Consumers would be lost to the firm.

The disproportional levels of consumption amongst Co-Creation Consumers combined with their larger representation in the consumer base establishes a clear value for the firm. That these individuals are unaffected by community levels of authorship and commenting provides challenges to marketing managers attempting to directly influence this segment. Yet a strong relationship between consumption and their own comment activity suggests these consumers are heavily engaged in the online community, just not influenced by others within the community. Management and influence of this segment may be best achieved through maintenance of a healthy community and indirectly through management of the Co-Creation Creator segment.

Core Consumers represent an important segment unique to the post-purchase co-creation context. These individuals represent a large proportion of the total consumer base, but a smaller percentage of total consumption. Interestingly, they are not entirely ignorant of the co-creation process, as at least some Core Consumers are influenced by the conversation in the Co-Creation Consumer community. These findings suggest that marketing managers may be capable of converting consumers into Co-Creation Consumers, and reaping the increased value associated with that conversion.

Online Communities

Support for the influence of online brand communities on consumption is further supported within the post-purchase co-creation context. The role that these communities play are complex and varied across the different segments of consumers however. The consumption of Co-Creation Creators is influenced by fellow creator's social interaction, but not fellow creator's author activity. Furthermore, Co-Creation Creator consumption appears unaffected by Co-Creation Consumer community activity, despite the fact that often the consumer is the creator's target market.

As noted previously, the role of the online community for Co-Creation Consumers seemed tied exclusively to their own interaction in that community. Beyond direct social interactions, the overall activity of either creator or consumer communities appears not to influence Co-Creation Consumers. Somewhat surprisingly, Core Consumers, who are segmented as such by virtue of their lack of engagement in co-creation, are still somewhat influenced by Co-Creation Consumer community activity. While this effect is small, it suggests that the co-creation community has an influence outside of those involved in co-creation.

Strategic Marketing Actions

Product promotion strategies have a rich and detailed history in marketing research and are one of the primary tools marketing managers have at their disposal. Traditionally, promotions have been studied and utilized as a tool to motivate product purchase. However, this research would suggest that product promotions have a role beyond the purchase decision. Amongst two of the three co-creation segments, product promotions stimulate consumption. Both Co-Creation Creators and Core Consumers exhibit increased levels of consumption in the presence of product promotions, though it is likely that the drivers motivating this consumption are different for each group. Top-of-mind promotion strategies may be useful tools to trigger product consumption. For firms that generate value through consumption, product promotion strategies could provide mechanisms to extend the customer's relationship with the product, and thus increase the likelihood of increased loyalty, word-of-mouth, and lifetime value.

Earned and owned media exposure has also been of interest to both marketing researchers and managers. Results from this study would suggest that generating media mentions specifically related to co-creation actually provide no benefit to the firm, and actually may damage relations with customers. Co-Creation Creators and Co-Creation

Consumers see no change in the presence of a higher proportion of mod stories. Core Consumers however see a decrease in consumption as a result of those higher mentions. If this effect is the result of an aversion to co-creation by this customer segment, it would follow that firms should avoid actively seeking media coverage for co-creation. Instead, firms may benefit more from allowing these customers to discover and learn about co-creation from the community itself. Thus, strategies that bridge the gap between Core Consumers and the co-creation community may be more beneficial than specifically targeting more broad media exposure.

Platform Influences

Increasingly, online and media products are being delivered through product platforms that provide an interface between the consumer and the firm. Therefore, it is interesting to examine different characteristics of that platform to better understand its effects. Increased platform consumption appears to be associated with higher levels of focal product consumption for both Co-Creation Creators and Core Consumers. This should provide encouraging evidence to both platform owners and firms that these platforms provide a benefit beyond simple access to products. A platform inertia effect may provide increased levels of consumption to firms who chose to sell their products through a successful platform.

However, the opposite seems to be the case with platform investment. The more a consumer is invested in a single platform, the less their level of consumption for each individual product. As the overall level of investment increases, the consumer has an increasing draw on their limited time from each unique product, likely driving this effect. That Co-Creation Consumers are resistant to either platform consumption or platform investment is potentially interesting and worthy of further study. Perhaps firms can leverage some characteristic of this group to benefit from the increased consumption effect but insulate themselves from the increased investment effect.

The interrelationship between platform consumption and platform investment provides a confusing and counterintuitive situation for firms. Highly successful platforms provide an increase in consumption, but these same platforms are likely to attract an increasing number of firms that facilitates more deeply invested consumers. How these two characteristics of a platform influence purchase and consumption are worthy of future research and could reveal interesting phenomenon associated with online platforms.

Limitations and Future Research

Limitations in such a complex set of data and analysis should of course be considered. While product co-creation can occur in a wide select of different product categories, this research focused on a single category, video games, and on a single product within that category. Post-purchase co-creation occurs across digital and physical goods, across low-cost and high-cost items, and across durable and consumer packaged goods products. Future research should explore different product categories to more fully understand post-purchase co-creation.

Post-purchase co-creation activity may further change significantly over the lifecycle of a product. Often, product knowledge takes time to be gathered in such a context, and the creators in the community may share quite different types of mod projects as the maturity of the product develops. The product under study in this research was examined after it had reached maturity in the marketplace. It would be interesting to examine a product from product release to better understand the shifting influences of co-creation and community over time.

Conclusions

Post-purchase co-creation is a new but important concept for the marketing literature to grasp and understand. It provides opportunities to marry traditional product development and consumer-led co-creation in interesting and unique ways that can generate significant value. The results of this study suggest that very different constituents exist within the co-creation landscape, and that firms may need to implement very different strategies to influence each of those segments effectively. Both community management and more traditional marketing strategies can provide levers to affect consumption and downstream value, and this study provides evidence on how these drivers can be implemented.

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TABLE 3.1
EMPIRICAL MEASURES

Category	Measure	Description	Mean	Std. Dev.
Profiling Measures	**Frequency of Authorship Activity**	Number of time periods the individual uploaded or updated a mod over the entire study window. (0-16)	.110	.918
	Frequency of Commenting Activity	Number of time periods the individual commented on a non-owned mod over the entire study window. (0-16)	.330	1.12
Time Varying Individual Measures	**Focal Consumption**	Number of hours the individual played the focal game in the observed time period.	1.510	7.34
	Author Activity	Dummy representing whether the individual uploaded or updated a mod in the observed time period. (0/1)	.010	.083
	Comment Activity	Dummy representing whether the individual commented on a non-owned mod in the observed time period. (0/1)	.020	.138
Time-Varying Community Measures	**Creator Community Author Activity**	Number of total Creators who uploaded or updated a mod in the observed time period.	5.88	1.77
	Creator Community Comment Activity	Number of total Creators who commented on a non-owned mod in the observed time period.	5.12	1.73
	Consumer Community Comment Activity	Number of total Consumers who commented on a non-owned mod in the observed time period.	5.00	5.30
Controls	**Last Period Focal Consumption**	Number of hours the individual played the focal game in the previous time period.	1.56	7.49
	Platform Consumption	Number of hours the individual played another game on *Steam* besides the focal game in the observed time period.	27.41	39.95
	Platform Investment	Number of games owned on *Steam* in the observed time period.	117.98	142.88
	Connections	Number of connected friends on *Steam* in the observed time period.	34.83	51.78
Marketing Activity Measures	**Proportion of Mod Stories in Media**	Proportion of focal game media stories on co-creation to total focal game media stories in the observed time period. (0-1)	.089	.199
	Product	Dummy representing whether the firm engaged in a promotion	.063	.242

	Promotion	on *Steam* for the focal game in the observed time period. (0/1)		

TABLE 3.2
CORRELATIONS

		1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**
1	**Focal Consumption**											
2	**Author Activity**	.06 ***										
3	**Comment Activity**	.11 ***	.23 ***									
4	**Creator Community Author Activity**	.05 ***	.00	.00								
5	**Creator Community Comment Activity**	.06 ***	.00	.00	.29 ***							
6	**Consumer Community Comment Activity**	.08 ***	.00	.00	.40 ***	.77 ***						
7	**Last Period Focal Consumption**	.48 ***	.05 ***	.12 ***	.07 ***	.12 ***	.16 ***					
8	**Platform Consumption**	.10 ***	-.01	-.03 ***	.00	.02 *	.03 ***	.11 ***				
9	**Platform Investment**	-.03 ***	-.01	-.09 ***	-.05 ***	-.04 ***	-.05 ***	-.05 ***	.18 ***			
10	**Connections**	-.02 ***	.01	-.01	-.03 ***	-.03 **	-.03 ***	-.03 ***	.20 ***	.34 ***		
11	**Proportion of Mod Stories in Media**	.03 ***	.00	.00	.14 ***	.33 ***	.56 ***	.08 ***	.02 *	.00	.00	
12	**Product Promotion**	.04 ***	.00	.00	.16 ***	.28 ***	.39 ***	.04 ***	.02 **	-.03 **	-.02 *	.21 ***

TABLE 3.3

LATENT CLASS CLUSTER ANALYSIS

A: MODEL FIT COMPARISON

# of Classes	BIC	AIC	CAIC
1	-916	475	-1202
2	-1706	-329	-1989
3	-1762	-399	-2042
4	-1790	-442	-2067
5	-1780	-446	-2054

B: CLASS PROFILES – 4 CLASS MODEL

(Mean # of time periods active out of 16)

	Community Creator	Code Creator	Consumer	Core
Frequency of Authorship Activity	1.589	5.181	.052	.011
Frequency of Commenting Activity	9.384	1.069	1.508	.142
Cluster Size	.008	.014	.069	.910

C: MODEL COEFFICIENTS – 4 CLASS MODEL

	Community Creator	Code Creator	Consumer	Core	Wald Test
Frequency of Authorship Activity	1.801	2.996	-1.600	-3.197	329.79***
Frequency of Commenting Activity	2.049	-.124	.220	-2.145	543.867***
Model Fit (X^2)	5621.69*** (df 277)				

TABLE 3.4
CLUSTER-SPECIFIC DESCRIPTIVE STATISTICS

		Creator		Consumer		Core	
		Mean	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Consumption	**Focal Consumption**	5.322	10.149	5.926	16.761	0.776	4.781
	Platform Consumption	24.070	35.626	25.196	31.671	27.260	40.597
	Platform Investment	83.703	90.682	90.891	95.200	122.160	147.624
Author Activity	**Authored Mods**	2.383	2.975	0.222	.739	0.0596	.297
	% Periods with Mod Activity	29.38%	45.62%	.66%	8.12%	.04%	1.89%
Comment Activity	**Comments**	0.994	4.084	0.185	1.211	0.002	.084
	% Periods with Comment Activity	25.63%	43.72%	7.58%	26.47%	0.13%	3.59%

Population	**% of Population**	2.08%	6.88%	91.04%
	% of Total Consumption	9.05%	33.27%	57.68%

TABLE 3.5
CONSUMPTION MODELS W/ PANEL CORRECTED STANDARD ERRORS
(CONSUMPTION: LN(GAME HOURS)

		Creator	Consumer	Core
Co-Creation Activity	**Author Activity**	.373***		
	Comment Activity	.278*	.585***	
Creator Community Activity	**Creator Community Author Activity**	.028	.014	
	Creator Community Comment Activity	.097***	.012	-.08
Consumer Community Activity	**Consumer Community Comment Activity**	-.021	.014	.008***
Strategic Marketing Activity	**Proportion of Mod Stories in Media**	-.325	-.098	-.075*
	Product Promotion	.440**	.079	.092***
Controls	**Last Period Focal Consumption**	.063***	.035***	.031***
	Platform Consumption	.186***	.007	.021***
	Platform Investment	-.002***	.000	-.00008***
	Connections	.003***	-.003***	.000
	Constant	-.449**	.345***	.106***

Serial Corelation	**F Test**	116.04***	113.99***	218.41***
Model Fit	**Wald Test**	331.04***	400.86***	246.45
Sample	**N**	20	66	874
	t	16	16	16
R2		.569	.334	.118

CHAPTER 4

COACHES AND CHEERLEADERS: LEADERS AND FOLLOWERS IN ONLINE BRAND COMMUNITIES[10]

[10] Smith, Keith Marion, Scott A. Thompson, and John Hulland. To be submitted to *Journal of Marketing*.

Abstract

Increasingly, marketers desire to engage in product or communication seeding, an attempt to identify influential consumers and utilize those consumer's connections to spread marketing communication and influence. Often this practice attempts to identify leaders and followers of brand community discussion as prime targets for seeding. Yet relying on traditional metrics of online discussion leadership might lead marketers to focus on the most vocal or most active consumers. Drawing on concepts from social identity theory, it is proposed that these individuals resemble followers of brand community discussion, and that an entirely different set of consumers may be more appropriate targets for product or communication seeding, depending on the goals of the firm. Utilizing a dataset collected from online brand communities comprising over 874,000 messages collected from more than 30,000 unique users across a 60 month period, an investigation into leadership and followership is conducted. Results support the concept that brand community conversation leaders participate across a wider range of communities, and at an earlier period than traditionally defined brand community leaders. The data further suggest that community leaders defined by volume of activity may actually be members of the rival brand community who enter the preferred brand community in order to evangelize and recruit to the rival brand community.

As the modern consumer has become more connected, firms have recognized the value of identifying influential online consumers who may be disproportionally capable of impacting the buying decisions of others. Whether by their more central position in a group, or through the knowledge or expertise they bring to bear regarding a product, these individuals are often perceived by consumers as a better source of evaluative information than the firm itself.

The use of influential consumers is not a new phenomenon attached to the growth of the online marketplace. Firms have implemented product sample strategies for years to increase exposure to their products. However, the relative anonymity and reach of the average online influential raises interesting questions and opportunities for the modern marketer. How firms have chosen to leverage influential online consumers has led to changes in the online marketplace in recent years.

The trend towards connected consumers and identification of influential online consumer has resulted in an increased importance in the relationships between consumers and marketers, and created a new role for marketers as a seeder of persuasive information (Kozinets et al. 2010). Increasingly, marketing managers provide free products and services to influential online consumers in order to obtain their endorsement or support, and potentially generate increased sales from the network of connected audiences through those influential consumers.

The search for influential online consumers has raised questions regarding the veracity or integrity of some online product claims. With the growing value that consumers place in peer evaluations, and the anonymity of online communications, the United States Federal Trade Commission issued explicit guidelines on disclosure rules in social media in 2015 (Beck 2015), limiting fictional claims and requiring online consumers to disclose if products or services were provided for free.

This process of influential online consumer seeding (an attempt to identify influential consumers and utilize those consumer's connections to spread marketing communication and influence) and the shared management of the marketing message between managers and consumers is only successful to the degree that the marketer identifies the right influential customers however. How are marketers identifying influential consumers? Marketing managers have often searched for vocal consumers with an audience of like-minded customers. Like cheerleaders of a sports team, these consumers shout the marketing message to the crowd, encouraging their audience to accept the common message and join other brand loyalists in their love of the firm and the firm's products. Are the cheerleaders the decision makers and persuaders in the community, however, or are they simply the voice of the crowd, aping the common brand beliefs and generating increased support and love for the brand?

If the goal is to provide new product experiences and early firm communication to the community, the target of seeding campaigns should be to identify consumers who can evaluate those new products and early communication. Like coaches developing the game plan in the days and months leading up to a sports contest, these individuals may not be vocal once the marketing message has been accepted by the community. In fact, these individuals may already be evaluating the next product cycle or the next set of actions by the firm, preparing that message for communication to the community.

This research attempts to identify cheerleaders and coaches of brand communication in online brand communities. Through an investigation of leadership and followership within these communities, the research examines language and conversation adoption in online brand communities and evaluates the influences on those consumers more likely to lead the conversation or follow the conversation of the group. Leveraging insights from social identity theory, contributions are made to the online brand community literature, the online leadership literature, and the social identity literature.

Theoretical Background

Brand Community

The role of brand communities in influencing a number of marketing outcomes has been well established in the literature, including sales and retention (Adjei, Noble, and Noble 2010), new product success (Gruner, Homburg, and Lukas 2014), product adoption (Thompson and Sinha 2008), and customer to customer helping behavior (Thompson, Kim, and Smith 2015). These communities, defined as "a specialized, non-geographically bound community, based on a structured set of social relationships among admirers of a brand,"(Muniz, Jr. and O'Guinn 2001, p. 412) provide a social context within which consumers create value for both themselves and the firm (Schau, Muñiz Jr, and Arnould 2009).

Brand communities are identified by three key characteristics: consciousness of kind, rituals and traditions, and a sense of moral responsibility (Muniz, Jr. and O'Guinn 2001). Consciousness of kind is defined as a common connection that brand community members feel, and a collective difference towards those not in the community (Muniz, Jr. and O'Guinn 2001), This collective consciousness provides a backdrop against which conversations that implement the rituals and traditions, and a sense of moral responsibility occur.

The rituals and traditions of the community are made real through the conversations that occur between members. Stories are shared about brand use, the brand's history is recounted, and the brand's future is debated. These community conversations further provide a mechanism by which moral responsibility is exhibited. Information is shared about existing and future products, and assistance in product use is provided to fellow brand community members. These conversations within the community are the source of value creation activities, including social networking, community engagement, impression management, and brand use (Schau, Muñiz Jr, and Arnould 2009). Therefore, in order to better understand brand community development, brand community leaders, and brand community followers, an examination of the conversations, and more specifically the patterns of language use is needed.

Language Use and Brand Communities

The words and language that consumers adopt communicate a large amount of information, and word choice is influenced by such things as mental, social, or physical state (Pennebaker, Mehl, and Niederhoffer 2003). A number of linguistic techniques have emerged from the literature to analyze word usage and meaning. While some rely upon qualitative or judgment based analysis, others utilize modern quantitative techniques to provide usage counts based on word patterns or related linguistic patterns

In the context of online communities, word use is influenced by the commonly accepted rituals, tradition, and wisdom of the community. Community legitimation processes are partly based on the degree to which a consumer adopts and reinforces the common group identity (Hogg and Terry 2000), including the commonly accepted word usage patterns within the community. Therefore, an examination of these word use patterns will provide not only an identification of group level language use, but can further make distinctions between different types of group member language patterns in relation to the group level language.

Coaches and Cheerleaders: Social Identity in Brand Communities

An investigation into the social processes in brand community membership has revealed that social identity plays a critical role (Algesheimer, Dholakia, and Herrmann 2005; Bagozzi and Dholakia 2006). Community members adopt a social identity from the group that provides a collective self-concept and guides their attitudes and behaviors. This group identity takes the form of a prototypical group member that typifies all the characteristics important to the group, and which group members strive to emulate (Hogg and Abrams 2003). Members with a strong identity to the group actively engage in reinforcement of the group prototype through normative behavior, shared norms, stereotyping, cooperation, and altruism (Hogg and Terry 2000).

The influence of social identity has important implications for community leadership. Ideal leaders from a community member's perspective are those that are most similar to the group prototype. These individuals derive their influence indirectly from most closely mirroring the attitudes and behavior of the group. Further, because they embody the prototypical behaviors of the group they are liked by group members. However, these individuals may not exhibit leadership qualities at all, instead simply exhibiting qualities associated with the group prototype because of their prototypicality. Beliefs and attitudes commonly accepted by the group are attributed to these individuals simply by nature of their embodiment of the group prototype (Hogg and Terry 2000). Further, in order to maintain their prototypical status, these individuals are motivated to agree with the group and to reinforce the already accepted norms and institutional knowledge of the group. These consumers can be likened to cheerleaders, enthusiastically rousing the support of other community members to reinforce the commonly accepted wisdom of the group.

In contrast, community members who introduce new ideas and challenge group norms and institutional knowledge are perceived as less prototypical. These individuals are likely to be largely ignored by group members with a strong group identity (Hogg and Terry 2000). Yet it is these individuals who introduce new ideas, and who debate the merits and flaws of the brand and/or the firm that are eventually accepted as the shared understanding of the group. These individuals can be likened to the coaches, working behind the scenes to develop a game plan and to solidify the institutional knowledge that is eventually adopted by the group.

In the context of brand community seeding, prototypical leaders ("cheerleaders") are those most likely to be identified as brand loyalists. These individuals are highly active in the community, acting to reinforce group norms and strengthen the prototype of the group. Yet these individuals are less likely to introduce new ideas or new products into the community because these ideas and products often challenge already accepted group norms, and thus challenge the common group identity that they so highly value. In reality, these individuals are more likely to be brand followers in that they adopt an idea or concept only after it has already been accepted as a core part of the group prototype.

Identifying Influential Consumers

The identification of influential consumers within a product market has long been a goal of marketers, and the marketing literature has investigated a number of different definitions of ‘influential’. Early work focused on the concept of opinion leaders and drew on a combination of knowledge or expertise in conjunction with some level of influence over others (Jacoby and Hoyer 1981; Midgley 1976). More recent work has made a distinction between leadership in the product category and leadership in the marketplace. The market maven was identified as a consumer whose influence still derived from knowledge or expertise, but not of the product. Instead, the maven’s influence derived from their knowledge and expertise with the marketplace (Feick and Price 1987).

With the growth and development of the online space and social media environments, the concept of an *online influencer* has developed. These individuals are often targeted by firms because of their assumed influence in the online marketplace. They are often the target of one-to-one communication by the firm in an attempt to identify influential consumers and utilize those consumer’s connections to spread marketing communication and influence, often termed seeding campaigns. Often they are the most active or most vocal individuals within the community, and at the least they are strongly connected to other consumers (Trusov, Bodapati, and Bucklin 2010). These influential consumers develop a direct relationship with the firm, receive the crafted marketing message, and disseminate some version of the message to other consumers, though only after customizing that message to more directly benefit themselves (Kozinets et al. 2010).

While existing research has examined the role of influential customers outside the context of brand communities, these customers do not exist within a social vacuum. It is their presence within brand communities, and their connections and relationships to other community members that potentially makes them valuable to marketers. Furthermore, this position within a social group influences their own behaviors and actions. Thus, any examination of leaders and followers need consider how those consumers engage with the brand community and with fellow community members.

Brand Community Leaders and Followers in Group Conversations

Previous research in brand communities has established a relationship between participation in a brand community and different marketing outcomes, including product adoption (Gruner, Homburg and Lukas 2014; Thompson and Sinha 2008), brand loyalty (Adjei, Noble and Noble 2010), and product risk (Algesheimer et al. 2010; Zhu et al. 2012). However, <u>when</u> that participation occurs may have an influence on whether a community member is identified as a leader or follower of the group conversation. The social identity literature would suggest that cheerleaders, or community members who reinforce already accepted group norms, would be most active while the community was discussing an idea, or just after it has been adopted. As a prototypical member, these individuals follow rather than lead the group conversation (Hogg and Terry 2000).

In contrast, community leaders of the conversation are likely to introduce ideas and discuss their merits well ahead of the rest of the community. These individuals are internally debating the merits and flaws of different products, and these conversations form the basis for eventual group adoption. As aprototypical members, these individuals differ from the group, and in fact lead the conversation (Hogg and Terry 2000).

Leadership and followership are unlikely to be specific categories into which community members can be included or excluded. Community leadership and followership are identified by Hogg and Terry (2000) as distinct and separate characteristics of each community member in terms of their relationship with the group prototype and their willingness to act counter to the group prototype. Therefore, it is helpful to conceptualize leadership and followership as separate continuums of community membership as opposed to discrete categories into which a member may be placed. Just like there are different levels of coaches (e.g. head coach, assistant coach, etc.) and different levels of cheerleaders (e.g. head cheerleader, team cheerleader, enthusiastic fan, etc.), individuals can have different levels of leadership or followership.

A community member's leadership or followership trait is most probably comprised of multiple dimensions. The current research examines the timing of community engagement and examines timing as a proxy for leadership/followership. An alternate dimension of leadership might be to examine volume of participation, and in fact this dimension is what is typically used in the literature. However, this focus on volume has been what has led the literature to focus on the loudest consumers, regardless of whether they lead community conversation or follow it. By studying the timing of engagement, interesting insights can be gleaned regarding the role and influence of social identity in brand communities.

Leadership and followership are additionally unlikely to be permanent traits associated with a community member. Rather, the degree to which a community member may behave like a leader or a follower in group conversation is likely to change over time, as the member's value in group membership changes, and as the community prototype changes. There is likely to be some level of persistence to leadership traits however, so it is helpful to conceptualize leadership or followership as a characteristic of an individual that can change from month to month or from quarter to quarter. For individuals with longer persistence in leadership a more granular conception will still capture that persistence.

Hypotheses

A number of expected relationships follow from the existing literature, including the roles that brand community participation, rival brand community participation, brand community concentration, product category community participation, and product category community concentration have on leadership and followership. These relationships are explored in the below sets of hypotheses.

Brand communities, rival brand communities, and product category communities can create a confusing collection of community interactions surrounding an industry. Brand communities are those communities focused on a specific firm, product, or brand, and have been the focal community of much of the brand community research. Rival brand communities are those communities focused on a firm, product, or brand that is in competition with the focal brand. Rival brand communities only exist in the context of industry competition, though they are critical to the process of identity formation for consumers of the focal brand (Thompson and Sinha 2008). Reflecting the multi-faceted competition structure of many industries, a number of different rival brand communities can exist depending on the industry.

Finally, product category communities are focused on a specific industry or collection of similar products, though again only exist in the context of a collection of different brand competitors. The product category community typically engages in discussions relevant to any product in the industry, not simply the products associated with a single firm or brand, and have been shown to have interesting influences on helping behavior (Thompson, Kim, and Smith 2015). One way to conceive of these types of groups are as superordinate communities that include the brand communities as sub-communities with them. Though recent research has demonstrated that rival-based behavior can still occur in certain contexts between superordinate and subordinate communities.

Understanding the timing of conversation is important to the conception of leadership in this study. After all, leadership is being defined in the context of the timing of word usage. Specifically, word use patterns of the individual are compared to word use patterns of the group, Leaders are defined as those individuals who have a word use pattern at some time prior to t that most closely matches the group at time t. Followers are defined as those individuals who have a word use pattern at some time following t that most closely matches the group at time t. Since multiple word categories are used in community conversation, an examination of overall word usage can examine multiple word categories within the community at different focal t time points (i.e. different community word use patterns over time).

It is important to note that word pattern usage and participation levels are not the same thing. Word pattern usage (i.e. leadership or followership) considers when the individual pattern of word use matches the group level of word use. Participation levels however measure overall volume of participation across all word categories.

Brand Community Participation

H1a, Hlb, H2a, and H2b provide a summary of the relationships between leadership, followership, and different windows of participation in the brand community. More specifically, consumers who have higher levels of participation in the months prior to the group conversation, and lower levels of participation at the same time as the group conversation are more likely to be identified as leaders of that conversation (coaches). Consumers who have higher levels of participation in the same month as the group conversation, and lower levels of participation in the months prior to the group conversation are more likely to be identified as followers of the conversation (cheerleaders)

H1a: Higher (lower) levels of brand community participation in the time prior to the group conversation (t-) increase (decrease) the likelihood of being identified as leaders of the conversation.

H1b: Higher (lower) levels of brand community participation in the same time as the group conversation (t) decrease (increase) the likelihood of being identified as leaders of the conversation.

H2a: Higher (lower) levels of brand community participation in the time prior to the group conversation (t-) decrease (increase) the likelihood of being identified as followers of the conversation.

H2b: Higher (lower) levels of brand community participation in the same time as the group conversation (t) increase (decrease) the likelihood of being identified as followers of the conversation.

Rival Brand Community Participation

In addition to brand community participation, rival brand community participation has been shown to have an influence on different marketing outcomes. Traditionally, brand community members are less likely to participate in rival brand communities (Muniz, Jr. and O'Guinn 2001). However, brand community leaders or followers of the conversation may differ in their participation within the rival brand community. Leaders of the community conversation may be more likely to develop expertise and seek out alternative perspectives from the rival brand community on concepts or ideas that are still under debate. They are less likely to be prototypical group members, and thus less concerned with in-group community behavior. Followers of the community conversation are more likely to be prototypical group members, and thus less likely to participate in the rival brand community out-group (Hogg and Terry 2000).

H3a: Higher (lower) levels of rival brand community participation in the time prior to the group conversation (t-) increase (decrease) the likelihood of being identified as leaders of the conversation.

H3b: Higher (lower) levels of rival brand community participation in the same time as the group conversation (t) increase (decrease) the likelihood of being identified as leaders of the conversation.

H4a: Higher (lower) levels of rival brand community participation in the time prior to the group conversation (t-) decrease (increase) the likelihood of being identified as followers of the conversation.

H4b: Higher (lower) levels of rival brand community participation in the same time as the group conversation (t) decrease (increase) the likelihood of being identified as followers of the conversation.

Brand Community Concentration

Brand community members can engage in conversations within the brand community, within rival brand communities, or across both, Consumers with a higher level of participation concentration in the brand community are more likely to be engaging in conversation with other brand members. These consumers may take on a coach leadership role and debate within the community the advantages and disadvantages of the brand. Alternatively, consumers with a lower concentration in the brand community are more likely to be a follower of the brand conversation. These consumers take on a cheerleader follower role and reinforce the commonly accepted group prototype. Furthermore, these individuals are more likely to enter rival brand communities in an attempt to evangelize and recruit to their preferred brand community (Schau, Muñiz Jr, and Arnould 2009), resulting in low concentration (rival brand members) consumers actively engaging in the brand community following idea adoption by the group.

H5a: Higher (lower) levels of brand community participation concentration in the time prior to the group conversation (t-) increase (decrease) the likelihood of being identified as leaders of the conversation.

H5b: Higher (lower) levels of brand community participation concentration in the same time as the group conversation (t) increase (decrease) the likelihood of being identified as leaders of the conversation.

H6a: Higher (lower) levels of brand community participation concentration in the time prior to the group conversation (t-) decrease (increase) the likelihood of being identified as followers of the conversation.

H6b: Higher (lower) levels of brand community participation concentration in the same time as the group conversation (t) decrease (increase) the likelihood of being identified as followers of the conversation.

Product Category Participation

The role that product category community participation has on brand community members has been little studied in the literature. There is some evidence to suggest that brand community members for some products will attempt to evangelize or recruit product category members. Given the role that evangelizing and recruitment play in prototypical group member behavior, it is logical to expect a higher level of activity in the product category community following adoption of a brand community prototype by group followers. These same followers are less likely to engage in these product category conversations prior to adoption of a common message by the group (Hogg and Terry 2000). Alternatively, brand leaders may make forays into the product category forums in the period prior to group adoption of a prototypical message in order to gather information and develop expertise. Yet once that message has been crafted and adopted by the group, their participation in the product category community is likely to decrease.

> H7a: Higher (lower) levels of product category community participation in the time prior to the group conversation (t-) increase (decrease) the likelihood of being identified as leaders of the conversation.
>
> H7b: Higher (lower) levels of product category community participation in the same time as the group conversation (t) decrease (increase) the likelihood of being identified as leaders of the conversation.
>
> H8a: Higher (lower) levels of product category community participation in the time prior to the group conversation (t-) decrease (increase) the likelihood of being identified as followers of the conversation.

H8b: Higher (lower) levels of product category community participation in the same time as the group conversation (t) increase (decrease) the likelihood of being identified as followers of the conversation.

Product Category Participation Concentration

Similarly to brand community participation concentration, community members who have a higher concentration of participation in the brand community compared to the product community are more likely to be engaging in conversation with other brand members, debating the advantages and disadvantages of the brand, and thus adopting the coach leadership role in the community. Alternatively, consumers with a higher concentration in the product category community are more likely to be a follower of the brand conversation, adopting the cheerleader follower role by participating in the product category community in an attempt to evangelize and recruit to their preferred brand community (Schau, Muñiz Jr, and Arnould 2009).

H9a: Higher (lower) levels of product category community participation concentration in the time prior to the group conversation (t-) decrease (increase) the likelihood of being identified as leaders of the conversation.

H9b: Higher (lower) levels of product category community participation concentration in the same time as the group conversation (t) decrease (increase) the likelihood of being identified as leaders of the conversation.

H10a: Higher (lower) levels of product category community participation concentration in the time prior to the group conversation (t-) increase (decrease) the likelihood of being identified as followers of the conversation.

H10b: Higher (lower) levels of product category community participation concentration in the same time as the group conversation (t) increase (decrease) the likelihood of being identified as followers of the conversation.

Empirical Study

Data were collected from online forums, an established context to study brand community behavior (Muniz, Jr. and O'Guinn 2001; Schau, Muñiz Jr, and Arnould 2009; Thompson and Sinha 2008). Online forums are internet based message boards where individuals create accounts and engage in written discussions with other members. Discrete 3D computer graphics cards (often referred to as video cards) were chosen as the product category from which brand community behavior was collected. Selection of the category was driven by the overwhelming dominance by two competitive brands (ATI and Nvidia), and thus two clear rival brand communities, and an established body of research utilizing the category as a rich source of brand community interactions (Thompson, Kim, and Smith 2015; Thompson and Sinha 2008). Choosing a study context with exactly two, relatively balanced brands provides a clearer investigation of the effects and influences of brand and rival brand communities. The same effects should be evidenced in industries with more dominant brands, though the effects of specific rivals would make it more difficult to observe and separate the effects.

Discussions in the brand forums provided an opportunity to examine the adoption and abandonment of specific word categories or topics, demonstrating the presence of traditional markers of brand community: consciousness of kind, rituals and traditions, and moral responsibility (Muniz, Jr. and O'Guinn 2001). Identification of these same word topics allows for an investigation of the leaders and followers of these topics within the brand community, and facilitates an investigation into the characteristics of these leaders and followers in the context of brand community interaction.

Sample

All messages posted in the three forums (ATI, Nvidia, and Video Cards) were collected, as well as all messages in the General forum that could provide control variables to future models. The posting data permitted the creation of a consumer level dataset that includes individual levels of community participation (how much and how often consumers posted in the different communities), community membership duration (how long a consumer had been an active member of the different communities), and community discussion leadership for each individual over a number of years.

From the four identified forums (ATI, Nvidia, Graphic Cards, General) a total of 874,105 messages were collected from 30,267 unique users across a 60 month period from January 2007 to December 2011. This time period was selected because it represented a time in the industry where innovation and competition were especially high, resulting in a healthy volume of forum discussion around product and rival product changes. The increased volume reflects a period of brand identity formation and change that makes it easier to capture leaders and followers in conversation topics over the five year timespan. In order to allow for different populations and different trends in leadership across the two brands, a separate dataset was created for each brand. Any individual who made at least one post in the brand forum during the 60 month study window was included in that brand dataset. Individuals who made a post in both the ATI and Nvidia brand forums were included in both brand datasets, though with separate and appropriate data values for their ATI vs Nvidia forum interaction.

The data was aggregated at the monthly level to reflect the fact that the social identity processes that govern brand community engagement and interaction do not occur instantaneously (Hogg and Abrams 2003). Furthermore, aggregating at the monthly level minimizes the impact of seasonal effects in these kinds of data that frequently occur around weekends, holidays, and other periods that reflect the leisure nature of the product category.

Measuring Community Leadership

Capturing community leadership at the individual level proved a challenging task given the subtle and shifting nature of leadership. While much of the previous literature in brand communities has identified leaders as the most vocal or most active members, social identity theory suggests that leadership in identify formation and leadership in identity reinforcement are embodied in different individuals. This distinction in leadership is inherently tied to the timing of identity-driven conversations.

Leaders in identity formation (coaches) introduce new ideas and debate those topics in order to generate group consensus for adoption. In contrast, leaders in identity reinforcement (cheerleaders) follow already accepted topics and simply amplify adoption by the rest of the community. Thus, in order to study the leadership of social identify through ideas and topics in a brand community, a measure of leadership must capture the timing of certain conversation topics by both the group and specific individuals. Identifying individuals that discuss a topic prior to the group will identify coaches (idea leaders), and identifying those that discuss a topic at the same time or after the group will identify cheerleaders (idea followers).

Such a measure necessitates the identification of the ideas or word topics being discussed within the brand community, both at the group level and the individual level. To facilitate this identification, quantitative content analysis was conducted on all messages within the brand forums during the study window. As noted, separate content analyses were conducted for the two different brand forums to accommodate different word topics developing between the brands. Topic identification was conducted utilizing the LIWC dictionary and supplemented with a Custom Graphic Card dictionary created for the purposes of this analysis.

The LIWC dictionary is a psycho-linguistic word dictionary that captures over 70 linguistic dimensions and has been developed and utilized throughout a large body of academic research (Pennebaker, Mehl, and Niederhoffer 2003). The Custom Graphic Card (CGC) dictionary was created by combining marketing materials released by ATI and Nvidia with a pair of experts in the graphics card product market (one of which was the author) to identify features and performance metrics specific to graphic cards and absent from the traditional LIWC dictionary.

Applying the LIWC-CGC dictionary to messages in each of the two brand forums generated a collection of word categories or topics. As an example, one category/topic from the LIWC dictionary was 'money', which identified whenever a consumer discussed something related to money or dollars in the forums. One category/topic from the CGC dictionary was 'multi-card', which identified whenever a consumer discussed using more than one graphic card in a single computer, a product innovation that was introduced to the market during the study window.

By identifying each time a consumer discussed each word category/topic, a count was calculated that captured how many total posts discussed the category/topic for each month. This monthly count was captured for each individual, and for the group as a whole so that individual word category use could be compared to overall group level word use. Selection of which word categories or topics to analyze further was based on the most frequently discussed topics. For the collected study window, these word categories included ‘multi-card’ (support for multiple graphic cards), ‘multi-monitor’ (multiple monitor support), ‘frame-rate’ (number of display frames rendered per second), ‘image quality’, ‘temperature’, and ‘money’. These categories/topics capture innovations and performance metrics of importance to the product category during the study window.

As noted previously, one way to identify leaders would be to identify those individuals whose word category usage precedes the word category usage of the group as a whole. This conception provides the advantage of not only identifying when the community adopts a word topic by observing an increase in word usage, but also when it abandons a topic by observing a decrease in word usage, and identifying the leaders and followers of that adoption or abandonment based on when their word use pattern most closely matches the group word use pattern. Word topic usage patterns were first calculated by taking the proportion of posts in which a topic was discussed compared to the total posts for each period, and these word topic proportions were calculated for each individual as well as for the group as a whole.

In an effort to measure the degree of leadership or followership in topic discussion, a score was calculated to capture when the individual’s pattern of word topic usage most closely matched the group’s pattern of word topic usage. The individual’s pattern of word usage from three periods preceding the current period, through to three periods following the current period were considered (three month windows of participation have been used in previous brand community literature and drove period selection). The group pattern of word usage (proportion of word topic usage out of total discussion) at the current time period was subtracted from the individual patterns of word usage (proportion of word topic usage out of total discussion) for each of those seven time periods. The time period closest to zero (where group and individual word usage patterns were most similar) was recorded as that individual's leadership score.

These leadership scores thus ranged from -3 to 3, representing the three periods preceding the current period (-3 to -1), the current period (0), and the three periods following the current period (1 to 3). As an example, an individual whose proportion of word topic usage at 2 periods preceding the current period most closely matched the group proportion of word topic usage at the current period would be coded as a -2. These scores were calculated for each individual, for each word topic, for each month after they had made their first post in the brand forum over the 60 month observation window.

$$Leadership_{it} = \min_{x=-3,\ldots,3} \left| \left(\frac{Word\ Topic\ Post\ Count_{i,t+x}}{Total\ Post\ Count_{i,t+x}} \right) - \left(\frac{Word\ Topic\ Post\ Count_{\mu t}}{Total\ Post\ Count_{\mu t}} \right) \right|$$

where i=1,…,n individuals, t=1,…,t time points, μ is the mean group score, and x= -3,…,3 time periods offset from t, where 0 is the current period.

Representing leadership as a comparison of the individual word usage pattern to the group word usage pattern provided a number of advantages. First, it allowed individuals to change in their leadership over time, across different product releases.

More than five major product releases occurred for each brand in the five year observation window, and the above calculation of leadership allowed individuals to display greater or lesser leadership depending on their engagement with each release. Second, it allowed leadership to differ across different word topics. Some consumers may exhibit leadership qualities around one word topic, but not around others. Third, it provided the opportunity to examine not only individual word topic leadership, but also overall leadership by combining the different similarity scores across different word topics. Finally, the formulation of similarity from -3 to 3 means that both leadership and followership can be studied. The more negative this value, the more the individual is engaged in word topic leadership (i.e. coach) and the more positive this value, the more the individual is engaged in word topic followership or amplification (i.e. cheerleader).

Measures

Detailed descriptions of the leadership and other measures collected for analysis follow. Brand and competitor measures were collected for both brand product datasets (ATI and Nvidia). In the effects that follow, for ATI, the focal brand is ATI and the competitor brand is Nvidia, while for Nvidia, the focal brand is Nvidia and the competitor brand is ATI. Descriptive statistics can be found in Table 4.1. Correlations for ATI and Nvidia can be found in Table 4.2 and Table 4.3 respectively.

Leadership and Followership. An overall leadership score for each consumer for each month was calculated by summing each of the six word category leadership scores for each consumer. This generated a score that ranged from -18 to 18 for each month. This aggregation was conducted to facilitate an analysis of overall community leadership.

While individuals may take a stronger leadership role on some word topics than others, it is their overall community leadership that is of interest to this study.

Furthermore, the individual word category leadership scores are ordinal, not interval values. An individual with a score of -2 in leadership is not twice as high in their leadership activities as an individual with a -1 in leadership. In order to reflect this more ordinal nature at the aggregate level, and to facilitate an ordinal analysis of the data, the overall leadership score was reduced in range.

Leadership was constructed to create a rank ordered measure of leadership, reflective of the categorical but ordered nature of leadership. A scale from 0-3 was constructed where overall leadership scores (ranging from -18 to 18 for strong leaders to strong followers) from 0 to 18 were coded as a 0, -1 to -6 was coded as a 1, -7 to -12 was coded as a 2, and -13 to -18 was coded as a 3. Thus, consistent leaders (i.e. coaches) across all six word topics received a three while consistent followers (i.e. cheerleaders) across all six word topics received a zero. This construction created a score that captured leadership across all six word categories, but scaled the value to match the original conception around the three period window.

A similar rank ordered measure of followership was constructed where overall leadership scores (ranging from -18 to 18 for strong leaders to strong followers) from 0 to -18 were coded as a 0, 1 to 6 was coded as a 1, 7 to 12 was coded as a 2, and 13 to 18 was coded as a 3. Thus, consistent followers (i.e. cheerleaders) across all six word categories received a three while consistent leaders (i.e. coaches) across all six word categories received a zero.

Community participation (current month). Four different forum participation variables were collected for the current month period. The number of posts made in the brand forum, the competitor forum, the product category forum (graphic cards) and the general forum were collected as concurrent measures of participation. These measures reflect current brand community participation and match measures commonly used by marketing managers to measure brand community engagement.

Community participation (previous 3 months). Three different forum participation variables were collected for the three months prior to the current month period. The number of posts made in the brand forum, the competitor forum, and the product category forum (graphic cards) in the previous three months were collected as measures of participation. These measures reflect long term participation and match how brand community participation has been measured in the literature (Thompson, Kim, and Smith 2015; Thompson and Sinha 2008).

Brand community concentration. The proportion of a consumer's participation in the brand forum relative to the competitor forum was captured to examine brand community concentration. This variable was created by first calculating the number of total posts made in both brand forums, and then computing the proportion of posts for both the brand and competitor forums over the combined total. Finally the competitor forum proportion was subtracted from the brand forum proportion to obtain a value that ranged from 1 to -1. A score of 1 would represent an individual who posted exclusively in the brand forum, while a score of -1 would indicate an individual who posted exclusively in the competitor forum. A score of 0 would reflect an individual who posted equally in both forums. These measures were collected for both the current month period and the previous three month period.

$$Brand\ Community\ Concentration_{it} = \left(\frac{Brand_{it}}{Brand_{it} + Competitor_{it}}\right) - \left(\frac{Competitor_{it}}{Brand_{it} + Competitor_{it}}\right)$$

Product category community concentration. The proportion of a consumer's participation in the product category forum relative to their participation in both brand forums was captured to examine product category community concentration. Similar to the brand concentration metric, the total number of posts across the product category forum and both brand forums were collected, and then a proportion of posts for both the product category forum and combined brand forums over the calculated total were computed. Finally, the combined brand forum proportion was subtracted from the product category proportion to obtain a value that ranged from 1 to -1. A score of 1 would indicate an individual who posted exclusively in the product category forum, while a score of -1 would indicate an individual who posted exclusively in the brand forums. A score of 0 would reflect an individual who posted equally in the product category forum and the combined brand forums. These measures were collected for both the current month period and the previous three month period.

$$Prod.Cat.Community\ Concentration_{it} = \left(\frac{Prod.Cat._{it}}{Prod.Cat._{it} + Brand_{it} + Competitor_{it}}\right) - \left(\frac{Brand._{it} + Competitor_{it}}{Prod.Cat._{it} + Brand_{it} + Competitor_{it}}\right)$$

Membership duration. The amount of time that a community member has been engaged in some level of interaction within the community provides an alternate measure of brand community investment. Previous research in group membership has found that the longer a member has been involved in a group, the higher their level of identification with that group (Ashforth and Mael 1989; Bhattacharya, Rao, and Glynn 1995). Furthermore, brand community research has established that the longer a member has been a member of a community, the more likely they have achieved a position of status within the community. In order to control for this influence, the number of days since a consumer's first post in each of the brand, competitor, and product category forums were collected. These measures were scaled to represent 10's of days.

Forum activity. The overall number of posts made by the entire brand community was captured as a control for overall forum activity. This measure was scaled to represent 10's of posts.

A visual overview of the timing of leadership, followership, and participation in the community is included in Figure 4.1 for clarification, where t represents the current period.

Model and Estimation

The rank ordered measures of leadership and followership calculated in the study capture the non-continuous but ordered nature of these phenomenon. Therefore, an ordered logistic regression model approach was adopted (Woolrdige 2010). The separate formulations of leadership versus followership ensured that separate models could be estimated and differential effects on leadership versus followership could be investigated.

As a result of collecting data from the forums each month for 60 months, multiple measures of leadership and followership exist for every individual in the dataset, and for each time point in the dataset. In order to correct for these potential sources of bias, panel ordered logistic regressions with random effects were estimated for all models (Baltagi 2013).

The ordered logistic regression models the ordinal dependent variable as an unobserved latent continuous variable with cutpoints at each of the borders between ordinal categories. The ordered logistic regression model is characterized as follows:

$$Leadership_{it} = \begin{cases} 0 \ if \ Leadership^*_{it} \leq \mu_1 \\ 1 \ if \ \mu_1 < Leadership^*_{it} \leq \mu_2 \\ 2 \ if \ \mu_2 < Leadership^*_{it} \leq \mu_3 \\ 3 \ if \ \mu_3 < Leadership^*_{it} \end{cases}$$

where $Leadership_{it}$ is the observed leadership score for each consumer at each time point, $Leadership^*_{it}$ is the unobserved latent continuous leadership for each consumer at each time point, and μ_1, μ_2, μ_3 are the cutpoints between the observed categories.

$$Followership_{it} = \begin{cases} 0 \ if \ Followership^*_{it} \leq \mu_1 \\ 1 \ if \ \mu_1 < Followership^*_{it} \leq \mu_2 \\ 2 \ if \ \mu_2 < Followership^*_{it} \leq \mu_3 \\ 3 \ if \ \mu_3 < Followership^*_{it} \end{cases}$$

where $Followership_{it}$ is the observed followership score for each consumer at each time point, $Followership^*_{it}$ is the unobserved latent continuous followership for each consumer at each time point, and μ_1, μ_2, μ_3 are the cutpoints between the observed categories.

As noted above, the unobserved latent continuous values of Leadership and Followership are the actual variables modeled in an ordered logistic regression. Thus, the models for the latent continuous processes for Leadership and Followership are characterized as follows:

$$Leadership^*_{it} = \beta_1 \ Brand \ Participation(current)_{it} + \beta_2 \ Competitor \ Participation(current)_{it} + \beta_3 \ Product \ Category \ Participation(current)_{it} + \beta_4 \ Brand \ Post \ Proportion(current)_{it} + \beta_5 \ Product \ Category \ Post \ Proportion(current)_{it} + \beta_1$$

$$Brand\ Participation(3month)_{it} + \beta_2\ Competitor\ Participation(3month)_{it} + \beta_3\ Product\ Category\ Participation(3month)_{it} + \beta_4\ Brand\ Post\ Proportion(3month)_{it} + \beta_5\ Product\ Category\ Post\ Proportion(3month)_{it} + \beta_{11}\ Brand\ Membership\ Duration_{it} + \beta_{12}\ Competitor\ Membership\ Duration_{it} + \beta_{13}\ Product\ Category\ Membership\ Duration_{it} + \beta_{14}\ Total\ Participation(current)_{it} + \beta_{15}\ Forum\ Postcount_t + \nu_i + \varepsilon_{it}$$

$$Followership^*_{it} = \beta_1\ Brand\ Participation(current)_{it} + \beta_2\ Competitor\ Participation(current)_{it} + \beta_3\ Product\ Category\ Participation(current)_{it} + \beta_4\ Brand\ Post\ Proportion(current)_{it} + \beta_5\ Product\ Category\ Post\ Proportion(current)_{it} + \beta_1\ Brand\ Participation(3month)_{it} + \beta_2\ Competitor\ Participation(3month)_{it} + \beta_3\ Product\ Category\ Participation(3month)_{it} + \beta_4\ Brand\ Post\ Proportion(3month)_{it} + \beta_5\ Product\ Category\ Post\ Proportion(3month)_{it} + \beta_{11}\ Brand\ Membership\ Duration_{it} + \beta_{12}\ Competitor\ Membership\ Duration_{it} + \beta_{13}\ Product\ Category\ Membership\ Duration_{it} + \beta_{14}\ Total\ Participation(current)_{it} + \beta_{15}\ Forum\ Postcount_t + \nu_i + \varepsilon_{it}$$

where i=1,...,n individuals, t=1,…,t time points, and ν_i is a panel-level random effect

In order to address potential serial autocorrelation in the data a Woolridge Autocorrelation test (Woolrdige 2010) was conducted for both Leadership and Followership in both the ATI and Nvidia models. All four tests indicated that significant autocorrelation was present in the data (test result reported at bottom of Table 4.4). Huber/White/sandwich estimators were thus implemented in all models to correct for the autocorrelation (Woolrdige 2010), which takes into account the variance of the disturbances when calculating the estimators, resulting in a more conservative estimate of significance.

Results

Separate analysis were conducted for the ATI and Nvidia forums to reflect the different processes potentially present in different communities, though the results are similar. The results discussion will collapse across the specific brands under study and simply focus on the brand/competitor relationships. The brand community leaders will be examined first, followed by the brand community followers. Complete model results for the individual brands can be found in Table 4.4.

Brand Leaders

The ATI and Nvidia Leader models both provide a significantly better fit to the data than a constants only model (ATI: Wald (18) = 1871.1, $p < .001$; Nvidia: Wald (18) = 1715.8, $p < .001$). The panel-level variance value demonstrates there is a unit-level effect (ATI: .169; Nvidia: .242) (Baltagi 2013), and that its influence is accounted for with the panel ordered logistic regression, further justifying the selection of that model.

Brand Participation. Both current month and previous three month versions of brand participation have significant, though opposite influences on the likelihood of a consumer being categorized as a leader. Current month brand participation has a negative influence on being categorized as a leader (ATI: $\beta = -.062$, $p < .001$; Nvidia: $\beta = -.062$, $p < .001$), while previous three month brand participation has a positive influence on being categorized as a leader (ATI: $\beta = .031$, $p < .001$; Nvidia: $\beta = .035$, $p < .001$).

These results suggest that the conversation of brand community leaders differs from the brand community itself. Specifically, brand community leader conversation patterns lead the brand community rather than mirror the brand community. This pattern of results provides support for H1, that brand community leaders are less engaged in brand identity reinforcement, and more engaged in the introduction and exploration of new ideas.

Competitor Participation. The influence of current month competitor participation is mixed with no apparent influence observed in the ATI community, though a weak but positively significant effect on being categorized as a leader in the Nvidia community (Nvidia: $\beta = .009$, $p < .001$). An examination of the previous three month version of competitor participation reveals a significant and positive influence on the likelihood of being categorized as a leader (ATI: $\beta = .006$, $p < .05$; Nvidia: $\beta = .009$, $p < .001$). These results suggest that brand leaders engage with the rival brand community, especially in the months prior to the brand community adopting a set of ideas. This provides support for H3 that brand community leaders develop expertise outside the focal brand community in order to better assess trends in the brand community.

Brand Concentration. Current month brand concentration leader (ATI: $\beta = .293$, $p < .001$; Nvidia: $\beta = .371$, $p < .001$) and previous three month brand concentration leader (ATI: $\beta = .834$, $p < .001$; Nvidia: $\beta = .891$, $p < .001$) both appear to have positive and significant influences on the likelihood of being categorized as a leader. These results provide support for H5 that brand leaders are predominantly focused on in-group conversation both during the current period and in the period leading idea adoption or abandonment by the brand community.

An examination of the pattern of results across brand participation, competitor participation, and brand concentration reveals an interesting story. Brand leaders essentially focus their activity to the months leading idea adoption or abandonment by the community, and their conversation is predominantly focused inside the brand community. However they are likely to seek out information and explore opinions outside the brand community.

Product Category Participation. An examination of the product category effects reveal a mixed set of results between the current period and the prior three month period that match the findings from brand participation. Current month product category participation has a negative and significant effect on the likelihood of being categorized as a leader (ATI: $\beta = -.013$, $p < .001$; Nvidia: $\beta = -.015$, $p < .001$). Previous three month product category participation has a significant positive influence on the likelihood of being categorized as a leader (ATI: $\beta = .013$, $p < .001$; Nvidia: $\beta = .009$, $p < .001$). These results mirror those of brand participation and provide support for H7, that brand leaders seek out information and develop expertise outside the brand community in the months leading brand community idea adoption or abandonment, but decrease their activity outside the brand once the community has agreed on a common set of ideas.

Product Category Concentration. Current month product category concentration (ATI: $\beta = .422$, $p < .001$; Nvidia: $\beta = .640$, $p < .001$) and previous three month product category concentration (ATI: $\beta = 1.271$, $p < .001$; Nvidia: $\beta = 1.515$, $p < .001$) both have a significant and negative influence on the likelihood of being categorized as a leader. These results provide support for H9, that brand leaders focus their concentration within the brand community rather than outside the community.

Comparing these results to the brand and competitor participation effects further reinforce the concept of a brand leader who is focused on conversations within the brand community during the months preceding idea adoption or abandonment. However, these brand leaders seek out information from the product category community to help formulate ideas and opinions in the months leading brand community conversation.

Membership Duration. An investigation of all three measures of membership duration indicate that brand membership duration has a significant positive effect on the likelihood of being categorized as a leader (ATI: $\beta = .003$, $p < .001$; Nvidia: $\beta = .003$, $p < .001$), and that competitor membership duration (ATI: $\beta = -.001$, $p < .001$; Nvidia: $\beta = -.001$, $p < .05$) and product category member duration (ATI: $\beta = -.001$, $p < .001$; Nvidia: $\beta = -.002$, $p < .001$) have significant negative effects on the likelihood of being categorized as a leader in the focal forum. A longer membership in the brand community and a shorter membership in the competitor brand community and product category community provide additional evidence that brand leaders are primarily focused inwards to the brand community.

Brand Followers

The ATI and Nvidia Follower models both provide a significantly better fit to the data than a constants only model (ATI: Wald (18) = 1844.8, $p < .001$; Nvidia: Wald (18) = 1669.9, $p < .001$). The panel-level variance value demonstrates there is a unit-level effect (ATI: .462; Nvidia: .461), and that its influence is accounted for with the panel ordered logistic regression, further justifying the selection of that model.

Brand Participation. Current month and previous three month brand participation have significant and opposite influences on the likelihood of a consumer being categorized as a follower. The pattern of results is exactly opposite from that of leaders however. Current month brand participation has a positive influence on being categorized as a follower (ATI: $\beta = .034$, $p < .001$; Nvidia: $\beta = .040$, $p < .001$), while previous three month brand participation has a negative influence on being categorized as a follower (ATI: $\beta = -.032$, $p < .001$; Nvidia: $\beta = -.025$, $p < .001$).

These results suggest that brand followers take an active role in the current month group conversation, but fail to engage in conversation when the group consensus is being formed, providing support for H2. These consumers effectively amplify previously introduced ideas and values that have already been adopted by the brand community.

Competitor Participation. Current month competitor participation has mixed results across brands. Competitor participation in the ATI brand community has no apparent influence on likelihood of being categorized as a follower, and competitor participation in the Nvidia brand community has a weak but significantly negative influence on the likelihood of being categorized as a follower (Nvidia: $\beta = -.010$, $p < .01$). An examination of previous three month versions of competitor participation reveals a similar pattern with no effect for the ATI community, and a significant negative influence for the Nvidia community (Nvidia: $\beta = -.011$, $p < .001$). These results provide support for H4, suggesting that brand followers are more likely to be prototypical group members, and thus less likely to participate in the rival brand community.

Brand Concentration. Current month brand post concentration has a significant negative influence on the likelihood of being categorized as a follower (ATI: $\beta = -.410$, $p < .001$; Nvidia: $\beta = -.510$, $p < .001$), as does previous three month brand post concentration (ATI: $\beta = -.884$, $p < .001$; Nvidia: $\beta = -1.013$, $p < .001$). These results provide support for H6, and suggest that brand followers are more likely to interact in the rival brand community than they are in the focal brand community.

The combination of results from brand participation, competitor participation and brand concentration paint a unique picture. Brand followers are more active within the brand community during the current and subsequent months, yet a higher proportion of their posts occur in the rival brand forums. These results suggest two potential groups of consumers could comprise brand followers: brand loyalists trying to spread the word in rival forums, and rival brand loyalists trying to spread the word in the focal forum.

Product Category Participation. An examination of the product category effects reveal a mixed set of results that are again nearly identical to the brand participation measures. Current month product category participation has a positive and significant effect on the likelihood of being categorized as a follower (ATI: $\beta = .008$, $p < .05$; Nvidia: $\beta = .006$, $p < .05$). Previous three month product category participation has a significant negative influence on the likelihood of being categorized as a follower (ATI: $\beta = -.017$, $p < .001$; Nvidia: $\beta = -.012$, $p < .001$). These results mirror those of brand participation and provide support for H8, suggesting that brand followers are engaging in evangelizing or recruitment behavior in the product category community.

Product Category Concentration. Current month product category concentration (ATI: $\beta = .323$, $p < .001$; Nvidia: $\beta = .442$, $p < .001$) and previous three month product category concentration (ATI: $\beta = .823$, $p < .001$; Nvidia: $\beta = .795$, $p < .001$) have a significant and positive influence on the likelihood of being categorized as a follower. Supporting H10, these results provide further evidence that brand followers are engaging in evangelizing and recruitment behavior in the product category communities regardless of whether these consumers are brand loyalists or rival brand loyalists.

Membership Duration. An investigation of all three measures of membership duration indicate that brand membership duration has a significant negative effect on the likelihood of being categorized as a follower (ATI: $\beta = -.004$, $p < .001$; Nvidia: $\beta = -.004$, $p < .001$). Competitor membership duration has a significant positive effect on the likelihood of being categorized as a follower, though for ATI only (ATI: $\beta = -.002$, $p < .01$). Finally, product category membership duration has a significant positive effect on the likelihood of being categorized as a follower (ATI: $\beta = .001$, $p < .01$; Nvidia: $\beta = .002$, $p < .01$). A longer membership in the competitor brand community and in the product category community, combined with a shorter membership in the brand community provide some clarity that brand followers are more likely to be associated with either the rival brand community or with the product category community.

Discussion

Brand community leadership has been little studied, and based on the results from this study, incorrectly misunderstood by practitioners. Leaders of brand community conversation do not appear to be the more vocal, active consumers, engaged heavily in conversation with the rest of the community about current trends. Instead, leaders of brand community conversation are more likely to gather information from alternative communities, including rival brand communities and the product category community. Despite their relatively increased presence outside the brand community, their activity is concentrated within the community. Furthermore, their activity typically precedes group acceptance of a word topic by many months.

These findings provide further support that these leaders of word topics and conversation in the brand community act as coaches, planning and discussing issues prior to the rest of the community. These individuals help to introduce new ideas, assess those new ideas, and establish potential common concepts that form the basis for future changes to the group prototype. These individuals are not perceived as ideal group members however. Their engagement with the rival brand community and with the product category community to gather information for idea formation and assessment marks them as potential deviant group members.

In contrast, brand community followers comprise two potential groups. One such group appears to be brand loyalists who interact within the brand community, but do so predominantly when the rest of the community is discussing a topic, not prior to the group level conversation. The second potential group of brand followers are brand loyalists who actively enter the rival brand community in an attempt to evangelize and recruit to the preferred brand community.

Both groups of followers are potentially interesting and worthy of further study. The first group, brand loyalists, represent the type of individual traditionally targeted for marketing campaigns by managers. These individuals are vocal and active, though that activity occurs concurrently with the overall group conversation. They are more likely to be ideal group members, and therefore appear more prototypical to other group members, and it is from this prototypicality that their influence from others is derived. Despite the fact they are not involved in idea formation, these individuals play a critical role in reinforcing accepted group norms and crystalizing the prototype.

The second group, rival brand loyalists, however has unique and interesting implications for social identity theory and the brand community literature. The results would suggest that this second group of brand loyalists entering the rival brand community are entirely unsuccessful in their mission of proselytizing. They are entirely unsuccessful in redirecting the conversation, and thus establishing themselves as leaders of the discussion. Instead, these individuals actually adopt the language and conversation patterns of the rival brand community in their evangelizing attempts. The fact that they follow the conversation suggests that they use the same language as the rival brand community, and that they do so long after the leaders of that conversation have established group conversation trends.

The strategic decisions related to marketing campaigns designed to maximize reach by leveraging consumer-to-consumer connections are complex and dependent heavily on the goals of the firm and the structure of the industry. For firms who hold a strong existing position, and who introduce products that are fundamentally similar or related to products already released by the firm, a focus on cheerleaders might be the preferred strategy. These individuals can take an already accepted product and amplify the message already accepted by the community. Doing so can leverage those individuals' connections as prototypical group members to spread adoption of commonly accepted products.

However, if firms hold a weaker position in the market, or if they introduce products that are far different than previously released products, targeting cheerleaders will result in rejection of 'new' ideas and products by prototypical group members who prefer to embrace ideas or products already accepted by the group. In contrast, these firms would benefit from targeting coaches of brand thought and working with these types of consumers to more quickly assess the value of the new offering in anticipation of future adoption by the group.

Industry structure provides another interesting factor that may influence who marketers might want to target when implementing targeted community campaigns. Industries with frequent innovations or changes in the product offering are likely to cause communities to constantly evaluate those innovations or changes. Consumer assessment of different products and of new innovations are most likely to be done by coaches based on their early focus prior to community adoption. Thus, marketing managers in industries with frequent innovation may benefit from targeting coaches in brand communities, not cheerleaders.

Limitations and Future Research

Community leadership and followership in this study was examined in a single product category. While it is a product category that has been studied in past literature, and in which rich online community behavior has been demonstrated, future research should more fully explore other product categories. This is especially the case in order to explore influences such as industry volatility, and industry maturity, where innovation may drive differences in community leadership and followership.

Alternate dimensions of community leadership and followership should additionally be more fully investigated. This study focused predominantly on the timing of community participation as the primary contributor to leadership. However, some past research has cast a more important role for participation volume as a primary marker of leadership. Both dimensions of leadership are likely to be important contributors to leadership and followership. Future research should consider in what contexts timing plays a critical role, and in what cases volume provides the more important marker of leadership.

Conclusions

The age of the connected consumer is a ubiquitous characteristic of the movements towards online commerce and internationalization. Understanding how consumers interact with each other in addition to how they interact with the firm is critical in these environments, and leveraging the connectedness of certain consumers can provide firms with competitive advantages. Identifying how consumer leadership and followership develop in these online contexts is the first step in identifying influential online consumers, and eventually impacting the buying decisions of others by virtue of their more central position in a group, or of their knowledge brought to bear regarding a product.

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TABLE 4.1
DESCRIPTIVE STATISTICS

	ATI		Nvidia	
	Mean	**Standard Deviation**	**Mean**	**Standard Deviation**
Leader Similarity	.681	.614	.684	.580
Follower Similarity	.416	.584	.383	.548
Brand Participation (current month)	2.902	8.404	2.389	6.963
Competitor Participation (current month)	1.746	7.107	1.736	7.404
Product Category Participation (current month)	4.577	13.184	4.283	12.719
Total Participation (current month)	9.960	28.070	9.122	1316.12
Brand Concentration (current month)	.016	.294	..015	.277
Product Category Concentration (current month)	.011	.321	.014	.308
Brand Participation (previous 3 months)	8.550	19.437	7.420	16.984
Competitor Participation (previous 3 months)	4.757	16.754	4.603	16.552
Product Category Participation (previous 3 months)	12.242	31.440	11.778	30.177
Brand Concentration (previous 3 months)	.031	.367	.037	.354
Product Category Concentration (previous 3 months)	.011	.381	.017	.375
Brand Membership Duration	626.85	643.81	648.63	620.71
Competitor Membership Duration	762.02	663.17	634.93	631.13
Product Category Membership Duration	896.01	737.67	834.50	703.03
Forum Postcount	2799.29	1464.54	2721.41	1316.12

TABLE 4.2: CORRELATIONS (ATI)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**Leader Similarity**																
2	**Follower Similarity**	-.79 ***															
3	**Brand Participation (current month)**	-.05 ***	.05 ***														
4	**Competitor Participation (current month)**	-.01 *	.03 ***	.36 ***													
5	**Product Category Participation (current month)**	-.04 ***	.06 ***	.56 ***	.63 ***												
6	**Total Participation (current month)**	-.03 ***	.05 ***	.60 ***	.64 ***	.77 ***											
7	**Brand Concentration (current month)**	-.07 ***	.02 ***	.39 ***	.07 ***	.22 ***	.23 ***										
8	**Product Category Concentration (current month)**	-.01	.03 ***	.11 ***	.13 ***	.32 ***	.23 ***	.21 ***									
9	**Brand Participation (previous 3 months)**	.31 ***	-.17 ***	.40 ***	.23 ***	.33 ***	.32 ***	.24 ***	.14 ***								
10	**Competitor Participation (previous 3 months)**	.10 ***	-.03 ***	.23 ***	.50 ***	.40 ***	.37 ***	.09 ***	.16 ***	.41 ***							
11	**Product Category Participation (previous 3 months)**	.16 ***	-.07 ***	.33 ***	.43 ***	.54 ***	.47 ***	.18 ***	.23 ***	.62 ***	.70 ***						
12	**Brand Concentration (previous 3 months)**	.44 ***	-.42 ***	.14 ***	.06 ***	.12 ***	.12 ***	.27 ***	.19 ***	.34 ***	.06 ***	.19 ***					
13	**Product Category Concentration (previous 3 months)**	.00	.02 **	.09 ***	.11 ***	.14 ***	.14 ***	.18 ***	.31 ***	.10 ***	.12 ***	.28 ***	.22 ***				
14	**Brand Membership Duration**	.06 ***	-.03 ***	-.04 ***	.01 ***	-.03 ***	.01 ***	.00	.02 ***	.04 ***	.03 ***	.04 *	.04 ***	.09 ***			

15	**Competitor Membership Duration**	.02 ***	-.02 ***	-.05 ***	-.07 ***	-.06 ***	-.04 ***	-.08 ***	-.08 ***	.01 ***	.01 ***	.01 ***	.04 ***	.05 ***	.74 ***		
16	**Product Category Membership Duration**	.03 ***	-.02 ***	-.05 ***	-.01 ***	-.06 ***	-.02 ***	-.02 ***	-.01 ***	.02 ***	.02 ***	.02 ***	.05 ***	.08 ***	.76 ***	.83 ***	
17	**Forum Postcount**	-.04 ***	.00	.07 ***	.01 ***	.03 ***	.03 ***	.09 ***	.02 ***	.02 ***	.00	.01 ***	.03 ***	.01 ***	.02 ***	.04 ***	.04 ***

TABLE 4.3: CORRELATIONS (NVIDIA)

		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1	**Leader Similarity**																
2	**Follower Similarity**	-.82 ***															
3	**Brand Participation (current month)**	-.04 ***	.04 ***														
4	**Competitor Participation (current month)**	-.02 ***	.04 ***	.36 ***													
5	**Product Category Participation (current month)**	-.05 ***	.07 ***	.62 ***	.56 ***												
6	**Total Participation (current month)**	-.04 ***	.05 ***	.64 ***	.60 ***	.77 ***											
7	**Brand Concentration (current month)**	-.05 ***	.02 **	.41 ***	.06 ***	.24 ***	.24 ***										
8	**Product Category Concentration (current month)**	-.03 ***	.05 ***	.13 ***	.11 ***	.32 ***	.23 ***	.22 ***									
9	**Brand Participation (previous 3 months)**	.28 ***	-.16 ***	.48 ***	.23 ***	.39 ***	.36 ***	.25 ***	.15 ***								
10	**Competitor Participation (previous 3 months)**	.09 ***	-.03 ***	.23 ***	.42 ***	.34 ***	.32 ***	.09 ***	.14 ***	.41 ***							
11	**Product Category Participation (previous 3 months)**	.15 ***	-.06 ***	.41 ***	.34 ***	.53 ***	.47 ***	.21 ***	.23 ***	.70 ***	.62 ***						
12	**Brand Concentration (previous 3 months)**	.43 ***	-.43 ***	.15 ***	.06 ***	.13 ***	.12 ***	.26 ***	.20 ***	.34 ***	.05 ***	.21 ***					
13	**Product Category Concentration (previous 3 months)**	.01 **	.00	.11 ***	.09 ***	.14 ***	.14 ***	.19 ***	.30 ***	.12 ***	.10 ***	.27 ***	.24 ***				
14	**Brand Membership Duration**	.04 ***	-.03 ***	-.05 ***	.00	-.05 ***	.01 ***	-.04 ***	.00	.01 ***	.03 ***	.02 ***	-.01 ***	.06 ***			

15	**Competitor Membership Duration**	.01 **	-.01	-.05 ***	-.05 ***	-.05 ***	-.04 ***	-.10 ***	-.08 ***	.00 *	.02 ***	.00 *	-.02 ***	.03 ***	.75 ***		
16	**Product Category Membership Duration**	.02 **	-.01 *	-.05 ***	-.01 ***	-.06 ***	-.02 ***	-.05 ***	-.02 ***	.00 ***	.02 ***	.01 ***	.00 *	.05 ***	.81 ***	.79 ***	
17	**Forum Postcount**	-.01 *	.00	.08 ***	.02 ***	.04 ***	.03 ***	.10 ***	.01 ***	.03 ***	-.01 ***	.01 ***	.07 ***	.00 **	-.22 ***	-.20 ***	-.21 ***

TABLE 4.4

PANEL ORDERED LOGIT W/ ROBUST STANDARD ERRORS - BRAND LEADER AND FOLLOWER SIMILARITY RANK SCORES

Variable	**ATI Leader (0-3)**		**ATI Follower (0-3)**		**Nvidia Leader (0-3)**		**Nvidia Follower (0-3)**	
Brand Participation (current month)	-.062	***	.034	***	-.062	***	.040	***
Competitor Participation (current month)	.003		-.003		.009	*	-.010	**
Product Category Participation (current month)	-.013	***	.008	*	-.015	***	.006	*
Brand Concentration (current month)	.293	***	-.410	***	.371	***	-.510	***
Product Category Concentration (current month)	-.228	***	.323	***	-.316	***	.442	***
Brand Participation (previous 3 months)	.031	***	-.032	***	.035	***	-.025	***
Competitor Participation (previous 3 months)	.006	*	-.004		.009	***	-.011	***
Product Category Participation (previous 3 months)	.013	***	-.017	***	.009	***	-.012	***
Brand Concentration (previous 3 months)	.834	***	-.884	***	.891	***	-1.013	***
Product Category Concentration (previous 3 months)	-.672	***	.823	***	-.649	***	.795	***
Brand Membership Duration (10s of days)	.003	***	-.004	***	.003	***	-.004	***
Competitor Membership Duration (10s of days)	-.001	***	.002	**	-.001	*	.001	
Product Category Membership Duration (10s of days)	-.001	***	.001	**	-.002	***	.002	**
Total Participation (current month)	.001		.000		.000		.001	
Forum Postcount (10s of posts)	.000	*	-.0005	***	.000		.000	
Cutpoint 1	-.090	***	-.009	***	-.284	***	.316	***
Cutpoint 2	3.523	***	2.829	***	3.688	***	3.407	***

Cutpoint 3	6.403	***	5.185	***	6.787	***	5.964	***
Panel-level Variance	.169		.462		.242		.461	
Woolridge Autocorrelation F-Test	1220.2	***	1451.0	***	984.1	***	1338.6	***
Constants Only Model Comparison: Wald (df=18)	1871.0	***	1844.8	***	1715.8	***	1669.9	***

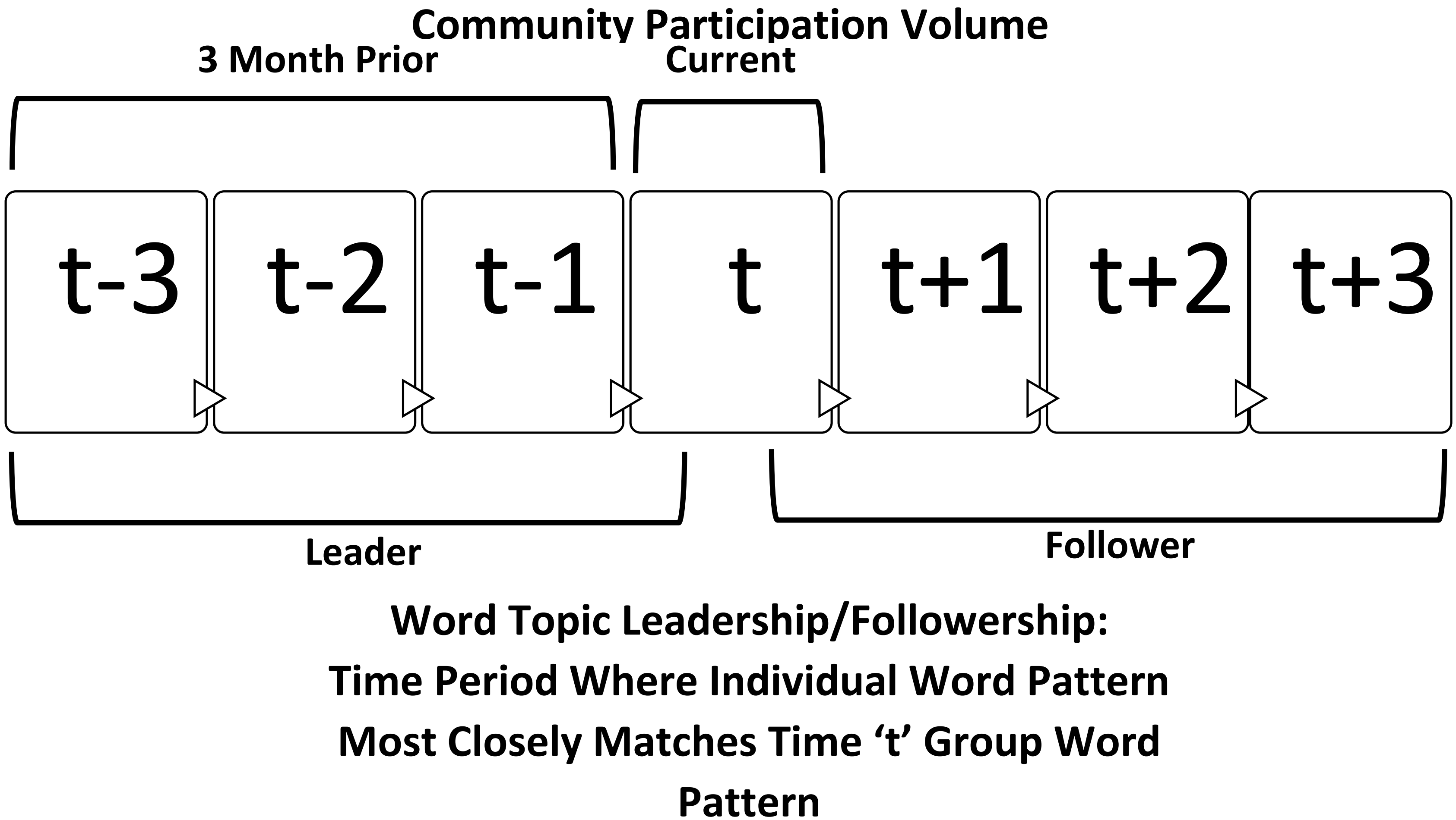

FIGURE 4.1
TIMING IN COMMUNITY PARTICIPATION VOLUME AND WORD TOPIC LEADERSHIP/FOLLOWERSHIP

CHAPTER 5

CONCLUSION

Some would argue that all of marketing is the act of influencing consumers to buy products and services. Yet the three essays in this dissertation demonstrate that consumers can play a far more involved role than simply being the target of marketing managers' actions. Furthermore, consumers are increasingly engaging in online communication, both with marketers and fellow consumers, and this engagement has the potential to influence the consumer's role in marketing strategy and marketing activities associated with a product, especially following the purchase of a product or service.

The trend towards digital products and online communication is not slowing down, and it is not unreasonable to consider that in less than a generation or two, any product or service that can be represented digitally will be available predominantly in digital form and/or in an online space. These essays begin to carve out an understanding of how consumers interact around these types of products, and within the online space differently than has been studied in the past, and lay out a groundwork for future research in digital products and online marketing.

Three primary themes run through each of these essays: digital product post-purchase engagement, post-purchase customer control of marketing, and online behavior. A return to these three themes provides an opportunity to consider the influence these essays can have on the literature and on marketing managers.

Digital Product Post-Purchase Engagement

The research in marketing on digital products is still in its infancy, with the majority of work focused on physical/digital product bundles. These essays begin to demonstrate, however, that there are key differences between digital goods and physical goods, and that these differences impact post-purchase engagement. Whether it be the imperishable nature of digital goods that has the potential to influence consumption, or the fact that digital goods can be more easily modified and changed following purchase, digital goods represent a different type of product when compared to physical goods.

Beyond the simple imperishable or modifiable nature of these goods, these essays further demonstrate that social interaction around these goods introduces a new factor that has the potential to change how consumers use these products. Consumers' social interactions are often mediated by the sales and consumption platforms associated with the products they use, and as these platforms (Amazon, Apple iTunes & App Store, Steam) become more popular, or become the solitary avenue for purchase, they play a more critical role in the consumer experience. These essays begin to investigate the role that social interaction and these platforms may have on the consumer experience.

Post-purchase Customer Control of Marketing

Whether it be influencing fellow consumers in shared consumption of a product, making changes to a firm's already released product, or influencing other consumers by identifying and sharing the key advantages/disadvantages of a product, it is clear that the consumer has a greater level of control over marketing actions than has typically been afforded in the past. Kozinets et. al. (2010) introduced the concept of the Networked Narrative, the idea that it is a network of consumers and marketers that together create marketing narratives about a product. Yet these essays begin to demonstrate that perhaps a Networked Narrative is too narrow a concept to capture the entire post-purchase picture.

Post-purchase customer control of marketing is perhaps better represented by an entire Networked Product Experience, wherein customers and marketers are engaged in shared activities that extend far beyond a product narrative. As demonstrated in these essays, shared product consumption, product development, and product communities all exist within a network of fellow consumers and marketers, and this network influences the actions of different parties in the network in different ways.

Online Behavior

The online environment has grown in recent years as a source of interest in the marketing literature and to marketing managers. Actual behavioral actions can be captured far more easily in an online space where everything is recorded. Consumer purchase behavior, consumption, product modification, and communication all occur online and provide insight beyond customer intentions to actual actions. These essays have demonstrated that online data collection techniques provide a window into consumer patterns of product use and customer interaction that are more difficult to capture offline.

In addition to leveraging online data collection techniques, these essays demonstrate that online communities play an important role in the product experience. Communities provide consumers the opportunity to influence fellow consumers in the same way that marketers do, through information and manipulation. However, these online communities provide far more than an avenue for social influence. Marketing managers can at best provide a one to one relationship with customers, and their ability to do this is limited by simple resources. The depth of any relationship between marketers and consumers is necessarily limited by the resources of the firm.

In contrast, online communities provide the opportunity to be a part of a group of fellow-minded consumers, with similar interests, values, and goals, at the least around a product, if not a lifestyle. These essays demonstrate that online communities have a significant influence on many different aspects of the consumer experience, from purchase and consumption to product modification and consumer-to-consumer interactions.

Future Research

While these essays establish the first steps in understanding digital product post-purchase engagement, post-purchase customer control of marketing, and online behavior, there is still much to be understood. Therefore, each essay should provide a path for future research to better understand these concepts.

Essay 1: Game On: Aggregate Digital Consumption, Digital Product Design, and Social Interaction

Future work will explore individual level influences of digital product design and social interaction on individual consumption. In addition to exploring consumption, downstream elements of the product experience will be studied, including future product purchases, product extension purchases, and word-of-mouth behavior. Finally, an attempt to marry social interaction and leaders and followers in digital consumption will examine how leaders and followers are identified in post-purchase consumption, how these individuals compare to online community leaders, and how they may influence other members of the online and consumption community.

Essay 2: Post-Purchase Co-Creation: Consumer Segmentation in Consumer-Driven Collaborative Product Development

There is much to explore in future research. First and foremost, a single product was examined in this essay, and it was a relatively mature product. A comparison to another product, and further a product earlier in its release stage would provide interesting insight into product co-creation over the product life cycle. Data is already collected for this second product and will be analyzed with comparisons in mind. The primary marketing outcome of study in the essay was product consumption. However, much of the existing product co-creation literature has investigated outcomes such as co-creation activity or knowledge creation. These same outcomes are available in the post-purchase co-creation context, and could provide interesting insights regarding the interconnectedness of creation and consumption in these consumer communities.

Essay 3: Coaches and Cheerleaders: Leaders and Followers in Online Brand Communities

A focus on the timing of word usage in online communities drove the identification of leaders and followers in product discussion. However, the essay focused on a single product category. An obvious extension is to examine these effects across alternative product categories. Initial data is already collected to do just that in the CPU product category, though custom dictionary definition is still required. In addition to investigating the timing of word use, it would be worthwhile to consider the volume of word use as well. It is likely that different types of leader groups, separate from followers, are characterized by a combination of their timing and volume of word usage. Exploring this interaction could provide interesting insights into community formation. A wealth of different areas for exploration exist in this study context, including the evolution of leaders over time, leadership of idea growth versus idea death, leadership roles in innovation heavy versus innovation light product categories, and many others.

Digital product post-purchase engagement, post-purchase customer control of marketing, and online behavior are relatively new and not well understood phenomenon in the marketing literature. Further, they are areas that most marketing managers must manage on a daily basis, and many are seeking best practices in the area to achieve the best results. These essays demonstrate that clear value for the firm and for consumers can be generated from these phenomenon. While it is too early to establish and declare best practices in the field, this research is a first step down that road, and provides evidence that the phenomenon are worth of future research and understanding.