COMMERCE, CAMILLE, AND CONSUMPTION: THREE ESSAYS EVALUATING SOCIAL COMMERCE INFLUENCES ON CONSUMER PURCHASING BEHAVIOR

by

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(Under the Direction of Sheri Worthy)

ABSTRACT

Social commerce is a context of online consumption at the intersection of social networking and e-commerce technologies that is gaining scholarly attention. Its study began in more technical and web-based infrastructure areas of research but is increasingly associated with consumer-centric academic inquiry. Social commerce itself is varied and exists in numerous online settings including integrated social commerce platforms, social networking sites that influence offsite and potentially offline consumption, and highly specialized markets characterized by the involvement of subject matter experts. This dissertation embarks upon three very distinctive studies, utilizing quantitative, qualitative, and mixed-methods analyses to evaluate the influence of social commerce in three different online consumption scenarios. Essay 1 suggests the social cues and social networking functionality of integrated social commerce sites positively influence consumer purchasing. In Essay 2, observations show that social network site-based brand communities usher members through the online consumer purchase decision process with group associations that endure on subsequent e-commerce platforms in cross-platform social commerce. The final essay alludes further research is needed to appropriately investigate the impact of brand signals in specialty industry social commerce settings like online real estate listings.

INDEX WORDS: Social commerce, Social identity, Brand communities, Content analysis, Etsy, Twitter, Scandal, Atlanta beltline, Real estate, Hedonic pricing, Signaling, Online consumption

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DEDICATION

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TABLE OF CONTENTS

Page

LIST OF TABLES

Page

LIST OF FIGURES

CHAPTER 1

INTRODUCTION

1.1 INTRODUCTION & STATEMENT OF THE PROBLEM

Historically, a central tenet of the Consumer Sciences, based in family ecology theory posits that influences on the family or households are minimal or local, protected by a fairly closed ecological structure (Bulbolz, Eicher, & Sontag, 1994; Bulbolz & Sontag, 1993). The now ubiquitous nature of social media has completely changed this dynamic. If we consider the broader nature of forces that shape family and household consumption behavior (Nickols, S.Y. et al, 2010), outside stimuli from online and social media facilitated sources must factor prominently into such discussions (Shanmugam, et al., 2016).

Traditional e-commerce focuses on system-based user-experience enhancements to the shopping experience, such as product categorization and analytically based, targeted product recommendations. By contrast, social commerce is centered on the shared consumption experiences between consumers communicated through social media or online social networking actions (Chen & Shen, 2015). Social commerce may be found in sites like Etsy, Amazon, or specialty sites like TripAdvisor. It may also exist in traditional social networking sites like Facebook, Twitter, or Instagram. Social commerce is a relatively recent phenomena influencing consumer purchasing behavior. As online, mobile, and social media networking platforms have become regular media of consumer buying and purchasing influences, the context has grown in importance regarding consumer behavior. Historically social commerce scholarly research is viewed through a lens of infrastructure and focused in e-commerce and computer engineering targeted journals and scientific inquiry. Presently, there exists a need and opportunity to evaluate the social and behavioral aspects of consumer behavior implications of social commerce.

In the past five to seven years, early scholarly exploration into the consumer implications of social commerce has evaluated the existence of meta analyses of the existing body of work on the subject. Actual empirical analysis or applications of the context seem to be limited.

1.2 PURPOSE & JUSTIFICATION OF STUDIES

The purpose of the studies that follow are to add multiple evaluations of social commerce as an applicable and explanatory context through which to study consumer behavior and purchasing habits. Social media, online social networking, and social commerce platforms continue to become an ever increasingly ubiquitous channel and conduit of commerce activity. The need for academic inquiry into the effects and influences of this mode of consumerism and consumption becomes progressively more apparent and necessary. The nuanced nature of the potential for significant social implications intertwined with purchasing behavior and consumption-related decision-making lends itself to be a subject of consumer research.

1.3 BACKGROUND

1.3.1 Rationale

This dissertation makes the assertion that social commerce research is a form of consumer research and not simply limited to the realm of technology research. Generally, consumer research intends to make sense of, or provide knowledge regarding, consumer behavior (Calder & Tybout, 1987). In their 1987 defining work on consumer research, Calder & Tybout outline that such consumer knowledge can be broadly categorized three ways. They posit that *everyday knowledg*e evaluates the shared knowledge of consumers and is best done via qualitative analysis. *Scientific knowledge*, by contrast, requires empirical testing of theories regarding consumer behavior. Finally, Calder & Tybout suggest that *interpretive knowledge* uses a system of ideas to evaluate consumer behavior. During his tenure as editor of the *Journal of Consumer Research*, Dreighton (2007), wrote an editorial piece in which he dissected multiple types of consumer research. One such qualifying category is that in which a researcher isolates a phenomenon of consumption behavior and uses scientific inquiry to account for it. Further, (Lynch et al., 2012), also support a broad definition of consumer research and state that such research can either build or expand theory, or aid in understanding a substantive phenomenon.

1.3.2 Significance

This body of work is a group of three essays, each examining the context and phenomena of social commerce in distinct ways. The collection of work flows from both the need for expanded research of the consumer behavior implications of social commerce, and the multiple ways in which to undertake acceptable academic inquiry into consumer research. Collectively, the essays provide analysis and exploration of social commerce using an evaluation of the evolution of social commerce research and practice (*interpretive knowledge*), a qualitative review of a consumer identity and social commerce phenomenon (*everyday knowledge*), and an empirical analysis of industry specific social commerce implications (*scientific knowledge*). Through a diverse approach of scholarly research, these distinct studies seek to clarify social commerce as suitable and varied enough for robust consumer research inquiry.

1.3.3 Need For Studies

In addition to expanding the application of social commerce to consumer (behavior) research, social commerce itself has a complex and nuanced existence. Online social networking capabilities and social media platforms exist in many incarnations. Thereby, opportunities for observing and evaluating social commerce phenomena are equally numerous. Another important contribution of this dissertation is that the essays herein will examine three different types of social commerce environments.

1.4 CONCEPTUAL BACKGROUND FOR ESSAY 1

The first essay provides a historical review of the evolution of scholarly works in social commerce as they transition from technical to social and consumer applications. In it, an extended literature review chronicling the antecedents of social media - general social media phenomenon, electronic word-of-mouth, consumer-to-consumer helping behavior, and online shopping behavior, are reviewed and discussed. The essay continues with a definition of social commerce and its progress and closes with an evaluation and discussion of social commerce phenomenon on a social commerce online platform. Though not intended to be a purely empirical study, a small amount of data collected from a social commerce site, “Etsy.com” are analyzed and included in the discussion. This data is meant to offer a preliminary test of the existence of an actual influence of social influences on commerce measures from the platform. For that portion of the study's discussion the research question is:

1. *Is consumer purchasing behavior on "Etsy.com" influenced by the presence and degree of social and social networking cues present on a shop's page?*

1.5 CONCEPTUAL BACKGROUND FOR ESSAY 2

Essay number two continues the examination of social commerce, using a primarily qualitative approach, therefore providing explanatory knowledge. One of the more complex considerations of social commerce, is that which occurs across platforms. More specifically, unlike "Etsy.com" where the social (media) networking and commerce transaction occurs in a single platform, other forms of social commerce originate on one or more social networking platforms and culminate with a purchase elsewhere. Such is the case with the Camille 23-ounce red wine glass from US retailer Crate & Barrel. Content analysis is used to analyze and evaluate online Twitter conversations within the brand community of ABC's *Scandal* television show, and user generated content included in the product reviews for the wine glass at the "CrateandBarrel.com" website. Common patterns in references to *Scandal*'s main character, Olivia Pope, and social identity behavior markers help explore a link between the social media and *e-commerce* platforms. Descriptive analytics are used to explore consumer rating behavior amongst those providing reviews relating back to the television show community and those that do not. For this portion of the analysis, the research questions are:

1. *What can we observe about product purchase behavior within the Scandal brand community across the Twitter and Crate & Barrel e-commerce platforms?*

2. *Do consumers who associate the Camille wine glass with the Scandal television show exhibit higher product satisfaction than those who do not?*

1.6 CONCEPTUAL BACKGROUND FOR ESSAY 3

The final essay uses a simple content analysis coupled with a traditional hedonic pricing model to evaluate the potential of green space signal effects on home sales prices. Online MLS listing data for Atlanta, GA provide the dataset for the study. Content analysis will allow me to code the existence (or absence) of green space signals in listing descriptions accompanying property features and transaction details. I then include the binary variable for green space signal into the hedonic pricing model to determine the presence and magnitude of any price effect. Last, there may be some difference in price effect between a branded (Beltline) or generic (green space, park) signal. I use comparative dummy coding in the regression models to probe the possibility of such a difference. The evidence of price effect may lay with either the either sellers' (List Price), buyers' (Sales Price) or both groups' perceived value, and will be evaluated from each perspective in the study. Resulting research questions are as follows:

1. *Do buyers (and sellers) place positive value on green space signals, reflecting positive sentiment of green status consumption behaviors in residential real estate sales (and listing) prices?*

2. *Do buyers (and sellers) attribute greater value to branded versus generic green space signals in residential real estate prices?*

1.7 SUMMARY

As commerce and consumers alike find new ways to engage with and integrate social media and online social networking capabilities into the consumption experience, new opportunities for the research of online consumer behavior arise. The following dissertation is a collection of essays investigating three different applications of the phenomenon of social commerce. I use both quantitative and qualitative methodologies to explore three distinct data sets comprised of social media-related data and commerce indicators. In the first essay, “Putting the Social Back into Online Shopping: An Applied Analysis of Social Commerce,” I study the context within the “Etsy.com” social commerce platform. Essay number two, “*Scandal*, Wine, And Shopping, Oh My! An Analysis of Brand Communities, Identity, And Purchasing Behavior,” follows activity amongst members of ABC’s *Scandal* Twitter community from the social media site to an e-commerce outlet. Finally, the third essay, “Beltline Adjacent: An Analysis of Green Space Signals in Online Real Estate Listings,” presents a hedonic price effect analysis of text-based greenspace signals in online real estate listings and home prices in Atlanta, GA.

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CHAPTER 2

PUTTING THE SOCIAL BACK INTO ONLINE SHOPPING: AN APPLIED ANALYSIS OF SOCIAL COMMERCE

2.1 INTRODUCTION

There is a significant body of research investigating social media and consumer behavior. Much of this research leverages psychological and sociological theories and constructs to examine how social groups and communities are formed and behave in online settings. Traditional theories such as social identity theory and intergroup behavior are used to examine the dynamics of online social networking. Social media platforms have amplified consumer-to-consumer communications, communities, and influences (Kaplan & Haenlein, 2010). In doing so, social media has itself influenced e-commerce, creating a new online commerce category of social commerce. Social commerce sites are a specific type of newer e-commerce platform that combine traditional e-commerce features such as system-based user-experience enhancements to the shopping experience and social networking site features like profile pages, pictures, social exchanges and reviews (Shanmugam et al., 2016).

2.1.2 STATEMENT OF PURPOSE

Social commerce sites allow consumers and sellers to engage in two concurrent types of interaction during the buying process. These sites provide the addition of online social signals alongside traditional e-commerce product information. Through these social signals sellers communicate, and consumers react to, a variety of influences during the shopping experience. This study seeks to fill a gap in current research by investigating how the combined e-commerce and social networking functionality of social commerce sites may impact consumer purchasing behavior. More specifically, it focuses on those social signals specifically communicated through profile pictures, logos, and other social networking practices (e.g. “follows,” “likes”), and their correlation to retail shop performance indicators on a social commerce site. Following a discussion of social commerce phenomena and literature, I will use a sample of social and commerce performance indicators from US-based shops on “Etsy.com” to evaluate the influence of explicit and implicit social signals on consumer purchasing behavior.

2.2 REVIEW OF LITERATURE

2.2.1 SOCIAL IDENTITY THEORY

Social Identity Theory (SIT), developed in the 1960s as a means to explore intergroup behavior, seeks to explain and understand how the self is defined by group membership. The theory provides an opportunity to explore the identity of individuals and how they behave in group situations based on the components of their identity derived from one or more group associations or memberships. This distinction was made by Tajfel and Turner in their 1986 research, “The social identity theory of intergroup behavior,” as an alternative to personal identity, and the associated interpersonal situations and influences on a person. The theory has made a variety of contributions to socio-psychological research including in-group bias, response to status inequality, intragroup homogeneity and stereotyping and changing intergroup attitudes through contact (Brown, 2000).

Social identity theory emerged from several social psychology theories, particularly those concerning groups and group behavior. Group behavior research either focuses on behavior within groups or behavior between groups. Intergroup behavior is concerned with behavior between groups and has been noted as the initial field from which SIT was born (Brown, 2000; Hogg & Abrams, 2007). Hogg and Abrams (2007) suggest that social categorization of groups is required to identify separate groups and subsequently study the behavior between the two. The foundational and oft replicated research of intergroup behavior is the minimal group experiments. These experiments examined early indicators of intergroup behavior and found that relative to people who are not explicitly categorized, people who are categorized discriminate in favor of their group (Hogg & Abrams, 2007).

2.2.2 Consumer-To-Consumer Communications

Research into person-to-person and even consumer-to-consumer communications is not new. Consumers often rely upon other consumers as sources of information about products and purchases. It has been suggested that the best-established idea about the transmission of marketplace information is the importance of interpersonal communication (Feick & Price, 1987). Furthermore, prior research has demonstrated inter-personal information exchange is widespread, interpersonal communication affects preferences and choices, interpersonal sources are often the most important sources of information, and interpersonal sources are seen as more credible than non-personal sources (Feick & Price, 1987). In pursuit of interpersonal sources, consumers use social media to connect not only with friends and family but also strangers who may share a common goal as consumers (Kaplan & Haenlein, 2010).

There is growing evidence that consumers are influenced by opinions posted in online forums before making a variety of purchase decisions (Dellarocas, 2006). Information exchanges, particularly those in online settings, often happen among consumers who have no prior relationship with one another. The Internet has enabled individuals worldwide to share their personal experiences, thoughts, and opinions to the global community in an easily accessible manner. This has led to the creation of numerous online word-of-mouth communities and forums. Examples of such communities include online product review forums, Internet discussion groups, instant messaging chat rooms, mailing lists, and web logs [blogs] (Dellarocas, 2006). Providers and seekers of information interact in these online places and are heavily reliant on the recommendations, reviews, and ratings at sites such as “Amazon.com,” “Yelp.com,” or “Etsy.com” (Weiss, Lurie, & MacInnis, 2008). More specifically, evidence suggests that online forums play an increasingly important role in public opinion formation. Internet forums have led to the creation of “crowdsourcing,” replacing our societies’ traditional reliance on the “wisdom of the specialist” by the “knowledge of the many” (Dellarocas, 2006). Dellarocas (2006) further suggests that the main source of quality information for consumers is an online product review forum, where past consumers post opinions about their experiences with goods. New consumers read these opinions, form perceptions about the qualities of the products and make purchase decisions. However, it is important to note that consumers do not blindly absorb the information they encounter on social networking sites. When consulting other consumers online, information seekers must assess whether a particular consumer is providing valuable information and how much value they provide relative to that of other consumers (Weiss, Laurie, & MacInnis, 2008).

2.2.3 Social Networking Sites

A distinguishing characteristic of social networking sites is that the content is almost entirely user generated. The driving force of a site's vitality and attractiveness is produced by its users (Trusov, Bodapati, & Bucklin, 2010). Therefore, the success of Internet social networking sites depends on the number and activity levels of their user members (Trusov, Bodapati, & Bucklin, 2010). The core of a social networking site, such as "Etsy.com," is a collection of user profiles where registered members can place information that they want to share with others (Trusov, Bodapati, & Bucklin, 2010). Users are therefore involved in two kinds of activities on a social networking site:

1. Creating new content by editing their profiles (e.g., adding pictures, uploading music, writing blogs and messages) and,
2. Consuming content that others create (e.g., looking at pictures, downloading music, reading blogs and messages) (Trusov, Bodapati, & Bucklin, 2010).

2.2.4 Social Commerce

Consumers are influenced in their consumption choices via their interaction with active opinion leaders and influencers (posters) in social media platforms and online social networks. Social networks collectively, and opinion leaders individually, have an impact on consumer decision-making in social media settings. In online shopping environments, consumers have the option to post (openly communicate) their shopping experience with a particular product or vendor or not communicate their experience. Regardless of their choice, online consumers are influenced by the content of existing reviews and ratings already left by other consumers. Consumers who actively participate in online communities creating content are known as posters whereas those who belong to the online communities primarily as consumers of contents are referred to as lurkers. Both types of members evaluate the commentary and activity of other members, but may evaluate them differently (Schlosser, 2005). Typically, consumers or online community members are consuming user generated content of other members within the platform. It is the creation and consumption of this user generation content, often comprised of word-of-mouth, feedback, or other means of experiential product or service quality reviews that is characteristic of social commerce (Shanmugam, et al., 2016). This intersection of e-commerce and social media/social networking has only recently begun to be investigated by academics and practitioners.

Much of this early research focuses on how firms or proprietors use existing social networking platforms like Facebook, Twitter, and Instagram to sell products. However, very little research has investigated social influences on consumer behavior in sites that combine the user-experience enhancements and within-site transactions of e-commerce with shared social signals and consumer experiences of social commerce into a single community platform. An integrated platform, as described, is sometimes categorized as e-commerce oriented social commerce. In this model of social commerce, sellers and buyers engage within a single social and e-commerce platform as shown in Figure 2.1 (Diao, He, & Yuan, 2015). Prior analysis exists that investigates this type of social commerce environment, looking at social components and website functionality.

Findings suggest that quality of website functions and design considerations positively effect a consumer's intention to continue using the social commerce site, however, it does not provide direct assessment of implications of social cues and functionality on actual purchases (Liang, et al., 2011). Additional research conducted in the early beginnings of non-technical social commerce study used social network analysis to investigate value creation for firms using a social commerce model. Leveraging an e-commerce site for data collection, the study attributes larger economic value or sales performance to those shops with greater accessibility or connectivity in the network of shops (Stephen & Toubia, 2010). A firm-to-firm focused view as findings describe, still fails to measure social commerce influences on buyer behavior.   By contrast, my study undertakes an initial evaluation of the unique dynamics and consumer behaviors on social commerce sites.

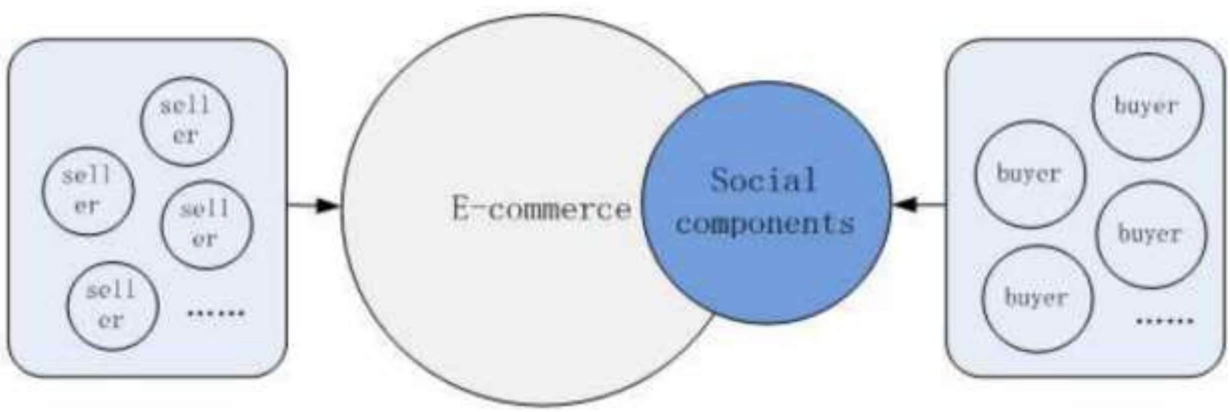

Figure 2.1. E-commerce Oriented Social Commerce (Diao, He, & Yuan, 2015)

2.3 METHODOLOGY

The purpose of this study is to provide empirical evidence to support the concept of the social commerce context. As the nomenclature suggests, social commerce includes both qualitative social considerations and quantitative purchase transaction components. Through an examination of qualitative and quantitative characteristics, the study seeks to evaluate if, and which, social networking factors may be influencing consumer purchasing decisions in social commerce environments. This section of the essay provides a detailed discussion of the research platform, data collection method, chosen variables, qualitative and quantitative data analyses, and research question to be used to further substantiate the social commerce context.

2.3.1 Research Platform

"Etsy.com" (hereafter, Esty) is an online retail collection of individual small businesses that sell handmade goods across a variety of product categories. The site's self-description states that it "*is a marketplace where people around the world connect, both online and offline, to make, sell and buy unique goods.*" In terms of social networking site categorization, Etsy is sometimes referred to as a social selling or social commerce site. There are over 1.6 million active sellers on the site, offering over 35 million unique items available for sale to more than 24 million active consumers. The Etsy platform allows each retail shop to maintain both a shop profile and a shop owner profile page. These paired profile pages combine to provide the qualitative data on social signaling (images) and the quantitative data for commerce measurement of consumer purchase behavior and are also where consumers may consume information about a respective shop's product offerings, prices, and social markers of the shop and the owner. Data elements from both profile pages for each respective shop in the ultimate data set will be used in this study.

2.3.2 DATASET

This study uses data collected from a sample of the associated shop and shop owner retail pages for a sample of registered Etsy retail outlets. On Etsy, retail outlets or shops and individual items can be favorited by registered users of the site, making them an “admirer” of the shop. Consumers may also rate shops (1-5 stars) for their experience with an actual purchase transaction with the shop. Additional social signals may be communicated at either the shop or shop owner-level via photos or images. Individual shop data includes a historical number of sales, number of times a shop has received unique favorite designations from registered users, geographic location of the shop, and an overall rating from customers. These different discrete data points offer many possibilities for testing consumer behavior regarding purchases, ‘favoriting’, or product associations. In summary, traditional and image-based data elements available from the paired Etsy Shop page and the Esty Shop Owner pages are used in this study.
Relevant data elements available to be mined from the visual rendering of Etsy Shop and Owner pages, and their respective descriptions are described in detail in Table 2.1.

Table 2.1. Detailed Descriptions of Etsy Variables

Data elements from the shop profile page:	
Shop Name	Selected name of registered Etsy retail outlet
Rating Value	Numerical value of the average rating for the shop (based on a 5-star rating system)
Review Rating Count	# of unique ratings available
Admirers	# of site users who have “favorited” the shop (may or may not have purchased an item from the shop)
Sales (# of transactions)	# (volume) of unique transactions for the shop (count, not value)
Location	Geographical location of the shop (may be marked private)
Shop Owner	Selected user name of registered Etsy retail outlet owner
# of items for sale	Total number of unique items for sale by the shop

Date Opened	Year the Etsy retail outlet was registered/opened
Data elements from shop owner profile page:	
Shop Owner Name	Selected user name of registered Etsy retail outlet owner
# of Followers	Number of registered Etsy members (consumers) who follow the shop (to receive updates & other information
Image Data Elements:	
Shop Image	Selected image associated with a respective registered Esty retail outlet
Shop Owner Image	Selected image associated with a respective registered Esty retail outlet owner

2.3.3 Data Collection Techniques

For this study, data collection required manual retrieval of both the traditional data elements and social signals requiring coding of the shop and shop owner-related images. There is a specific need in this study to analyze both quantitative and qualitative data. Images are a central focus of the data. These images allow for the assessment of the impact of one of the types of social cues that may be influencing purchasing decisions. Social cues can include considerations of gender, age, race/ethnicity, or income level. Given the nature of the image data, I focus on a more generalized social cue of whether or not an image is displaying a human likeness. In this respect, many of the images are straight forward, depicting clearly identifiable person or human image, or lack thereof. The nature of image data introduces a complexity that specifically lends itself to the need for a robust qualitative analysis supported by Qualitative Data Analysis Software, QDAS (Dempster & Woods, 2011). The qualitative nature of the images and human likeness signals allow for an analysis of the social aspects of social commerce while the commerce component is best analyzed via quantitative data. This dual requirement of qualitative and quantitative analysis are key characteristics of a study best suited for a mixed-methods approach (Tashakkori & Teddlie, 2004). The qualitative data consists of human likeness signals communicated though a series of images, and the quantitative data centers around counts of commerce-related performance indicators. The data exist in a single location on the respective webpages of the “Etsy.com” platform. Using QDAS, both types of data are collected simultaneously. This type of dually located data suggests the use of a concurrent nested mixed-methods approach, though should I decide to emphasize a gender advocacy angle in the study (as Consumer Economics often supports advocacy in research) a concurrent transformative mixed-methods approach may be better suited (Hanson et al., 2005). The qualitative data was coded and analyzed locally within the QDAS software, while the quantitative data was aggregated and exported for analysis in statistical software packages.

QDAS tools provide resources that assist in data collection, management, storage, coding, and qualitative analysis (Gilbert, Jackson, & diGregorio, 2014). Moreover, these tools provide a more efficient mechanism for conducting analysis of large sets of qualitative data in far less time than manual options (Bazeley, 2006). The NVivo Pro package was chosen for a more streamlined way to capture the web-based and image heavy data needed to conduct the analysis. NVivo Pro specifically includes the NCapture add-in, optimized for capturing web-based social media data. It served as both a data collection and data analysis tool without the need to refer between the source media (individual Esty webpages) and an Excel file for coding tracking. Using this software provided the ability to code the social signals from images, and quantitative commerce-related data elements in a single location. NVivo has been used successfully in the past to conduct this type of coding, sometimes referred to as constant coding, enabling researchers to discover more robust relationships and emergent themes among data than with other methods (Leech & Onwuegbuzie, 2011).

2.3.4 Sample

A sample of 200 US-based Etsy retail outlets was gathered for data mining to create a usable dataset. For this analysis, I am most interested in those shops that are actively engaging in commerce activities and generating sales by consumers. To increase the likelihood that my sample of Etsy retail outlets includes those with observable activity, I utilized the site's filtering capabilities in the search functionality. First, I applied a broad filter within the generic "All Shops" search by a selecting a flag of "Most Recent." This flag indicates those shops that are active registered participants on Etsy and have made at least a minimum level of content update at the time of data collection. The resulting listing of registered retail outlets was captured and reviewed via the NVivo software package and method previously described.

2.3.5 Variables And Operationalizing

Recall the example Esty registered shop and shop owner associated pages provided earlier in the discussion. The table included in that discussion offered a detailed listing of components from the Esty webpages, operationalized for use as variables in this study. Similarly, when describing the data collection techniques and need for QDAS software, I mentioned the need to code images to gather information on social cues. I applied dummy coding to indicate which images for shops and owners display a human likeness:

0. Human likeness <u>not</u> present
1. Human likeness present

An image was considered to have a human likeness present if there if contained a picture of a person(s) face or full body. If an image did not include one or more faces or full body images, it was coded as not having a human likeness present. Images in this category may have had no picture, a logo, or a picture of merchandise.

As discussed in the social commerce literature, there are both discrete social and commerce-related characteristics in social commerce sites like the “Etsy.com” platform. Therefore, I consider the Etsy retail shop performance indicators in two separate groups – *social* (# of Admirers and # of Followers) and *commerce* (# of Transactions).

Given the nature of the research question, seeking to determine if social cues and social networking characteristics (social) are influencing consumer purchasing behavior (commerce), number of transactions (# of transactions) is the dependent variable. If a consumer has chosen to complete a purchase and engage in a commerce transaction with a given registered Esty retail shop, it is accounted for in this variable. Note that # of sales counts unique transactions over the life of the business, but not product counts. Meaning, if a consumer purchased two items from a given Etsy retail shop it counts as a single commerce transaction.

The independent variables in the analysis are those variables representing the social cues and social networking features available to registered Etsy consumers while shopping on the site. These variables represent the “social” characteristics of social commerce that make it distinctly different from traditional social commerce. The coded Owner Image and Shop Image observations comprise the social cue variables. Likewise, three social networking variables representing the existence of user generated content (# of Reviews), the popularity of an Etsy retail shop (# of Admirers), and the sphere of influence or connectivity of Etsy shop (# of Followers) make up the last three independent variables.

Several covariates will also be included in the model. These covariates represent additional characteristics, representing neither social nor commerce considerations, that also influence a given Etsy shop's commerce performance or likelihood of consumer purchase. Age of Shop represents the time since an Etsy shop was registered as a retail outlet on the site and the date of data collection (rounded to the nearest year). Finally, the total number of items available for purchase by consumers at the date of data collection is accounted for in the variable # of Items.

2.3.6 Data Analysis Methodology

The purpose of this applied analysis of social commerce is to test the premise that the social cues and social networking functionality of a social commerce site like Etsy are, in fact, influencing consumer purchase behavior on such sites. The analysis has been structured to test the broad research question with two hypotheses:

Is consumer purchasing behavior on Etsy influenced by the presence and degree of social and social networking cues present on a shop's page?

H_{1A}: Consumers are more likely to purchase (# of transactions) from Esty retail shops with social cues (shop and owner images) present on the platform.

H_{1B}: Consumers are more likely to purchase from Esty retail shops with higher social networking engagement (#of admirers, # of followers, # of reviews) present on the platform.

To do so, I use a stepwise approach to build a fully specified linear regression analysis. This allows the social cues and social networking variables to be added in blocks to see how the effects may progress. For the initial model, I regress the commerce-related dependent variable (# of Transactions) on the operational independent variables (# of Items, and Age of Shop). The second model introduces the social cue independent variables (Owner Image, and Shop Image). Finally, the third model adds the social networking-related independent variables (# of Admirers, # of Followers and # of Reviews). This is a stepwise approach in that I am adding the independent variables in two blocks of "social" variables and not one-by-one. Each of the specified models are explained in detail as follows:

Model 1 $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2$

Model 2 $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$

Model 3 $Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 + \beta_5 X_5 + \beta_6 X_6 + \beta_7 X_7$

Where:

Y = # of Transactions,	X_4 = Shop Image,
X_1 = # of Items,	X_5 = # of Reviews,
X_2 = Age of Shop,	X_6= # of Admirers,
X_3 = Shop Owner Image,	X_7 = # of Followers

Recall that our dependent variable, # (number) of (unique) transactions, is counting the number of transactions and is, therefore, considered a count variable. As such, I have chosen to use a negative binomial regression in lieu of a linear multiple regression model. While the data does include eight observations with a zero value for the dependent variable, this is not excessive, and a negative binomial regression model may be used. It is important to note that in some cases, it is common practice to use an offset variable to standardize the length of observation time in this type of model. However, for this study, the effect of age of a shop is considered part of the operational characteristics of a shop, and it is included as an independent variable in the model as opposed to being standardized and controlled for across the sample.

2.4 RESULTS, DISCUSSION & IMPLICATIONS

2.4.1 Results

Upon running descriptive statistics for the 200 shops included in the sample for this study I found the following average values across key variables. The sample represents a collection of shops of varying size and activity levels. Number of items for sale by shop ranged from zero, suggesting a new shop or one recently on hiatus, to 9,870 suggesting a very productive shop or one that sells a variety of parts or supplies. The average number of items for sale across all shops was roughly 360. Likewise, the age of shops in the sample ranged from newly opened shops less than a year old (denoted by a zero) to 10 years old, with a mean age of just over six years. The number of unique transactions per shop also spanned a range of zero to 137,433. The mean number of unique transactions for shops in the sample was 4,861, with nearly one quarter of all shops reporting transaction volume at or above the mean.

Given the dummy coding of the image-based social cue variables of owner image and shop image, their ranges are not meaningful. However, the mean value for each was .49 and .10, meaning 49% of shop owner images and 10% of shop images were of a human likeness.

Finally, we can review the descriptive statistics for the social networking variables. Number of admirers, a shop-related variable, ranged from zero to 65,337, with a mean value of 2,524. The corresponding owner-related variable, number of followers, shows a range of zero to 4,433, with a mean of 324. Number of reviews indicates the number of times a customer of a shop chose to leave a review of their purchased product and/or consumption experience. I observed the mean value of this variable to be 1,133 with observations ranging from zero to 45,957. For additional details regarding the descriptive statistics of the sample, please refer to Table 2.2.

Table 2.2. Descriptive Statistics for Selected Etsy Variables

Variable	Mean	Std Dev	Minimum	Maximum
Number of Transactions	4,861.39	13,678.18	0	137,433
Number of Items	359.69	903.93	0	9,870
Age of Shop	3.85	2.52	0	10
Shop Image	0.10	0.30	0	1
Owner Image	0.49	0.50	0	1
Number of Admirers	2,524.57	72,226.61	0	65,337
Number of Followers	323.97	697.83	0	4,433
Number of Reviews	1,133.95	3,878.46	0	45,957

Note. N=200.

In Table 2.3, selected Etsy variables other than the binary image variables are detailed in a correlation table. The table shows that only number of reviews and number of transactions are highly correlated, or greater than a .80 correlation coefficient. This relationship is not surprising, given that a consumer may only leave a review if they have engaged in a transaction with a shop.

Table 2.3. Correlation Table for Selected Etsy Variables

	Num of Transactions	Num of Items	Age of Shop	Num of Admirers	Num of Followers	Num of Reviews
Num of Transactions	1					
Num of Items	0.27**	1				
Age of Shop	0.24**	0.03	1			
Num of Admirers	0.69**	0.12*	0.28**	1		
Num of Followers	0.66**	0.16**	0.36**	0.67**	1	
Num of Reviews	0.92**	0.18**	0.25**	0.65**	0.58**	1

Note. N=200.
**p<.05.*p<.10.

For this analysis I chose to step into the fully indicated model discussed above. The progressive models follow the categorization used in the earlier operationalizing of variables. Model 1, as shown in Table 2.4, represents the "simple" model, including only the traditional operational independent variables of number of items for sale and age of shop. The results of this model show that both variables are significant at the .05 level having *p* values of *p*<.001 and 0.0113, respectively. Number of items had a parameter estimate of 0.006, for each additional item a shop has available for sale, the difference in the logs of expected number of unique transactions is expected to change by 0.0006. Results for age of shop indicate that it has greater significance and a larger impact than number of items. For every additional year a shop has been open, it is expected that the difference in the logs of expected number of transactions will change by 0.4253, representing a parameter estimate of 0.4253. The dispersion estimate for Model 1 is 2.9054, and indicates the dependent variable, number of transactions is over-dispersed.

Table 2.4. Negative Binomial Regression Results for Models 1 through 3

	Parameter Estimates		
Variable	Model 1	Model 2	Model 3
Intercept	6.117 **	6.0465 **	6.1797 **
Number of Items	0.0006 **	0.0007 **	0.0005 **
Age of Shop	0.4253 **	0.4397 **	0.0523
Shop Image		-0.6946 *	-0.3702
Owner Image		0.0805	0.5058 **
Number of Admirers			0.0000
Number of Followers			0.0006 **
Number of Reviews			0.0004 **
Pearson Chi-Square	347.7091	333.2216	145.5581
Δ Pearson Chi-Square		*-14.4875*	-187.6635
Value/DF	1.7650	1.7088	0.7581
Δ Value/DF		*-0.0562*	*-0.9507*
Dispersion	2.9054 **	2.8818 **	2.1678 **

Note. n=200.
**p<.05.*p<.10.

Model 2, found in Table 2.4, builds upon Model 1 by adding in the social cue variables related to the shop and owner images. In this "simple + social cue" model, number of items and age of shop continue to be significant at the .05 level with *p* values of 0.0070 and *p*<.001. Number of items loses some of its significance in this model, though its effect essentially flat, with a parameter estimate of 0.0007. There is no change in the significance of age of shop, and limited change in its effect, with a parameter estimate of 0.4397. Of the social cue variables added in Model 2, only the shop image is significant, at the .10 level, with a *p* value of .0942. It has a negative effect on number of transactions, with a parameter estimate of -0.6946, corresponding to an expected decrease of 0.6946 in the difference of logs of expected number of transactions when a shop image uses a human likeness. This finding does not support $H_{1A.}$ Model 2's dispersion estimate is slightly lower than Model 1, at 2.8818, still indicating an over-dispersed dependent variable. Model fit can be assessed by looking at chi-square and degrees of freedom (DF). Value/DF represents chi-square/degrees of freedom. A Value/DF closer to 1 is preferred. This second model is an improvement in model fit over the first model as shown by the improved model fit. Model 2 has a 1.71 that is roughly 0.06 lower than Model 1.

The final, fully loaded Model 3 introduces the social networking variables into the model for a "simple + social cue + social networking," model (see: Table 2.4). In this model, age of shop ceases to be significant. Number of items for sale continues to be significant at the .05 level with a *p* value of 0.0294, with a relatively flat effect on number of transactions, as shown by its parameter value of 0.0005. Shop image also ceases to be significant in Model 3, while owner image becomes significant with a *p* value of 0.0205. H_{1A} is only partially supported by this result, with one social cue variable having a significant and positive effect in the model. Unlike shop image, owner image has a positive effect on number of transactions with a parameter value of 0.5058. This indicates an expected increase of 0.5058 in the difference in the logs of expected number of transactions for a shop whose owner image is of a human likeness. Furthermore, two of the three social networking variables are significant in the model, indicating partial support for H_{1B}. Number of admirers is not significant. Number of followers and number of reviews are significant with p values of 0.0272 and 0.0002 respectively. Their parameter estimates of 0.0006 (followers) and 0.0004 (reviews), suggest a similar effect on number of transactions as number of items sold. This translates into a slight 0.0006 increase in the difference in the logs of expected number of transactions for each additional consumer who follows a given shop, and a similarly slight 0.0004 increase in the difference in the logs of expected number of transactions for each additional consumer who leaves a review for a given shop. For Model 3, the dispersion estimate is the lowest of all three models, at 2.1678, consistently indicating the over-dispersion of the dependent variable. Model 3 is the best fitting of the models with a Value/DF of 0.76.

2.4.2 Discussion

The results of the statistical analyses provide some very interesting insight into consumer behavior on Etsy. By using the step approach to build the model, I can see how the addition of the social measures, the cues and the social networking components effect consumption levels within the Etsy shops. Starting with the descriptive statistics, certain behaviors and possible preferences are evident. The mean values for the social cues of shop image (10%) and owner image (49%) clearly show that human images are more likely to be found in owner profile pictures as opposed to the shop picture. This could be because a shop image may often display the shop logo, a picture of merchandise, or even a featured product instead of a human image. Conversely, owners choose to show a human image, often their own photo about as often as they choose to show some other image. It could be that when opting not to provide a human likeness for their profile picture, owners are duplicating the image from the shop they own. The mean values of the social networking variables, followers (324), an owner level variable and admirers (2,526) a shop level variable, provides additional insight into consumer behavior. Comparing the means of these two variables leads to a conclusion that Etsy consumers choose to connect to and receive updates at the shop level more so than at the owner level. Finally, looking at the mean number of unique transactions (4,861) and number of reviews (1,134), suggests that consumers are choosing to communicate information about their consumption experience with a given shop, nearly 25% of the time, or for almost 1 in 4 transactions.

A review of the statistical analysis of Models 1 through 3 provide additional insight into the data. As the models progress, the number of items available for sale remains a significant contributor to the number of unique transactions, or consumer transactions for each shop. This conclusion is a logical one, a consumer has more opportunities to engage in a purchase transaction if a shop has more products available. The age of a shop is also significant in the first two models, “simple” and “simple + social cues” but fails to be significant in Model 3 which includes social networking variables. The effect of the added social networking variables in Model 3 are less than the effect of the age of shop from the earlier models, however, this shift in significance suggests that a newer shop may overcome some of the effect of its limited time in operation by increasing the number of followers and customers who leave reviews.

The social cue variables also offer interesting context to review. It is quite striking that the shop-level and owner-level images have opposite effects on number of unique transactions per shop, with the former being negative and the latter positive. Adding only the social cues to the operational variables leads to only the shop image having a statistically significant effect on transactions. However, once social networking variables are also introduced, this relationship flips, and only the positive effect of the owner image is significant. The effect size of owner image is much larger in Model 3 than in Model 2, coupled with no effect (or statistical significance) for number of admirers. Recall that both variables are owner-related. It appears that when evaluating cues about a shop owner, consumers are influenced more by the image or profile picture of the owner than by the number of other Etsy users who have chosen to "admire" or receive updates for a given owner. This is likely due to the layout of the related shop and owner pages. An Etsy shopper can easily see the owner's image from the shop page where merchandise listings, reviews, transactions, followers and age of shop are visible. The number of admirers for an owner is visible only from the actual owner profile page. This may suggest many Etsy consumers rely on the limited owner data viewable from the shop page and are not commonly delving further into the available owner information accessible by an additional click through.

2.4.3 IMPLICATIONS

The findings of this study have implications and offer insight for navigating social commerce contexts in single site settings. For Etsy shops specifically, the study reinforces the importance of leveraging the social networking functionality of the platform, encouraging consumers to follow a shop and leave reviews. It also highlights the importance of using the owner profile, at a minimum, to offer an authentic human likeness or personal picture. Leveraging the social networking functionality is especially key for younger shops, to overcome their "newness" on the platform. The Etsy platform is associated with an image of handmade or artisan products provided by individuals. This is different than social commerce platforms like Amazon, more commonly associated with products sold by businesses. Though businesses do sell on Etsy, and individuals on Amazon, it is likely that consumers shop on the respective sites with these commonly held assumptions in mind. Therefore, a human likeness signal from an owner on Etsy may be contributing to the sense of authenticity in the transaction, leading to increased consumption. Of course, these findings may also provide insight to similarly structured integrated social commerce sites offering social cues at both the shop and owner-level.

2.4.4 Future Studies

The effects and findings of the preceding are somewhat limited to the small sample size of shops utilized in the analyses. A logical follow up study would be a scaled-up version to see if the social cue and social networking trends hold true for a sample of 1,000-2,000 shops. Remember that this data set focused solely on shops based within the United States. A larger study of internationally based shops, or shops in specific countries or regions, may provide insight into how these social cues and social networking variables influence consumer purchasing when the seller is not domestic.

There may be great value in an analysis that delves further into the authenticity implications found in this study. The role of human images and personalization of the shopping experience appears to have a strong influence on consumption, replacing the age of a shop as a significant predictor. Further study may allow for insight into the mechanism behind this relationship. Is authenticity truly at play? Does the human likeness represent credibility? Moreover, understanding interactions between the social signals and other variables like age of shop or social networking variables, could be investigated in future studies.

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CHAPTER 3

SCANDAL, WINE, AND SHOPPING, OH MY! AN ANALYSIS OF BRAND COMMUNITIES, IDENTITY, AND PURCHASING BEHAVIOR[1]

3.1 INTRODUCTION

Social commerce occurs in a variety of online settings, from integrated social commerce platforms, to social media conversations culminating in offline purchases (Stephen & Toubia, 2010). In the latter scenario, purchase decisions often develop from conversations in online brand communities. In addition to brands of consume products and services, brand communities may also refer to networked followers of television, who congregate virtually through “second screen” engagement, using related hashtags facilitating conversation on Twitter and Instagram (Giglietto & Selva, 2014). In these communities, the television franchise and related characters replace the typical idea of brand. Traditional notions of consumer identity combine with the unique phenomenon of second screening to provide a means through which to observe how social media activity may influence subsequent consumption behavior elsewhere.

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[1] Data collection, methodology, and initial concept development for this essay are related to a working paper of which I am a co-author.
Bryant, M. M., Wood, N., & Burkhalter, J. (2016). *Call me Camille: A grounded theory approach to understanding the potential impact of prominently integrating unbranded products into television programs*. Manuscript in preparation.

3.1.2 Statement Of Purpose

The purpose of this study is to provide an exploratory and explanatory examination of a specific type of social commerce behavior. When social media activities lead to consumption on other sites or at brick-and-mortar locations, it can be quite difficult to connect the influences. The before-and-after nature of this kind of social commerce makes it a less attractive target for research. However, by leveraging second screen engagement, a more targeted evaluation is possible. This study explores a subset of online conversations and product purchases affiliated with the ABC television show, *Scandal*. I have collected two sets of online consumer-to-consumer data, one Twitter based, and one e-commerce based. Data include audience engagement and conversation on Twitter, and related ratings and review content on the product's e-commerce site. Consumer interest in the product, Camille, a 23-ounce, long-stemmed red wine glass from Crate & Barrel, is first detected via the Twitter activity of the *Scandal* brand community and later associated with ratings and reviews on the product e-commerce site. The textual and image data from Twitter and "CrateandBarrel.com" offer insight into consumer sentiment, purchase intentions and behavior, and consumer identity with the product and the show characters. The Twitter data illustrates early consumer awareness of the wine glass, and a collective effort to determine and share the specific product information. In some cases, it also provides purchase intentions of *Scandal* audience members.

3.2 REVIEW OF LITERATURE

3.2.1 SOCIAL IDENTITY AND CONSUMER COMMUNITIES

The concept of community underpins much of the discussion and research into social settings and interactions (Muniz Jr & O'guinn, 2001). While the traditional notions of community may conjure up images of physical neighborhoods, families, or specific organizations, community also applies in consumer settings. Brand communities are focused on a service or product, do not require geographic boundaries, and are based on a collection of shared social relationships among those who have a high regard for a brand (Muniz Jr & O'guinn, 2001). As previously discussed, social media-based television brand communities adhere well to this model.

Consumer attitudes shared via social media may prove helpful for research into consumer sentiment or behaviors (Kozinets, 2002). Literature on brand communities has found that members develop a social identification based on the community (Algesheimer, Dholakia, & Herrmann, 2005), and social identity theory can be a helpful tool when examining consumer behaviors related to brands (Lam, Ahearne, Hu, & Schillewaert, 2010). Therefore, it follows, to examine the *Scandal* Twitter brand community conversations through a social identity lens.

We can view brand communities as having both the social system and communication channels necessary to disseminate information about products. As such, brand communities may potentially alter members' adoption behavior by exposing them to information about products (Thompson & Sinha, 2008). Given the similarity of brand communities to brand communities, social identity theory can be helpful in understand some of the motivations for product purchasing behavior.

Prior studies have shown that the best-established idea about the transmission of marketplace information is the importance of interpersonal communication (Feick & Price, 1987). Television show social media brand communities share a significant amount of information through online interpersonal communication. Within the communities one or more members may emerge as a market maven or key influencer characterized by general market experience (Feick & Price, 1987). In some cases, like with *Scandal*, the key influencer may not be a member but rather a character from the show. When this is the case, as is with *Scandal*'s main character, Olivia Pope, that maven takes on the role of a group prototype. A group prototype represents a preferred ideal collection of characteristics, but not necessarily a specific person. For individual group members, the more favorable (or close) their association with the prototype, the higher their own self-esteem (Hogg & Terry, 2000).

3.2.2 Self Enhancement, Products, and Consumer Identity

In 1966 Dichter identified four primary motives for WOM communication – product involvement, self-involvement, message involvement and other involvement. Other researchers have reported similar results. For example, Sundaram, Mitra, & Webster (1998) identified product involvement, anxiety reduction, advice seeking, self-enhancement, the desire to help others and the company and in the case of negative WOM, vengeance as drivers of WOM. Similarly, Blackwell, Miniard, & Engel (2001) claim that product involvement, message intrigue, dissonance reduction, concern for others and self-enhancement as primary motivators.

Shen, Hu, & Rees Ulmer (2015) report that a consumer's motivation for engaging in electronic WOM by writing online reviews is similar to the reasons that individuals engage in traditional offline WOM communication. In an examination of conversations that occur in internet opinion platforms Hennig-Thurau, Gwinner, Walsh, and Gremler (2004) found that consumers' motivation to engage in eWOM is fueled by their desire for social interaction, economic incentives, out of the concern for others and to enhance their self-image. Similarly, Cheung and Lee (2012) report, sense of belonging, to help other and to enhance personal reputation as primary motivators.

Self-enhancement "relates to people's need to seek experiences that improve or bolster the self-concept" (Wien & Olsen, 2014, p.418). Consumers like to feel good about themselves and seek recognition and positive evaluations from others (Jones, 1973). These consumers strive to enhance their self-concept, self-image, and self-esteem (Sedikides, 1993). This can be accomplished in a variety of ways including, presenting themselves as intelligent shoppers (Sundaram et al., 1998), by strategically selecting products to discuss online (Jensen Schau & Gilly, 2003) and by making recommendations that gain them attention (Engel, Kegerreis, & Blackwell, 1969). Consumers who are motivated to share information for self-enhancement purposes are more likely to engage in generating positive WOM about products that they own (Alexandrov, Lilly, & Babakus, 2013; Angelis, Bonezzi, Peluso, Rucker, & Costabile, 2012).

One way to gain positive attention is to discuss new or scarce products. Products have symbolic value (Lee, Gregg, & Park, 2013). Scarce products are often perceived to be unique and therefore highly desirable (Frank, 1985). Owning and discussing unique and scarce products, can help to position consumers as distinctive (Brewer, Kelley, & Jozefowicz, 2009; Wu, Lu, Wu, & Fu, 2012) and privileged (Frank, 1985). Sharing positive experiences and even bragging about them may enhance self-image (Alexandrov et al., 2013; Dichter, 1966).

Desire for stronger self-enhancement encourages individuals to seek strong positive social identities. Within community settings, this desire manifests as motivation to also protect the status or reputation of the group with which they associate. This desire for a more favorable association to the group in turn supports actions towards higher levels of self-esteem (Hogg & Terry, 2000). Consumers play an active role in choosing and shaping their identities which in turn affects their consumption choices. They are, indeed, deliberate actors making identity-focused consumption choices to receive the greatest return (Thompson & Loveland, 2015).

3.2.3 Social Commerce

The concept of social commerce can be found as early as the 1990's and appears in popular literature and academic research in the early to mid-2000's (Huang & Yu, 2016). In its most basic description, social commerce is commerce activity that leverages social networking through the use of social media platforms (Curty & Zhang, 2011). Consumer-to-consumer social influence and communication around purchasing decisions is not a new phenomenon but takes on a different set of characteristics in a social media setting (Huang & Benyoucef, 2013; Kim & Srivastava, 2007). Social networks collectively, and opinion leaders individually, have an impact on consumer decision-making in social media settings (Bryant & Thompson, 2017). The collective concept of community is central to the effectiveness of social commerce. While e-commerce revolutionized the shopping experience through a series of continuously evolving advancements in user-experience, the commercial experiences shared between consumers through social media-supported consumption activities are central to social commerce (Chen & Shen, 2015).

The nature of online activity proves to be problematic when trying to determine the boundaries of where a consumer starts or ends a shopping activity (Curty & Zhang, 2011). Therefore, social commerce is rather broad and exists in several contexts online. There are social commerce sites, like “Etsy.com” that combine the shopping functionality of an e-commerce site, with social networking features, along with the ability to complete a purchase within the site. There are other social commerce environments, including forums or sites like “polyvore.com” that provide reviews, ratings, or other sentiments about products without an integrated shopping option. Alternatively, social commerce activity can originate in a social networking platform like Twitter or Facebook, facilitating a broad conversation about specific products, brands, or product categories. Important to note, is that a commerce functionality need not explicitly exist to facilitate social commerce (Curty & Zhang, 2011).

Literature suggests that contexts of social commerce are varied, as are the definitions related to the phenomenon (Liang & Turban, 2011). There is a consensus that social media and commercial activities are key to both the definition and study of social commerce, and several broad frameworks have been proposed to aid in guiding research interest in the area. Themes of social support and trust are common across the social commerce literature landscape (Liang et al., 2011). One study examined the effect of emotional and informational components of social support combined with trust of the community as a whole, and individual members as it related to shopping and sharing intentions of social commerce. The study found that both commitment to community and trust toward the community were the essential antecedents of social commerce intentions (Chen & Shen, 2015). Research has shown that people engage in helping behaviors in online settings (Mathwick, 2002). And further examinations of trust and consumer decision-making in online shopping support the finding that trust precedes purchase intention (Kim, Ferrin, & Rao, 2008).

Community is central to the social support aspect of social commerce. The consumer content created through actions of rating, reviewing, and other communications is a hallmark of social commerce (Shanmugam, et al., 2016). And it is this act of sharing consumer generated content and information on consumption experiences that influences community commitment of members (Hajli, 2014). It is further suggested that in online purchasing experiences, it is the degree of trust as a function of community commitment, which mitigates risk in ultimate purchase decisions (Lee, 2015).

An important next step for literature focused on consumer decision-making in social media is to build on marketing applications. What can the observed interactions of social support, community commitment, trust, and purchase intention offer for marketing managers? Recall that social commerce exists in several different online contexts, confounded by the fact that it is difficult to follow the boundaries where online shopping activities start or stop (Curty & Zhang, 2011). Consider also, that prior literature suggests that social commerce facilitates a connection from business to consumers or more prevalent, consumer to consumer (Huang & Yu, 2016). Furthermore, it has been suggested that social commerce uniquely facilitates the consumer decision process through four distinct phases. These phases (Figure 2) are need recognition, pre-purchase activities, purchase decision, and post-purchase activities (Yadav, et al., 2013). In this study, the focus is on social commerce originating within the conversations of a distinct community on Twitter, progressing through the four phases of the decision process in a unique consumer to business transaction culminating at a major retailer's e-commerce site.

Adapting the two far left columns of Figure 2.2 provides highlights the interconnectivity and progression of conversation from Twitter to Crate & Barrel. More specifically, doing so provides context to the continuum of the consumer decision-making process in social commerce across platforms. Continuing the application, need recognition corresponds to seeing the TV character utilize the product, while pre-purchase activities include consulting the *Scandal* brand community on Twitter. Downstream purchase and post-purchase decisions happen on the Crate & Barrel e-commerce site including ratings and reviews. Post purchase activities may also appear back on Twitter, to share evidence of the purchase or possession back to the brand community.

Facilitative role of CMSEs at different stages of consumer decision making.

Stage of consumer decision process		Facilitating role of CMSEs	Contingency factors	Illustrative CMSE activities
Need recognition	Consumer becomes aware of problem or need	–Social network acts as source of inspiration and referral for consumer's pending purchase –Identifying with or conforming to reference groups	–Consumed in private vs. in public –Necessity vs. luxury product –CMSE's tie strength	Wish-lists, 'like', 'check in', 'bought by', 'pinned'
Pre-purchase activities	Consumer searches for information and evaluates alternatives	–Social network acts as source of information and approval for planned purchase –Reducing functional, financial and social risk	–High vs. low functional, financial and social risk of products –Share of experts, market mavens or social opinion leaders in CMSEs	Reviews, recommendations, discussion forums, blog posts, tweets, polls
Purchase decision	Consumer decides what, where and when to buy (or not to buy at all)	–Social network acts as source of information about where and when to buy –Social network helps coordinate group purchases	–High vs. low effort products –High vs. low social component of purchase or consumption –CMSE's tie strength	'buy now', group-purchase, price comparison sites, gift (coupon) delivery
Post-purchase activities	Customer determines satisfaction and may recommend or talk about purchase	–Social network acts as a sounding board for consumption experiences –Signaling identity, bonding and sharing experience, helping others	–High vs. low identity/social value –Fit between product and consumers' desired identity in CMSEs	'like', 'check in', 'bought by', 'pinned', blog posts, tweets, reviews, referrals, recommendations

Note: CMSEs refer to computer-mediated social environments. In column 1, propositions are shown in parentheses.

Figure 2.2. Online Consumer Purchase Decision Process (Yadav, et al, 2013)

3.3 METHODOLOGY

At the heart of this study is a desire to observe and follow conversations within the *Scandal* brand community from Twitter to the Crate & Barrel e-commerce site. The goal is to document and gain insight into some of social and consumer identity markers present in consumer messages related to purchasing the Camille wine glass used by main character, Olivia Pope. The nature of the study's goals requires a qualitative approach to analysis, to categorize consumer sentiment and expressions of identity. These expressions can then be tied to levels of post purchase satisfaction. Therefore, the research questions are as follows:

What can we observe about product purchase behavior within the Scandal brand community across the Twitter and Crate & Barrel e-commerce platforms?

Do consumers who associate the Camille wine glass with the Scandal television show exhibit higher product satisfaction than those who do not?

3.3.1 Data Collection & Sample

To follow the effects of social commerce from social media (Twitter) platform to e-commerce (“CrateandBarrel.com”) platform, this study requires two distinct datasets from each setting.

Twitter data was collected corresponding to a three-month period (9/15/13-/12/16/13) using social media tracking service Keyhole (www.keyhole.co). Using the search terms “Wine Glasses” and “*Scandal*” Keyhole retrieved 78 distinct tweets that included both search terms. In addition to the capturing the text component of the message, Keyhole also recorded the hashtags, URLs, and any media (e.g., photographs) that was included within each tweet.

Product reviews were collected from Crate & Barrel’s website by downloading the entire webpage for the 23-ounce Camille Wine Glasses into the qualitative data analysis package, Dedoose® on June 28, 2016. The page contained a total of 856 reviews. Each review includes a star rating (measured from 1 to 5), a user name and a time frame in weeks, months or years (e.g., Posted two weeks ago). Since Crate & Barrel’s reviews require a star rating but not comments, some reviews contain ratings but no feedback. Customers are also able to include a photograph with their rating and review comments. Where available, these photos are included in the dataset as well.

3.3.3 Variables And Operationalizing

According to Bales (1950), communication acts are single thoughts or behaviors. Given that a tweet can contain more than one thought it is possible for a single tweet from a single source to contain multiple units of analysis. Multiple units of analysis can result in multiple codes being assigned to each Tweet. In addition to the text component of the Tweet, emoticons, punctuation and URLs may also analyzed and coded. Like the product reviews, data may be analyzed with the assistance of the Dedoose® quantitative analysis software. Tweets will be analyzed for content, structure and emotion.

The Camille product reviews from “CrateandBarrel.com” also offer additional, more traditional variables or units of observation. Though still requiring assignment of codes in Dedoose®, these variables may allow for more of a comparative analysis of results. Review data allows for variables representing *Year* (or time), *Star Rating* (from 1-5), *Use of Image* (or not), presence (or not) and perhaps type of *Scandal Reference*. These additional variables lend themselves to simple quantitative analysis of commerce implications. During which, *Star Rating* would be a probable dependent variable.

3.3.4 Data Analysis Methodology

Opinion mining and sentiment analysis may be used to uncover individuals’ views and perceptions regarding various phenomena based upon text written in a natural language (Bose, 2013). And since this research is meant to understand the behavior under study – and not theory testing – grounded theory will be used. Grounded theory is an inductive process through which researchers collect, analyze and test data. Data collection and theory development are refined as the process persists (Mahnke, Benlian, & Hess, 2015) with analysis and data collection continuing until theoretical saturation has been reached. Data collection, then, is controlled by the emerging theory (Glaser, 1978).

3.4 RESULTS, DISCUSSION & IMPLICATIONS

3.4.1 DISCUSSION OF RESULTS

As this is an exploratory and qualitative analysis the results of the undertaking are primarily descriptive. The goal of the study is to follow social commerce activity in its hard-to-track state from a social networking platform (Twitter) to off platform consumption (Crate & Barrel). The analysis started with the 78 wine and *Scandal*-related tweets from the fourth quarter of 2013. This timeframe is essential to the analysis as it represents the initial identification and communication of the wine glass as a Crate & Barrel product to the *Scandal* brand community on Twitter. Coding of the tweets reveal a strong connection to ABC's *Scandal* television show, validating that the observed conversation is occurring within the target brand community. To that end, 76 of 78 tweets refer to the main character of the show, Olivia Pope along with 15 that references the actress, Kerry Washington, who plays Pope. Further review shows that 16 of the tweets refer to the network ABC, 51 to the show name, *Scandal*, 15 to the actress, and two to Shonda Rhimes, the show's creator. Yet another five tweets refer to Gladiators, a term often used by the main character in the show, and commonly used to refer to fans of the show.

Following the progression of online consumer purchase decision process from Figure 2.2, the tweets also exhibit consumers' identification of a need or desire for the Camille wine glass. Need recognition is followed by pre-purchase activity, in the decision process. Online pre-purchase activity often includes searches and consulting online communities. The *Scandal* brand community facilitates the pre-purchase phase of purchasing the Camille wine glass as evidenced by 14-member tweets expressing a need or desire for the wine glass, along with 10-member tweets explicitly seeking help in purchasing the wine glass seen on the television show. Another 14 tweets from community members provide information on the product, 15 include product descriptions and two others refer specifically to product availability. These 31 *Scandal* brand community tweets presumably assist other community members actively in the purchase decision process. Even more clear, are the 21 tweets specifically communicating an explicit intent to purchase the Camille wine glass to other community members.

The final stage of the online consumer purchase decision process, as shown in Figure 2.2, is the Post-Purchase stage. In this stage consumers may communicate purchase satisfaction, identity congruence, and social value. The social identity concept of a group protype factors heavily into this final purchase decision phase. Recall that in the realm of the *Scandal* brand community, Olivia Pope represents the ideal set of characteristics held by the protype. Group members desire to engage in activities to more closely resemble the group prototype and receive group validation for doing so (Hogg & Terry, 2000). Brand community members are observed displaying post purchase behavior on both Twitter and the Crate & Barrel website. On Twitter, community members shared 12 tweets reporting emulation of Olivia Pope, eight tweets related to using the product while watching Olivia Pope in the television show, and 1 tweet with a real time check-in while purchasing the Camille wine glass in a Crate & Barrel store.

The majority of post-purchase activity occurred directly on the Crate & Barrel Camille 23-ounce wine glass product page. Of the 857 product reviews collected, 394 or 46% referred back to *Scandal* either by show name, Olivia Pope reference, network or actor name. Table 3.1 below shows the number of reviews by year that did and did not have show-related references.

Table 3.1. Crate & Barrel Camille Wine Glass Reviews by Show Reference

	Year						
Review Reference	2011	2012	2013	2014	2015	2016	*Totals*
Non Show Related	1	6	9	78	261	108	463
Show Related	0	0	9	92	213	80	394
Totals	1	6	18	170	474	188	857

Note. 2016 reviews through June 28, 2016 only.

The table also shows a striking upward trend in number of total reviews left for the product from 2011 to 2016. In the first three years of availability, the Camille wine glass only received a total of 25 product reviews. Recall that the Twitter data shows the *Scandal* brand community identified the product in the latter part of 2013. Beginning in 2014, total reviews increase by more than nine times the 2013 level. This initial year following the brand community identification is also the only year in the observed data where show-related reviews outnumbered non-show-related reviews. The upward trend in product reviews continued for 2015, more than doubling from the year prior, before showing signs of decline by mid-year 2016. If the later half of 2016 saw the same volume of reviews, 2016 recorded roughly 100 less reviews than 2015.

Satisfaction with purchase is also an important concept to measure in the purchase decision process. Ratings that accompany a written consumer review aid in determining consumer satisfaction. On Crate & Barrel's site, a consumer may leave a star rating (1 to 5 with 5 being the highest rating) even if they do not leave written review. Table 2.2 provides the dispersion of star ratings by year for the Camille wine glass. The initial years, pre-*Scandal* community association saw little variance in star ratings with all ratings at 4-stars or 5-stars. The influx of reviews beginning in 2014 sees the introduction of ratings in the 1 to 3-star range. However, the Camille wine glass continues to receive predominantly higher ratings in the observed period. Perfect 5-star ratings represent more than 80% of all ratings in each year, with more than 90% of the ratings left through June 28, 2016 being 5-stars. Less than 5% of the ratings per year between 2014 and 2016 represent 3-stars or less. Considering ratings by show reference, 98% of all show-related references (for all years observed) were a 4-star or 5-star rating, higher than the 92% of 4-star or 5-star ratings for those ratings not referencing *Scandal*.

Table 3.2. Crate & Barrel Camille Wine Glass Star Ratings by Year

	Year						
Star Rating	2011	2012	2013	2014	2015	2016	*Totals*
1	0	0	0	2	12	3	17
2	0	0	0	4	10	2	16
3	0	0	0	1	11	1	13
4	0	1	3	21	57	7	89
5	1	5	15	142	384	175	722
Totals	1	6	18	163	441	182	811

Note. 2016 ratings through June 28, 2016 only.

Crate & Barrel reviews were also coded for a content and thematic analyses. Coding started by looking for reviews referencing product attributes as opposed to *Scandal*-related attributes. Initially, product features were coded individually, categorizing reviews that referred to the words *design*, *tall*, or *stem*. Through the iterative coding process, these three categories were combined into a product attribute (or product design) theme. Nearly 30% of all reviews observed were associated with a product attribute theme, representing 31%, 29%, and 24% of reviews in 2014, 2015, and 2016 respectively.

Further analysis of the Crate & Barrel reviews indicated some negative sentiment among consumers. Reviews were coded for references to the words *fragile*, *delicate,* and *break* (or broke or broken). Ultimately these categories were collapsed into a single negative design theme. Again, nearly 30% of all reviews referred to one of the negatively associated design elements of the Camille wine glass with similar dispersion for 2014 (26%), 2015 (33%), and 2016 (22%). I should note, however, that for some consumers who purchase wine, delicate or fragile may be acceptable or even preferred characteristics for wine glasses.

Finally, reviews were coded for positive post purchase associations. A positive image theme emerged from combining reviews coded for *beautiful, elegant, sexy, luxury/luxurious*, *chic, sophisticated*, and *class*. There was a total of 493 (46%) reviews in this theme from 2011 – 2016, with at least 55% of all reviews in each year from 2014 – 2016 falling within the theme. Of the 493 total positive image reviews, 96% were rated 4-stars or higher and 45% were from show-related reviews.

3.4.2 Implications

The results of the preceding analysis provide useful insight into consumer purchasing behavior. First, the study illustrates how brand communities assist cross-platform social commerce in guiding consumers through the online purchase decision process. As the Twitter data show, consumers may communicate or be influenced by the community to develop a desire or want for a given product. When the product is closely and positively aligned to a clearly defined group prototype, such as a popular television character, purchase decisions are strongly influenced by the community. This influence includes help seeking, and information provision behaviors along with explicit recommendations to a second product specific e-commerce platform. Consumers will then exhibit prototype association and even emulation on both the originating brand community platform and the product e-commerce platform, allowing for clear between-platform association.

Furthermore, the positive association with a brand community group protype appears to have lingering and halo effects. The lingering effects allow consumers to maintain positive post purchase satisfaction despite negative product attributes. The Crate & Barrel Camille Wine Glass reviews show that reviewers making a *Scandal* connection were less likely to report a negative design theme in their review (46%) than non-show-related reviewers (54%). Moreover, show-related reviewers reporting a negative design theme still left a 4 or 5-star rating 96% of the time. The halo effect is evident in the overall upward trend in reviews shown in Table 4.1 following the *Scandal* and Camille wine glass association in the latter part of 2013. The halo also carries over into the non-show reviewers, who despite accounting for a greater percentage (83%) of 3-star and below ratings, still give a 4-star or higher review more than 90% of the time. Likewise, though non-show-related reviews represent 54% of the negative design theme reviews, these consumers still left a 4-star or greater review 86% of the time. Ultimately, the general positivity and positive associations of the product by brand community members may influence even those consumers who have not explicitly expressed a *Scandal* show affiliation.

3.4.3 Future Studies

One of the limitations of this study was a lack of multiple coders for some of Crate & Barrel reviews. Ideally, future research would include additional coders allowing for a larger volume of tweets and reviews to be coded. This research centered on a product and brand community associated with a female group prototype. It may be interesting to do a similar analysis for a television show brand community and product for a male associated group prototype character. Beyond the explanatory value, there may be comparative value in any contrasting or divergent behaviors found compared to the initial findings of this study. Alternatively, this study could be expanded to include the study of the phenomenon associated with different types of products, or television shows not appearing on network television. Might we observe differences with cable television shows or streaming platform (i.e. Netflix, Amazon, Hulu) original content?

Lastly, *Scandal*'s series finale aired in the spring of 2018. It may be interesting to collect additional reviews picking up where this study ended and running through a year after the end of the series. This may provide insight into how long positive character associations continue after the end of a show, or when a show is in rerun syndication including rerun streaming availability.

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CHAPTER 4

BELTLINE ADJACENT: AN ANALYSIS OF GREEN SPACE SIGNALS IN ONLINE REAL ESTATE LISTINGS

4.1 INTRODUCTION

Major metropolitan areas around the United States are experiencing a return to urbanization and a rise in the popularity of central city living. Residents are leaving the suburbs and ex-urbs in favor of inner city living. Expensive high-rise, townhomes/city homes, and urban rehabs are increasingly sought after. Simultaneously, public-private development, amenities and consumer-focused attractions are also returning to inner city neighborhoods (Katz, 1994). Occasionally, what follows, is a displacement of the resident communities who never left central city neighborhoods. These neighborhoods are often lower income communities of color (Rothstein, 2017). This type of urban economic development aids in neighborhood gentrification. Research shows that certain brand names associated with sustainable types of development provide a price premium for certain homes (Eppli & Tu, 1999). This, in turn, may price out the original residents renewed economic development is intended to benefit.

4.1.2 Statement Of Purpose

Gentrification is happening in central city districts of major cities throughout the United States (Bohl, 2000; Burchell, et al, 2000). A renewed interest in inner city living is often associated with a new focus on active and green lifestyles associated with parks, green spaces, and sustainably built homes. Previously undesirable, working class neighborhoods are now highly sought after and increasingly more expensive (Ding & Knapp, 2010). These shifts are partially attributable to a continued and possibly increasing home buyer preference for proximity to green spaces (Lane, 2015). Such descriptions now often appear in thousands of online real estate listings.

These prominently-featured green attributes act as a signal for conscious or green consumption. That is, they represent status whose valence can transfer to consumers if they purchase the affiliated property. There is much research on consumer behavior and buying status, and a growing interest in status and green consumption (Gilg, Barr, & Ford, 2005). However, there seems to be a research gap in consumer behavior and green consumption in residences not associated with sustainability or eco-friendly features. This study seeks to understand the buying status effects when applied to housing purchases and green space signals.

4.2 REVIEW OF LITERATURE

4.2.1 Residential & Neighborhood Satisfaction

Real estate is a unique domain for conducting consumption behavior research. Home buying incorporates many factors and considerations that are not found in consumer goods purchasing decisions, particularly those related to neighborhood characteristics associated with the home being purchased. While the concept of utility or purchase satisfaction endures, home buying centers on two specific types of satisfaction. Residential satisfaction is often focused on and influenced by housing satisfaction, the degree to which a housing structure is aligned with occupants’ norms (Morris & Winter, 1975). Neighborhood satisfaction moves beyond the housing unit itself, to evaluate specific aspects of neighborhood quality or characteristics that contribute to satisfaction with a given neighborhood (Galster & Hesser, 1981; Gruber & Shelton, 1987). Think of residential satisfaction in the same vein as private consumption. In this association, residential satisfaction and home features are primarily consumed by the home buyer as he or she goes about daily life in the home, in private. Conversely, neighborhood satisfaction is more akin to the concept of public consumption. In this instance, the neighborhood, its features and reputation are readily known by others and is a visible or tangible attribute of the home by which others may draw inferences about the home buyer. It is in the public consumption realm of neighborhood satisfaction where buying status becomes applicable to home buying. Prior studies in neighborhood satisfaction show that spatial and vegetative density of communities influence satisfaction (Hur, Nasar, & Chun 2010) as does the location and availability of shared communal spaces (Kearny, 2006) and aesthetics and appearance related to features like landscaping and general upkeep (Lovejoy, Handy, & Mokhtarian, 2010).

4.2.2 Online Real Estate Listings

In the home buying process, consumers gather, process, and decide on potential properties and neighborhoods by searching through real estate listings. As the Web 2.0 has become a more integral part of the shopping experience for Americans, it has expanded into the home-buying process. Real estate agents have long used the Multiple Listing Service (MLS) as listing exchange for our national real estate marketing. However, in recent years, the MLS has become a web-based tool that agents may share with clients (Ford et al, 2005; Zumpanno, et al, 2002). Likewise, consumer-centric online sources comprised of public records and consumer-sourced real estate listing information, have also come to market. “Zillow.com” is one such platform and prominent brand for consumer access to an interactive, online database of national and local real estate inventory.

Historically, user-generated content is researched extensively in social media and other online platform settings, but not particularly in real estate focused e-commerce environments where content is created by agents as subject matter experts. In their 2011 study, Gelman and Wu evaluate the accuracy of records-based data versus agent-generated content by comparing “Zillow.com,” MLS, and public records for a sample of national real estate listings. They conduct an empirical study of the quality and implied reliability of record-based versus agent-generated content-based information in property listings on the “Zillow.com” website. Ultimately, the authors find that agent-generated content contributes to the completeness of individual listings. Furthermore, the study evaluates the primary drivers of observed errors in listings and finds a range of contributing factors. These factors range from functional design flaws in the site contributing to a diminished user-friendly interface to a lack of nationally standardized conventions for classification and reporting of essential property characteristics. The web-based MLS listing tool that real estate agents share with clients contains agent-generated content regarding features and attributes of listings.

Innovative work by Nowak & Smith (2016) built on this early online real estate listing study and operationalized textual content into variables. There variables were then applied in hedonic pricing models to isolate the value contribution of these textual comments to home prices. The study explores the value implications of textual content on relative real estate prices. Using agent-generated content from MLS listings, the authors construct a hedonic pricing model to evaluate textual contributions to real estate valuation. The researchers assert that textual content reflects inherent market knowledge of the real estate agents who create and manage MLS listings. This text is converted into tokens, or representative categories, for which estimated prices are derived when input into linear models. Findings show a 25% improvement of pricing errors in online estimates of housing prices versus actual transactional price. In other words, the study provides strong evidence that agent generated textual content in online real estate listings has real monetary value that endures through the closing purchase transaction.

These studies illustrate just how important additional information on home, property, and neighborhood characteristics can be to online real estate listings. This agent generated content can be thought of like the "megaphone effect" found in blogs and other forms of social media. The megaphone effect refers to the phenomenon of "regular" consumers creating web-based content that generates large followings and influence despite the lack of an institutional affiliation (McQarrie et al, 2012). In this application, the additional property listing characteristics are provided by real estate agents (or owner-sellers) outside of the authority of the municipally documented property details and records. The magnifying, or megaphone effect is seen in that online listings are far more popular and garner more interest when these agent-generated details are present, than for listings lacking such textual content beyond the record-generated details. The megaphone effect is often associated with research concerning consumer products or traditional consumer behavior phenomenon, often in exploration of aspirational purchasing behavior.

The effectiveness and benefits of online real estate listing capabilities exceed informational accuracy. Listing real estate properties online brings with it the general accretive value of internet marketing including lower transaction costs and wider audience reach (Ford et al, 2005). Furthermore, brokers can exploit the control over messaging and marketing (Kummerow & Lun, 2005) also provided through textual descriptions and agent generated content of online listings.

4.2.3 Green Consumption and Real Estate

Consumers have long used consumption to signal status or otherwise gain favorable association for purchasing or owning certain products or product categories. Furthermore, status research has identified that there are two key types of status at play in consumption, “social status,” or caché and “financial status,” or wealth (Bellezza et al., 2017). Home buying presents consumers an opportunity to exhibit both types of status.

Typically, buying status behavior is most commonly associated with luxury products. However, in recent years, healthy lifestyle and environmentally friendly product categories have also become affiliated with positive, “green” associations (Ward & Dahl, 2014). Likewise, Griskevicius et al (2010), conducted several studies regarding consumption choices, status, and green conservation implications. Their studies specifically looked at buying status proclivities in private consumption and public consumption conditions. They found that status motives strengthened purchase intentions for green products in public consumption conditions, and when green products were priced at a premium to non-green products. This supports prior green consumer segmentation work by Finisterra do Paco and Raposo (2010), which used consumers’ willingness to pay a premium for green products as a grouping factor.

Much of the prior research into green marketing and consumption behavior defines green through environmental (sustainability), ecological, or social implication lenses (Moisander, 2007; Brown & Wahlers, 1998; McDaniel & Rylander, 1993). Even when applied specifically to product purchases, the subject matter tends to focus on food (Shaw et al, 2005), clothing, or degree of sustainability associated with the use or production of household goods (Vantomme et al, 2005). Studies of green consumption in home buying or real estate applications are often concerned with the use of sustainable materials or eco-friendly appliances and technology (Bloom, Nobe & Nobe, 2011; Young et al., 2010), green certification of buildings (Fuerst, McAllister, 2011) and typically focused on commercial real estate (Eichholtz, Kok & Quigley, 2013 & 2010; Miller, Spivey & Florance, 2008). When green residential studies have been pursued, they have been related to multifamily properties (Couch, Carswell & Herbert, 2015; Carswell & Smith, 2009). Where residential real estate value has been studied in the context of green space much of the work estimates value and pricing implications of the presence of trees (Anderson & Cordell, 1998; Luttik, 2000), proximity to urban forests (Price 2004; Tyrväinen, 1997), or ample open space near the home (Bolitzer & Netusil, 2000; Geoghegan, 2002). Even more limited is research that considers the implications of economic development projects in general (Strand & Vågnes, 2001) or those designed to specifically address parks and green spaces (Burgess, Harrison & Limb, 1988; Voicu & Been, 2008). This study fills a gap in the literature through the evaluation of residential home price effect of green space oriented economic development projects. Further, it considers an overlooked application of green consumption and neighborhood satisfaction tied to a preference for an outdoor lifestyle, and the potential halo effect of status and luxury implications tied to branding of such projects.

4.2.4 The Atlanta Beltline

The Atlanta Beltline is an urban green space project under development within the City of Atlanta, GA. The project repurposes a circular series of 22 miles of dormant, unused railroad tracks that enclose the central business district and central residential neighborhoods of the city (Kirkman, Noonan, & Dunn, 2012). Its original purpose was to use the land to create parks, running and biking trails, and light rail to reconnect urban neighborhoods in the city, previously disjointed and cut off to economic growth by the development of Interstates 20, 75, and 85. It is a large public and private partnership undertaking, estimated to take some 20 years to be fully implemented. The project was borne out of a master's thesis written by Ryan Gravel towards fulfillment of requirements for his Master's in Architecture and Design from Georgia Institute of Technology, in midtown Atlanta (Gravel, 1999). In 2004, Shirley Franklin, the sitting mayor of Atlanta at the time, assembled a committee commissioned to conduct a formal feasibility study to turn the thesis into a viable municipal undertaking. Four years later, in 2008, the first Beltline Trail/Park section opened in Atlanta's Historic West End Neighborhood. A map of the current and future Beltline development is available in Figure 4.1. Since then, several phases have been completed and opened to the public and have spurred corresponding development and increased real estate activity in neighborhoods along the project. Previously stagnant working-class neighborhoods like Old Fourth Ward, where early green space and trails have opened, now enjoy competitive real estate markets with state of the art new construction and historic homes selling well above $600,000 (Immergluck, 2009).

Figure 4.1. Map of the Atlanta Beltline

4.3 METHODOLOGY

The unique design of the Beltline urban renewal project lends itself to conducting a study on public consumption of home buying and green status. The circular boundaries of the project and phased roll out create a natural delineation for isolating neighborhoods in which to explore public consumption behaviors. Recall that neighborhood satisfaction refers to a home buyer's satisfaction with the neighborhood characteristics of his or her home. As such, this study uses neighborhood characteristics to test public consumption behavior in home buying. More specifically, I use specific references to the Beltline project and related green spaces found in the user generated content within online MLS listings. As such, the analysis requires a mixed-methods approach combining a content analysis of the user generated content of listings, with a quantitative analysis of associated home prices. The following section discusses the dataset, variables, and methodology used to conduct the study.

4.3.1 Dataset

The sourced dataset consists of publicly available real estate database content from the Atlanta metropolitan real estate market online Multiple Listing Service (MLS). The initial download of the MLS database consists of 224,000 Atlanta metropolitan real estate listings from 2007-2013 includes both traditional public records-based listing data and the online real estate agent created content and home descriptions. The inclusion of agent created content allows for the content analysis of green space signals along with the traditional housing data.

4.3.2 Sample

The data accessed for the study is furnished by the Multiple Listing Service, and therefore represents all real estate brokerage facilitated home sales transactions for the reported time period. Of course, this would not include any transactions completed outside of the auspices of broker facilitated or MLS listed home sales, such as some For Sale by Owner sales. As these types of transactions tend to be relatively small compared to the broader real estate market, it is assumed that their exclusion from this analysis does not have a material effect.

The Beltline project encompasses only some of the neighborhoods in the City of Atlanta and Greater Atlanta Metropolitan real estate market. This study's sample will be comprised of all the transactions in the dataset identified within the target neighborhood(s) of Beltline project. I have chosen the Old Fourth Ward and Poncey Highland neighborhoods given their location adjacent to each other inside of the Beltline project, and proximity to two different Beltline parks, a dog park, and walking/biking trails.

Using these neighborhoods, narrowed the broader Greater Atlanta (inclusive of the 13 counties around the City of Atlanta) down to 162 observations. This subset was further reduced after removing errant entries and duplicate entries. On occasion, a property may be listed and removed multiple times during a sales cycle. Sometimes this may be due to the wishes of the seller, a failed purchase contract, or switching Realtors®. When this was determined in the data, duplicate listings were removed, keeping the listing pertaining to the final sales transaction. Note that in some instances, a home was sold more than once in unrelated transactions between 2007 and 2013. Transactions of this type were kept as separate and distinct observations in the data set, bringing the number of observations down to 124.

Nearly 40 other homes were listed on the MLS within the date range of the data set but did not have sales prices recorded before the cutoff date. For these observations, final sales prices and dates were sourced through the Fulton County real estate records database. Where available and occurring within the final cut off year of the broader data set, 2013, final sales price was recorded for the missing observations. The final number of observations available for the subsequent analysis is 111.

4.3.3 Variables And Operationalizing

The comprehensive nature of the Multiple Listing Service database means it includes internal and external characteristics of each home, information on each respective transaction, and in some cases, neighborhood characteristics. Additionally, listings created since the MLS began offering online listings also include the text-based property descriptions provided by listing agents to accompany traditional home details. This rich and robust collection of data and information provides a significant number of potential variables for use in this study. Following generally observed practices in real estate scholarly research, I have chosen variables that represent basic internal and external attributes of a home, transaction-related variables including price and timing, and several specialty variables concerning unique features of a property or neighborhood (Cebula, 2009).

At the heart of this study is understanding consumers' motivations for buying "green" goods. The goods in question are real estate, or homes more specifically, with the "green" affiliation coming from association with the Beltline project. The attachment of this "green" characterization may be signaled by both buyers and sellers of homes, thus requiring two separate dependent variables reflecting sellers' sentiments and buyers' sentiments respectively. The final home list price (net of any market adjustments) represents a seller's belief of the value of their home, inclusive of their sentiment. The final home sales price (in dollars), reflects the realized outcome and market value of the real estate transaction and represents a buyers' revealed preference regarding a property's value.

As mentioned previously, most of the independent variables in the analysis represent traditional home characteristics. Basic home attributes to be modeled include the number of bedrooms, bathrooms (including partial bathrooms), interior square footage, age of home, the year in which the home sold, and presence of a garage. Note that lot size was excluded from this study. There are many listings missing lot size information and very little variance in lot size for those listing reporting lot size. This is likely due to the urban nature of the sample neighborhoods, where lots are typically much smaller than suburban homes.

The Beltline project encircles the current central business district and much of the original footprint of the City of Atlanta. Of course, the independent variable of interest in the analysis is also a binary variable indicating a reference to either the Beltline specifically (as in a brand name), or green space/ parks (generic mention) in the textual property description. A detailed listing of operationalized variables described above may be found in Table 4.1.

Table 4.1. Detailed List of Multiple Listing Service (MLS) Variables.

Dependent Variables

1. **Sales Price –Final sales price *(in dollars)*** of a respective property
2. **List Price – Final list price *(in dollars)*** at which a property is offered for sale. List price may be revised up or down before sale. For this analysis it is inclusive of any adjustments made while on the market

Independent Variables

1. **Beltline Signal**: Did listing include a branded green space signal? **(Y=1, N=0)**
2. **Green Space reference**: Did listing include generic green space signal? **(Y=1, N=0)**
3. **Sales Year – Year** in which home sold
4. **Age of Home** – Calculated as the difference in year built and year sold

5. **Square Footage** – Reported **square footage** of the home's living space *(space meeting code requirements)*
6. **Bedrooms** – **Number of bedrooms** *(as defined by code: window + closet + door)*
7. **Bathrooms** – **Number of bathrooms** *(occasionally reported in fractions ½ = toilet & sink; ¼ = sink and vanity; ¾ = toilet, sink, & shower only)*
8. **Garage** – Does the home include a garage? (at least 1 car or more) **(Y=1, N=0)**

4.3.4 Data Analysis Methodology

This purpose of this study is to evaluate the distinct value of green space signals in online real estate listings on home prices. I intend to show the perceived value of such references from both sellers' and buyers' perspectives, including any difference between branded or generic versions of such signals. The following research questions set up the analysis to be done:

Do buyers (and sellers) place positive value on green space signals?

> **H_{2A}** Green space signals in online listings contribute greater value for related list and sales prices of a given property

Do buyers (and sellers) attribute greater value to branded versus generic green space signals in residential real estate prices?

> **H_{2B}** Branded green space signals are attributed higher value than generic green space signals in online real estate listings for related list and sales prices of a given property

Content Analysis

The primary independent variable of interest, related to Beltline and green space signals, come from the agent generated textually based content included in the dataset. A simple content analysis was completed to code the text entries into a binary dummy variable as previously described. The property description for each listing and transaction was evaluated for two types of signals from real estate agents/sellers. If the brand name of Beltline was mentioned in the description I assigned a 1 for Yes, otherwise a 0 for No. Likewise, if a generic green reference is mentioned such as park, dog park, trail, or green space, I assigned a 1 for Yes, or a 0 for No. Having two layers of signals allows me to understand if the branded reference has a different impact on pricing than the generic green space reference overall.

Hedonic Pricing Analysis

Hedonic pricing models are the most common method used to evaluate the value of real estate in applied and academic analyses. The underlying premise of this approach is that a home represents a bundle of desirable and undesirable characteristics to a consumer seeking to maximize their utility. This is similar to the concept of Lancaster's consumer demand theory, where consumer preferences are comprised of underlying bundle of characteristics (Lancaster, 1966). Collectively, these characteristics contribute to the market value of a property which is ultimately revealed through a sale or market transaction (Cebula, 2009). But it is important to note the hedonic analysis is focused on valuing the bundle of characteristics and not the actual value of the home itself.

Hedonic analyses allow one to evaluate the relative value of the individual characteristics of a product and their relationship to the product's overall price or market value (Monson, 2009). The job of hedonic analysis in real estate, then, is to investigate the relationship between the existence and amount of all these characteristics and the price consumers are willing to pay (Coulson, 2008).

Hedonic price models require a two-step process. The first step is to set up a linear regression analysis with the desired price focused dependent variable, and independent variables representing the bundle of housing attributes you wish to value. Once the regression is run, the resulting correlation coefficients are then used in the original equation to form the hedonic pricing model. The model can then be used to predict housing prices based upon the modeled attributes.

Generally, hedonic price models take on the following form:

$$\text{Price} = f(\text{Physical Characteristics, Other Factors}).$$

That is, price is a function of the physical characteristics of a given home and other, often environmental factors of the home. In this analysis, association with the Beltline or generic green space is the primary "other factor" of interest. In practice, hedonic models can be estimated using the absolute value of price, or, more commonly, with a log transformed version of price. The latter form is referred to as a semi-log hedonic model with a natural log of price regressed on unlogged (absolute value) independent variables (Sirmans, Macpherson & Zietz, 2005). Benefits of using the semi-log form include the ability to interpret coefficients as a percentage change in price relative to a one unit change in the independent variable, and mitigation of heteroscedasticity problems (Malpezzi, 1980).

In this study, the hedonic price model takes the form:

$$ln\text{Price} = f(\text{Physical Characteristics, Transaction Details, Green Space Signals}).$$

Remember the use of a green space signal can reflect home value sentiments of both sellers and buyers. Sellers' beliefs are reflected in the offering or list price of a home. Buyers' beliefs are revealed in the final sales price or realized market value of a home. Two models are needed to accurately investigate the potential effect of a green space signal for sellers and buyers, the natural log of *List Price* is the independent variable for the former, with the natural log of *Sales Price* as the independent variable for the latter.

The corresponding regression models are:

(2) $ln\text{ListPrice} = \beta_0 + \beta_1 Age + \beta_2 Sqft + \beta_3 Bdrms + \beta_4 Bthrms + \beta_5 Garage + \beta_6 SalesYr + \beta_7 GreenBrand + \beta_8 GreenGeneric$

(3) $ln\text{SalesPrice} = \beta_0 + \beta_1 Age + \beta_2 Sqft + \beta_3 Bdrms + \beta_4 Bthrms + \beta_5 Garage + \beta 6 SalesYr + \beta_7 GreenBrand + \beta_8 GreenGeneric$

There may be a difference in price effect between the branded green space signal, Beltline, and a generic reference to park, trail, or green space. The content analysis of listings allows for coding of the number of listings in each of the branded and generic green space categories. This structure effectively provides the ability to compare the effect – positive or negative – between the branded Beltline signal, generic green space signal, and listings having no signal at all.

4.4 RESULTS, DISCUSSION & IMPLICATIONS

4.4.1 RESULTS

A review of the descriptive statistics provides an overview of the resulting dataset of online MLS listings. Of the 111 unique listings, the average sales price was about $234,200, slightly below the average list price of $258,500. The profile of the average house in the sample is representative of a 67-year-old, 1,989 square foot dwelling with 3 bedrooms and 2.5 baths. Just under 40% of the homes in the sample reported have a basement (finished or unfinished). Slightly less than 30% of listings referenced green space in the agent-provided listing description, 16% of which used a branded reference to the Beltline project, and 13% referring simply to a park or trail. Additional detail for the descriptive statistics of the sample of listings may be found in table 4.2.

Table 4.2. Descriptive Statistics of Select MLS Listing Variables

Variable	Mean	Std Dev	Minimum	Maximum
Sales Price	234,234.50	0.13	0	705,000
List Price	258,520.30	169,557.30	15,000	775,000
Square Feet	1,989.61	896.83	707	7,518
Bedrooms	3.30	1.16	2	8
Bathrooms	2.53	1.17	1	8
Age of Home	67.45	36.06	0	118
Basement	0.38	0.49	0	1
Beltline Signal	0.16	0.37	0	1
Generic Signal	0.13	0.33	0	1

Note. N=111.

Finally, a review of the correlation matrix in Table 4.3 illustrates expected relationships among variables. Age of a home is negatively correlated across variables, and Sales Price and List Price are very highly correlated. None of the other variables exhibit unexpectedly high correlation.

Table 4.3. Correlation Matrix of Selected MLS Listing Variables

	Sales Price	List Price	Bedrooms	Bathrooms	Age of Home	Square Feet
Sales Price	1					
List Price	0.91	1				
Bedrooms	0.29	0.31	1			
Bathrooms	0.52	0.55	0.57	1		
Age of Home	-0.27	-0.36	-0.07	-0.47	1	
Square Feet	0.44	0.45	0.62	0.60	-0.20	1

Note. N=111.

A total of four hedonic pricing models were run in the analysis. Models A and C test the hypotheses from the sellers' perspective, using the log transformed List Price (lnList Price), as the dependent variable, for 103 observations. Models B and D test the hypotheses from a revealed preference perspective of the buyers' using the log transformed Sales Price (lnSales Price), as the dependent variable for 97 observations. All models exclude homes with more than six bedrooms, and listings where sales value is equal to zero resulting in 103 and 97 observations for List Price and Sales Price models, respecitively. Models A and B include the branded Beltline signal and a generic park signal as separate independent variables. By contrast, Models C & D combine (Beltline + generic) greenspace signals into a single binary variable. In all models, the square foot variable was divided by 1,000 for ease of interpretation. In the initial running of the models, bedrooms consistently resulted in a negative effect, contradictory to real estate hedonic pricing analyses. Further evaluation of the data found 8 observations with 6 to 8 bedrooms, several of whom appeared to have uncharacteristically low sales and list prices. Excluding all 8 observations having 6 or more bedrooms corrected the sign of effect. Models A and C with 103 observations reflect this smaller observation set. The same is true for Models B and D with 97 observations. Note that a total of 7 observations have sales prices of zero dollars which cannot be log transformed, reducing available observations with lnSales Price as the dependent variable to 97.

Table 4.4 provides side-by-side comparison of the model results for Models A through D. A review of Models A and B evaluates buyer and seller value implications comparing branded versus generic greenspace signals. As expected, age of home has a negative effect, as newer homes typically fetch a higher price. Furthermore, the statistically significant variables in the models are square footage and bathrooms at the *p* <0.05 level and year of sale and presence of a basement at the *p*<.10 level. It is important to note that neither the branded (Beltline) nor generic greenspace signals are significant in Model A or B, representing a lack of support for hypothesis $H_{2A.}$ Despite the lack of significance, however, there appears to be some support for H_{2B}, in that for both Models A and B, the parameter estimates for the branded Beltline signal are higher than those for the generic park signal. It also follows that sellers place a slightly greater value on both branded and generic green space signals than buyers, given the parameter estimates for these variables in Model A (lnList Price) are higher than the corresponding variables in Model B (lnSales Price).

Table 4.4 Summary Hedonic Price Results for Models A through D

Variable	Parameter Estimates			
	Model A *n=103*	Model B *n=97*	Model C *n=103*	Model D *n=97*
Intercept	-268.375	-274.057	-269.222	-274.673
Age of Home	-0.003	-0.003	-0.003	-0.003
Square Feet	0.387 **	0.387 **	0.388 **	0.389 **
Bedrooms	0.020	0.060	0.019	0.059
Bathrooms	0.227 **	0.236 **	0.226 **	0.237 **
Season	0.107	0.162	0.106	0.161
Year	0.140 *	0.142 *	0.14 *	0.142 **
Basement	0.225 *	0.234 *	0.222 *	0.233 *
Beltline Signal	0.175	0.129		
Generic Signal	0.113	0.101		
Combined Greenspace Signal			0.149	0.116
F	9.940 **	10.830 **	11.280 **	12.320 **
R^2	0.490	0.528	0.490	0.528

Note. lnList Price is dependent variable in Models A and C.
lnSales Price is dependent variable in Models B and D.
*p<.05.**p<.10.

Ultimately what the results of a hedonic pricing model represent are that the value of the Listing Price or Sales Price of a home is a function of the included variables. Take for example, bathrooms, which had the biggest influence in value for all models observed. For all models, the observed results suggest that for a given home in Old Forth Ward or Poncey Highlands sold between 2011 and 2013, one additional bathroom represents an increase of roughly 23% to the list price or sales price, holding all other characteristics constant. Despite our branded and generic green space signals not being significant, we can still interpret the value suggested by the model results. Given these are binary variables, they are interpreted differently in the model (Halvorsen & Palmquist, 1980). First, the parameter estimates are exponentiated, then subtracted from 1. The remainder is then converted to a percentage by multiplying by 100. After controlling for traditional home characteristics, a branded Beltline signal in a listing contributed to a 19% increase in list price and a 14% increase sales price. A generic green space signal accounted for a smaller price premium, representing 12% and 11% increases in list price and sales price, respectively. Finally, considering the models with a combined branded and generic signal, we see the trend upheld. Having either a branded or generic green space reference contributes to a list price that is 16% higher and a sales price that is 12% higher, all other variables held constant.

4.4.2 Discussion

The lack of a statistically significant result for either of the green space variables is unfortunate but not entirely discouraging. A major limitation of this study design is the small sample size of observations and limited time span. As such, it is quite difficult to detect a true effect of the green space signaling. However, some of the descriptive information in the data does suggest that a fuller analysis and larger data set may provide support for hypothesis H_{2A}. Recall that in real estate studies, neighborhood satisfaction is akin to a public consumption condition. Remember also, that prior work in status consumption, especially that related to "green" products, suggests that in public consumption conditions, consumers will pay a premium for such products. Consider this finding when evaluating the average list and sales prices shown in Table 4.5 below. For both branded and generic green space signals, consumers were willing to pay up to a $70,000 higher price on average than for those homes lacking a green space signal in the listing. Sellers and their listing agents also appear to anticipate this willingness to pay more, as represented by up to nearly a $75,000 higher list price on average for homes including a green space signal listing over those without. Furthermore, these average home prices also show additional support for H_{2B}. On average, sellers are listing homes with a branded green space signal at a $50,000 premium to those with a generic park reference. Consumers also show a preference for greater value placed on a branded green space signal, paying on average a $34,000 premium for such listings over those having a generic signal.

Table 4.5. Average Prices by Green Space Reference

Variable	Beltline *n=18*	Generic *n=13*	Neither *n=73*
Avg Sales Price	286,322	251,961	216,406
Avg List Price	313,372	263,026	238,571

Note. Excludes listings with 6 or more bedrooms.

4.4.3 IMPLICATIONS

The findings of this study, while not completely conclusive, do suggest the possibility of an interesting relationship. While social commerce is primarily concerned with consumer-communicated content like reviews, consumers are also influenced by signals from sellers. This study evaluated green space signals in online real estate listings. The findings suggest that in a specialty area like real estate, such signals can influence consumer buying behavior. Furthermore, the evidence of a premium value implication of branded over generic signals has deeper consequences for economic development affiliated green space projects. Often, these projects include considerations or set asides of affordable housing stock at the rental level. However, should a larger scale version of this study produce statistically significant results for the green space signals, it could suggest the need for public policy mechanisms in the housing sales market. For example, consumer response to green space signals in listings are resulting in higher listing and sales prices of homes, which could quickly outpace the buying power of residents native to the neighborhoods where development projects are undertaken. Branding may be used by municipalities as a marketing strategy to foster public and private support for economic development initiatives. However, when used as a signal in online real estate listings, this same branding can introduce unintended economic implications counter to the project's original aims.

This study evaluated the signal of nearby green space but did not explicitly investigate proximity to such spaces. Future studies should incorporate definitive consideration of proximity to green space and possibly even proximity to consumer-centric neighborhood features through the use of walkability scores.

4.4.4 Future Studies

This analysis has many opportunities for expansion and future studies. First would be a general extension of the currently designed study, adding online MLS listings for Old Forth Ward and Poncey Highlands in the remainder of 2013 through 2016 or 2017. Furthermore, comparing hedonic price results for these neighborhoods versus other Atlanta neighborhoods not adjacent to the Beltline project could offer interesting insight. The Martin Luther King, Jr. Memorial and National Park along with the site of the invention of Coca-Cola are also within the Beltline footprint. As a result, there are some historic landmarks and districts within the zone of the project and thus this analysis. An expanded analysis could also introduce a binary variable indicating a home's historic status to account for any value implications historic status may contribute to home prices. Lastly, the first associated project of the Beltline opened after the onset of the Great Depression and housing bubble in 2007 (Ellen & Dastrup, 2012). The financial conditions of the country led to an increased prevalence of foreclosure, short sale, and other bank-related home sales.

Of additional interest, would be an evaluation of the green space signal of Beltline adjacent neighborhoods north and south of Interstate 20. Historically, this delineation represents clear differences in racial composition and socio-economic status of neighborhoods, one that the Beltline project aims to mitigate. The MLS database offers census tract data for listings than can aid in adding a demographic component to test the green space signaling effects. It could be interesting to see if there are differences in the rates, magnitude, and effect of green space signals both branded and generic between such neighborhoods

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CHAPTER 5

CONCLUSION

5.1 FINAL CONCLUSIONS

The body of work included in this dissertation leverages three different environments, phenomena, and methodologies to explore and investigate the concept of social commerce. The analyses contained herein represent different approaches to the evaluation of social commerce contexts.

Essay 1 provided a pilot study evaluation of an integrated social commerce site. It found that consumers are influenced by social cues or signals represented by human likenesses in shop images. Further, it found that social networking components of social commerce, especially the existence of consumer reviews and followers influence consumer purchasing on the “Etsy.com” site.

Essay 2 detailed an explanatory analysis of cross-platform social commerce originating within the *Scandal* television show brand community. It found that the brand community social networking engagement helped funnel consumers through the online consumer purchase decision process, leading them to a specific product e-commerce location. Brand community affiliation was found to endure on the second platform, appearing in post purchase communications within product reviews. There was evidence of positive association of the product to the brand community’s ideal prototype, based upon the show’s main character. This social identity mechanism helped to mitigate negative product attributes on purchase satisfaction, resulting in high product ratings even for self-reported negative product features.

The third essay evaluated the impact of green space signals within online real estate listings. In this study, real estate agent-created listing descriptions replace consumer reviews as the source of user created online content. While essay 1 evaluated on platform social signals from sellers, this essay evaluated on platform branding signals from sellers. The results from this study were limited but suggest that both branded and generic green space signals potentially have an accretive impact on list and sales prices of residential properties and that a branded signal may be of more value than a generic signal.

Each of the studies reviewed provides an introductory view into its respective domain of the broader social commerce context. Many opportunities exist to expand these studies through quantitative and qualitative inquiry to further explore the impact of social commerce phenomena on consumer purchasing behavior. As new social networking and purchasing technologies emerge and evolve, so too may the study of social commerce.