

The Effect of Social Interactions on Demand and Service Levels  
of Online Retailers in the Social Shopping Context

by

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## ABSTRACT

Social shopping has emerged as a popular online retailing segment. Social shopping revolves around online communities that bring consumers together to shop for deals. Online retailers have been making significant investments to encourage consumers to join online communities linked to their websites in the hope that social interactions among consumers will increase consumption rates. However, the assumption that social interactions increase consumption rates in social shopping remains largely untested in empirical settings. Also, the mechanisms of such an effect remain unclear. Moreover, extant literature has overlooked the role played by elements of the marketing mix, including product characteristics and the commercial context, in defining the effect that social interaction mechanisms have on consumption rates in this focused context. Furthermore, common knowledge in the operations management discipline challenges the largely held assumption, in the social interactions literature, that increasing consumption rates will always be beneficial to online retailers. Higher consumption rates may lead to stockouts, leading to lower service levels. This dissertation develops and empirically tests a theoretical framework that addresses these managerially relevant issues. Specifically, the investigation centers on the effects of social interaction mechanisms on consumption rates in social shopping. In turn, it assesses the nature of the relationship between consumption rates and service levels, after controlling for inventory provision. Finally, it assesses the role played by elements of the marketing mix in defining the relationship between social interaction mechanisms and consumption rates in this focused context.

The research methodology uses experiments as the primary source of data collection, and employs econometrics techniques to statistically assess the conceptual framework. The results from the empirical analysis provide interesting insights. First,

they unveil influential consumers in social shopping according to relational and structural elements of the social network of consumers and time of purchase. Second, the influence of early buyers' purchases on consumption rates becomes weaker when the quality of the products being offered as part of a deal increases, but it becomes stronger when the price of those products increases. Finally, as deals' consumption rates increase, their service levels decrease at a faster pace.

DEDICATION

To my parents, Léa and Francisco, and to my grandmother, Beatriz.

*(in memoriam)*

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*“Dicebat Bernardus Carnotensis nos esse quasi nanos, gigantium humeris insidentes, ut possimus plura eis et remotiora videre, non utique proprii visus acumine, aut eminentia corporis, sed quia in altum subvenimur et extollimur magnitudine gigantea.”*

John, of Salisbury, Bishop of Chartres  
Metalogicon (1159)

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## TABLE OF CONTENTS

	Page
LIST OF TABLES .....	x
LIST OF FIGURES.....	xi
CHAPTER	
1 INTRODUCTION .....	1
2 RESEARCH BACKGROUND.....	8
Social Interactions and Consumption in Online Settings .....	8
The Nature of Social Shopping .....	11
Why are Social Interactions Influential in Social Shopping? .....	13
Social Influence Models and Their Applicability in the Social Shopping Context .....	14
3 HYPOTHESES.....	17
Social Interactions Mechanisms and Consumption in Social Shopping ...	20
Relational Models of Social Influence.....	21
Structural Models of Social Influence .....	23
The Moderating Role of Marketing Activity .....	28
Product Characteristics: Product Popularity and Quality.....	30
Commercial Context: Product Price .....	32
Consumption Rates and Service Levels .....	35
4 METHODOLOGY .....	46
Data Collection.....	54
Experimental Grounding.....	54
Deal Selection.....	55
Web-based Application Development .....	56



CHAPTER	Page
Subjects recruitment, Selection, and Experimental Assignment .	60
Experimental Protocol.....	67
Experimental Validity.....	68
Measures.....	80
Endogenous Variables.....	81
Independent Variables.....	82
Moderators.....	91
Control Variables.....	92
Statistical Analysis.....	101
The Relationship Among Consumption Rate, Social Interactions, Product Characteristics, and the Commercial Context.....	102
The Relationship Between a Deal’s Service Level and Its Consumption Rate.....	103
Understanding the Hazard Function.....	105
The Hazard Function Conditional on Time-Invariant Covariates .....	108
Unobserved Heterogeneity.....	108
Semiparametric Estimation: Cox’s Regression Model.....	109
Parametric Estimation.....	110
Estimation of the Econometric Model.....	111
5 RESULTS.....	114
Descriptive Statistics.....	114
The Effects on Consumption Rate of Social Interactions and Marketing Activity.....	116

CHAPTER	Page
The Effects on Service Level of Consumption Rate.....	120
Semiparametric Estimation of Cox Models .....	120
Parametric Estimation of AFT Models.....	122
Results Summary .....	127
6 DISCUSSION AND CONCLUSION .....	129
Discussion of Results .....	129
The Effects on Consumption Rates of Social Interactions	
Mechanisms .....	129
The Effects on the Relationship Between Social Interactions	
Mechanisms and Consumption Rates of Marketing Activity ....	131
The Effects on Service Levels of Consumption Rate.....	134
Academic Contribution.....	135
Managerial Implications .....	137
Limitations and Directions for Future Research .....	139
REFERENCES .....	142
APPENDIX	
A SEMIPARAMETRIC ESTIMATION LIKELIHOOD FUNCTION .....	160
B PARAMETRIC ESTIMATION LIKELIHOOD FUNCTION .....	162

## LIST OF TABLES

Table		Page
1.	Thirty-two combinations of independent variables in the factorial design for the randomized experiment .....	53
2.	Eight types of deals in the randomized experiment .....	53
3.	Goals of the participation incentives .....	62
4.	Demographics comparisons between samples of subjects .....	64
5.	Comparison of relational and structural properties between samples of subjects .....	65
6.	Comparison between the groups of confederates and actual early buyers.....	72
7.	Convergent and discriminant validity of manipulation and confounding checks (moderating variables) .....	75
8.	Discriminant validity of confounding checks (independent variables) .....	75
9.	Measures .....	80
10.	Reliability indices for the discussion forum posts ratings .....	98
11.	Commonly used distributions in survival data analysis .....	106
12.	Descriptive statistics .....	115
13.	OLS estimation of consumption rate using a robust covariance matrix ...	116
14.	Semiparametric estimation of Cox's models .....	121
15.	Parametric estimation of AFT models without unobserved heterogeneity	125
16.	Parametric estimation of AFT models with unobserved heterogeneity .....	125
17.	Results summary .....	128

## LIST OF FIGURES

Figure		Page
1.	High-level set of concepts and relationships.....	17
2.	Conceptual Framework.....	19
3.	Determination of optimal order quantity for the newsvendor model .....	38
4.	Cumulative consumption over time .....	42
5.	Screen shot of the application displaying one of the deals actually offered ..	59
6.	Exemplary small network of 15 participants .....	85

## Chapter 1

### INTRODUCTION

Social shopping is becoming increasingly popular (Knight 2011). Social shopping is a form of e-commerce that allows consumers to participate in the marketing of deals in online communities (Stephen and Toubia 2010). Simply put, it is an application that merges online retailing and social networking by connecting online consumers (Gordon 2007; Tedeschi 2006). In essence, social shopping attempts to mimic *social interactions* found in offline retailing (Tedeschi 2006). Thus, it revolves around the influence of consumer-generated media on business outcomes (Chevalier and Mayzlin 2006; Godes and Mayzlin 2004). As social shopping communities grow in number and size, the importance of social interactions as a selling mechanism in online retailing has become widely recognized (Jing and Xie 2011; Palmer 2008).

Indeed, a growing list of online retailers, including *Woot.com!*, *Ideeli*, *Gilt*, and *Kaboodle*, have dedicated resources to this innovative selling mechanism by encouraging consumers to join and participate in online communities linked to their websites. These firms are making these investments because of the fundamental assumption that social interactions in online communities will increase consumption rates (Godes et al. 2005). Thus, it is not surprising that recent studies have attempted to model (Brock and Durlauf 2010; Jing and Xie 2011) and empirically validate this assumption (Aral and Walker 2011; Hartmann 2010; Iyengar et al. 2009).

Yet, whereas most research has focused on *whether* social interactions increase consumption rates, the academic community has paid much less attention to *how* and *why* such an effect occurs. Also, the resulting *business outcomes* from the use of social interactions as a selling mechanism remain largely unexplored in the social shopping

context. Moreover, the predominant focus on viral marketing strategies (Hill et al. 2006; Manchanda et al. 2008; Nam et al. 2010) overlooks attributes of deals that might foster (or hinder) the effects of social interactions on consumption rates in this focused context. Furthermore, research on social interactions has largely assumed unlimited (i.e. unconstrained) supply. In doing so, such a stream of literature has overlooked product availability issues due to limited/constrained supply (Ho et al. 2002; Kumar and Swaminathan 2003; Swami and Khairnar 2003) that are inherent in online retailing settings (Jing and Lewis 2011). This dissertation addresses these shortcomings in the extant literature to advance managerially relevant knowledge in the disciplines of marketing and operations management.

From a marketing standpoint, this investigation is of primary importance because social interactions may magnify a stimulus to one consumer by its dispersion through the online community of consumers (Bikhchandani et al. 1998; Christakis and Fowler 2011; Iyengar et al. 2011a). In some cases, a marketing message to a consumer (e.g. mass media communication or email blast), can spill over to other consumers in a social shopping community. This would allow the latter to learn about a deal despite not being directly exposed to that message. In other cases, consumers may not only share information or spread information through the online community, but may actually care about whether other consumers in the community make similar choices. In these latter cases, a consumer's choice generates a feedback to her through the choices of other consumers in the social shopping community, thereby multiplying the effect of any initial stimulus to this consumer (Aral 2011). In both cases, social interactions imply that the aggregate-level effect of marketing activity to consumers becomes much larger than just the sum of the individual-level effects (Hartmann et al. 2008). Therefore, identifying influential consumers in social shopping is of interest, since their choices may help shape

demand through social interactions. This dissertation is relevant because there is a growing debate on how to determine who the influential consumers might be in several social networking contexts (Iyengar et al. 2011b). On the one hand, the specialized media (Duffy 2011; Rosebloom 2011; Stevenson 2012) has questioned the efficacy of emerging tools, such as Klout, PeerIndex, and Twitter Grader, which provide “scores of influence” in online communities. This is because they use proprietary (hence secretive) algorithms. On the other hand, analytical models of influential consumers (Trusov et al. 2010) remain largely untested in empirical online retailing settings.

From an operations management standpoint, this investigation is of primary importance because social interactions may induce demand uncertainty (Economides 1996; Granovetter and Soong 1986; Johari and Kumar 2010), which will ultimately affect service levels (Porteus 2002; Xu et al. 2010). In the social shopping context, service levels reflect inventory availability to satisfy demand during a deal. How and why social interactions may ultimately impact service levels reflecting inventory availability in social shopping is of interest because poor inventory service entails costs (Jing and Lewis 2011; Walter and Grabner 1975), thereby leading to missed profit opportunities (Cachon and Kök 2007; Jing and Lewis 2011; Porteus 2002). Moreover, stockouts are a known source of customer dissatisfaction and lost sales in the long-run (Anderson et al. 2006; Schwartz 1966; Zinn and Liu 2001). The proposed investigation is relevant to the literature on inventory provisioning and availability in online retailing because there have been accounts of sub-optimal service levels in social shopping. As a result, recent articles in the specialized media have suggested that social shopping may be a fad (Knight 2011; Parr 2011), and academic studies have questioned both the efficacy and the efficiency of this innovative selling mechanism (Anand and Aron 2003; Jing and Xie 2011).

Unfortunately, in the social shopping context, it is difficult to separate whether service levels decrease due to social interactions, an explicit scarcity strategy in supply, the marketing mix (i.e. product popularity, quality, and price), or a combination of some of these elements. Therefore, the fundamental research questions guiding this research are:

*In social shopping, do social interactions have an effect on service levels? If so, how and why? Also, under which circumstances do online retailers' inventory management and marketing activity interfere with such an effect in this focused context?*

This study contributes to both the social shopping and the online retailing literatures. First, it provides a more comprehensive conceptualization of social interactions than the predominant notion of word-of-mouth (WOM) influence. Second, it examines the mechanisms through which social interactions induce demand uncertainty in social shopping by affecting a deal's consumption rate. In turn, it investigates the nature of the relationship between a deal's consumption rate and its inventory performance in this focused context. As such, this study overcomes limitations in extant stochastic inventory management literature (Agrawal and Seshadri 2000; Dana Jr and Petruzzi 2001; Petruzzi and Dada 1999), which has assumed independence among consumers when investigating optimal inventory policies in retailing contexts. In doing so, it empirically assesses the veracity of the assumption that social interactions affect consumption rates in the focused social shopping context. Third, this study challenges the predominant notion in the social interactions literature that increasing a deal's consumption rate is always beneficial to online retailers. This is because the study



incorporates into the social interactions literature the fundamental inventory management premise that increasing a deal's consumption rate may lead to undesired stockouts, thereby impacting service levels negatively. Poor inventory service is associated with short- and long-run costs, which are detrimental to profitability. Fourth, this study identifies limiting conditions in the relationships among social interaction mechanisms, a deal's consumption rate, and its service level. Specifically, it assesses whether these relationships hold according to certain elements of the marketing mix – product characteristics and the commercial context – after controlling for inventory provision.

The research methodology involves experiments as the primary source of data collection. Experiments may overcome common identification issues in social interactions studies that rely on archival panel data. These identification issues arise due to the challenge of separating correlations in observed consumer choice from the true causal effects of one consumer's choice on another's (Brock and Durlauf 2010; Hartmann et al. 2008; Manski 2000). Experimentation has been also successful in the study of social interactions because it allows researchers to observe differences in the ways consumers operate under varying conditions, and learn about the nature of social interactions among consumers and their outcomes under those conditions (Babbie 2007). Furthermore, there has been growing interest in using experiments to identify and better understand the behavioral factors that affect operational outcomes (Croson and Donohue 2002; Knemeyer and Naylor 2012) in online retailing contexts (Chen et al. 2009; Kauffman et al. 2010b).

The statistical assessment of the conceptual framework uses econometrics techniques that deal with the common identification issues in social interactions studies and appropriately handle pooled cross section analysis of experimental data. The

statistical results provide interesting insights into how and why social interaction mechanisms affect consumption rates in social shopping. Specifically, the results identify three types of influential early buyers of a deal whose purchases influence other consumers to purchase that same deal, thereby increasing the deal's consumption rate. Those types of influential early buyers are: (1) opinion leaders, (2) consumers highly integrated into the network, and (3) consumers who link groups of consumers that would be disconnected otherwise. Also, the findings further our understanding of the role played by elements of the marketing mix on such an influence. Specifically, increasing a product's quality will diminish the effect of social interaction mechanisms on a deal's consumption rate. Conversely, increasing a product's price will magnify such an effect. Finally, this study's findings imply that managing demand by affecting a deal's consumption rate will have significant service level implications. Specifically, the results show that increasing a deal's consumption rate will negatively impact its service level in a non-linear, monotonically decreasing fashion.

In trying to achieve its goals, this study answers calls for integrative research in marketing and operations management to promote a better understanding of the interface between these two functional areas (Corrêa et al. 2007; Frankel et al. 2008; Ho and Tang 2004; Karmarkar 1996; Malhotra and Sharma 2002; Rinehart et al. 1989). Specifically, the study performs a joint analysis of supply-related decisions and the corresponding demand dynamics that should allow managers to better plan operationally while targeting marketing efforts towards a specific set of consumers in the focused social shopping context. The research also follows calls for use of innovative data sources and estimation techniques that contribute to empirical research in operations (Banker and Khosla 1995; Croson and Donohue 2002; Flynn et al. 1990; Gattiker and Parente 2007; Scudder and Hill 1998) and marketing management in the presence of social interactions among

consumers (Hartmann et al. 2008; Hirano and Hahn 2010; Van den Bulte and Iyengar 2011).

The remainder of this dissertation proceeds as follows: Chapter 2 provides the research background. Chapter 3 develops the conceptual framework. Chapter 4 describes the research methodology used to test the conceptual framework and to operationalize its constructs. Chapter 5 presents the results of the empirical analyses. Finally, Chapter 6 discusses the results' implications and offers directions for future research stemming from this research.

## Chapter 2

### RESEARCH BACKGROUND

#### **Social interactions and consumption in online settings**

The increasing recognition of the role of social interactions among consumers as an important selling mechanism has spurred renewed interest in modeling and understanding the implications of these interactions in numerous settings, including online retailing. The existing literature in this area comes from a variety of academic disciplines, including economics (Maurer and Meier 2008), sociology (Centola 2010), computation (Forman et al. 2008; Hu et al. 2008; Kempe et al. 2003), and marketing (Chevalier and Mayzlin 2006; Dellarocas et al. 2007; Fleder and Hosanagar 2009). However, there are few social interactions studies in the discipline of operations management. This is surprising, since modeling demand uncertainty is fundamental in stochastic inventory theory (Porteus 2002), and managing demand is regarded as key for operational excellence in online retailing settings (Rabinovich 2007).

Recent marketing studies have attempted to provide empirical evidence that social interactions may contribute to consumption in online retailing contexts by focusing on word-of-mouth (WOM) phenomena. For instance, Chevalier and Mayzlin (2006) found that an improvement in a book's online reviews leads to an increase in that book's online sales. Dellarocas (2006) observed that the manipulation of discussion forums to provide positive information regarding the quality of a product increases the likelihood of consumers of purchasing that product. Li and Hitt (2008) examined how idiosyncratic preferences of a deal's early buyers can affect other consumers' consumption of that deal. The authors provide managerial prescriptions regarding how online retailers might encourage those consumers who are likely to yield positive reports to generate positive influence for new products. Finally, Godes and Mayzlin (2009) investigated how WOM

drives consumption and which consumers are most effective at creating this kind of influence.

However, Godes et al. (2005) argue that the focus on traditional WOM, that is, “the one-to-one and face-to-face exchange of information about a product or service”, is a narrow definition of the phenomenon of social interactions in online retailing contexts. This is because information exchanged in online communities is one-to-many in nature, even though it shares many common features with traditional WOM. Also, influence does not require face-to-face interaction; indeed, the only precondition for influence is information (which allows social comparison) about the choices of other consumers (Godes et al. 2005; Marsden and Friedkin 1993). Influence does not require deliberate or conscious attempts to affect consumers’ choices. It simply involves “the spontaneous pickup or imitation by other consumers of a choice made by one consumer in the reference group, in which the initiator did not display any intention of getting the others to do what she did” as well as direct influence “in which the consumer makes choices which have the manifest objective of affecting the choices of another consumer in the reference group” (Lippitt et al. 1952).

Thus, Godes et al. (2005) offer a definition of social interactions in which *influence stems from observations of others’ actions* in online communities. This research builds on Godes et al. (2005) to conceptualize social interactions in social shopping as *interdependencies in which consumers’ choices influence others’ choices in a direct and meaningful way*. This conceptualization stipulates that, in social shopping, the observation of other consumers’ purchases may influence a consumer to purchase a deal.

This conceptualization leaves room for a variety of influence processes, including those that raise *awareness* of a deal or its features as well as those that

*persuade* consumers to change their expectations of the utility derived from features which they are already aware of. This formulation also leaves room for influence processes that operate on *imitation* (perhaps by status differences) as well as *social learning* (Aral 2011). The conceptualization of social interactions I provide is therefore flexible enough to incorporate several social influence processes.

Although this conceptualization is flexible in its view of influence mechanisms, it is rigid in its treatment of cause and effect. Social interactions are about how consumer behavior changes other consumer's expected utility and thus change the likelihood that – or extent to which – this consumer will engage in the behavior. Such a conceptualization defines influence as causal and excludes correlated and confounding effects, making causal estimation essential to social interactions identification. To be influential, consumers must cause behavior in the online community rather than simply being connected to or passing information on to a significant number of consumers. This conceptualization also regards social interactions as part of a dynamic system in which a variety of feedback loops continuously affects behavior in a constantly evolving fashion. Endogenous link formation may drive relationship formation, which may in turn drive changes in behavior, which then feed back into relationship formation decisions and again into influence on behaviors. In this way, it is both causally driven and dynamically involving (Aral 2011).

This conceptualization also allows influence to operate at social distance (Akerlof 1997), through connections of connections. For example, a friend of mine may buy a video-game deal, and although I have no interest in buying that deal, I may encourage others who have the same specialized interest to buy the deal based on the influence my friend has on my perception of its value to someone with that interest.

Finally, this conceptualization allows for indirect influence in cases where some subset of the online community is constrained in some way from buying a deal. For example, I may encourage my video gaming friends to buy a deal of a video-game device because my other video gaming friends use that device.

### **The Nature of Social Shopping**

The business model of online retailers who invest in social shopping is very peculiar. These websites offer limited-time, limited-quantity deals of a single stock-keeping unit (SKU) per deal. There is no replenishment involved, so deals run while inventory lasts or until they reach a preset deadline. On these websites, SKU selections range from apparel to wine, jewelry, toys, consumer electronics, and computers (Tedeschi 2006).

In addition, in social shopping, online retailers sell “deteriorating inventory” at marked down prices (Heine 2010). Deteriorating inventory refers to perishable units that were leftover from previous periods. In the case of perishable SKUs, unsold units suffer a quality reduction and therefore affect consumer choice behavior by providing lower valuations to consumers (Ferguson and Koenigsberg 2007). This definition of deteriorating inventory encompasses, for instance, old generations of a product line, off-season products, as well as remanufactured SKUs.

In contrast, the limited availability of social shopping deals due to time and quantity restrictions affects consumer choice behavior by providing higher valuations to consumers through a psychological effect known as “the scarcity principle”. This principle posits that opportunities seem more valuable to consumers when they are less available, and vice-versa (Cialdini 1985). The scarcity principle derives its strength from two major sources. The first source is consumers’ tendency to adopt heuristics in their

decision-making process (i.e. whether to purchase a deal). Verhallen (1982) showed that consumers use purchase restrictions as informational cues to evaluate deals. Consumers typically evaluate better deals that are difficult to get than those that are easy to get (Lynn 1991, 1992). Also, consumers often use a deal's availability to quickly and correctly decide on its quality (Cialdini 1985).

The second source of strength of the scarcity principle comes from the consumers' desire to preserve the freedoms they already possess. Constraining the opportunity to own or experience a product being offered as part of a deal signifies a "loss of freedom". In an attempt to negate this loss, consumers have a tendency to desire deals on which online retailers place such limitations (Inman et al. 1997; Verhallen 1982; Verhallen and Robben 1994).

Generally speaking, by placing limitations on social shopping deals, online retailers are attempting to create a sense of urgency among consumers, which should result in increased consumption rates, shorter searches, and greater satisfaction with the purchase. The underlying idea is that the notion of scarcity will raise a deal's perceived value, thereby influencing the consumers' intention to purchase it. This is because the motivating effect to buy a deal in social shopping goes beyond its price (Schindler 1998). Being able to take advantage of a limited deal creates, among buyers, a sense of being "smart shoppers" (Babakus et al. 1988). Purchasing a deal becomes "winning" a deal, which provides both utility and hedonic fulfillment (Garretson and Burton 2003). Schindler (1998) explains that buyers of a limited deal experience this "joy-of-winning", i.e. a pride-like satisfaction of having won in an implied game against other consumers. That is, limited deals put consumers in competition with one another. Online retailers



stand to benefit from such competition, because it should enhance the deals' effectiveness (i.e. their ability to sell) (Aggarwal et al. 2011).

### **Why are social interactions influential in social shopping?**

Social interactions may be influential in social shopping because they provide prospective consumers (1) information and (2) utility. These factors, in turn, enhance consumers' valuation of a deal, thereby leading to more purchases and consequently higher consumption rates.

First, on the Internet, consumers are only able to partially ascertain the value (i.e. worth) of a social shopping deal. To do so, they may use *information* provided by the online retailer (including product pictures, list of features, and description), discussion forums (Dellarocas 2006), other consumers' product recommendations (Fleder and Hosanagar 2009; Senecal and Nantel 2004), online search engines (Brynjolfsson and Smith 2000), etc. Such information is incomplete, however, because social shopping deals offer deteriorating inventory, so consumers would need to physically inspect a product to fully ascertain its value. However, in online retailing contexts, consumers will only be able to physically inspect a product after a purchase (Rabinovich 2007; Rabinovich and Bailey 2004; Rabinovich et al. 2008a). In order to obtain additional information, consumers may rely on others' purchases as a screening device (Nelson 1970). Hence, social interactions are influential in social shopping because consumers may resort to this selling mechanism to make informed decisions.

Second, the *utility* a consumer receives from purchasing a deal may depend directly on the purchases of other consumers (Duesenberry and Stemble 1949; Economides 1996; Granovetter and Soong 1986; Leibenstein 1950). This is referred to as the principle of network externalities (also known as "bandwagon effects") (Katz and

Shapiro 1985). An example would be a deal of a videogame. The utility a consumer receives from purchasing such a deal increases as other consumers purchase the same deal because she will be able to play her videogame with them. In the presence of such network externalities, social interactions will induce a tendency for conformity in behavior across members of a reference group (Bikhchandani et al. 1998). Further, as described by Bernheim (1994), even when the underlying intrinsic utility from the actions differs widely across consumers due to heterogeneity of individual characteristics, the presence of this desire to conform may create either a tendency towards common behavior or towards a few polarized types of behavior within a reference group. Hence, social interactions are influential in social shopping because they enhance consumers' valuations of deals by providing consumer utility.

### **Social influence models and their applicability in the social shopping context**

Social influence models that provide the basis for the study of social interactions effects trace their origins to the sociology literature, in particular to the seminal works of Schelling (1971), Granovetter (1978), and Marwell et al. (1988). These models posit that influence flows through certain channels over time among members of a social system (Rogers 1995). As such, the influence process consists of four key elements: the influence on choice behavior, communication channels, time, and the social system.

The communication channels are the means that transmit influence to or within the social system. These means are both external and internal to the social system. External means of influence in social shopping consist of the mass media, email blasts, or even software that will alert a consumer that a deal matching her requirements is on. Internal means of influence in social shopping consist of social interactions among consumers in an online community. Members of the social system (i.e. the consumers in

the online community) have different propensities for relying on or access to those two sources of influence when seeking information about a deal.

For over forty years, marketers have been using the Bass model (Bass 1969) to empirically investigate influence processes in consumption. The Bass model is a theoretical model leading to empirical support for the existence of the S-shaped pattern of consumption to represent “growth” (i.e. cumulative distribution of consumption over time). It presents the level of spread of consumption of a deal among a given set of prospective consumers over time (Mahajan et al. 1990; Mahajan et al. 1995). The model assumes that there are no repeat buyers and purchase volume per buyer is one unit. So, the number of buyers defines the unit sales for the deal. In the social shopping context, the Bass model focuses on the development of a cumulative consumption curve and serves the purpose of depicting the successive increases in the number of buyers.

In the development of his model, Bass (1969) assumes that buyers comprise two groups. The first group is comprised of “innovators”, who are the early buyers that initiate the model. These consumers will purchase a deal exclusively because of external sources of influence. The model posits that early buyers of a deal are the first  $p*m$  consumers to purchase that deal, where  $p$  is a coefficient of innovation (to be estimated from the data) and  $m$  is the potential number of ultimate buyers. The second group of buyers is comprised of “imitators”, who will purchase a deal because of internal sources of influence, i.e. social interactions. The number of imitators grows over time according to a coefficient of imitation,  $q$  (also estimated from the data). Hence, social interactions are important influences in determining the speed and shape of consumption processes in a social system (Mahajan et al. 1990; Valente 1991). The basis of the Bass model is the two-step flow of influence principle (Katz 1957; Katz and Lazarsfeld 1955), which posits

that external sources will influence “innovators” to make a purchase who, in a second step, will influence through their purchases the “imitators” to follow suit (Marsden and Friedkin 1993; Valente 1996, 2005).

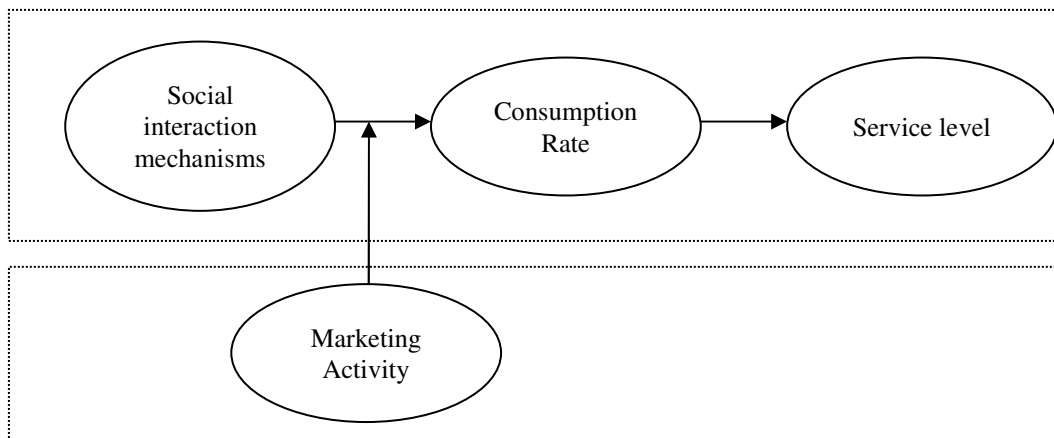
However, while the Bass model finds support in numerous settings (for a comprehensive review see Mahajan et al. 1995), it falls short in explaining or predicting why both its coefficients of external and internal influence will differ across products and deals. This issue is addressed by network models of social influence, which postulate that consumers differ in the degree they influence other consumers (Granovetter and Soong 1986). These network models posit that such differences are a cause of individual differences in time of consumption (Geroski 2000). For instance, some consumers purchase a deal when few others have done so, yet others purchase a deal only after many others have done so. It follows that such heterogeneity among consumers may have a potentially important role to play in explaining different consumption rates across deals.

The general principle of these network models of social influence is that the social distance of two consumers in a social network is associated with the occurrence of interpersonal influence between the consumers in different degrees (Burt 1987; Granovetter 1973, 1983; Marsden and Friedkin 1993). Such network models of social influence are divided into two categories: *relational models*, which postulate that influence is determined by the directional links among consumers, and *structural models*, which postulate that influence is determined by structural characteristics of the social network. Both relational and structural network models of influence suggest that social network links and social network positions influence consumer choice behavior. In the next chapter, I will introduce these models to support the theoretical development of the conceptual model.

## Chapter 3

### HYPOTHESES

To answer its research questions, this dissertation builds on network models of social influence to hypothesize relationships between social interaction mechanisms and a deal's consumption rate in the social shopping context. In addition, it builds on the scarcity and information economics literatures to hypothesize a moderating role of marketing activity on those relationships. Further, this dissertation builds on the behavioral operations management literature to hypothesize a relationship between a deal's consumption rate and its service level in this focused context. Figure 1 depicts this set of high-level constructs and relationships.



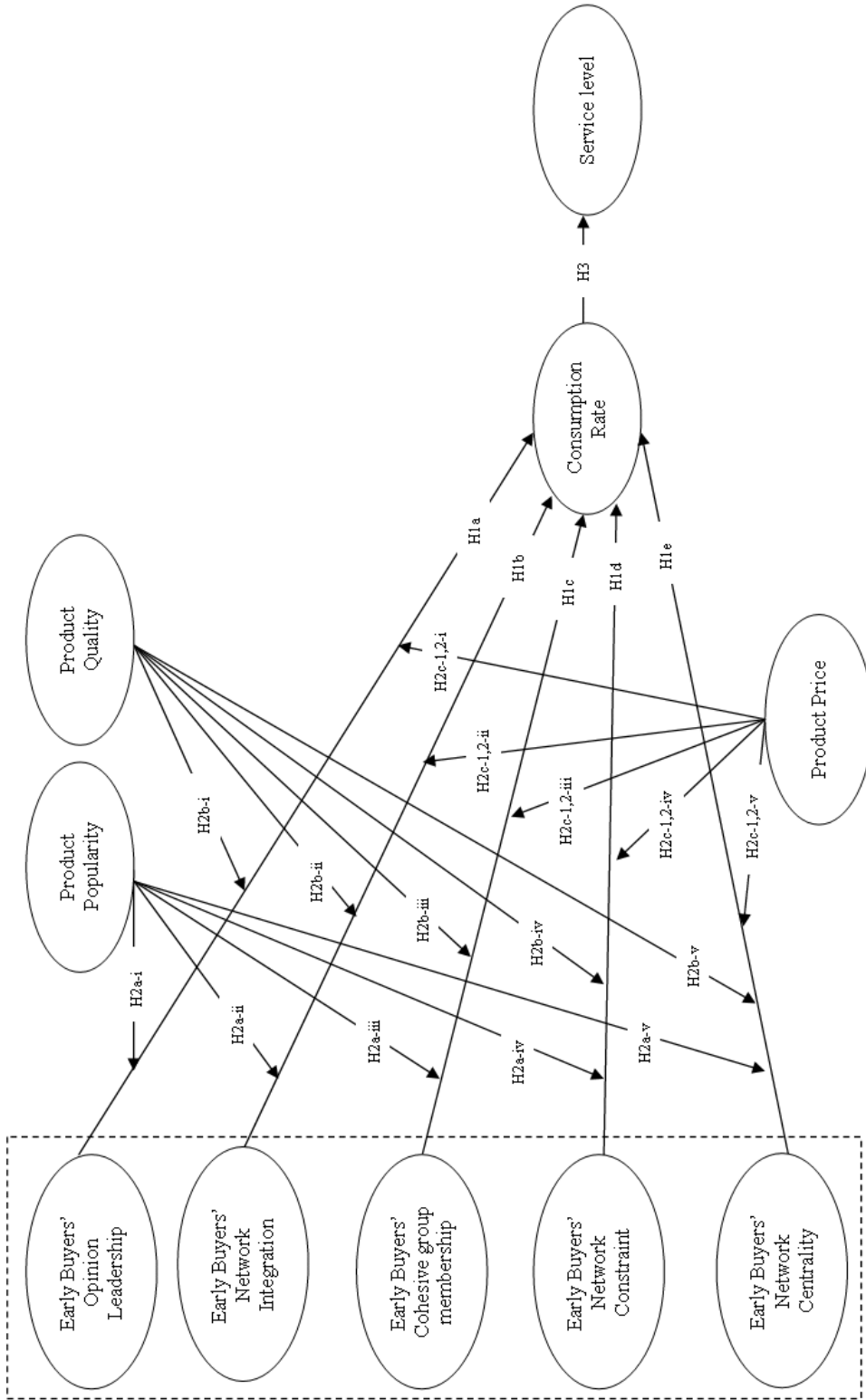
**Figure 1: High-level set of concepts and relationships**

The framework (Figure 2) breaks down the high-level elements in Figure 1 into this dissertation's constructs and hypothesized relationships. In this research, the level of analysis is the deal. Therefore, the research positions the constructs and relationships depicted in Figure 2 at the deal level of analysis.

The model depicts five social interaction mechanisms which are hypothesized to affect a deal's consumption rate. They represent the main mechanisms of interpersonal influence flow in the sociology and marketing literatures. These mechanisms are a deal's early buyers' (1) opinion leadership, (2) network integration, (3) cohesive group membership, (4) network constraint, and (5) network centrality.

In turn, the model depicts three elements of the marketing mix which are hypothesized to moderate the relationships between those five social interaction mechanisms and a deal's consumption rate. These elements refer to a deal's product's popularity, quality, and price. These are the main elements of the marketing mix that are related to utility, information, and scarcity effects in the marketing literature, and consequently might interfere with the main effects of social interactions on a deal's consumption rate.

Finally, the conceptual model depicts the hypothesized relationship between a deal's consumption rate and its service level.



**Figure 2: Conceptual Framework**

### **Social interaction mechanisms and consumption rate in social shopping**

In social shopping, a consumer is able to nominate another consumer in her online community by “following” her. This is done by the nominating consumer by allowing some digital platform (e.g. the online retailer’s website) to provide her updates regarding the nominated consumer’s actions (i.e. her purchases of the online retailer’s deals). In doing so, the nominating consumer creates a directional link to the nominated one. While the link is outgoing from the former, it is incoming to the latter. A link in a social shopping community may be bi-directional, inasmuch as two consumers are able to nominate each other. The collection of consumers and the links among consumers in a social shopping community form a social network (Wasserman and Faust 1994), in which social influence is likely to operate (Valente 2005) .

In order to better understand how social influence operates in social networks, scholars have developed two types of network models of social influence based on the two-step flow of influence principle. The first type of network models of social influence refers to *relational models*. These models postulate that directional links among consumers determine influence. According to these models, influence flows in the opposite direction of the links so it matters who makes and who receives the nominations. That is, in the social shopping context, these models posit that influence flows from the nominated to the nominating consumer, as purchases made by the former influence the latter’s choice behavior. The second type of network models of social influence refers to *structural models*. These models postulate that structural characteristics of the social network determine influence. Here, the direction of the links in the social network is irrelevant.



In the social shopping context, both relational and structural network models of social influence suggest that social interactions influence consumer choice behavior according to both social network links and social network positions. In the next two subsections, I will introduce these models to support the theoretical development of the conceptual model in Figure 2.

### **Relational models of social influence**

The first relational model of social influence considered in this dissertation is the *opinion leadership* model. To the best of my knowledge, the first study to use the opinion leadership model to investigate social influence was Moreno (1934), even though Bonacich (1972) popularized it. The main idea of this model is that influential consumers are “prestigious”. A prestigious consumer is the one who is the object of extensive immediate incoming links<sup>1</sup>. This implies that the model focuses solely on the consumer as a recipient of immediate nominations (and, consequently, sender of influence). The prestige (i.e. opinion leadership) of a consumer increases as the consumer becomes the object of more nominations.

Opinion leadership models are arguably the most tested models of social influence in marketing. However, it is striking that there is still a debate on whether the model’s assumptions hold (Aral 2011; Godes 2011; Iyengar et al. 2011b), since it has been nearly eighty years since Moreno’s (1934) seminal study. Namely, the opinion leadership model’s assumptions are: (1) social influence among consumers is at work, (2) some consumers’ purchases have a disproportionate influence on others’ purchases, and

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<sup>1</sup> Immediate links are those for which the geodesic linking the consumer to her contacts is 1. The geodesic is the length of the shortest path of links between two consumers in an online community.

(3) observers (both scholars and managers) are able to identify and target those opinion leaders.

This dissertation will join this longstanding debate. Here, I propose a conceptualization of social interactions that captures influence among consumers, and design an experiment that rigorously assesses whether purchases by identifiable opinion leaders have a disproportionate influence on others' purchases. Based on the two-step flow of influence principle and on the Bass model, the theoretical argument put forth here is that opinion leaders acting as "innovators" by becoming early buyers of a deal will trigger consumption of that deal by "imitators", thereby increasing the deal's consumption rate. That is, when opinion leaders become early buyers of a deal, it will sell faster. In formal terms, I state this dissertation first hypothesis:

**HYPOTHESIS H1A:** *Greater opinion leadership of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.*

The second relational model of social influence considered in this dissertation is the *network integration* model. One of the main controversies surrounding the opinion leadership model described above is that it restricts influence flows to the immediate links to the influential consumers (the opinion leaders). In order to relax this limiting definition of who the influential consumer are, Valente and Foreman (1998) developed the concept of *network integration*, which is the degree to which a consumer links to other consumers in her network through received nominations. In doing so, Valente and Foreman (1998) provide a sociometric measure based on links beyond direct ones. According to those authors, an integrated consumer is that one whose nominating consumers are also nominated by many others, and so on. In fact, in the network of an integrated consumer, her nominating consumers are likely to nominate one another as

well (Valente and Foreman 1998). Network integration models thus purport that influence flows from the integrated consumer through the network via nominations.

In the social shopping context, more nominations among consumers facilitate influence flow through the network, thus representing, on average, a greater likelihood that an integrated consumer's purchase of a deal will influence other consumers to purchase it, thereby increasing the deal's consumption rate. Therefore, based on the two-step flow of influence principle and on the Bass model, I offer the following hypothesis for empirical scrutiny:

**HYPOTHESIS H1B:** *Greater integration of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.*

### **Structural models of social influence**

Structural models of social influence postulate that the rate and character of influence are determined by structural characteristics of the social system within which the influence occurs. Extant social interactions literature reveals three different views of how consumers become influential in social networks. First, the *cohesive group membership* model stresses that influential consumers are strongly connected by having links to many other consumers, which promotes a normative environment that facilitates influence flows (Burt 1987; Coleman et al. 1966). That is, influential consumers belong to a strongly connected group. Second, a competing model of *network constraint* argues that influential consumers explore brokerage opportunities created by dispersed links among groups of consumers who are strongly connected among themselves, within their groups (Burt 1992, 1999). Thus, influential consumers are positioned between strongly

connected groups. Finally, a more traditional model of network centrality posits that influential consumers are closer to all other consumers in the network (Freeman 1979).

The *cohesive group membership* model of social influence focuses on strongly connected subgroups of consumers within a network. Strongly connected subgroups are subsets of consumers among whom there are relatively “strong” links. That is, the links among consumers are intense and direct. Friedkin (1984) examines the use of cohesive group membership as an explanatory variable in network models of social influence:

“[Network] cohesion models are founded upon the causal propositions that pressures toward uniformity occur when there are positively valued interactions between two persons, that these pressures may occur by being ‘transmitted’ through intermediaries even when two persons are not in direct contact, and that such indirect pressures toward uniformity are associated with short indirect communication channels connecting persons”. (p. 236)

Consequently, proponents of cohesive group membership models of social influence expect greater homogeneity among consumers who have relatively frequent contact (hence end up forming links) or who are linked through intermediaries, and less homogeneity among consumers who have less frequent contact (hence end up not forming links) (Friedkin 1984). This argument is reinforced by Burt (1987), who claims that connection strength is important because the more tightly consumers are tied into a network, the more they are affected by the group.

Strongly connected subgroups are theoretically important because of influence operating through (1) direct contact among subgroup members, (2) indirect conduct transmitted via intermediaries, or (3) the relative connection strength within as compared to outside the subgroup. Bringing this idea into the social shopping context, I propose that

consumers who are members of strongly connected groups will be able to influence other consumers in those groups through social interactions. Such an influence should increase consumption rates. Therefore, based on the two-step flow of influence principle and the Bass model, I propose the following hypothesis:

**HYPOTHESIS H1C:** *Greater cohesive group membership of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.*

In turn, the *network constraint* model of social influence proposes an alternative view of the relationship between network structure and influence ability by members of the network. The argument here describes ability to influence as a function of “brokerage” opportunities (Burt 1992), and draws on network concepts that emerged in sociology, most notably Granovetter’s (1973) “strength of weak ties”.

According to Granovetter (1973), “weak” links representing less intense, indirect links between subgroups in a social network are “holes” in the structure of the network. These holes in social structure – simply put, “structural holes” – create ability of influence for individuals whose relationships span the holes (Burt 1977, 1980, 1992). However, the structural hole between two subgroups does not mean that individuals in the subgroups are unaware of one another. It only means that the individuals are focused on their own activity internal to the subgroup (e.g. purchases among consumers of a same subgroup), such that they do not attend to the activities of individuals in the other subgroup. Individuals on either side of a structural hole circulate in different flows of influence. Structural holes are thus an opportunity to broker the flow of influence between individuals (Burt 1992; Granovetter 1973).

Structural holes separate non-redundant sources of influence. That is, they separate sources that are more additive than overlapping. In contrast, connection strength, as described above, is an indicator of redundancy. Strong links are likely to have the same sources of influence and therefore be exposed to redundant influence.

The network constraint principle refers to the fact that an individual is a broker in the network. Network constraint is the extent to which an individual's links are redundant (Burt 1992). To the extent that an individual's links are non-redundant, she is less constrained in the network.

Integrating this concept into the social shopping context, an influential consumer will be that consumer who will occupy a structural hole. That is, she will bridge links, which gives her an advantageous ability to influence others. This consumer has higher levels of influence because she reaches more consumers indirectly. In addition, the diversity of her links across separate groups means that her higher level of influence contains fewer redundant bits of influence. Furthermore, since she is positioned at a "crossroads" of social organization, she is likely to learn early about purchases in diverse groups, and likely to pass on influence to other consumers by making purchases herself (Burt 1999).

Therefore, according to the network constraint model of social influence, the two-step flow of influence principle, and the Bass model, it is reasonable to expect that early purchases of a deal by consumers who fill structural holes (hence are *less* constrained) will likely influence other consumers to purchase that deal, thereby increasing its consumption rate. In formal terms,

**HYPOTHESIS H1D:** *Greater network constraint of early buyers of a deal is negatively associated with greater consumption rate in that deal, ceteris paribus.*

The third structural model of social influence – and our final model in the theoretical development of relationships between social interaction mechanisms and consumption rates – is the *network centrality* model of social influence. This model is similar to the network integration model of social influence. However, instead of considering directional links, the centrality measure considers the overall pattern of links in the social network, irrespective of their direction, and thus represents a structural measure. It captures the degree to which individuals concentrate the links among other individuals. A centralized social network contains a few individuals who are the locus of contacts, whereas a decentralized social network has the connections spread among many of its members. Influence stemming from central individuals' actions is therefore able to reach out easier to other individuals in the network than influence stemming from less central, more peripheral individuals (Bonacich 1987; Freeman 1979; Marsden 2002).

Bringing this notion of network centrality to the social shopping context, we should expect to observe central consumers influence others through purchases and, as a result, increase consumption rates. In turn, when peripheral consumers make purchases, it takes longer to observe who is purchasing a deal, so in these cases, consumption rates should be lower. Hence, based on the two-step flow of influence principle and the Bass model, we should expect to observe higher consumption rates in deals when early buyers are central consumers. Therefore,

**HYPOTHESIS H1E:** *Greater network centrality of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.*

### **The moderating role of marketing activity**

The previous set of hypotheses (**H1A** through **H1E**) offers important insights into how and why social interaction mechanisms may influence consumption rates in social shopping. The theoretical argument builds on the two-step flow of influence principle and the Bass model to posit that purchases made early by influential consumers are likely to influence other consumers' choice behavior, thereby increasing consumption rates. Each hypothesis offers different theoretical accounts of social interactions, each describing a different mechanism of social influence. However, although these social influence mechanisms are conceptually distinct, their expressions in data may often be indistinguishable, making it impossible to identify the exact nature of the mechanism at work (Van den Bulte and Lilien 2001).

Unfortunately, one may confound social interactions effects with common contextual effects (Brock and Durlauf 2007; Manski 1993; Van den Bulte and Lilien 2001). Classic studies (Coleman et al. 1966; Katz and Lazarsfeld 1955) documented that awareness or an attitude toward consumption can be affected not only by social interactions but also by firms' marketing efforts. More recent research (Bemmaor and Lee 2002; Van den Bulte and Stremersch 2004) has further challenged the empirical support for the role of social interactions in consumption by showing that S-shaped consumption patterns, often interpreted as evidence of social interactions, can result from population heterogeneity rather than influence. These results support concerns that the positive relationship between the prevalence of prior purchases among a consumer's social network connections and the likelihood of the consumer's future purchases – typically interpreted as evidence of social interactions – is often produced by factors that are excluded from the model.



However, I contend that inconclusive and often conflicting results (Marsden and Friedkin 1993; Valente 1996; Van den Bulte and Lilien 2001) have overlooked potential *contextual moderators* in the relationship between social interactions and consumption. In general terms, a moderator is a variable that affects the direction and/or strength of the relationship between an independent variable and a dependent variable. That is, a variable is a moderator if the relationship between two variables is a function of its level. This definition indicates an interaction between the independent variable and the moderator, or a non-additive relation, where the dependent variable is regarded as a probabilistic function of the two interacting variables. Specifically within a correlational analysis framework, a moderator is a third variable that affects the zero-order correlation between two other variables. A moderator effect within a correlational framework may also be said to occur where the direction of the correlation changes (Baron and Kenny 1986; James and Brett 1984).

Thus, instead of looking for confounds, this research will hypothesize and empirically assess the role played by contextual factors acting as potential moderators in the relationship between social interaction mechanisms and consumption rates in the focused social shopping context. In doing so, this research joins an ongoing debate.

As discussed earlier, the nature of social shopping deals – i.e. they are limited and offer deteriorating inventory – affects consumers' valuations by (1) affecting *utility*, (2) providing incomplete *information*, and (3) promoting *scarcity* effects. However, social interactions are also a source of utility, information, and scarcity effects in social shopping. Hence, social interactions will be more (or less) influential in social shopping inasmuch as the marketing mix will be less (or more) effective in affecting consumers' deals valuations.

In order to identify which elements of the marketing mix may interfere with social interactions effects on consumption rates, I adopt a parsimonious approach and build on previous studies in the scarcity and information economics literatures (Debo and Van Ryzin 2009; Rabinovich et al. 2003; Tereyagolu and Veeraraghavan 2011). Three primary factors in these literatures that are related to utility, information, and scarcity effects are a product's popularity, quality, and price. While product popularity and quality correspond to attributes that reflect the level of awareness for, and the conditions of a particular SKU, product price captures the appreciation that the marketplace has assigned to the SKU.

#### **Product characteristics: product popularity and quality**

The first contextual factor hypothesized to moderate the effect of social interaction mechanisms on a deal's consumption rate is the *popularity* of the product being offered as part of that deal. Research suggests that product popularity is associated with greater shopper knowledge and less willingness to search for *information* (Chevalier et al. 2000; MacDonald 2000). Thus, consumers considering buying a deal become less dependent on other consumers' purchases to make informed decisions as product popularity increases. This is particularly heightened in online settings, as information pertaining to popular products is readily and extensively available (Bakos 1997; Brynjolfsson and Smith 2000; Smith and Brynjolfsson 2001). This availability of information provides cues regarding product functionality and ease of use, thus reducing its perceived complexity and making it easier for consumers to assess its results. Product popularity may also increase *utility* because popular products, in general, dictate or follow dominant standards, thus being more compatible with other products (Katz and Shapiro 1985). Finally, product popularity may induce *scarcity effects*, since consumers

are likely to infer that more popular products will sell faster thereby increasing the likelihood of becoming unavailable (Stock and Balachander 2005; Verhallen 1982).

According to previous arguments, I expect that greater product popularity will convey information, provide utility, and induce scarcity effects, thus overcoming consumers' needs to resort to the observation of purchases by others to make a decision regarding whether to purchase a deal. I expect, then, that:

**HYPOTHESIS H2A:** *Greater product popularity will negatively moderate the relationship between a deal's consumption rate and that deal's early buyers' i) opinion leadership, ii) network integration, iii) cohesive group membership, iv) network constraint, and v) network centrality.*

The second contextual factor hypothesized to moderate the effect of social interaction mechanisms on a deal's consumption rate is the *quality* of the product being offered as part of that deal. Consumers often rely on previous purchases as a screening device when shopping for experience goods (Nelson 1970). In social shopping contexts, ascertaining the quality of a product is very complex, since websites in this online retailing segment sell deteriorating inventory. However, most online retailers still provide cues of a product's quality, for instance by *informing* consumers, on their website, whether the product is not "mint in box" (i.e. it has been refurbished, remanufactured, or returned). It has been shown that consumers negatively react to the notion that a product has already been touched by another consumer (Morales and Fitzsimons 2007). Also, prior studies have shown significant variations in buyer experience across product categories for remanufactured products (Subramanian and Subramanyam 2008). That is, deteriorating products – i.e. of lower quality (Ferguson and Koenigsberg 2007) – are likely to provide consumers lower *utility* than those "mint in box" – i.e. of higher quality.

Furthermore, consumers generally conclude that high quality products are scarce, and vice-versa (Cialdini 1985; Stock and Balachander 2005). As already discussed, such *scarcity effects* are likely to influence consumption thereby negatively affecting the influence of social interactions in social shopping contexts.

The aforementioned arguments suggest that consumers will resort less to observing other consumers' purchases as the quality of the product being offered as part of a deal increases. In formal terms:

**HYPOTHESIS H2B:** *Greater product quality will negatively moderate the relationship between a deal's consumption rate and that deal's early buyers' i) opinion leadership, ii) network integration, iii) cohesive group membership, iv) network constraint, and v) network centrality.*

### **Commercial context: product price**

The third contextual factor hypothesized to moderate the effect of social interaction mechanisms on a deal's consumption rate is the *price* of the product being offered as part of that deal. According to the signaling literature in information economics, a deal's price should be expected to signal its actual value (i.e. the deal's worth). Here, such a measure of worth is based purely on the *utility* derived from the purchase of a deal. That is, utility derived value allows us to measure a deal in terms of the outcomes of its purchase (Tirole 1988). Value signaling is relevant in this study because it affects consumer choice behavior by providing valuation *information* to consumers (Milgrom and Roberts 1986; Wolinsky 1983). A consumer should be expected to resort less to observing others' purchases in order to purchase a deal the closer that deal's valuation gets to her own reservation value.

Unfortunately, extant literature provides mixed results on the extent that prices indeed signal value. Bagwell-Riordan's (1986) model of intertemporal pricing suggests that online retailers offering high-value products would signal the products' value through high prices. This is because a high-value product is more costly to source than a low-value product. Hence, online retailers offering a high-value product as part of a deal have incentive to signal value with a high price instead of a low one.

However, it may be the case that a low price may signal a high product value. This is because high-value products generate more repeat purchases (Nelson 1974). By consistently offering high-value products at low prices, online retailers attract and/or retain consumers. This in turn, yields profits in the long-run. Hence, they have incentive to signal value with a low price instead of a high one. Simply put, online retailers are telling the market that making low profits by offering high-value products at low prices as part of a deal in the short-run is a strategy. This is because they are confident their consumers will be satisfied with their purchases, and as a result will come back for future purchases.

Thus, the circumstances under which a low or a high price signals high-value differ. Such differences are likely to blur the *informational content* of prices in social shopping, so it is unclear whether consumers would resort to observing purchases of others to make a decision.

A closely related issue is that online retailers tend to overprice deals, given inherent *scarcity* (Lynn 1991, 1992) in social shopping. Indeed, it has been shown that, in some contexts, scarcity may signal value (Debo and Van Ryzin 2009; Debo and Veeraraghavan 2010), which may command higher prices (Milgrom and Roberts 1986; Wolinsky 1983). Moreover, consumers may be tempted to buy a scarce/highly priced

product because of desire for “exclusivity” (Leibenstein 1950). Such psychological effects imply that consumers would buy more as fewer consumers are present in the market when prices become too high. That is, according to scarcity literature, an increase in prices would change the sign and the magnitude of the direction of the relationship between social interactions and consumption rate.

However, recall that consumers in social shopping are in general bargain hunters. Bargain hunting may be related to a number of motivations that provide *utility*, such as role enactment, which describes normative economic behavior, including finding a real bargain and searching for the optimum value (Westbrook and Black 1985), price consciousness, which involves purchasing the cheapest products and saving money by shopping for bargains (Donthu and Garcla 1999), and value shopping, which refers to shopping for sales, looking for discounts, and hunting for bargains (Arnold and Reynolds 2003). Knauth (1949) explains that consumers inspecting a deal may be induced to purchase that deal if they are in a “bargain-hunting mood”.

In fact, recent studies have documented impulse buying in online retailing (Ahuja et al. 2003; Jeffrey and Hodge 2007; Parboteeah et al. 2009). In the social shopping context, such behavior may be induced when the online retailer sets prices that appear to be below consumers’ reservation values. Hence, according to the bargain hunting literature, a decrease in prices would decrease the impact of social interactions on consumption rates. Conversely, higher prices should induce bargain hunters to rely more on social interactions to make consumption decisions.

In sum, the aforementioned arguments offer different predictions for the effects of prices on the relationship between social interactions and consumption rate. While there is no clear prediction on the informational content of prices, it appears that high

prices may induce scarcity and desirability effects, while low prices may provide bargain hunters high utility. Thus, it is unclear whether consumers would resort more or less to others' purchases to make a consumption decision as prices increase/decrease. There are justifiable arguments for both directions of moderating effects of prices on the relationship between social interactions and consumption rate. In order to unveil the actual role played by product price in the social shopping context, I offer the final set of *alternative* hypotheses for empirical scrutiny:

**HYPOTHESIS H2C-1:** *Greater product price will positively moderate the relationship between a deal's consumption rate and that deal's early buyers' i) opinion leadership, ii) network integration, iii) cohesive group membership, iv) network constraint, and v) network centrality.*

**HYPOTHESIS H2C-2:** *Greater product price will negatively moderate the relationship between a deal's consumption rate and that deal's early buyers' i) opinion leadership, ii) network integration, iii) cohesive group membership, iv) network constraint, and v) network centrality.*

### **Consumption rates and service levels**

We turn now our attention to the fundamental relationship between demand and supply in social shopping. So far, the theoretical argument has centered on demand management. However, what are the business outcomes of managing demand in the presence of social interactions among consumers?

In this research, we are particularly interested in the effects on service levels of consumption rate increases. Building on extensive literature on operations and inventory management, this research conceptualizes a deal's service level in social shopping as the

probability that a demand is met directly from inventory (or, conversely, the maximum acceptable probability that a demand is not met from inventory) during the deal. That is, the service level represents the probability of no stockout in a deal, being a stockout the occasion when the on-hand inventory drops to the zero level. This definition of service level is commonly referred to as “ $P_1$  service”, “type 1 service”, or “cycle service level” (Nahmias 2004; Porteus 2002; Silver et al. 1998).

Assessing the demand-related factors that impact a deal’s service level is important because online retailers facing stockouts incur costs (Jing and Lewis 2011; Walter and Grabner 1975) including both the lost profits from the immediate lost sale, and the long-run costs if stockouts reduce the likelihood of future purchases. For online retailers, the choice of service level is usually based on the underlying stockout costs, but such costs are very hard to obtain (Anderson et al. 2006; Schwartz 1966; Zinn and Liu 2001).

Unfortunately, when demand varies substantially, as is the case across social shopping deals, it may become very expensive to maintain high service levels (Agrawal and Seshadri 2000; Schwartz 1970). So, I contend that increasing a social shopping deal’s consumption rate will ultimately affect its service level negatively, which may be detrimental to an online retailer’s profitability. In doing so, I dispute the largely accepted assumption, in social interactions studies, that suggests that increasing the consumption rate will always be beneficial to online retailers. This is because of the fundamental principle, in operations management, that, under specific conditions, an increase in the consumption rate may lead to a disproportionate decrease in the service level. In the theoretical development that follows, I put forth arguments that support the notion that an increase in a deal’s consumption rate will lead to a much higher decrease in the deal’s



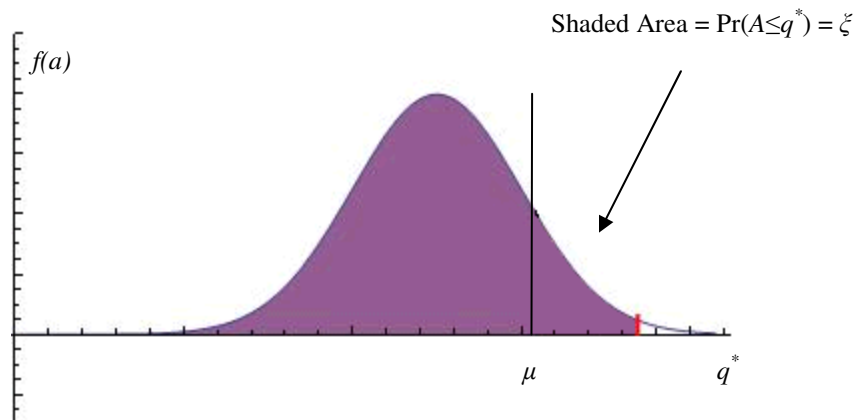
service level. That is, I hypothesize that the relationship between a deal's consumption rate (demand) and its service level (probability of stockout) is non-linear, monotonically decreasing.

The newsvendor model literature provides both theoretical and empirical guidance in the development of this dissertation's final hypothesis. The newsvendor model is certainly among the most important models in operations management and inventory theory. In this model, a manager sells a single SKU during a short selling season with stochastic demand. The manager has one opportunity to order inventory before the selling season, and no further replenishments are possible. If the order quantity is greater than the realized demand, the manager must dispose of the remaining stock at a loss. If the order quantity is lower than the realized demand, the manager forgoes some profit. Therefore, in choosing an order quantity, the manager must balance the costs of ordering too little against the costs of ordering too much.

The newsvendor model applies in a broad array of settings. For instance, fashion apparel retailers often must submit orders well in advance of a selling season, without opportunity for replenishment during the season. Social shopping deals usually present a similar problem: order too little and the online retailer may face irate consumers, but order too much and the online retailer incurs additional inventory holding costs as it slowly sells the excess inventory.

Formally, in the newsvendor model, a decision maker chooses an order quantity,  $q$ , which arrives before the start of a single selling period,  $i$ . Let  $A$  be stochastic demand during this period, described by the strictly increasing, continuously differentiable cumulative probability function,  $F(a)$ , on the interval  $[\underline{a}, \bar{a}] \subset \mathfrak{R}^+$ , with strictly positive

probability density function,  $f(a)$ . Let  $\mu = \int_a^{\bar{a}} af(a)da$  denote the expected value of demand  $A$ . The decision maker purchases each unit for cost  $c$  and sells each unit at price  $p > c$ . When  $q > A$ , the decision maker can salvage each unit remaining at the end of the period for  $s < c$ . It is well known that the optimal (and unique) order quantity that maximizes the expected profit,  $q^*$ , is given by  $F^{-1}(\zeta)$ . Here,  $F^{-1}$  is the inverse cumulative distribution function of demand, and  $\zeta \equiv (p-c)/(p-s)$  is the “critical fractile”. The critical fractile is the probability of satisfying all the demand during deal  $i$  if  $q^*$  units are provisioned at the start of the deal, i.e.,  $\zeta \equiv F(q^*) \equiv \Pr[A \leq q^*]$  (see Figure 3). Therefore,  $1-\zeta \equiv (c-s)/(p-s)$  is the optimal stockout probability reflecting the optimal service level for deal  $i$  (for a comprehensive review refer to Khouja 1999 and Petruzzi and Dada 1999).



**Figure 3: Determination of optimal order quantity for the newsvendor model**

Traditional literature on the newsvendor model is based primarily on the paradigm of perfect rationality. In existing models, the inventory manager is a perfect

optimizer: she will always choose order quantities that attain the maximum possible level of expected profits. Many results – and implications – are based on such paradigm.

However, a growing body of analytical literature investigating the newsvendor model has suggested that, in general, managers facing demand uncertainty tend to order less than the optimal order quantity,  $q^*$ , because they are boundedly rational (Loch and Wu 2007; Su 2008). The first study to provide support for this claim was Eeckhoudt et al. (1995). Based on the rational expectations framework (Muth 1961), the authors found that a risk-averse newsvendor will systematically order less than the optimal quantity. Also based on the rational expectations framework, Wang and Webster (2009) showed that the order quantity decreases as risk-aversion increases, whereas Wang et al. (2009) found that the order quantity decreases as the selling price increases. Agrawal and Seshadri (2000) also found that a risk-averse newsvendor will order less than the optimal order quantity under the assumption of a multiplicative demand distribution. However, the ordered quantity will depend on the demand sensitivity to the selling price under the assumption of an additive demand distribution and known demand sensitivity. Based on the rational expectation equilibrium analysis, Wang and Hu (2011) concluded that a risk-averse newsvendor will order less than the optimal order quantity in the presence of forward-looking (i.e. strategic) consumers who anticipate future sales and choose purchasing timing to maximize their expected utility. Finally, based on a min-max approach, Perakis and Roels (2008) identified that a newsvendor will order less than the optimal quantity in order to minimize his maximum “regret” of not acting optimally.

Empirical evidence provides support to the analytical results outlined above. For instance, Schweitzer and Cachon (2000), Brown and Tang (2006), and Benzion et al. (2008) conducted experiments to investigate ordering decisions in the newsvendor

context. The three studies observed a bias between practical ordering decisions and the newsvendor solution. That is, when facing uncertain demand, managers are likely to order less than the optimal quantity.

Su (2008) and Bendoly et al. (2010) explain that data of limited validity based on environmental or situational factors that, in theory, should not matter, lead to such ordering distortion. This is because decision makers make subjective judgments which are processed according to heuristic rules. They “anchor” their decisions unduly on otherwise irrelevant past observations and experiences. If decision makers are susceptible to anchoring, then unrelated but mentally available factors will influence their decisions. However, adjustments of these “anchored” estimates to the current context are typically insufficient. That is, different starting points yield different estimates, which are biased towards the initial values (Tversky and Kahneman 1974). In fact, anchoring is likely to influence inventory managers’ ordering decisions (Bendoly et al. 2010; Loch and Wu 2007; Su 2008). And because adjustments are typically insufficient, this procedure should lead to underestimation (Tversky and Kahneman 1974) and consequently lower service levels.

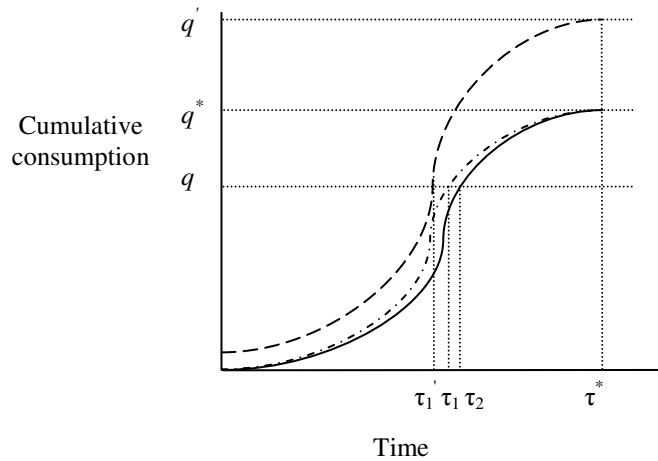
The trick with using anchoring models for prediction of demand is that one needs to know *what the anchor is*, which influences the decision at hand (Bendoly et al. 2010). One available factor that boundedly rational inventory managers often use as an anchor when determining next periods’ ordering is previous periods’ demand. Based on the seminal study of Tversky and Kahneman (1974) on judgment under uncertainty, Su (2008) identifies two underlying effects of ordering distortion based on such an anchoring approach: (1) the midpoint bias and (2) the rare-event bias.

First, when managers are boundedly rational, they tend to distort order quantities toward the midpoint of the range of possible demand realizations. This is called “the midpoint bias”. When the demand density  $f(a)$  has support  $[\underline{a}, \bar{a}] \subset \mathfrak{R}^+$ , so that  $\underline{a}$  and  $\bar{a}$  are the smallest and largest possible demand realizations, the midpoint is  $m \equiv (\underline{a} + \bar{a})/2$  (Su 2008).

Second, when managers are boundedly rational, they tend to distort order quantities in the direction of low-probability demand realizations. This is called the “rare-event bias”. One potential behavioral explanation is that managers tend to place excessive weight on rare low demand occurrences. That is, because of anchoring, managers tend to underestimate the magnitude of demand probabilities (as in the bias in the evaluation of conjunctive and disjunctive events, as explained by Tversky and Kahneman 1974:1128-1129).

Bringing together these two underlying behavioral effects of ordering distortion (i.e. the midpoint bias and the rare-event bias) and the formulation of the newsvendor model, the notion that the relationship between consumption rates and service levels will be non-linear, monotonically decreasing becomes quite intuitive. I will provide an example to illustrate the rationale.

Recall that the inventory manager stipulates the order quantity prior to the beginning of the deal. The perfect optimizer inventory manager will choose an order quantity,  $q^*$ , which is depleted in some time  $\tau^* \leq \tau$ , where  $\tau$  is the deal deadline. Suppose that the solid curve in Figure 4 represents the cumulative consumption (i.e. inventory depletion) over time during the deal.



**Figure 4: Cumulative consumption over time**

The dashed-dotted curve in Figure 4 (whose tipping point occurs slightly earlier than the tipping point in the solid curve) might well represent the cumulative consumption over time during the deal, in which inventory is completely depleted at time  $\tau^*$ . As the boundedly rational inventory manager orders  $q$  instead of the optimal quantity  $q^*$ , the deal will sell out at time  $\tau_2 < \tau^*$ , and a demand equal to  $q^* - q$  will be left unfulfilled. Notice that, in the case of the cumulative consumption represented by the dashed-dotted curve, the deal will sell out at time  $\tau_1 \leq \tau_2$ , and the unfulfilled demand will be equal to  $q^* - q$  as well.

However, it is reasonable to expect that cumulative consumption curves whose tipping point will occur earlier than the tipping point in the solid curve will resemble more the dashed curve than the dashed-dotted one. This is because curves that “tip” earlier are more likely to represent higher consumption rates (Mahajan et al. 1990), which imply higher levels of demand. Thus, in our example, the dashed curve implies a

cumulative demanded quantity at time  $\tau^*$  of  $q' \gg q^*$ . Based on this notion, as the boundedly rational inventory manager orders  $q$ , we might expect a deal exhibiting a consumption pattern similar to the dashed curve to sell out at time  $\tau_1' \ll \tau_1 \leq \tau_2$ . Correspondingly, in this example, the unfulfilled demand would be  $q' - q \gg q^* - q$ .

Such an increase in unfulfilled demand due to underordering should be expected to be more salient at higher consumption rates than at lower consumption rates. This is because lower consumption rates imply lower levels of demand and consequently, less room for error due to underordering. Conversely, even small differences in consumption rates at higher levels should lead to large levels of unfulfilled demand due to underordering, and consequently, sharp decreases in service levels.

We may formally demonstrate such an intuitive idea. At the beginning of the deal, the inventory manager faces an ordering decision. Her inventory level choice depends on the sequence of past demands representing a sample drawn from the same distribution that governs the future demands. The inventory manager will attempt to maximize the minimum expected profit for all demand distributions (Scarf 1958).

Deals that face high levels of consumption rate usually display monotonically increasing demand probability density,  $f(a)$ . This is because increasing density suggests that demand is more likely to be high (Su 2008). That is, the expected demand,  $E[A]=\mu$ , is high for deals that face high consumption rates. However, because the inventory manager is boundedly rational, the rare-event bias may distort order quantities (decided prior to the beginning of the deals) toward low demand probabilities when a deal is more likely to face a high consumption rate. Moreover, the midpoint bias may distort order quantities toward the midpoint of those low demand probabilities rather than to the midpoint of the high demand probabilities (Su 2008). So, as the actual demand realization will be high

due to a high consumption rate, the likelihood that a boundedly rational manager has underordered will be high. As the actual demand level becomes much higher, being reflected by a higher consumption rate, it is reasonable to expect that such underordering behavior will become more salient due to those managerial heuristics and biases. As a result, we should observe much worse service levels at higher consumption rates than at lower consumption rates.

Consider the cumulative demand distribution,  $F(a)$ . The expected probability that the ordered inventory quantity,  $q$ , will be able to satisfy demand,  $A$ , i.e. the service level,  $\varphi(q, a)$ , is given by (Dana Jr 2001; Dana Jr and Petruzzi 2001; Deneckere and Peck 1995):

$$\begin{aligned}\varphi(q, a) &= E \left[ \frac{\text{Sales}(q, a)}{\text{Demand}(a)} \right] = \int_a^{\bar{a}} \frac{\min(q, aF(a))}{aF(a)} \frac{af(a)}{\mu} da = \frac{\int_a^{\bar{a}} \min(q, aF(a)) f(a) da}{\mu F(a)} \\ &= \frac{\mu - E[A - q/F(a)]^+}{\mu}\end{aligned}$$

Since the service level depends on  $q$  and  $a$  through the stocking factor,  $z=q/F(a)$  (Petruzzi and Dada 1999), we can rewrite  $\varphi(q, a)$  as:

$$\varphi(z) = 1 - \frac{E[A - z]^+}{\mu}$$

Since  $E[A - z]^+ = \int_z^{\bar{a}} (a - z)f(a)da = \int_z^{\bar{a}} [1 - F(a)]da$ , the service level is a strictly positive, continuous function of the stocking factor with derivative  $\varphi'(z) = \frac{1-F(z)}{\mu}$ .

Clearly, the service level will decrease in a non-linear fashion as the actual mean demand,  $\mu$ , which is defined by the deal's consumption rate, will increase. Such an effect should be expected to be stronger as a decision-maker decreases the stocking factor due to the rare-event bias, which may distort inventory order quantities down *away* from the



actual mean demand,  $\mu$ . So, based on the aforementioned arguments, we should expect to observe service levels to decrease at a faster pace as the mean demand shifts upward due to higher consumption rates. Therefore, I submit the last hypothesis to empirical scrutiny.

In formal terms:

**HYPOTHESIS H3:** *Increasing the consumption rate in a deal will decrease the service level in the deal, after controlling for initial inventory provision. This relationship is monotonically decreasing.*

## Chapter 4

### METHODOLOGY

The two goals of this research are to determine (1) how and why social interactions affect inventory performance in the social shopping context and (2) how online retailers can explore such an effect in order to achieve superior inventory performance by offering products with certain characteristics and setting prices accordingly. Therefore, the investigation will center on *endogenous social effects*, wherein the propensity of a consumer to make a purchase will likely vary with other consumers' purchases in her social shopping community. Unfortunately, there is a lack of consensus in the academic community about the existence of such endogenous effects. Many economists and marketers regard social interactions to be spurious phenomena explainable by processes operating entirely at the level of the individual consumer (Durlauf and Ioannides 2010; Iyengar et al. 2009; Van den Bulte and Iyengar 2011). Even among sociologists, there is still a lack of consensus on the nature of social interactions (Lee et al. 2011).

Why does the academic community seem unable to converge to common conclusions about the channels through which a reference group influences a consumer's choice? In a seminal paper, Manski (1993) argued that this is because empirical analyses of social interactions present severe identification problems, since peer influence is typically endogenous. According to Manski (1993), these identification problems arise due to the challenge of separating correlations in observed consumer choice from the true causal effects of one consumer's choice on another's. Only causal effects can result in a social interaction effect (Manski 2000).

The primary confounding factors that are sources of bias in social interactions analysis are endogenous group formation, correlated unobservables, and simultaneity (Manski 1993, 2000). The *endogenous group formation* problem arises because consumers with similar tastes and preferences may tend to form social groups, hence, subsequent correlation in their choices may reflect those common tastes and preferences, and not a causal effect of one's choice on another's. For instance, correlations in observed online purchasing activity between two consumers in a website specialized in videogames may simply be driven by common tastes for videogames that induced those consumers to navigate in the website in the first place. Therefore, a researcher cannot conclude directly from observation in choices that there exists a causal effect of a consumer's purchase on purchasing decisions of others in her reference group.

A second source of endogeneity corresponds to *correlated unobservables* (to the inventory manager and to the researcher) that drive similar consumption patterns across all consumers in a reference group. These are exogenous effects (also known as "contextual" effects), wherein the propensity of a consumer to make a purchase varies with exogenous characteristics of the reference group. For instance, there is an exogenous effect if purchases tend to vary with the socio-economic composition of the reference group.

Finally, a *simultaneity problem* arises due to the potentially simultaneous nature of decisions by the focal consumer and others in her reference group. Due to simultaneity, correlation in subsequent purchases could simply reflect the fact that a consumer's choice affects her group's choices, and at the same time, the group's choices affect the consumer's choice. This has been referred to as the "reflection problem" (Manski 1993). The reflection problem is similar to the problem of interpreting the

almost simultaneous movement of a person and her reflection in a mirror. That is: does the mirror image reflect the person's movements or cause them?

Each of the aforementioned three factors, if not controlled for, could generate spurious correlation in observed purchases, which might lead to misattribution of correlated choices to causal social interaction effects, biased parameter estimates, or highly unreliable standard tests and confidence sets of such causal effects (Durlauf and Blume 2010). Based on my literature review, I want to emphasize that these issues are pervasive in all empirical settings that try to assess social interactions effects using behavioral data across many disciplines.

One commonly used solution to identification problems in studies of causal social interactions includes the availability of panel data (Blume and Durlauf 2005; Brock and Durlauf 2007; Hartmann et al. 2008; Manski 1993). With panel data, one can control for some of the aforementioned identification problems via fixed or random effects, or by including a rich specification for heterogeneity. Both fixed and random effects here serve the role of picking up common aspects of group preferences and tastes. These random effects may also control for time-invariant aspects of unobservables driving consumers' choices (Batalgi 2001; Durlauf and Blume 2010; Greene 2003; Wooldridge 2002). Also, exclusion restrictions may be imposed. That is, one can use instrumental variables that affect a focal consumer's choice, but can be a priori excluded from the choice of others in her reference group (Blume and Durlauf 2005; Hartmann et al. 2008). Unfortunately, while the use of panel data can clearly avoid the issues of correlated unobservables and simultaneity, it falls short of solving the issue of endogenous group formation. This poses a severe threat for the validity of this research.

Neither of these identification issues arises in randomized experiments (Godes et al. 2005; Hartmann et al. 2008; Manski 1993), which allocate consumers into different groups. This eliminates the problem of consumers selecting each other based on observable and unobservable characteristics. Random assignment implies that a consumer's own characteristics are uncorrelated with other consumers' characteristics. Moreover, in setting up randomized experiments, we can affect the relational and structural characteristics of the social network in randomly selected experimental groups. This makes it possible for us to evaluate the impact of such an intervention on the selected experimental groups' consumption rates, which would be direct evidence of social interactions effects. Furthermore, the proposed randomized experiment (described below) will subject all consumers to the same set of deals. This eliminates the self-selection problem of consumers choosing which deals to inspect based on observable and unobservable characteristics. The self-selection problem stems from the fact that self-interest drives consumers to choose to inspect those deals that are more likely to yield the highest utility for them, even though, in principle, every consumer can inspect any deal. Finally, another attractive feature of a random sample generated by the known rule that all consumers are equally likely to be sampled is that it becomes increasingly accurate in describing a population's characteristics as a sample size increases. Heckman (2010) explains:

“A sample selected by any rule not equivalent to random sampling produces a description of the population distribution of characteristics that does not accurately describe the true population distribution of characteristics no matter how big the sample size. Unless the rule by which the sample is selected is known or can be recovered from the data, the selected sample cannot be used to produce an accurate description of the underlying population”. (p. 242)

Indeed, because of the aforementioned arguments, randomized experiments have been considered to be one of the most effective ways to obtain unbiased estimates of causal social interactions (Banerjee and Duflo 2008; Duflo et al. 2007; Hirano and Hahn 2010; Sacerdote 2001). Thus, it is not surprising that social interactions studies have been increasingly using this approach to investigate causal relationships. For instance, Chen et al. (2011) used a unique natural experimental setting resulting from information policy shifts at the online retailer *Amazon.com* to conduct experiments aimed at investigating the effects of social interactions on consumption. In another recent study, Goette et al. (2012) conducted an experiment to compare social interactions effects within randomly assigned groups to those effects within randomly assigned groups involving social links such as kinship (i.e. groups with social context).

For the purposes of this research, an experiment is also useful because it allows us to gauge the extent to which consumers' choices cause empirical regularities in operations. By conducting an experiment, we can control the environment each consumer faces. Also, an experiment can help us understand the relative strength of multiple sources of social interactions among consumers in social shopping in the empirical data. Moreover, we can use an experiment to test operations theory, much as many scholars have used experiments to test economic and marketing theory (Gattiker and Parente 2007). Indeed, marketing studies have largely used experiments to investigate the effects of social interactions on consumption in contexts that are similar to those in this research (Hartmann et al. 2008; Hirano and Hahn 2010). Furthermore, an experiment may help us uncover the often complex social and behavioral elements involved in operations management (Boyer and Swink 2008; Croson and Donohue 2002). More specifically, it may help us understand how and why social interactions and online retailers' inventory management and marketing activity in social shopping induce demand uncertainty, which

is widely recognized to be a fundamental driver of inventory performance. Finally, we can use an experiment to measure the impact on inventory performance of varying supply and marketing factors in the presence of consumer choice. Experimental work is thus an important complement to theoretical work in operations research (Croson and Donohue 2002). Therefore, this study will conduct an experiment to empirically assess the hypothesized relationships **H1A** through **H3**.

The unit of analysis of the current research is a *deal*. Therefore, the conceptual framework, depicted in Figure 2, refers to constructs and relationships at the deal level. The conceptual framework consists of two endogenous variables related to observed outcomes in a single deal (deal consumption rate and deal service level), five independent variables related to both relational and structural properties of early buyers of the deal (opinion leadership, integration, cohesive group membership, network constraint, and network centrality), and three moderating variables related to the product characteristics and the commercial context of the deal (product popularity, quality, and price). Since there are five independent and three moderating variables, this study consists of eight factors.

The randomized experiment consisted of a 2-level (high and low) full factorial design. Because there are eight factors, this is a  $2^8$  experiment. In a full factorial design (also known as “fully crossed” design), each factor level is combined with each other factors’ levels. That is, the observational units (i.e. deals) take on all possible combinations of the factor levels across all such factors. In doing so, a full factorial experiment allows studying the effect of each factor on the response variables of interest, as well as the effects of interactions among factors on those response variables (Fisher 1935; Hicks 1963). In his classical “The Design of Experiments” book, Fisher (1935)

argued that complex experimental designs, such as a full factorial one being employed here, are advantageous because (1) they are more efficient than one-factor-at-a-time experiments, and (2) all data are used in computing all effects. Thus, a full factorial design allows the effect of several factors and even interactions between them to be determined with the same number of trials as are necessary to determine any one of the effects by itself with the same degree of accuracy. This is appropriate for the current research, since the investigation here relies on direct effects of independent variables as well as moderated effects, which are best represented by interactions between the independent and the moderating variables (Baron and Kenny 1986; James and Brett 1984).

I recursively designed the  $2^8$  full factorial experiment. First, I created the  $2^5$  (=32) possible combinations among the five independent variables, as presented in Table 1. Then, for each of those 32 combinations, I assigned  $5 \cdot 2^3$  (=40) replications of deals. This replication procedure allows for estimation of measurement error in a very reliable way (Fisher 1935). I replicated 5 times each of the  $2^3$  (=8) possible deal types (see Table 2) in order to increase the power of the statistical analysis. This yielded 40 different deals for each of the 32 combinations of independent variables, which resulted in 1280 deals overall.



Combination	Opinion Leadership	Network Integration	Cohesive group membership	Network Constraint	Network Centrality
1	Low	Low	Low	Low	Low
2	Low	Low	Low	Low	High
3	Low	Low	Low	High	Low
4	Low	Low	Low	High	High
5	Low	Low	High	Low	Low
6	Low	Low	High	Low	High
7	Low	Low	High	High	Low
8	Low	Low	High	High	High
9	Low	High	Low	Low	Low
10	Low	High	Low	Low	High
11	Low	High	Low	High	Low
12	Low	High	Low	High	High
13	Low	High	High	Low	Low
14	Low	High	High	Low	High
15	Low	High	High	High	Low
16	Low	High	High	High	High
17	High	Low	Low	Low	Low
18	High	Low	Low	Low	High
19	High	Low	Low	High	Low
20	High	Low	Low	High	High
21	High	Low	High	Low	Low
22	High	Low	High	Low	High
23	High	Low	High	High	Low
24	High	Low	High	High	High
25	High	High	Low	Low	Low
26	High	High	Low	Low	High
27	High	High	Low	High	Low
28	High	High	Low	High	High
29	High	High	High	Low	Low
30	High	High	High	Low	High
31	High	High	High	High	Low
32	High	High	High	High	High

**Table 1: Thirty-two combinations of independent variables in the factorial design for the randomized experiment**

Product Popularity	Product Quality	Product Price
Low	Low	Low
Low	Low	High
Low	High	Low
Low	High	High
High	Low	Low
High	Low	High
High	High	Low
High	High	High

**Table 2: Eight types of deals in the randomized experiment**

## **Data collection**

### **Experimental grounding**

To ground the randomized experiment, I collected data from the “daily deals” online retailer *Woot.com!* and developed a web-based application with similar appearance and “feel” to that website. The reason to choose *Woot.com!* as the focal online retailer and the basis for the experiment is generalizability. First, *Woot.com!* was the pioneer in social shopping (Heine 2010). The website debuted on July 12, 2004, and it remains very popular to date – currently, it is ranked 174<sup>th</sup> in online traffic in the United States (Alexa 2012). This has caused several other online retailers to mimic the industry pioneer in many business aspects, including designing websites similar in appearance to *Woot.com!*'s and offering daily and limited-quantity deals.

Second, *Woot.com!* often sells a piece of computer hardware or an electronic gadget as part of every deal (Woot 2011). This restricts the sample of products to similar categories for the deals in our experiment. Also, *Woot.com!* usually offers products that are of older generations. Hence, information regarding the functionality of the products and their respective features is largely available online through search mechanisms, other online retailers' websites, product recommendations, etc. Such a large availability of information should preclude consumers resorting to observing others' purchases (i.e. social interactions) to make informed decisions. Thus, if we are able to observe peer effects in the *Woot.com!* data, this would allow us to infer that the results would be generalizable to other categories of products for which information is narrowly available and for which consumers are more willing to rely on social interactions to make consumption choices.

Third, approximately seventy percent of the deals offered by *Woot.com!* to date sold out, and there is considerable variability in products' popularity, quality, and price across deals offered in this website. This provides us a rich dataset to sample from, since it exhibits large variability among main constructs.

Finally, *Woot.com!* provides a discussion forum, in which consumers may discuss issues pertaining to the deal being currently offered or just chat about random topics. As explained below in the operationalization of measures, it is important to control for the potential influence that stems from the interactions among consumers through discussion forums. This research will use actual data of posts to control for such potential confounding factor.

### **Deal selection**

Data pertaining to deals offered by *Woot.com!* from Feb 22<sup>nd</sup>, 2006 to Mar 10<sup>th</sup>, 2012 were available directly from the online retailer's website. Specifically, for each deal, *Woot.com!* disclosed the name of the product being offered, a full description of the product features, condition (refurbished or "mint in box" – i.e. new), price, as well as the contents of the discussion forum. Overall, there were 4893 distinct deals among all 9494 offered in that period<sup>2</sup>. However, this study only used data from the 469 deals offered by *Woot.com!* in 2012<sup>3</sup>. This was necessary to ensure proper operationalization of both popularity and price constructs, which depended on time sensitive data. The collection of

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<sup>2</sup> The number of distinct deals is smaller than the total because there are some repeated deals that are offered at different dates. *Woot.com!* frequently reserves some days to offer flash sales (known as "woot offs"), when leftover SKUs from previous deals (known as "woots") are salvaged. Contrary to common "woots", which last for 24 hours, "woot offs" have no set expiration time. They may last for seconds, or hours, while there is remaining stock. This information of how long a woot off may last and how many units are made available is undisclosed to consumers.

<sup>3</sup> In spite of the fact that there are 70 days from January 1<sup>st</sup>, 2012 to the last day data were gathered (March 10<sup>th</sup>, 2012), there are 469 deals in the sample because *Woot.com!* offered woot-offs (i.e. several deals in a same day) between January 17<sup>th</sup> and 19<sup>th</sup>, and between February 21<sup>st</sup> and 23<sup>rd</sup>.

recent (i.e. “fresh”) data was necessary to reflect actual attributes of the products being offered as part of deals during the experimentation, since a product’s popularity and price tend to follow trends over long periods of time. Moreover, relying on recent data avoided the introduction of bias in the research due to seasonality. For instance, a product’s popularity and price may oscillate considerably during the end of year’s holidays.

I then classified the 469 deals into eight categories, according to their products’ price, popularity, and quality. This classification schema corresponds to the eight possible deal types depicted in Table 2. I classified a deal as “low price” if its product’s price was below the mean price across all 469 deals, otherwise, I classified it as “high price”. Analogously, I used the mean products’ popularity across all 469 deals to classify the deals according to their products’ popularity. I classified a deal as “low popularity” if its product’s popularity was below the mean popularity across all 469 deals, otherwise, I classified it as “high popularity”. It was unnecessary to follow a similar procedure for classifying deals according to their products’ quality, since the measure is binary – *Woot.com!* informs consumers whether a product being offered as part of a deal is refurbished (“low quality”) or new (“high quality”). So, eventually, I classified each of the 469 deals into a unique category among the possible eight deal categories. Finally, for each of the eight deal categories, I selected five deals classified in it, in order to satisfy the full factorial design described at the beginning of this chapter. This procedure yielded the 40 (=5\*8) deals used in the randomized experiment.

### **Web-based application development**

The web-based application displayed information in a similar fashion to that displayed at *Woot.com!* (see Figure 5). By emulating an actual online retailer’s website, this research avoided introducing bias due to the use of an experimental platform. This is

because website characteristics such as appearance, ease of use, and “friendliness” may introduce interactive testing effects by interfering with a consumer’s decision-making process (Boyer and Olson 2002; Mollenkopf et al. 2007).

The application displayed, on the central portion of the screen, a picture of the product, its name, condition, price (including \$5 shipping, irrespective of the product, which is standard at this online retailer), and a brief description of the product’s features. Also, on the right portion of the screen, the application displayed the discussion forum with a scroll bar, thus allowing subjects to browse it before making a decision. Furthermore, at the top of the screen, the application displayed the remaining time of a current deal. When a deal was over, the application automatically refreshed the subjects’ screens to display a new deal and reset the countdown clock.

In addition, the application displayed in real time, on the left portion of the screen, the names of the subjects who had bought the deal being offered. This is a feature that is available in most social shopping websites, and is central to this research. This is because, by definition, social interactions’ influence stems from observation of others’ purchases. Hence, in our experiment, subjects should be able to observe others’ purchases.

Subjects had the option to click one of two buttons: (1) to make a purchase (“I want one”) or (2) to balk (“I don’t want one”). When a subject “purchased” a deal, the application decreased his/her allowance by the amount of the price charged in that deal. It also decreased the amount of available inventory by one unit. The button to balk had the purpose to keep subjects focused on the task throughout the entire experiment. This is because only those subjects who clicked either button in all 40 deals were entitled to the participation benefits of the experiment (I explain this in more detail in the next section).

Finally, in the case that a deal sold out, the application no longer allowed subjects to make a purchase; they had to wait until the beginning of the next deal.

Prior to running the experiment, I validated the experimental platform in several ways. First, I wrote and tested controls to curb subjects' inconsistent behavior that might generate spurious data. This included, among others, forbidding consumers to click both available buttons during a same deal or opening multiple sessions (windows) of the experiment. Second, I performed stress tests on the portion of the application code that handled simultaneous purchases of multiple subjects. For instance, only one subject was allowed to buy a unit of inventory at a time, which avoided inconsistency in the database. Third, I tracked database updates as I performed multiple purchases during test trials, and confirmed that the application was handling data accordingly. Finally, I ran two complete experimental sessions (i.e. 40 deals) with the programming team that involved 5 people overall, and another complete experimental session with 25 guest subjects – who were not selected to join the actual experiment – to ensure that the application could handle multiple consumers properly. I observed that the application behaved as expected before running the actual experiment.

Woot Experiment... - Mozilla Firefox  
 File Edit View History Bookmarks Tools Help  
 Woot Experiment...  
 asu.edu https://reports4.wpcrmv.asu.edu/def/wt.aspx  
 Most Visited Customizable Links Free HTML Web Site Gallery  
 Woot Experiment... Secure Search

You are logged in as - Annibal Sodero


**woot!** EXPERIMENT

**YOUR REMAINING TIME IS 2:35**

**YOUR REMAINING ALLOWANCE : \$1500**

**JVC Everio 8GB HD Camcorder**  
**Price : \$164.99**  
**Condition : Refurbished**

**I want one!**  
**DON'T I want one!**



**People who already bought this deal**  
 Influential User 1  
 Influential User 2  
 Influential User 3

**8GB built-in flash memory, SD/SDHC/SDXC memory card slot, and 1280 x 720p HD video capture. Upon output your footage can be up-converted to 1920 x 1080p quality for even more detail and vibrant color.**

**USER REVIEWS:**  
**jeureau :**  
 I have this camcorder and I love everything about it. It has never given us any trouble and it works great in all lighting.  
**BigRedDogATL :**  
 Woot pulled a Leap Day joke on all of us. Here we are expecting something special and all we get is another Video Camera. At least this Video Camera is a new one, not a refurb.  
**potter412 :**  
 Here's the link to Amazon (193.51).  
<http://www.amazon.com/8GB-Flash-Memory-Camera-Black/dp/B004LBSAJK> Four 5 star reviews  
**midwaychilibeau :**  
 Happy Leap Day everyone! Don't need this camera, my DSLR works even better.  
**teylmanbws :**  
 Is 720p really HD in today's camera world?

Figure 5: Screen shot of the application displaying one of the deals actually offered.

### **Subjects recruitment, selection and experimental assignment**

I recruited subjects to participate in the experiment among a pool of undergraduate students enrolled in supply chain management (SCM) courses at the W.P.Carey School of Business at Arizona State University during the Spring 2012 semester. This research complied with the university's Institutional Review Board (IRB), which reviews all proposed research involving human subjects to ensure that they are treated ethically and that their rights and welfare are adequately protected. The approval procedure involved providing the IRB the background, purpose, and design of the research, description of the tests, instruments, and measures, description of the recruitment process, and stipulating the number of participants, among other requirements.

The use of departmental subject pools has emerged as one strategy for minimizing volunteer bias (Chastain and Landrum 1999). Volunteer bias may arise because subjects may be motivated to participate in an experiment by a desire to contribute to the advancement of science (Orne 1962). If that is the case, then participants may act as "good subjects" who will do what is necessary to help the experimenter accomplish the research's scientific goals. Such a desire will lead participants not only to be receptive to the presence of task-orienting cues but also motivated to use these cues to map out their subsequent behaviors in ways that will presumably advance scientific knowledge. Volunteer bias also may arise because subjects may be motivated to participate in an experiment to "look good" rather than to promote scientific knowledge (Rosenberg 1969). When participants enter an experimental situation, they know that their behavior will be under scrutiny. This awareness arouses anxiety in participants who then look for cues on how to elicit a favorable evaluation. In situations in which these two desires conflict, the desire to look good seems to prevail (Rosnow et al. 1973).



Participation incentives had four objectives. The first objective was to gather a large pool of subjects which I could sample from, so that I could build the 32 experimental groups as designed. The second objective was to ensure that selected subjects would show up to participate at the experiment at their allocated place and time. The third objective was to ensure that participating subjects would attempt to make rational and informed consumption decisions, rather than just purchase deals randomly. Finally, the fourth objective was to ensure that participating subjects would engage and keep focused on the task at hand.

In order to achieve those four objectives, I offered extra course credit for all students who volunteered to participate. Participating students also qualified for financial compensation, as well as to have their names entered into a random drawing for one “mint in box” iPad 2. Finally, participating subjects who attempted to purchase one of the products that I actually displayed during the experiment had their names entered into a random drawing for that product. However, I only let participating subjects know which product I would randomly draw after all 32 experimental groups performed the experiment. This procedure avoids bias toward purchase because subjects’ virtual allowance was limited, as explained in the previous section. Moreover, statistical tests (see Experimental Validity below) suggest the absence of bias toward purchase in our experiment.

Those subjects who volunteered to participate but whom I dropped from the final sample automatically received the extra credits. However, those subjects whom I selected to participate only received the extra credits and qualified for the additional benefits if (1) they indeed showed up at their allocated place and time and (2) engaged and stayed focused on the task at hand by clicking either button (“I want one”/“I don’t want one”)

during each of the 40 offered deals. Table 3 depicts the participation incentives structure and the goals I attempted to achieve by offering each of them.

Extra course credit <sup>(1),(2)</sup>	Financial compensation <sup>(2)</sup>	Mint in box iPad 2 <sup>(2)</sup>	Product actually offered in one of the deals <sup>(3)</sup>
Gain access to a large pool of subjects	Ensure subjects would show up	Ensure subjects would show up	Ensure participating subjects would attempt to make informed and rational decisions

(1) All subjects who volunteered to join the experiment but were not selected to participate received extra course credits.

(2) Participating subjects only qualified for these benefits if they clicked either button (“I want one” / “I don’t want one”) during each of the forty offered deals.

(3) Participating subjects only qualified for this benefit if they actually attempted to purchase the offered product.

**Table 3: Goals of the participation incentives**

I recruited all subjects via verbal announcements in front of their classes. In addition, I posted electronic messages that explained the experiment in the courses’ educational platform (Blackboard). This recruitment approach is consistent with a large body of research in operations and marketing research (e.g. Wu and Katok 2006, Carter and Stevens 2007, Gattiker et al. 2007, Mantel et al. 2007). A total of 849 undergraduate students volunteered to join the experiment. The sample consisted of 447 males (52.65%) and 402 females (47.35%). The mean age of the sample was 22.23 years (standard error = 5.33).

The experiment proceeded in two steps. In the first step of the experiment, subjects filled out a confidential form to provide individual information. In the form, subjects named a maximum of twenty fellow students who might be enrolled in their same SCM courses with whom they had had contact during their academic life, in any capacity, in the recent past. Specifically, I asked subjects:

Looking back over the past six months, who are the students that may be enrolled in any session of this course with whom you shared any experience at Arizona State University, such as working together in academic projects or

laboratory assignments, being members of the same fraternity or student association, being roommates, etc?

Subjects also provided their own nickname and an alternative name by which their fellow students might recognize them. This allowed me to correctly match subjects when someone did not know other one's real name.

I assigned each subject a number from 1 to 849. Then, based on the information that the subjects provided, I built a local (also known as ego-centered) social network consisting of all 849 subjects. A local social network consists of a focal respondent (ego), a set of alters who have links to the ego, and measurements of the links from ego to alters and on the links between alters (Wasserman and Faust 1994). Chen and Chen (2008) showed that this procedure is feasible and much more effective than randomized sampling for reconstruction of social networks when complete information is not available (Kossinets 2006; Marsden 1990; McCallister and Fischer 1978).

Next, I computed all 849 subjects' individual scores for opinion leadership, network integration, cohesive group membership, network constraint, and network centrality in the social network. I used the mean of each of the five scores across all 849 subjects as a reference to classify participant subjects as either "high" or "low" in the respective score as I built the 32 experimental groups.

To build the 32 experimental groups, I partitioned 480 subjects into 32 smaller networks of 15 subjects each in an interactive manner. These 480 subjects were the individuals whom I eventually invited to participate in the experiment. Building the 32 experimental groups was a cumbersome procedure. It required adding/removing subjects to/from groups in an interactive way. I started with the 849 subjects and segregated them based on patterns I found in the network (by observing the network diagram) and on their

individual scores. As I made changes to groups, the individual scores changed, of course. This recursive procedure lasted until I eventually was able to form 32 distinct groups of 15 subjects. So, in the end, I dropped 369 subjects from the sample.

There are no systematic differences between the 480 subjects I selected to participate in the experiment and those 369 subjects whom I dropped from the final sample. First, there are no significant demographic differences between both groups (at the .05 level). Table 4 depicts the statistical analysis results. Based on the Pearson chi-squared test ( $\chi^2$ ) for a 2X2 two-way contingency table for large sample sizes (greater than 10) and categorical variables, we cannot reject the hypothesis that the probability of a being a male (or female) in the group of 480 participants is equal to the probability of being a male (or female) in the group of 369 dropped subjects (at the 0.05 level). Also, based on the Wilcoxon rank-sum test (also known as Mann-Whitney U tests), we cannot reject the hypothesis that both samples have equal distributions for age (at the 0.05 level). Wilcoxon rank-sum tests are non-parametric tests that make no assumption in regard to the distribution of the population, in contrast to the paired Student's t-test, which assumes normality (Gehan 1965; Wilcoxon 1945). Under the null hypothesis, the distributions across both groups are equal.

Demographics	480 selected participants	369 dropped subjects	Statistical test
Gender	Males (256 = 53.33%) Females (224 = 46.66%)	Males (191 = 51.76%) Females (178 = 48.23%)	Pearson $\chi^2$ test: <i>p-value</i> = .21
Age	Mean: 21.59 Standard deviation: 4.98	Mean: 23.06 Standard deviation: 5.61	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .08

**Table 4: Demographics comparisons between samples of subjects**

Second, there are no significant relational or structural differences between both groups in the original network consisting of 849 subjects (at the .1 level). Table 5 depicts

the results of Wilcoxon rank-sum tests for equal distributions. The tests suggest that there are no statistical differences among the distributions of opinion leadership, network integration, network constraint, and network centrality (at the 0.1 level) across both groups of participating and dropped subjects in the original network consisting of 849 subjects. Moreover, a Pearson chi-squared test for a 2X2 two-way contingency table for large sample sizes and categorical variables shows that we cannot reject the hypothesis that the probability of a being a member of a cohesive group among the 480 participating subjects is equal to the probability of being a member of a cohesive group among the 369 dropped subjects (at the 0.1 level).

<b>Relational or structural property</b>	<b>480 participating participants</b>	<b>369 dropped subjects</b>	<b>Statistical test</b>
Opinion leadership	Mean: .19 Standard deviation: .14	Mean: .18 Standard deviation: .13	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .23
Network integration	Mean: .18 Standard deviation: .13	Mean: .17 Standard deviation: .13	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .21
Network constraint	Mean: .28 Standard deviation: .14	Mean: .30 Standard deviation: .16	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .16
Network centrality	Mean: .23 Standard deviation: .12	Mean: .21 Standard deviation: .13	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .20
Cohesive group membership	Members (53 = 11.04%) Non-members (427 = 88.96%)	Members (29 = 7.86%) Non-members (340 = 92.14%)	Pearson $\chi^2$ test: <i>p-value</i> = .12
Structural equivalence	Mean: 3.89 Standard deviation: 1.97	Mean: 3.65 Standard deviation: 1.76	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .10

**Table 5: Comparison of relational and structural properties between samples of subjects**

In addition, there are no significant differences among subjects in both groups in regards to the patterns of the links that the subjects have formed with others in the original network consisting of 849 subjects. A Wilcoxon rank-sum test shows that the distribution of the measures of structural equivalence among participating subjects and all other subjects is no different from the distribution of measures of structural equivalence among dropped subjects and all other subjects (at the 0.1 level). As I explain in more detail in the measures operationalization section, structural equivalence is a mathematical

property of subsets of subjects in a network (Lorrain and White 1971), in the sense that two subjects are structurally equivalent if they have identical links to and from all other subjects in the network. To the extent that exact structural equivalence is very difficult to obtain, subjects will be more similar (in the sense that their patterns of connections in the network are akin) as their structural equivalence measure becomes smaller.

I required that each experimental group had a set of subjects consisting of three individuals whose relational and structural characteristics matched the requirements of a distinct configuration among those 32 depicted in Table 1. This was a parsimonious approach to ensure that, for each configuration in Table 1, there was a unique network with three subjects (later assigned as “early buyers”, as described below) displaying altogether high/low scores of opinion leadership, network integration, cohesive group membership, network constraint, and network centrality. For instance, I deemed an experimental group to have low opinion leadership among early buyers when the corresponding aggregate score for opinion leadership among three subjects in that group was below the mean opinion leadership score initially computed among the 849 subjects in the complete social network of subjects.

Selecting three subjects to act as early buyers in each experimental group allows the aggregate scores of opinion leadership, network integration, network constraint, cohesive group membership, and network centrality to adequately reflect the respective characteristics of a *group* of influential consumers in this research setting. This is because smaller numbers of subjects acting as early buyers would cause aggregate scores to reflect the characteristics of a single individual or a couple of individuals at most – hence not a group’s. Conversely, larger numbers of subjects (four and above) acting as early buyers would cause aggregate scores to reflect the characteristics of the larger group of

buyers of a deal, rather than the characteristics of a select group of potential influential ones only (i.e. the “innovators”). Moreover, inventory availability was limited, so increasing the number of early buyers would restrict considerably the number of potential “imitators”, whose behavior we are interested in.

### **Experimental protocol**

In the second step of the experiment, I invited subjects to use the web-based application. I contacted by email each of the 480 selected subjects to require confirmation of presence at a specific date/time at a computer laboratory at W.P. Carey School of Business. Each email ratified the subject’s importance to the experiment and the benefits of showing up – i.e. I reminded the subjects of the participation incentives. I sent four follow-up emails, including one email on the eve and another email at the beginning of the day of the experiment. Both this procedure and the participation incentives were effective in securing the presence – and consequently participation – of all 15 subjects allocated to each experimental group on her corresponding experimental trial.

Upon arrival to the computer laboratory, I briefed participating subjects on how the experiment would run. I also explained how to use the web-based application. To reduce interviewer bias, I read instructions from a script and avoided interacting with participants during the experiment. In addition, to reduce interactive testing effects, all participating subjects used identical hardware and software.

Prior to the beginning of each experimental session, I picked as “confederates” those three subjects who matched the expected relational/structural characteristics for early buyers in their respective experimental group. That is, I “planted” those subjects as “early buyers” and instructed them to buy the products in the deals as soon as the experimental application made the deals available. In doing so, I attempted to enforce

that the set of early buyers of each deal exhibited the expected relational/structural characteristics matching the corresponding configuration among those listed in Table 1. To reduce testing effects, I performed this procedure unbeknownst to the other subjects (i.e. the “non-confederates”).

When non-confederate subjects gained access to the online application, they also received a virtual allowance of \$1500 to make their purchases. This limited subjects’ ability to purchase many deals, so it reinforced the priming effect of social interactions and the marketing mix. This is because limiting subjects’ ability to purchase many deals provided them an incentive to make rational choices based on utility, information, and scarcity effects, so that they only would attempt to purchase those deals whose products they actually wanted to possess. Recall that subjects were unaware of which product being offered would be actually given away at the end of the experiment. However, subjects were aware that only those who attempted to purchase that product would have their names entered into the drawing.

For each experimental group, I offered the same 40 deals sampled from *Woot.com!*, as described above. Thus, the task was identical for all the groups. Each deal lasted for 3 minutes, so overall each experimental session lasted for two hours. I allowed participants to search for product information in external sources, such as *Amazon.com* and *Walmart.com*. In fact, this procedure mimics what happens in real life when consumers buy at *Woot.com!*

### **Experimental validity**

One of the primary advantages of experiments is the degree of control we may obtain in identifying the causal relationships between dependent variables and the covariates (i.e. treatments) (Babbie 2007). However, researchers have largely recognized



the important trade-offs that exist between experimental control and outside realism (Altman 2006; Cook and Campbell 1976, 1979). In this section, I focus on these trade-offs by examining the types of validity that may be used to interpret experimental results – internal, external, and construct validity – and issues related to realism.

*Internal validity* refers to the structure of the experiment itself and the extent to which we may infer causal relationships from the results. A cause-and-effect relationship can only be asserted if there is true covariation between the variables under investigation, the procedures used to gather the data demonstrate that the cause preceded the effect, and that alternative explanations have been ruled out. Internal validity asks the question “to what extent are the covariates (i.e. treatments) the sole source of the distribution of the dependent variables?” The key in assessing internal validity is to examine the experiment to identify aspects of the decision environment, beyond the covariates, that could influence the experimental results. A good experiment makes use of the ability to observe behavior and decision making in a controlled environment, controlling the variation between treatments to ensure that participants receive the same stimuli and experience the same conditions. As a result, the differences in observed behavior and the outcomes of such behavior can be attributed to the differences participants encounter in the treatments (Babbie 2007; Cook and Campbell 1976).

The internal validity of an experiment is often questioned when there is noise in the experimental protocol or there are uncontrolled stimuli affecting participants’ decisions in the experiment, which does not seem to be the case in the current study. In order to obtain internal validity, this research took advantage of an experiment’s ability to eliminate confounding factors that affect behavior, as already described in the experimental protocol section above, thereby limiting differences between experimental

groups and deals to a selected number of treatments. In this way, I could neatly identify the effect of the treatments on subjects' decision making in the absence of confounds by other mitigating factors.

In addition, a critical tool for achieving internal validity is random assignment. That is, if individuals are randomly assigned, as it is the case in this dissertation, then ex ante heterogeneity among the population of participants is controlled for insofar as there are no other factors that may directly differ between the experimental groups. Thus, given a properly designed experiment in which only the covariates differ across experimental groups, random assignment solves the problem of internal validity.

*External validity* addresses the extent to which the causal relationship identified in the experimental setting can be generalized to other populations, measures, times, places, and contexts. More subtly, external validity refers to the particular causal relationship gleaned from an experiment and the extent to which this relationship is robust in other environments (Babbie 2007; Cook and Campbell 1976).

Questions of external validity often revolve around the participant pool used in the experiment. Indeed, a longstanding criticism of the social interactions experiments conducted in sociology, psychology, and more recently in the social sciences, is that the groups whose interactions are observed are formed artificially for the sake of the experiment. This raises obvious questions about the generalizability of the research (Flynn et al. 1990; Meredith 1998). It is often suggested that experimental research would be much more generalizable if the experiments were performed on randomly selected subjects (Knemeyer and Naylor 2012). This can be difficult to achieve because studies of social interactions require characteristics of the individuals and the reference group which they are embedded in, not only the individual that comprises the group.

However, it is worth asking here how important external validity is to behavioral operations management. In some sense, research in behavioral operations management has been founded on the desire to develop a richer theory of decision making, building on classical models but incorporating insights from research in psychology and sociology (Loch and Wu 2007; Su 2008). Thus, many of the experiments in operations management were devised to test existing theory and models rather than to make generalizations that might inform, for instance, inventory policy (Bendoly et al. 2010; Bendoly et al. 2006). Indeed, as explained by Knemeyer and Naylor (2012), “using undergraduate students as subjects [in behavioral operations management experiments] may be appropriate if researchers are interested in fundamental human processes”. This argument is supported by Bendoly et al. (2006), who argue that well-designed experiments do not test how students act in certain contrived situations. They explain:

“[Experiments] test whether *representative humans* react in a predictable manner to controlled stimuli. Properly designed experiments are used to test and develop general theories. It is these theories, not the ‘specific’ experimental scenarios themselves, which are intended for application. If the theory is accurate, then it should hold in the laboratory. If it does hold, then the theory gains support and evidence.” (p. 739)

*Construct validity* challenges neither the internal consistency of an experiment nor the causal relationship between the variables inferred from the experiment’s results. Rather, construct validity explores how these variables are measured in an individual’s decision making and looks at the underlying relationship between these variables. That is, it concerns how well the measures employed fit the theories for which a test is designed. Measures and manipulations must be faithful (or valid) representations of constructs in order for us to make valid inferences. A natural way to think of construct validity is in

terms of how the variables are factored into an individual’s decision calculus (Babbie 2007; Cook and Campbell 1976).

One concern in this research is that the experimental procedure could not ensure that the picked confederates would be the *only* early buyers of each deal, since anyone was allowed to buy a deal as soon as it began. In order to assess if this issue posed a threat to this research’s construct validity, I performed a statistical analysis and found no significant differences in terms of relational/structural properties between the actual group of early buyers and the group of “confederates” (at the .05 level). Table 6 depicts the results of Wilcoxon rank-sum tests for equal distributions. The tests suggest that there are no statistical differences among the distributions of opinion leadership (*p-value* = .19), network integration (*p-value* = .11), cohesive group membership (*p-value* = .09), network constraint (*p-value* = .14), and network centrality (*p-value* = .13) across both groups of actual early buyers and confederates.

Measure	Confederates	Actual early buyers	Statistical test
Opinion leadership	Mean: .23 Standard deviation: .09	Mean: .21 Standard deviation: .14	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .19
Network integration	Mean: .24 Standard deviation: .10	Mean: .20 Standard deviation: .13	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .11
Cohesive group membership	Mean: .39 Standard deviation: .24	Mean: .43 Standard deviation: .35	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .09
Network constraint	Mean: .26 Standard deviation: .11	Mean: .23 Standard deviation: .18	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .14
Network centrality	Mean: .25 Standard deviation: .11	Mean: .22 Standard deviation: .17	Wilcoxon rank-sum test for equal distributions: <i>p-value</i> = .13

**Table 6: Comparison between the groups of confederates and actual early buyers**

Another concern in this research is whether the experimental treatments are effective, in the sense that the measures reflecting the three deal-specific attributes (i.e. popularity, quality, and price) accurately represent subjects’ perceptions. In this regard, treatment checks are essential in order to demonstrate the validity of the experiment

carried out (Perdue and Summers 1986). Without checks to validate such treatments, the conclusions drawn with respect to the impact of the treatment classes acting upon key dependent variables may become suspect (Bacharach and Bendoly 2011). As a result, the credibility of this experiment hinges on such validation, particularly because we intend to extrapolate our results toward practical application and subsequent theory development.

To address this concern, I surveyed a sample of non-confederates after the end of the experiment. 172 respondents indicated their perceptions regarding the levels (low/high) of the three deal-specific attributes (i.e. popularity, quality, and price) of each of the 40 offered deals. Then, I performed manipulation and confounding checks to assess the ability of the treatments to characterize different levels of the three attributes. Manipulation checks focus on the convergent validity of the treatments. They test whether the participating subjects accurately perceive the appropriate levels of the deal-specific attribute being manipulated (Perdue and Summers 1986; Wetzel 1977).

Table 7 displays the results of a multivariate analysis of variance (MANOVA) comparing subjects' perceptions to the actual levels of the attributes. The diagonal elements of the table (in bold) provide evidence of convergent validity. All three  $\chi^2$  results are significantly different from zero (at the 0.01 level), meaning that subjects' perceptions regarding popularity, quality, and price are accurate.

I also performed confounding checks to ensure that individual treatments do not confound other theoretically independent issues of interest. Confounding checks focus on discriminant validity. They test whether the treatment levels inadvertently impact participating subjects' perceptions of other supposedly independently controlled issues (Wetzel 1977). As explained by Perdue and Summers (1986),

“What if, however, the manipulation themselves are confounded (i.e. manipulations that are meant to represent a particular variable can be interpreted plausibly in terms of more than one construct, each at the same level of reduction)? In such a situation, confidence in the investigator’s causal explanation (expressed in theoretical terms) of the experimental results is greatly reduced because the construct validity of the manipulation as operationalization of the variables would be questionable.” (p. 317)

In situations in which the main effects of manipulated factors have statistically significant effects on other manipulated factors, discriminant validity turns out to be unsure (Perdue and Summers 1986). The off-diagonal elements on Table 7 table provide evidence of discriminant validity. All six  $\chi^2$  results are not significantly different from zero (at the 0.1 level), meaning that subjects’ perceptions regarding each deal-specific attribute (i.e. popularity, quality, and price) are not affected by each other.

The results of the MANOVA (Table 8) relating treatments that subjects faced in their corresponding experimental groups (i.e. opinion leadership, network integration, group membership, network constraint, and network centrality of early buyers) to their perceptions regarding deal-specific attributes (i.e. popularity, quality, and price) provide further evidence of discriminant validity. All fifteen  $\chi^2$  results are not significantly different from zero (at the 0.01 level), meaning that subjects’ perceptions regarding popularity, quality, and price are not affected by the treatments the subjects were exposed to.

Actual measure	Perceived popularity					Perceived quality					Perceived price				
	Low		High		$\chi^2$	Low		High		$\chi^2$	Low		High		$\chi^2$
	$\mu$	$\sigma$	$\mu$	$\sigma$		$\mu$	$\sigma$	$\mu$	$\sigma$		$\mu$	$\sigma$	$\mu$	$\sigma$	
Popularity	<b>0.44</b>	<b>0.50</b>	<b>0.57</b>	<b>0.50</b>	<b>&lt;0.01</b>	0.51	0.50	0.50	0.50	0.13	0.51	0.50	0.51	0.50	0.47
Quality	0.51	0.50	0.50	0.50	0.69	<b>0.06</b>	<b>0.24</b>	<b>0.94</b>	<b>0.24</b>	<b>&lt;0.01</b>	0.49	0.50	0.50	0.50	0.76
Price	0.50	0.50	0.51	0.50	0.28	0.50	0.50	0.50	0.50	0.38	<b>0.36</b>	<b>0.48</b>	<b>0.62</b>	<b>0.49</b>	<b>&lt;0.01</b>

**Table 7: Convergent and discriminant validity of manipulation and confounding checks (moderating variables)**

Actual measure	Perceived popularity					Perceived quality					Perceived price				
	Low		High		$\chi^2$	Low		High		$\chi^2$	Low		High		$\chi^2$
	$\mu$	$\sigma$	$\mu$	$\sigma$		$\mu$	$\sigma$	$\mu$	$\sigma$		$\mu$	$\sigma$	$\mu$	$\sigma$	
Opinion Leadership	0.51	0.50	0.57	0.50	0.82	0.50	0.50	0.50	0.50	0.97	0.49	0.50	0.49	0.50	0.68
Network Integration	0.51	0.50	0.50	0.50	0.96	0.50	0.50	0.50	0.50	0.66	0.50	0.50	0.49	0.50	0.32
Group Membership	0.50	0.50	0.51	0.50	0.91	0.50	0.50	0.50	0.50	0.44	0.50	0.50	0.49	0.50	0.31
Network Constraint	0.50	0.50	0.50	0.50	0.67	0.50	0.50	0.50	0.50	0.84	0.49	0.50	0.49	0.50	0.91
Network Centrality	0.51	0.50	0.50	0.50	0.67	0.50	0.50	0.50	0.50	0.50	0.50	0.50	0.49	0.50	0.19

**Table 8: Discriminant validity of confounding checks (independent variables)**

Finally, an important issue that we must consider in performing experiments is what would be casually referred to as *realism* (Altman 2006). Due to the conditions of an experiment and the desire to control for outside influences on behavior, experiments often lack *mundane realism* in that the circumstances individuals are encountering are unlike to arise in the real world (Aronson and Carlsmith 1968). From this research's perspective, mundane realism may not be the most important aspect of the experimentation procedure, since I grounded the experiment on *Woot.com!* Rather, in the interest of bringing psychological insights into the realm of behavioral operations management, this research is more concerned with experimental realism and psychological realism.

*Experimental realism* is defined as the extent to which the situations constructed in the experiment actively engage participants. In turn, *psychological realism* refers to the extent to which the psychological processes occurring in an experiment are comparable with the psychological processes occurring in ordinary decision making (Aronson and Carlsmith 1968).

With respect to experimental realism, the main criticism of experiments centers on the fact that individuals' behaviors and decision making are not motivated by adequate incentives or deception was employed. The results obtained from experiments with insufficient incentives may be suspect, as individuals may not be able to "put their money where their mouth is" and their decisions had no consequences. That is, the behavior observed in such experiments may be only "cheap talk" and an inadequate reflection of what individuals would do if real incentives or costs were involved. Similarly, if participants believe that they may be deceived in an experiment, they have no reason to try to make an optimal choice. Given that participants may be wary of the decision



environment in the experiment, deception may imply that they do not even know how to make an optimal choice in that environment (Aronson and Carlsmith 1968). So, since we are interested in studying decision making in this research, the experiment employed here gave participants accurate (although maybe not all) information necessary for them to engage in good decision making, and allowed participants to freely look for additional information as they found fit.

With respect to psychological realism, the fact that the actual benefits in an experiment are delivered by the experimenter may alter the way individuals think in the experiment. Thus, experiments may lack psychological realism in that the type of decision making that participants display in the experiment may be very different from that employed in real-world situations. Moreover, there may be strong interactions between incentives and personal or social motivations. So, I use caution when interpreting the experimental results as directly testing the psychological processes utilized in decision making taking place beyond the laboratory.

Based on my literature review, I deem that the incentives and the experimental protocol used in this research are adequate. However, in order to further strengthen this judgment, I performed a parsimonious investigation to assess whether there might have been bias in the selected participants' behavior. To that end, I inspected the data to investigate whether any non-confederate participant might have been clicking randomly without making rational decisions. Recall that I required all participants to click either button ("I want" or "I don't want one") during each deal. This allowed me to capture the time it took for each participant to make a choice regarding each deal (i.e. to make a purchase or to balk). For each of the 1280 deals, I computed the average time it took for the non-confederate participants to make a choice. Then, I found which participant

subject's choice times (i.e. the time to click during a deal) were consistently beyond one standard deviation from the group's mean choice time. My investigation revealed that three subjects consistently made choices (either to make a purchase or to balk) later than one standard deviation from the group's mean choice time. However, it appears that those subjects were not following a random choice pattern. This is because all of them made purchases later than the group's mean time in some cases only, which suggests that they were spending time gathering enough information to make rational decisions. Moreover, none was consistently deciding to make a purchase or to balk towards the end of the deals, which suggests that they were not waiting to click just for the sake of qualifying to the participation benefits.

My investigation also revealed that five subjects consistently made choices (either to make a purchase or to balk) earlier than one standard deviation from the group's mean choice time. However, it appears that none was following a random choice pattern either. This is because all of them made purchases earlier than one standard deviation of the group's mean choice time in few cases only. Moreover, none was consistently deciding to make a purchase or to balk early in the deals. In fact, while some of them chose "to balk" only a few times earlier than all confederates had made their purchases, all of those five subjects always chose to "make a purchase" later than all confederates had made their purchases. This suggests that the individuals were indeed spending some time gathering enough information to make rational decisions.

In sum, based on the aforementioned arguments, I am confident that the way I sampled subjects and conducted the experiment will not pose a threat to the validity of this research. First, the use of undergraduate students is adequate in the current research's context. Second, I conducted extensive checks and found no evidence of significant

threats to this research's internal and construct validity. Finally, I found no evidence of biased behavior among participating subjects.

### **Measures**

Whenever possible, I grounded measures in existing literature in the disciplines of marketing, sociology, economics, and operations management. Table 9 provides a summary of the measures used in this research, their nominal description, and source of reference.

<b>Measure</b>	<b>Nominal description</b>	<b>Source</b>
<b><i>Endogenous variables</i></b>		
<i>Service level</i>	The probability that a demand is met directly from inventory.	Nahmias (2004), Porteus (2002), Silver et al. (1998)
<i>Consumption rate (<math>t_i^*</math>)</i>	The time into the deal at which the consumption rate is faster. It is the tipping point of the cumulative curve of consumption, computed from the Bass model.	Bass (1969)
<b><i>Independent variables</i></b>		
<i>Opinion leadership of early buyers (<math>OL_i</math>)</i>	The average number of received nominations by early buyers.	Freeman (1979)
<i>Network integration of early buyers (<math>integration_i</math>)</i>	The average of the extent to which early buyers link to other consumers in their network through received nominations only.	Valente and Foreman (1998)
<i>Cohesive group membership of early buyers (<math>cohesion_i</math>)</i>	The relative number of early buyers who are members of a 2-clan.	Adapted from Wasserman and Faust (1994)
<i>Network constraint of early buyers (<math>constraint_i</math>)</i>	The average of the extent to which early buyers link to consumers in their network who, in turn, are already linked to each other.	Burt (1992), p. 55, eq. 2.4
<i>Network centrality of early buyers (<math>centrality_i</math>)</i>	The average distance from early buyers to all other consumers in the social network.	Freeman (1979)
<b><i>Moderating variables</i></b>		
<i>Product popularity (<math>popularity_i</math>)</i>	The product's position at <i>Amazon.com</i> 's sales ranking.	Li and Hitt (2008), Rabinovich and Bailey (2004), Rabinovich et al. (2003), Rabinovich et al. (2008a)
<i>Product quality (<math>quality_i</math>)</i>	The product is remanufactured (low quality) or "mint in box" (high quality).	
<i>Product price (<math>price_i</math>)</i>	The relative magnitude of the markdown offered with respect to the manufacturer's suggested retail price.	Rabinovich (2007), Rabinovich et al. (2003), Rabinovich et al. (2008a)
<b><i>Control variables</i></b>		
<i>Discussion forum tone (<math>tone_i</math>)</i>	The average sentiment across all posts in the discussion forum.	Shin et al. (2008, 2010)
<i>Structural equivalence (<math>SE_i</math>)</i>	The extent to which all buyers of a deal have identical links to and from all other consumers in the social network.	Burt (1987)
<i>Initial inventory provision (<math>Q_i</math>)</i>	The amount of inventory available at the beginning of a deal.	

**Table 9: Measures**

### Endogenous variables

Researchers typically measure consumption rate by first estimating a specific consumption model, and then using one or more of the parameter estimates as an indication of consumption rate.

Related research has consistently stipulated that the cumulative pattern of deal  $i$ 's consumption follows a growth pattern approximated by a simple one-parameter logistic function, such as:

$$y_{i,t} = \beta_{i,0} + \frac{1}{1 + e^{-\beta_{i,1}t}} \quad (1.1)$$

where  $y_{i,t}$  is the proportion of consumers who bought deal  $i$  at time  $t$ ,  $\beta_{i,0}$  is the intercept, and  $\beta_{i,1}$  is the consumption rate parameter to be estimated. We can use this simple model to compare consumption rates for various deals. However, the model is extremely limited in its applicability.

Bass (1969) and many others (for a review please refer to Mahajan et al. 1990) considerably improved the logistic model in equation (1) by creating a two parameter model:

$$y_{i,t} = \beta_{i,0}m + (\beta_{i,1} - \beta_{i,0})Y_{i,t-1} - \frac{\beta_{i,1}}{m}Y_{i,t-1}^2 \quad (1.2)$$

where  $y_{i,t}$  is the proportion of consumers who bought deal  $i$  at time  $t$  ( $t=0,1,\dots,179$ ),  $Y_{i,t-1}$  is the cumulative (total) number of consumers of that deal at the end of time  $t-1$ ,  $m$  is the total number of consumers who eventually bought that deal,  $\beta_{i,0}$  is the coefficient of external influence (the innovation rate), and  $\beta_{i,1}$  is the coefficient of social

influence (the imitation rate)<sup>4</sup>. In this model, the parameters  $\beta_{i,0}$  and  $\beta_{i,1}$  provide us information about the consumption rate in deal  $i$ . A high value for  $\beta_{i,0}$  indicates that the consumption has a quick start but also tappers off quickly. A high value of  $\beta_{i,1}$  indicates that the consumption is slow at first but accelerates after a while. Once one estimates  $\beta_{i,0}$  and  $\beta_{i,1}$ , it is possible to calculate the time  $t_i^*$  at which the consumption rate is faster, i.e. when the peak number of buyers per time occurs (Mahajan et al. 1990):

$$t_i^* = -\frac{\ln\left(\frac{\beta_{i,1}}{\beta_{i,0}}\right)}{\beta_{i,0} + \beta_{i,1}} \quad (1.3)$$

This research uses the measure  $t_i^*$  to assess a deal  $i$ 's consumption rate. The interpretability of results is straightforward, since an increase in 1 unit in  $t_i^*$  means that the tipping point increases by 1 unit of time (that is, the consumption rate decreases).

Ultimately, we are concerned with the deal  $i$ 's service level. As I explain below in the statistical analysis section, to assess a deal  $i$ 's service level, this research uses the time the last unit is sold during the deal,  $t_{s,i}$ , in the estimation of a hazard model. This measure is right censored, since a deal may end with leftover inventory. In case deal  $i$  ends with leftover inventory, we consider  $t_{s,i}$  to be the duration of that deal. As I explain in detail in the statistical analysis section, the estimation procedure takes care of this issue.

### **Independent variables**

This study has five independent variables. They refer to relational and structural properties of early buyers of each deal, and represent mechanisms through which social interactions may influence consumer choice. The five independent variables are: opinion

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<sup>4</sup> There are 180 intervals of time  $t$  during a deal, each corresponding to 1 second.

leadership, network integration, cohesive group membership, network constraint, and network centrality of a deal's early buyers. I grounded all measures in extant social network analysis literature.

One of the primary uses of social network analysis is the identification of the most influential (i.e. prominent) consumers in a reference group (e.g. a social shopping community). All measures used here attempt to describe and measure properties of "consumer location" in the social network. Consumers who are the most influential (or prominent) are usually located in strategic locations within the network (Bonacich 1987; Freeman 1979).

I begin by assuming that one subject has measurements on a single, dichotomous relation with another subject. I consider a subject to be influential (or prominent) if his/her links make him/her particularly visible to the other subjects in the social network. Knoke and Burt (1983) were the first to equate influence to prominence. Marsden and Friedkin (1993) noted that we should measure influence by looking not only at direct or adjacent links, but also at indirect paths involving intermediaries. That is, to determine which subjects are influential in a social network, one needs to examine not only all recommendations made by a consumer (outward links) and all nominations received (inward links), but indirect links as well.

For each deal  $i$  ( $i=1,2, \dots, 1280$ ), I find who its actual early buyers are according to the following procedure proposed by Bass (1969). First, I estimate the coefficients of innovation,  $\beta_{i,0}$ . Next, I obtain the total number of buyers of each deal,  $m_i$ , by counting the number of units sold in each deal<sup>5</sup>. I multiply  $\beta_{i,0}$  by  $m_i$ , and round the results to the nearest integer to estimate the total number of early buyers of each deal,  $b_i$ . Finally, I take

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<sup>5</sup> Each buyer is allowed to purchase only one unit of inventory.

the first  $b_i$  subjects who bought deal  $i$  as its early buyers. Based on this procedure, only 54 out of the 1280 deals (i.e. 4.22% of the observational units) had more actual early buyers than the planted confederates. Among those 54 deals, 47 had 4 early buyers (i.e. the confederates plus an additional buyer) and 7 had 5 early buyers (i.e. the confederates plus two additional buyers). As explained in the experimental validity section, this will not pose a threat to this research's construct validity.

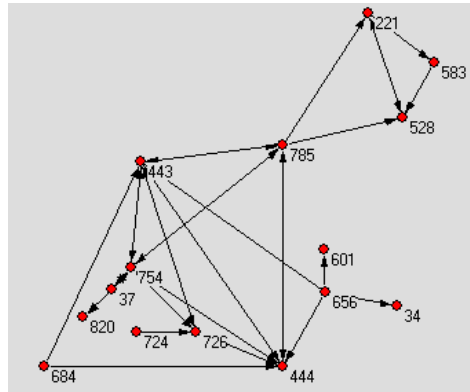
Then, for each early buyer, I operationalize his/her *individual-level* measures of opinion leadership, network integration, cohesive group membership, network constraint, and network centrality. All five individual-level measures are *deal invariant*. They refer to relational and structural properties of each subject in his/her corresponding social network.

Finally, for each deal  $i$ , I take the average of each individual-level measure of its  $b_i$  early buyers to obtain *group-level* measures that are *deal-dependent*. For instance, to obtain a measure of deal  $i$ 's early buyers' opinion leadership, I compute individual-level opinion leadership measures for all deal  $i$ 's early buyers and then take the average of these measures.

The first independent variable in this study is the measure of *opinion leadership of deal  $i$ 's early buyers*,  $OL_i$ . The individual early buyer  $n$ 's measure of opinion leadership,  $P_n$ , also known as "degree centrality" in social network analysis parlance, posits that an influential subject must be prominent in the sense that he/she receives relatively many nominations from other consumers in the network. This is very easy to see in Figure 6. In this small social network, 6 subjects nominated subject 444. In turn, no subject nominated subject 684. Subject 444 is clearly very prominent, and one could view



this high level of prominence as a large potential to influence. This very prominent subject should thus have a large individual opinion leadership index,  $P_{444}$ .



**Figure 6: Exemplary small network of 15 participants**

In order to increase the interpretability of the measure, I standardize it based on the size of the network,  $g$ . That is, I divide the measure by  $g-1$ . Such standardization gives us the proportion of subjects in the network who nominated early buyer  $n$ , which is called a “relative indegree”. The larger this index is, the more influential the early buyer is. Maximum individual opinion leadership occurs when  $P_n=1$ , that is, when all subjects in the network nominate early buyer  $n$ . Conversely, minimum opinion leadership occurs when  $P_n=0$ , that is, when early buyer  $n$  has zero nominations (Freeman 1979). In our example using Figure 6,  $P_{444}=6/14=.429$  and  $P_{684}=0/14=0$ .

The measure of opinion leadership of early buyers of deal  $i$ ,  $OL_i$ , is the average of the individual opinion leadership measures  $P_n$  of all early buyers of that deal. The index, which will always be between 0 and 1, is:

$$OL_i = \frac{\sum_{n=1}^{b_i} P_n}{b_i}, \quad (2)$$

where  $b_i$  is the number of early buyers of that deal.

The second independent variable in this study is the measure of *integration of deal i's early buyers, integration<sub>i</sub>*. The individual early buyer  $n$ 's measure of integration,  $d_n$ , refers to the extent to which the early buyer links to many and diverse others in the network through incoming links only. An integrated early buyer can be reached by many others rapidly.

We can measure integration by using a distance measure such as the directional geodesic. The directional geodesic indicates the length of the shortest path linking two subjects through unidirectional links in their social network. Here, we use the directional geodesic and reverse it. For instance, subject 785 is two steps apart from subject 684 in Figure 6. The maximum directional geodesic length of this social network, i.e. its directional diameter, is seven. To compute the reverse directional geodesic between both subjects, we add one to the value of the directional diameter before subtracting the directional geodesic (so that zero can represent the measure of subjects who received zero nominations). This procedure yields a measure of six.

To further increase interpretability of results, I standardize each individual measure of integration based on the size of the network,  $g$ . Thus, the equation

$$d_n = \frac{\sum_{j \neq n} RD_{jn}}{g-1} \quad (3.1)$$

gives us early buyer  $n$ 's individual measure of integration, where  $RD_{jn}$  is the reverse distance computed from the directional geodesic between subjects  $j$  and  $n$ .

The measure of integration of early buyers of deal  $i$ ,  $integration_i$ , is the average of the individual integration measures  $d_n$  of all early buyers of that deal (from equation 3.1). The index, which will always be between 0 and 1, is:

$$integration_i = \frac{\sum_{n=1}^{b_i} d_n}{b_i}, \quad (3.2)$$

where  $b_i$  is the number of early buyers of that deal.

The third independent variable in this study is the measure of *cohesive group membership of deal  $i$ 's early buyers*,  $cohesion_i$ . The individual early buyer  $n$ 's measure of cohesive group membership,  $nclan_n$ , is a binary measure that holds the value of 1 if the early buyer is a member of a 2-clan, or 0 otherwise.

By definition, all  $n$ -clans are  $n$ -cliques. An  $n$ -clique is a maximal subset of subjects in a social network in which the largest geodesic distance between any two subjects is no greater than  $n$ . An  $n$ -clan is an  $n$ -clique in which the geodesic distance,  $d(i,j)$ , between all subjects in it is no greater than  $n$  for paths within it. We can find the  $n$ -clans in a social network by first examining all  $n$ -cliques and then excluding those that include pairs of subjects whose geodesics require non-members (i.e. other subjects that are not in the  $n$ -clique). For instance, in Figure 6, consumers 785, 443, 444, 684, 656, and 754 form a 2-clan.

Given the small size of each social network in this study (15 subjects), I set  $n=2$  to limit cohesive group membership to a few subjects only. Having most subjects in our sample belonging to an  $n$ -clan was undesirable, since this would preclude us from having variability in the measure of cohesive group membership among early buyers.

Specifically, 42 subjects across the 32 experimental groups (i.e. 8.75% of the sample) were deemed to belong to a 2-clan. On average, there were 1.31 subjects belonging to a 2-clan per experimental group. Setting  $n$  to larger values would lead to scenarios in which most subjects in the social network would become members of  $n$ -clans. Specifically, 153 subjects across the 32 experimental groups (i.e. 31.88% of the sample) would be deemed to belong to a 3-clan, had I set  $n=3$ . In turn, 233 subjects across the 32 experimental groups (48.54% of the sample) would be deemed to belong to a 4-clan, had I set  $n=4$ . Under such scenarios, on average, there would have been 4.78 subjects belonging to a 3-clan and 7.28 subjects belonging to a 4-clan per experimental group<sup>6</sup>.

The measure of cohesive group membership of early buyers of deal  $i$ ,  $cohesion_i$ , is the average of the individual cohesive group membership measures  $nclan_n$  of all early buyers of that deal. The index, which will always be between 0 and 1, is:

$$cohesion_i = \frac{\sum_{n=1}^{b_i} nclan_n}{b_i}, \quad (4)$$

where  $b_i$  is the number of early buyers of that deal. For instance, when only one early buyer of a deal  $i$  belongs to a 2-clan, our measure of cohesive group membership for that deal,  $cohesion_i$ , is equal to 1/3 (assuming a set of three early buyers in the deal).

The fourth independent variable in this study is the measure of *network constraint of deal  $i$ 's early buyers*,  $constraint_i$ . The individual early buyer  $n$ 's measure of network constraint,  $SH_n$ , refers to the extent to which the early buyer links to others who, in turn, are already linked to each other. The more "constrained" the subject, the fewer

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<sup>6</sup> A post-hoc analysis showed that setting  $n=3$  or  $n=4$  would not change significantly the results of the statistical analysis.

the opportunities to broker influence flows. The idea of network constraint is an important one because it points out that subjects who have many links to others may actually limit the flow of influence, rather than facilitate it, as discussed in the theoretical development.

If the early buyer's links in the social network all have one another as links, then the early buyer is highly constrained. The "constraint" is characterized by a lack of structural holes around each of her neighbors. However, if the early buyer's links have a few other links, then they are unable to "constrain" the early buyer to broker influence flows. In this case, we say that the early buyer "fills a structural hole" by linking two subgroups that would be disconnected otherwise. This is because a structural hole refers to the absence of links between two parts of a network (Burt 1980, 1992). For instance, subject 785 in Figure 6 fills a structural hole by linking groups of consumers that would be otherwise disconnected.

This study uses Burt's (1992:55) equation 2.4 to operationalize the individual early buyer's measure of constraint:

$$SH_n = \sum_{j \neq n} [p_{nj} - \sum_{q \neq j, n} p_{nq} p_{jq}]^2 \quad (5.1)$$

where  $p_{nq} = \frac{(z_{nq} + z_{qn})}{\sum_j (z_{nj} + z_{jn})}$ , ( $j \neq n$ ), is the proportion of a subject  $n$ 's links also linked to subject  $q$  ( $z_{nq} = 1$  if subject  $q$  nominates subject  $n$ ,  $z_{nq} = 0$  otherwise). That is,  $p_{nq}$  is the proportional strength of subject  $n$ 's relationship with subject  $q$ . In Equation (5.1), the contact specific constraint,  $[p_{nj} - \sum_{q \neq j, n} p_{nq} p_{jq}]^2$ , ( $j \neq n$ ), varies from 0 to 1 with the extent to which subject  $n$ 's relations are concentrated in a single contact ( $p_{nj}$ ) or subject  $n$ 's contacts concentrate their relations in one single contact ( $\sum_{q \neq j, n} p_{nq} p_{jq}$ ). That is, the

contact specific constraint measures the extent to which subject  $n$ 's connections strength depends directly or indirectly on subject  $j$ 's connections strength.

The measure of network constraint of early buyers of deal  $i$ ,  $constraint_i$ , is the average of the individual network constraint measures  $SH_n$  of all early buyers of that deal (from equation 5.1). The index, which will always be between 0 and 1, is:

$$constraint_i = \frac{\sum_{n=1}^{b_i} SH_n}{b_i}, \quad (5.2)$$

where  $b_i$  is the number of early buyers of that deal.

The fifth independent variable in this study is the measure of *network centrality of deal  $i$ 's early buyers*,  $centrality_i$ . The individual early buyer  $n$ 's measure of network centrality,  $c_n$ , refers to the extent to which the early buyer is close to the other consumers in the network. This type of centrality depends not only on direct links, but also on indirect links, especially when any two consumers are not adjacent<sup>7</sup>. We define the standardized individual early buyer's measure of network centrality as:

$$c_n = \frac{g-1}{[\sum_{k=1}^g D_{nk}]} \quad (6.1)$$

where  $D_{nk}$  is the geodesic linking consumers  $n$  and  $k$ , and  $g$  is the size of the network.

The measure of network centrality of early buyers of deal  $i$ ,  $centrality_i$ , is the average of the individual centrality measures  $c_n$  of all early buyers of that deal (from equation 6.1). The index, which will always be between 0 and 1, is:

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<sup>7</sup> While there are other measures of centrality (Bonacich 1987, Freeman 1979), closeness centrality is the most adequate measure for the purposes of this study. This is because closeness centrality directly relates to a particular consumer's *distance* to other consumers, which allows us to relate this measure to the two-step flow of influence principle.

$$centrality_i = \frac{\sum_{n=1}^{b_i} c_n}{b_i}, \quad (6.2)$$

where  $b_i$  is the number of early buyers of that deal.

### **Moderators**

This study requires the *popularity* of each product. Unfortunately, *Woot.com!* is unable to provide information on how popular a product is. However, most of the products once sold by *Woot.com!* are still available at its parent company, *Amazon.com*. I used a product position at *Amazon.com*'s sales ranking in its respective product category (at the same quality offered by *Woot.com!*, i.e. refurbished or "mint-in-box") as a measure of a deal's product popularity (*popularity<sub>i</sub>*). The operationalization of this measure assumes that the higher in the ranking (i.e. the higher the popularity), the smaller the ranking number. For instance, Kindle, which is currently the most popular product in the electronic tablets category (Amazon.com 2012), occupies the position number 1 in its respective ranking. I captured the sales ranking of a deal's product at its *Amazon.com*'s corresponding category one day prior to the beginning of the experiment for all 40 products offered as part of a deal in the experiment. I took the natural log of sales ranking to correct for skewness in the measure, since its distribution has a very long tail. This operationalization is consistent with studies using a product's ranking to assess its popularity (Li and Hitt 2008; Rabinovich and Bailey 2004; Rabinovich et al. 2003; Rabinovich et al. 2008a).

The deal's *product quality* (*quality<sub>i</sub>*) is a categorical measure. I set it to 0 to represent low quality (i.e. the product is remanufactured) and 1 to represent high quality (i.e. the product is "mint in box").

Finally, the deal's *price* ( $price_i$ ) is a normalized measure. It captures how large the mark down offered in deal  $i$  is. I operationalize the measure as:

$$price_i = \frac{p_{d,i} - p_{MSRP_i}}{p_{MSRP_i}} \quad (7)$$

where  $p_{d,i}$  is the deal  $i$ 's charged price, and  $p_{MSRP}$  is the manufacturer's suggested retail price, which is also obtained from *Amazon.com*.

### **Control variables**

The first control variable is the *deal's discussion forum tone* ( $tone_i$ ). Prior studies have identified that the nature of the posts in an online discussion forum can influence consumer choice (Dellarocas 2006) and as such may be a confounding factor in our assessment of social interactions effects. A distinction must be clearly made: the potential influence of a deal's discussion forum tone on consumer choice would refer to WOM influence, whereas social interactions would refer to the influence on consumer choice stemming from observation of other's choices (i.e. purchases), according to the definition of social interactions put forth in this research.

In fact, some discussion forum posts at *Woot.com!* suggest that the discussion forum tone might be influential. Here are some examples of posts at *Woot.com!* on Feb 28<sup>th</sup>, 2012:

*OGauge4Me: THX for all the positive comments. I am in for one. I have an older Sony that does not support internet streaming. Looks like this box will do the job and then some.*

*Gina3graces: Everyone's helpful posts convinced me this would make a great gift for a friend's birthday, in for 1.*



*Clemell: the negative comments about speed make me question whether it is reliable. I'm still debating on it though...*

A deal's discussion forum tone is a normalized measure ranging from -1.0 (very negative tone) to 1.0 (very positive tone). It refers to an aggregate measure reflecting how positive, negative, or neutral all posts in that deal's discussion forum are altogether. Unfortunately, reading posts is an extremely time consuming task, and the measures obtained are very noisy, as argued by Chevalier and Mayzlin (2006) and shown by Godes and Mayzlin (2004). Thus, to operationalize the measure, I will adopt a parsimonious approach, based on the notion of online consumer "sentiments" (Shin et al. 2008, 2010).

The first step in operationalizing this measure was to consider all posts in the actual discussion forum of *Woot.com!* of each of the 40 deals in our sample. Overall, there were 3,825 posts in our dataset. Then, three raters assessed independently the tone of each actual post (negative, neutral, or positive) conveying a consumer's "sentiment". These raters were United States based, native English speakers raters hired from *VWorker.com*, a crowdsourcing website that allows tasks to be distributed to a large group of people. Overall, nine raters performed the rating tasks, each rating 1,275 posts.

I asked raters to judge whether the tone of a post reflected positive, negative, or neutral "sentiments". Thus, in this research, ratings take the form of judgments of kind, in which a rater answers the following question: in which category does this unit belong? To make their assessment, I provided raters a list of subjective positive and negative adjectives defined in the General Inquirer (<http://www.wjh.harvard.edu/~inquirer>) (Kennedy and Inkpen 2006; Stone et al. 1966). For instance, these are examples of posts deemed to convey positive sentiments:

*TJFoxxx: These seem like pretty good gadgets. I'm in for one!*

*Ralf32: I love using my Roku (with NetFlix on my older) TV. I wish I had gotten one sooner.*

*Coreylamb: wow.. What a buzz kill.. I have ordered & installed 2 Roku 2 XS's & a Roku LT in the last couple weeks. All so I can stream from Plex.. This deal would have saved me a big chunk of change.*

*Syninthecity: if you've got kids, i cannot in good conscience recommend getting anything but an XS. with rapidly expanding, dirt cheap games, the 1 xs i have gets more use than any of the other 3 older models. Several flavors of angry birds, some tower defense, regular updates and under 5 bucks, they're a nice addition to what's otherwise still a solid deal for a high quality netflix box. I heard from torrentfreak scene releases will now be coming in mp4...which the roku plays natively, so local streaming should get a whole lot easier shortly as well. If you don't have one, but want to see what cutting the cable might feel like, pick up one of these, and grab a netflix trial membership. it's a cheap investment compared to a monthly cable bill, (i saved enough to get faster internet for better streaming) (did i mention it gets free internet grown up videos, via private roku channels?) I'm not a schill, just a Roku convert.*

In turn, the following are examples of posts deemed to convey negative sentiments:

*Kitepower: I bought one of these (XDS) after reading everyone here rave over theirs, when they were on woot about a month or so ago and have been quite disappointed with the speed of it steaming via wifi. Plugged in direct via ethernet has been better but it still takes a really long time to start the stream going. In comparison to the Apple TV, the Apple TV streams a lot faster (even on wifi compared to the Roku over ethernet). I love the ability to add channels (but I found out that it very quickly ran out of space to add more channels) which the Apple TV doesn't have. Being able to stream news networks*

*like Russia Today, and Al Jazeera are a big plus. So all in all where it is a really cool piece of kit, it just doesn't work as smoothly as I would like, but still its handy to be able to have another tv access Netflix. Maybe if it were \$10-15 cheaper then it would really be a great deal.*

*RickDuhrkopf: I was all set to do this. Then I went to the Roku site. The new Roku 2 XD (new and newer model) is \$10 off making it \$69.99 and free shipping. For \$5 more, I get the newer model and it is not a refurb.*

*Richspirit: I'm always leery of refurbished products when they don't have full warranties. What's the likelihood this will be ok/or fail right after the 90 days?*

*twig123: I had a Roku XDS that I purchased from Amazon last year... I found that the menu transitions were horrendously slow, in addition no local network streaming (without a bunch of work), no local storage and just overall was very disappointing and had buyers remorse within a couple hours. I gave it a go for a couple days, but the promptly returned it to Amazon and purchased the WD TV Live Hub. I was instantly impressed how much faster the device was, it also supports more services than Roku. In addition it also has 1TB of storage and supports a vast array of file types and codecs. For streaming to the Roku, you need a PC running with a transcoder and a special app installed on the device itself. Trying to get 1080p to stream to the Roku is a joke, and you would be lucky if you can play 720p smoothly. Take my advice, skip the buyers remorse and just buy the WD TV Live Hub instead!*

Finally, the next posts are examples of posts deemed to convey neutral sentiments:

*Worldwidewebfeet: Wooted the Roku XD in December, overall happy with it but far from perfect. Graphical user interface is slow. Channels are so-so, many interesting channels are pay for. Free channels like Crackle (movies) some*

*good choices, but will drive you crazy with the same ads over and over, and they interrupt program at stupid points. Hulu Plus, pay for, I had 1 month trial but cancelled after 2 weeks, horrible movie selection, horrible user interface, streaming would lock up on occasion requiring hard reboot of Roku. Terrible selection of sports and news channels. Yes did require credit card to start Roku setup.*

*Lintball: If I'm not mistaken, this model also has 5GHz WIFI for dual-band routers. The newest models dropped the 5GHz radio (only 2.4).*

*jasonking0351: Keep in mind that since this is the XDS model that can connect to either a 2.4ghz or 5.0ghz networks if you have that type of router. In my case I have one of these ROKU's from Woot and I connect it using the 5ghz network which has far fewer devices in my home connected to it (very nice feature). However (and there is always a gotcha), there is one small thing to consider. If you are using the official ROKU IOS app (<http://itunes.apple.com/us/app/roku/id482066631?mt=8>) to control your ROKU, it uses the SSID of the wireless connection that your iPhone uses. Since my iPhone 4s can only see 2.4ghz networks, the IOS app is useless unless I switch the ROKU to use the same 2.4ghz network...which defeats the dual band benefit.*

The second step in operationalizing the  $tone_i$  measure was to obtain a measure of sentiment for each post by averaging its three ratings. Finally, to compute a deal  $i$ 's discussion forum tone,  $tone_i$ , I averaged the sentiment of all posts in that deal's discussion forum.

When relying on human raters, one concern is the reliability of the data. Reliability is the extent to which the scores remain consistent over repeated ratings of the

same subject (i.e. a post) under identical conditions (Crocker and Algina 1986; Spitzer et al. 1967). This implies that a test is reliable if it yields constant results for the same measure. Another interpretation is that there is lack of random error in measurement. In this research, we expect that the data being used in the analysis reflect properties of the posts and are not the result of irreproducible human idiosyncrasies.

Among the kinds of reliability – stability, accuracy, and reproducibility – the latter is arguably the strongest and most feasible kind to test (Hayes and Krippendorff 2007). It amounts to evaluating whether a coding instrument, serving as common instructions to different raters of the same set of posts, yields the same data within a tolerable margin of error. The key to reliability is the agreement observed among independent raters. The more raters agree on the data they generate, the more comfortable we can be that their data are exchangeable with data provided by other set of raters, trustworthy, and reproducible.

We may estimate reliability through a variety of indices. In this study, I used three of the most commonly used reliability indices in social sciences: Cronbach's alpha, Fleiss's kappa, and Krippendorff's alpha. Cronbach's (1951) alpha ( $\alpha_C$ ) is a statistic for interval or ratio-level data that responds to the consistency of raters when numerical judgments are applied to a set of units. It quantifies the consistency by which a set of raters judge units on an interval scale without being sensitive to how much the raters actually agree in their judgments. It is appropriate as a measure of the reliability of an aggregate measure across raters, such as the arithmetic mean judgment, even though it does not directly index the extent to which raters actually agree in their judgments.

In turn, Fleiss's Kappa ( $\kappa_F$ ) is a measure of inter-rater agreement (Fleiss et al. 1969; Fleiss et al. 2003). Contrary to Cohen's (1960) Kappa, which has shortcomings –

including being limited to the percent agreement between two raters, Fleiss’s Kappa indeed constitutes a numerical scale of agreement among 2 or more raters, whereas perfect agreement is set to 1.000 (or 100%), while the absence of agreement, typically indicated by .000, represents a situation in which the posts bear no statistical relation to how they end up being identified, coded, or described.

Finally, Krippendorff’s (2004) Alpha ( $\alpha_K$ ) defines a large family of reliability indices. It calculates disagreements instead of correcting percent agreements, avoiding shortcomings faced by other indices. In its two-rater ordinal data version,  $\alpha_K$  is identical to Spearman’s rank correlation index  $\rho$ . Its extension to many observers is stated in analysis of variance terms (Krippendorff 1970).

As a rule of thumb, a reliability of .70 or higher is deemed to be acceptable. However, given the nature of the rating employed in this research – raters that possibly lacked familiarity with the subject were hired through a crowdsourcing tool, it is reasonable to demand that reliability must not be below .8.

Table 10 provides the results for the reliability tests. It can be noticed that all three reliability indices -  $\alpha_C$ ,  $\kappa_F$ , and  $\alpha_K$ , are well above the required .80 level. In fact,  $\alpha_K$ , arguably the best suited among all three indices for this research’s ordinal data (Hayes and Krippendorff 2007), is .85, so the risk of accepting the data as reliable when they are not is quite low.

Index	Estimate	Source
Cronbach’s Alpha ( $\alpha_C$ )	.869	Cronbach (1951)
Fleiss’s Kappa ( $\kappa_F$ )	.860	Fleiss et al. (1969) Fleiss et al. (2003)
Krippendorff’s Alpha ( $\alpha_K$ )	.851	Krippendorff (1970,2004)

**Table 10: Reliability indices for the discussion forum posts ratings**

The second control variable in this study is the *structural equivalence* among all consumers who bought a deal  $i$ ,  $SE_i$ . Structural equivalence is a mathematical property of subsets of consumers in a network (Lorrain and White 1971). In short, two consumers are structurally equivalent if they have identical links to and from all other consumers in the network. Thus, in this research's context, it is a measure of similarity between two consumers in an online community. Structurally equivalent consumers are posited to have similar behavior and as such are likely to have similar purchase times (Burt 1987). Therefore, structural equivalence among consumers is likely to influence consumption rates (Valente 2005) in social shopping and act as an undesirable confounding factor to social interactions effects. Structural equivalence among buyers of a deal is a control rather than an independent variable in this study because it is unrelated to the two-step flow of influence principle.

Structural equivalence is a mathematical property that is actually difficult to obtain in a set of social network data. For various reasons, including measurement error and variability in respondents' answers, it is unlikely that two consumers will be exactly structurally equivalent in a set of network data. Analytical methods based on structural equivalence, therefore, seek to locate and identify subsets of consumers who are "approximately" structurally equivalent (Wasserman and Faust 1994).

Burt (1987) developed a measure of structural equivalence based on the Euclidean distance. Let  $z_{jk}$  be the value of the link from consumer  $j$  to consumer  $k$  on a single relation, where  $z_{jk}=1$  if the link is present and  $z_{jk}=0$  otherwise. We define a distance measure of structural equivalence for consumers  $j$  and  $p$  as the Euclidean distance between the links to and from these consumers:

$$SE_{jp} = \sqrt{\sum_k^g [(z_{jk} - z_{pk})^2 + (z_{kj} - z_{kp})^2]} \quad (8)$$

for  $j \neq k, p \neq k$ .

If consumers  $j$  and  $p$  are structurally equivalent, then the Euclidean distance between them will be equal to 0. To the extent that two consumers are not structurally equivalent, the Euclidean distance between them will be greater than 0. The Euclidean distance has the properties of a distance metric: the distance from an object to itself is 0 ( $SE_{jj}=0$ ), it is symmetric ( $SE_{jp}= SE_{pj}$ ), and all distances are greater than or equal to 0 ( $SE_{jp} \geq 0$  for all  $j, p$ ).

To compute the final measure of structural equivalence among all deal  $i$ 's buyers,  $SE_i$ , I first computed the structural equivalence for each pair of consumers in each experimental group. Then, for each deal  $i$ , I averaged the structural equivalence among all pairs of consumers who bought that deal.

The third control variable is the deal's *initial inventory provision*,  $Q_i$ . It is a measure of the number of units made available at the beginning of deal  $i$  in respect to the size of the network of consumers. Thus, initial inventory provision is operationalized as a percentage, rather than as an absolute measure, to increase the interpretability of the statistical results.

I set the deal's initial inventory provision according to the following procedure: unbeknownst to the participants to avoid "end-of-game" behavior, I drew a random number,  $O_U$ , uniformly distributed between  $N/3$  and  $2N/3$ , where  $N=15$  is the total number of participating subjects in each experimental trial, at the beginning of each deal. I then used such drawn random number as the mean of a normal distribution with



standard deviation  $N/10$  ( $N=15$ ). A new random number,  $O_N$ , was then drawn from this normal distribution. I rounded this number up to the nearest integer, and then used this rounded integer value as the deal's initial inventory provision.

The initial inventory provision was never exceedingly low or high. The assumption behind this approach is that all participants in the controlled experiment were aware of each deal when it was taking place (which is usually not the case in actual online communities). As such, initial inventory provision should be at most  $N$ , otherwise, the experiment would induce overstocking. Moreover, the initial inventory provision should ideally reflect available inventory for the fraction of those  $N$  consumers who might be interested in the purchase. Very low levels of inventory (close to 0 units) would induce stockouts even if a small fraction of consumers might be interested in the purchase. Hence the sampling of  $O_U$  from either low- or high-mid ranged uniform distributions in respect to the total number of participants,  $N$ . The normal distribution introduced additional “uncertainty” to the “decision-making process”. This was aimed at capturing the bounded rationality of inventory managers. That is, in face of uncertain demand due to social interactions, inventory managers will provide  $O_N$  units of inventory, which is unlikely to be an optimal quantity. In the statistical analysis, I multiplied the absolute number of units offered at each deal by  $100/N$  (where  $N=15$ ), so that  $Q_i$  reflects the desired percentage. This increases the interpretability of the results.

### Statistical analysis

To empirically assess the conceptual model (Figure 2 **Error! Reference source not found.**), I developed an econometric model consisting of two equations. The first equation in the econometric model assesses the relationship between a deal's consumption rate and the social interaction mechanisms (hypotheses **H1A** through **H1E**),

as well as the moderation effects of product characteristics and the commercial context on such a relationship (hypotheses **H2A** through **H2C-2**). The second equation in the econometric model assesses the relationship between a deal's service level and its consumption rate (hypothesis **H3**). I used functions and customized macros in the software package SAS 9.3 to perform the statistical analysis.

**The relationship among consumption rate, social interactions, product characteristics, and the commercial context**

To assess hypotheses **H1A** through **H2C-2**, we express the consumption rate,  $t^*$ , measured as the inflection point of the cumulative consumption curve computed from the Bass model in equation (1.3), as an unobserved effects model (also known as a hierarchical linear model):

$$t^* = \beta'_{10} + \sum (\beta'_{11}\mathbf{w} + \beta'_{12}\mathbf{m} + \gamma'_{11}\mathbf{w} * \mathbf{m} + \delta'_1\mathbf{x}) + \mathbf{e}_1 + \mathbf{u} \quad (9)$$

where  $\mathbf{w}$  represents the vector of social interactions variables (*opinionleadership, integration, cohesion, constraint, and centrality*),  $\mathbf{m}$  represents the vector of moderators (*popularity, quality, price*),  $\mathbf{x}$  represents the vector of control variables (*tone, SE, and Q*), and  $\mathbf{e}_1$  represents measurement errors, while  $\mathbf{u}$  controls for unobservable effects due to clustering in my dataset. Note that a multidimensional vector of coefficients is assigned to each multidimensional vector of variables.

In this research, data are clustered because the forty deals are repeated across thirty-two groups of participants. Consequently, observational units are correlated as a result of unobserved cluster effects. This issue is somewhat easy to handle. While we allow the units within each cluster to be correlated, we assume interdependence across clusters. When the explanatory variables are exogenous, as it is the case in equation 14,

the ordinary least squares (OLS) estimator is consistent and asymptotically normal. However, we need to adjust the asymptotical covariance matrix (Greene 2003; Wooldridge 2002).

This research uses the the robust “sandwich” covariance matrix estimator (White 1980) to perform such an adjustment. This matrix differs from the typical ordinary least squares (OLS) covariance matrix, in the sense that it uses the regression’s residuals as its diagonal elements to adjust for potential distinct variances – hence the commonly used term “heteroskedasticity-robust standard errors” that describes their purpose. This estimator is valid in the presence of any heteroskedasticity (including homoskedasticity) or serial correlation in this research, since each cluster here consists of relatively few units compared with the overall sample size of 1280 observational units (White 1980; Wooldridge 2002).

### **The relationship between a deal’s service level and its consumption rate**

To assess hypothesis **H3**, I conducted a survival analysis. Survival analysis is the name for a collection of statistical techniques used to describe and quantify time to event data. In survival analysis, we use the term “failure” to define the occurrence of an event of interest – i.e. stocking out in a deal. Here, the term “survival time” measures the duration of time, from the beginning of a deal (at time zero), until it stocks out, and the set of covariates hypothesized to be associated with the failure time variable. The purpose of survival analysis is to model the underlying distribution of the failure time variable and to assess the dependence of the failure time variable on the covariates of interest (Kalbfleisch and Prentice 1980; Maddala 1983).

An intrinsic characteristic of survival data is the possibility for censoring of observations. That is, the actual time until the event may not be observed. Such censoring

arises in this research since all the deals in my experiment have a limited preset time. Because the dependent variable is the actual duration of a deal, some of the possible failures may not occur when deals terminate at their limited time. We say that these observations are right censored. One may not ignore censored data because, among other considerations, deals that last long until they stock out are generally more likely to be right censored. Thus, the method of analysis employed in this research takes censoring into account and correctly uses the censored observations as well as the uncensored observations. I explain the procedure that accounts for the right censoring in our data in the Appendix.

The distribution of survival times is characterized by three functions: (1) the survivorship function, (2) the probability density function, and (3) the hazard function. Let  $T$  denote the survival time. The survivorship function,  $S(t)$ , which is the probability of “surviving” past time  $t$ , is defined as  $S(t) \equiv 1 - F(t) = P(T > t)$ , where  $F(t)$  is the cumulative distribution function (cdf) of  $T$ .  $S(t) = 1$  when  $t=0$ , and  $S(t) = 0$  when  $t=\infty$ . The graph of  $S(t)$  is known as the survival curve, which begins at  $S(0)=1$  and decreases to 0 as  $t$  increases to infinity. It is assumed here that  $T$  is continuous – and, in fact, has differentiable cdf – because this assumption simplifies statements of certain probabilities.

The probability density function, defined as  $f(t) = dF/dt(t) = \lim_{\Delta t \rightarrow 0} P(t < T < t+\Delta t)/\Delta t$ , gives the unconditional failure rate. In turn, the hazard function, defined as  $h(t) = f(t)/[1-F(t)] = \lim_{\Delta t \rightarrow 0} P(t < T < t+\Delta t | T > t)/\Delta t$ , gives the conditional failure rate<sup>8</sup>. It is a measure of the propensity to failure as a function of the time elapsed during a deal, in the sense that the quantity  $\Delta t * h(t)$  is the expected proportion of deals lasting until time  $t$  that will stock out (i.e. a failure) in the short interval from  $t$  to  $t + \Delta t$ . Obviously, the three

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<sup>8</sup> The hazard function is also known as instantaneous failure rate, or conditional mortality rate.

functions are mathematically related. If one of them is known, the other two can be derived. Specifically,  $h(t) = f(t)/S(t)$ .

### **Understanding the hazard function**

In the simplest case, the hazard function is constant, that is,  $h(t) = \lambda$ , for all  $t \geq 0$ . This function means that the process driving  $T$  is memoryless. That is, the probability of failure in the next time interval is a random event independent of how much time has been spent in the initial state, when there is inventory to be sold. It can be shown that  $F(t) = 1 - \exp(-\lambda t)$ , which is the cumulative distribution function of the exponential distribution. Conversely, if  $T$  has an exponential distribution, it has a constant hazard.

We say that the process exhibits duration dependence when the hazard function is not constant. Assuming that  $h(t)$  is differentiable, there is positive duration dependence at time  $t$  if  $dh(t)/dt > 0$ , if  $dh(t) > 0$  for all  $t > 0$ , then the process exhibits positive duration dependence. With positive duration dependence, the probability of stocking out (i.e. exiting the initial state) increases the longer a deal lasts (i.e. it is in the initial state). If the derivative is negative, then there is negative duration dependence. That is, the probability of stocking out decreases the longer a deal lasts. Table 11 lists five commonly used distributions in survival analysis with their density,  $f(t)$ , survival function,  $S(t)$ , and hazard function,  $h(t)$ . In the next few lines, I provide a cursory review of the remaining four distributions, besides the exponential, that will help us interpret the results presented in the next chapter.

Distribution	Parameter	Density and survival functions	Hazard function
Exponential	$\lambda > 0$	$f(t) = \lambda \exp(-\lambda t)$ $S(t) = \exp(-\lambda t)$	$h(t) = \lambda$
Weibull	$\lambda, \gamma > 0$	$f(t) = \lambda \gamma t^{\gamma-1} \exp(-\lambda t^\gamma)$ $S(t) = \exp[-(\lambda t)^\gamma]$	$h(t) = \lambda \gamma t^{\gamma-1}$
Generalized Gamma	$\lambda, \gamma > 0$	$f(t) = [\lambda \alpha / \Gamma(\gamma)] (\lambda t)^{\alpha \gamma - 1} \exp[-(\lambda t)^\alpha]$ $S(t) = \int f(x) dx$	$h(t) = f(t)/S(t)$ . Note: The hazard function does not have a closed form.
Lognormal	$\mu, \sigma > 0$ $a = \exp(-\mu)$	$G(y) = 1 - \int_0^y \frac{1}{\sqrt{2\pi}} \exp(-u^2/2) du$ $f(t) = \frac{1}{t\sigma} \sqrt{2\pi} \times \exp[-1/2\sigma^2(\log at)^2]$ $S(t) = 1 - G(\log(at/\sigma))$	$h(t) = \left\{ \frac{1}{t\sigma} \sqrt{2\pi} \times \exp\left[-\frac{1}{2} \sigma^2 (\log at)^2\right] \right\} \times \left\{ 1 - G\left(\frac{\log(at)}{\sigma}\right) \right\}^{-1}$
Log-logistic	$\lambda, \gamma > 0$	$f(t) = \lambda \gamma t^{\gamma-1} [1 + \lambda t^\gamma]^{-2}$ $S(t) = [1 + \lambda t^\gamma]^{-1}$	$h(t) = \lambda \gamma t^{\gamma-1} [1 + \lambda t^\gamma]^{-1}$

**Table 11: Commonly used distributions in survival data analysis**

The Weibull distribution is characterized by two parameters,  $\gamma$  (shape) and  $\lambda$  (scale). When  $\gamma=1$ , the hazard rate remains constant as time increases, which is equivalent to the exponential case. The hazard rate increases when  $\gamma>1$ , and decreases when  $\gamma<1$ . Thus, we may use the Weibull distribution to model the survival distribution of a population with increasing, decreasing, or constant hazard, and therefore has a broad application. Graphical representations of  $\log S(t) = -(\lambda t)^\gamma$  will assist us to determine whether the data came from a Weibull distribution. When  $\gamma>1$ , the survivorship function is a straight line with a negative slope. In turn, when  $\gamma<1$ , the survivorship function decreases very slowly from zero and then approaches a constant value. Finally, when  $\gamma>1$ , the survivorship function decreases sharply from zero as  $t$  increases.

The generalized gamma distribution is also characterized by two parameters,  $\gamma$  (shape) and  $\lambda$  (scale)<sup>9</sup>. When  $0 < \gamma < 1$ , the hazard rate decreases monotonically from infinity to  $\lambda$  as time increases from zero to infinity. When  $\gamma > 1$ , the hazard rate increases monotonically from zero to  $\lambda$  as time increases from zero to infinity. When  $\gamma = 1$ , the Weibull distribution is implied if  $\lambda \neq 1$ , otherwise, when  $\gamma = \lambda = 1$ , the hazard rate equals  $\lambda$ , a constant, as in the exponential case. Finally, when  $\gamma = 0$ , the lognormal distribution is implied. Thus, a nice characteristic of the generalized gamma distribution is that it nests some of the other parametric approaches as special cases, which is useful for adjudicating between some competing models when testing specification.

We can define the lognormal distribution as the distribution of a variable whose logarithm follows the normal distribution. Consider the random variable  $T$  such that  $\log T$  is normally distributed with mean  $\mu$  and variance  $\sigma^2$ . The hazard function increases initially to a maximum and then decreases, almost as soon as the median is passed, toward zero as time approaches infinity. Thus, the lognormal distribution describes a first increasing and then decreasing hazard rate.

Similar to the lognormal distribution, if the variable  $\log T$  has a logistic distribution, the variable  $T$  follows the log-logistic distribution. The log-logistic distribution also has two parameters,  $\gamma$  and  $\lambda$ . When  $\gamma < 1$ , the hazard rate decreases from infinity toward zero, when  $\gamma = 1$ , it decreases from  $\lambda$  toward zero, and when  $\gamma > 1$ , it increases from 0 to a maximum and then decreases toward zero. The special features of the hazard function of the log-logistic distribution provide a good alternative to the Weibull, generalized gamma, and lognormal distributions.

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<sup>9</sup> The generalized gamma is not the standard gamma distribution.

### **The hazard function conditional on time-invariant covariates**

In this research, we are interested in a hazard function conditional on a set of covariates. Since these are time-invariant, the hazard is simply defined conditional on the covariates. Thus, the conditional hazard is  $h(t)=\lim_{\Delta t \rightarrow 0} P(t < T < t+\Delta t \mid T > t, \mathbf{x})/\Delta t$ , where  $\mathbf{x}$  is the vector of covariates.

An especially important class of models with time-invariant covariates consists of proportional hazard (PH) models. We can write a proportional hazard as:

$$h(t|\mathbf{x}) = h_0(t) \cdot \varphi(\mathbf{x}, \beta) \quad (10a)$$

where  $\beta_i$  indicates the effect of the covariates ( $q_i$  and  $Q_i$ ) on the hazard rate, and  $h_0(t)$  is the baseline hazard function. The baseline hazard is common to all observational units and it captures the longitudinal effects associated with the duration dynamics, while the function  $\varphi(\mathbf{x}, \beta)$  adjusts  $h_0(t)$  up or down proportionately to reflect the effect of measured covariates.

### **Unobserved heterogeneity**

When observational units are naturally or artificially clustered, as it occurs in the current research's survival analysis, the failure times of observational units within a cluster are correlated. Thus, modeling unobserved heterogeneity is an important consideration in survival analysis, since the failure to do so can seriously bias parameter estimates.

This research follows the traditional approach of using a shared frailty model, in which we incorporate into the model unobserved heterogeneity due to cluster effects by using a random component for the hazard function. The inclusion of the random term



allows for the possible correlation between the failure times within a cluster. In the context of the PH model, we incorporate heterogeneity as follows:

$$h(t|\mathbf{x}) = h_0(t) \cdot \varphi(\mathbf{x}, \beta) \cdot \psi(\tau) \quad (10b)$$

The function  $\psi(\tau)$  models the functional form for random effects representing unobserved heterogeneity (Lancaster 1979, 1990). Thus, this approach captures the logic that some deals are intrinsically more (or less) likely than others to stock out, i.e. those who are most “frail” will experience failure earlier than others. The estimation of the model allows us to test for duration dependence conditional on observed covariates as well as unobserved heterogeneity. We can then perform a Wald chi-square test of the null hypothesis that the effect of unobserved heterogeneity is equal to zero, in which case there is no difference between the shared frailty model and the model without unobserved heterogeneity.

### **Semiparametric estimation: Cox’s Regression Model**

One way to assess the hypothesized relationship in **H3** is to investigate how the covariates shift the hazard function, in which case estimation of the baseline hazard,  $h_0(t)$ , is unnecessary. Cox (1972) obtained a partial maximum likelihood estimator for  $\beta$  that does not require estimating the baseline hazard.

The strength of Cox’s semiparametric approach is that it estimates the effects of covariates very generally, provided that the hazard is of the form of equations 10a or 10b. Typically, one would parameterize  $\varphi(\mathbf{x}, \beta)$  in equations 10a and 10b as  $\varphi(\mathbf{x}, \beta) = \exp(\mathbf{x}, \beta)$ , in which case the equation

$$h(t|\mathbf{x}) = h_0(t) \cdot \exp(\mathbf{x}, \beta) \quad (11a)$$

gives the hazard function of the survival time without unobserved heterogeneity, whereas the equation

$$h(t|\mathbf{x}) = h_0(t) \cdot \exp(\mathbf{x}\beta, \tau) \quad (11b)$$

gives the hazard function that incorporates unobserved heterogeneity.

This approach lends itself to a simple interpretation for the parameter estimates: as the value of a covariate increases by one unit, the hazard rate changes by  $[\exp(\beta)-1] \cdot 100$  percent. This is important, because the estimation allows us to capture a non-linear relationship between the covariate (consumption rate) and the dependent variable (service level) of interest in **H3**.

### **Parametric estimation**

The estimation of parametric models with a flexible baseline hazard offers an alternative to the Cox model. These models follow the parameterization:

$$\mathbf{y} = \mathbf{x}\beta + \sigma\mathbf{e} \quad (12)$$

where  $\mathbf{y}$  is usually the log of the failure time variable,  $\mathbf{x}$  is the vector of covariates,  $\beta$  is the vector of unknown parameters,  $\sigma$  is an unknown scale parameter, and  $\mathbf{e}$  is the error term. We specify the baseline distribution of the error term as one of the several possibilities, as discussed above (see Table 11).

These models are known as “accelerated failure time (AFT) models”. Here, we use the word “accelerated” to describe these models, because the parameter  $\theta = \exp(-\mathbf{x}\beta)$  acts like a time-scaling factor. If  $\theta > 1$ , the failure accelerates because the time passes more quickly (i.e. the survival time decreases). Conversely, if  $\theta < 1$ , the failure decelerates

because the time passes more slowly (i.e. the survival time increases). Finally, if  $\theta=1$ , the survival time passes at a normal rate.

The specification of the functional form of the baseline hazard function (also known as the duration dependence) is an important issue in many empirical applications, including the current research. If the characterization of the underlying duration dependence is accurate – i.e. if we use the right distributional function – then the resulting estimates of the parameters are more efficient (in the sense of having smaller standard errors than those in semiparametric models, in which the underlying duration dependence is left unspecified). In addition, full likelihood estimation results in more precise statistical inferences. Finally, interpretability of the results is also simple, and even more intuitive than the results obtained in the semiparametric approach: as the value of a covariate increases by one unit, the expected time for stocking out increases to  $\exp(\log(t)+\beta)$  for deals expected to stock out in time  $t$ .

So, there can be advantages to using parametric models. Problems arise, however, if we choose the “wrong” parametric function. In the next chapter, I will detail how I evaluated the choice for the parametric function (i.e. the shape for the duration dependence). I should note that, based on my literature review, scholars often provide little justification for the particular parametric model they use.

### **Estimation of the econometric model**

The econometric model of this research consists of an unobserved effects model (equation (9)) and a hazard model (equations (10a) and (10b)). We assess the dependence of a deal’s consumption rate,  $t^*$ , on a set of covariates, moderators, and control variables. In addition, we assess the dependence of the duration of time until a deal stocks out (the “failure time”) on the consumption rate,  $t^*$ , and the initial inventory level at the beginning

of the deal. Thus, in our estimation, we face a situation in which two variables might be jointly determined by a system of equations, also known as a simultaneous equation model (SEM).

Simultaneity bias is a major concern in the estimation of any SEM (Greene 2003; Wooldridge 2002). Simultaneity arises when at least one of the explanatory variables is determined simultaneously along with a dependent variable. If some explanatory variable is determined partially as a function of the dependent variable, then the explanatory variable and the error term are generally correlated. Ignoring such fact yields inconsistent (biased) parameter estimates. Conceptually, simultaneity is difficult to analyze, because we must be able to think of a situation in which we could vary that explanatory variable exogenously, even though both variables are generated simultaneously in the data that we collect.

However, for suitable application of *true* SEMs, we must understand the kinds of situations suitable for SEM analysis. A classical example of a legitimate SEM application is labor supply and wage offer. Labor supply functions usually describe individuals' behavior, and they are derivable from basic economic principles of individual utility maximization. Holding other factors fixed, labor supply functions in economics give the hours of labor supply at any potential wage facing the individuals. In turn, wage offer functions usually describe firm behavior, and, like labor supply functions, are self contained (Wooldridge 2002).

As Wooldridge (2002) explains, each equation in an SEM should represent a causal relationship. We should be interested in varying each of the explanatory variables – including any that are endogenous – while holding all the others fixed. That is, each equation in an SEM should represent some underlying conditional expectation that has a

causal structure. Here, conditional expectations are in terms of counterfactuals. For instance, in the above labor supply example, if we could run a controlled experiment, in which we exogenously varied the wage offer across individuals, then we would be able to estimate labor supply functions without ever considering the wage offer functions.

Generally, supply and demand examples satisfy the causality requirement, and simultaneous equations systems were originally developed for such applications. However, in our research, there is nothing “structural” about the proposed analysis. The choices made by consumers, which will determine a deal’s consumption rate, are completely unrelated to the stockout probability in that deal. That is, there is no causality implied in our demand function by any factor that determines the supply function (the hazard model). Specifically, the consumption rate,  $t^*$ , has causal interpretations (hypotheses **H1A** through **H2C-2**), which do not include stockout probability on the right-hand side.

Any attempt to estimate our econometric model by an SEM application would represent a misperception that “structural” and “simultaneous” are synonymous. As explained above, our simultaneous system is not structural because one equation violates the causality requirement. As a result, we may (and should) estimate the unobservable effects and the hazard models separately.

## Chapter 5

### RESULTS

#### **Descriptive statistics**

Table 12 provides descriptive statistics for the set of measures: means, standard errors, and correlations. The results show no correlation among the eight experimental factors (i.e. the five independent variables and the three moderators). This should be expected, since we have a full factorial design (“fully crossed) in which we obtain all possible combinations among factors holding low/high values. Moreover, the results in Table 12 show that a deal’s consumption rate is correlated with the following independent variables: opinion leadership, network integration, network constraint, and network centrality. However, it is not correlated with cohesive group membership. The results also show that a deal’s consumption rate is correlated with product quality and price, but not with product popularity. In addition, a deal’s consumption rate is correlated with its duration.

The results also show that five experimental factors – representing three independent variables and two moderators – are correlated with a deal’s duration. Specifically, a deal’s duration is correlated with opinion leadership, integration, constraint, product quality and popularity.

Regarding the control variables, structural equivalence is correlated with a deal’s consumption rate, whereas initial inventory provision is correlated with a deal’s duration.

Measure	Mean	Std. Error	1	2	3	4	5	6	7	8	9	10	11	12	13
1) t	143.35	48.73	1.00												
2) t*	58.97	3.12	.90**	1.00											
3) OL	.21	.14	-.19*	-.32**	1.00										
4) integration	.20	.13	-.15*	-.23**	.10	1.00									
5) cohesion	.43	.35	0.01	.12	-.06	-.16	1.00								
6) constraint	.23	.18	.19*	.25**	-.06	-.04	.04	1.00							
7) centrality	.22	.17	-.05	-.15*	.04	-.21	-.24	.14	1.00						
8) popularity	8.42	3.07	-.01	-.04	.02	-.07	.05	-.06	.05	1.00					
9) quality	.50	.50	-.01	-.16*	.02	-.06	.04	.05	.03	.10	1.00				
10) price	-.36	.26	.02	.20*	-.01	.02	.02	.02	.03	.12	.09	1.00			
11) tone	0.27	0.19	-.17*	-.22*	-.07	-.04	-.09	.04	.02	.14*	.11	-.06	1.00		
12) SE	3.47	1.45	.01	.01	.13	.12	.10	.11	.10	.04	.05	.05	-.03	1.00	
13) Q	48.73	12.28	-.02	-.04	-.05	-.02	-.04	-.03	-.02	.03	-.04	-.02	.05	-.03	1.00

\* p < .05, \*\*p < .01

Table 12: Descriptive statistics

### The effects on consumption rate of social interactions and marketing activity

Table 13 reports the results for the OLS using the robust covariance matrix estimator of Equation (9), in which a deal's consumption rate is the dependent variable, five variables representing social interaction mechanisms are predictors (*OL*, *integration*, *membership*, *constrain*, and *centrality*), three variables representing marketing activity are moderators (*popularity*, *quality*, *price*), and three variables are controls (*tone*, *SE*, and *Q*).

Parameter	Hypothesis tested	Model 1 <sup>(a)</sup>	Model 2 <sup>(a)</sup>	Model 3 <sup>(a)</sup>
<i>Intercept</i>		66.64 (19.91)**	18.773 (5.61)**	10.849 (3.22)**
Opinion leadership ( <i>OL<sub>i</sub></i> )	H1A		-70.428 (32.43)*	-50.489 (23.53)*
Integration ( <i>integration<sub>i</sub></i> )	H1B		-33.435 (15.88)*	-25.217 (11.30)*
Cohesive group membership ( <i>cohesion<sub>i</sub></i> )	H1C		-16.118 (11.32)	-13.733 (10.15)
Network constraint ( <i>constraint<sub>i</sub></i> )	H1D		20.341 (8.15)*	14.109 (6.70)*
Network centrality ( <i>centrality<sub>i</sub></i> )	H1E		43.122 (24.77)	32.901 (18.11)
Popularity ( <i>popularity<sub>i</sub></i> )				.813 (.638)
Quality ( <i>quality<sub>i</sub></i> )				-5.112 (3.845)
Price ( <i>price<sub>i</sub></i> )				-8.749 (5.941)
<i>OL<sub>i</sub></i> * <i>popularity<sub>i</sub></i>	H2A-i			1.685 (1.869)
<i>integration<sub>i</sub></i> * <i>popularity<sub>i</sub></i>	H2A-ii			.610 (.582)
<i>cohesion<sub>i</sub></i> * <i>popularity<sub>i</sub></i>	H2A-iii			1.120 (1.215)
<i>constraint<sub>i</sub></i> * <i>popularity<sub>i</sub></i>	H2A-iv			-.162 (.112)
<i>centrality<sub>i</sub></i> * <i>popularity<sub>i</sub></i>	H2A-v			2.747 (2.00)
<i>OL<sub>i</sub></i> * <i>quality<sub>i</sub></i>	H2B-i			24.508 (10.82)*
<i>integration<sub>i</sub></i> * <i>quality<sub>i</sub></i>	H2B-ii			1.264 (.48)*
<i>cohesion<sub>i</sub></i> * <i>quality<sub>i</sub></i>	H2B-iii			2.308 (1.69)
<i>constraint<sub>i</sub></i> * <i>quality<sub>i</sub></i>	H2B-iv			-0.983 (.40)*
<i>centrality<sub>i</sub></i> * <i>quality<sub>i</sub></i>	H2B-v			45.708 (25.09)
<i>OL<sub>i</sub></i> * <i>price<sub>i</sub></i>	H2C-1-i and H2C-2-i			-27.553 (12.15)*
<i>integration<sub>i</sub></i> * <i>price<sub>i</sub></i>	H2C-1-ii and H2C-2-ii			-3.010 (1.24)*
<i>cohesion<sub>i</sub></i> * <i>price<sub>i</sub></i>	H2C-1-iii and H2C-2-iii			-5.345 (3.69)
<i>constraint<sub>i</sub></i> * <i>price<sub>i</sub></i>	H2C-1-iv and H2C-2-iv			3.331 (1.56)*
<i>centrality<sub>i</sub></i> * <i>price<sub>i</sub></i>	H2C-1-v and H2C-2-v			-24.682 (15.24)
Discussion forum tone ( <i>tone<sub>i</sub></i> )		-15.08 (4.51)*	-1.634 (0.82)*	-.724 (.431)*
Structural equivalence ( <i>SE<sub>i</sub></i> )		1.44 (1.12)	.020 (.18)	.011 (.01)
Initial inventory provision ( <i>Q<sub>i</sub></i> )		.276 (.22)	.088 (.06)	.053 (.03)
R <sup>2</sup> (adjusted)		0.224	0.412	0.529
N		1280	1280	1280

(a) Standard errors in parentheses.

\*  $p < .05$ , \*\*  $p < .01$

**Table 13: OLS estimation of consumption rate,  $t^*$ , using a robust covariance matrix**



The estimation proceeded as follows. First, I introduced the three control variables (Model 1). This first step provides an initial understanding of which control variables might be relevant in our estimation. The results in Model 1 show that the estimate for  $tone_i$  is significant (at the .05 level). This result agrees with a large body of research in social interactions that posits that a discussion forum tone is a significant predictor of consumption rates. Omitting this relevant predictor would misspecify the full model (below), thereby leading to biased parameter estimates. Interestingly, the estimates for both  $SE_i$  and  $Q_i$  are non-significant.

Next, I introduced the five predictors (Model 2). In this new model, the estimate for  $tone_i$  became borderline significant (at the .05 level). The estimates for three predictors ( $OL_i$ ,  $integration_i$ , and  $constraint_i$ ) are significant (at the .05 level). However, the estimate for  $cohesion_i$  and  $centrality_i$  are non-significant.

Model 3 in Table 13 incorporates the direct effects of the moderating variables, as well as their interactions with the predictors. Adjusted R-square statistics for Model 3 suggest that moderation effects were important factors contributing to consumption rates. The inclusion of interaction terms representing such moderation effects increased the amount of variance explained, as measured by the adjusted R-square statistics, as well as the fit of the model. Variance inflation factors range from 1.349 to 3.350, all below the usual threshold of 10, so there is no evidence that multicollinearity has a significant impact on the results.

The results suggest that early buyers' opinion leadership is a predictor of a consumption rate. The parameter estimate for  $OL_i$  is negative and significant at the .05 level ( $\beta_{11,i}=-50.489$ ). This means that a deal's consumption rate will increase (i.e. the

tipping point,  $t_i^*$ , will decrease) as the aggregate opinion leadership of early buyers will increase. This result provides support for **H1A**.

The results also suggest that early buyers' integration into their social network is a predictor of consumption rate. The parameter estimate for *integration<sub>i</sub>* is negative and significant at the .05 level ( $\beta_{11,2}=-25.217$ ). In line with the above analysis, this suggests that increasing the integration of early buyers into their social network will increase consumption rate of a deal (i.e. decrease the tipping point,  $t_i^*$ ). This result provides support for **H1B**.

In addition, the results suggest that early buyers' network constraint is a predictor of consumption rate. The parameter estimate for *constraint<sub>i</sub>* is positive and significant at the .05 level ( $\beta_{11,4}=14.109$ ). Notice that low levels of constraint imply high levels of ability to broker. So, as early buyers' constraint increases (i.e. their ability to broker decreases), the tipping point also increases (i.e. the consumption rate decreases). This means that a deal's consumption rate will increase when early buyers are less constrained. This result provides support for **H1D**.

Regarding the effects of marketing activity, the results in Model 3 suggest that increasing quality will negatively moderate the relationship between consumption rate and early buyers' opinion leadership. The parameter estimate for the interaction between *OL* and *quality* is positive and significant at the .05 level ( $\gamma_{11,6}=24.508$ ). This means that, as the product quality increases, the overall effect of early buyers' opinion leadership on consumption rate (i.e. direct plus moderated) will still be positive yet not as large as the direct effect, since ( $\beta_{11,1} < \beta_{11,1} + \gamma_{11,6} < 0$ ). Therefore, the results provide support for **H2B-i**.

Similarly, the results suggest that quality will negatively moderate the relationship between consumption rate and early buyers' integration. The parameter estimate for the interaction between *integration* and *quality* is positive and significant at the .05 level ( $\gamma_{11,7}=1.264$ ). Akin to the above results, this suggests that, as product quality increases, the overall effect of early buyers' network integration on consumption rate (i.e. direct plus moderated) will still be positive yet not as large as the direct effect, since ( $\beta_{11,2}<\beta_{11,2}+\gamma_{11,7}<0$ ). Therefore, the results provide support for **H2B- ii**.

In addition, the results suggest that quality will negatively moderate the relationship between consumption rate and early buyers' constraint. The parameter estimate for the interaction between *constraint* and *quality* is negative and significant at the .05 level ( $\gamma_{11,9}=-0.983$ ). This suggests that, as product quality increases, the overall effect of early buyers' network constraint on consumption rate (i.e. direct plus moderated) will be negative yet not as large as the direct effect since ( $\beta_{11,4}>\beta_{11,4}+\gamma_{11,9}>0$ ). Again, notice that increases in constraint imply decreases in the ability to broker. Therefore, the results provide support for **H2B- iv**.

In regards to the role played by price, the analysis provides interesting insights. First, the parameter estimate for the interaction between *OL* and *price* is negative and significant at the .05 level ( $\gamma_{11,11}=-27.553$ ). This result suggests that, as prices increase, the effect of opinion leadership on consumption rate will be larger in magnitude. That is, consumers will resort even more to opinion leaders to make an informed decision ( $\beta_{11,1}+\gamma_{11,11}<\beta_{11,1}<0$ ). Therefore, the results provide support for **H2C-1-i**.

Similarly, the parameter estimate for the interaction between *integration* and *price* is negative and significant at the .05 level ( $\gamma_{11,12}=-3.010$ ). This implies that early buyers' integration is very important when prices become higher. At higher prices,

consumers will resort even more to observation of integrated early buyers' purchases to make informed decisions ( $\beta_{11,2} + \gamma_{11,12} < \beta_{11,2} < 0$ ). Therefore, the results provide support for **H2C-1-ii**.

Finally, the parameter estimate for the interaction between *constraint* and *price* is positive and significant at the .05 level ( $\gamma_{11,12} = 3.331$ ). This result suggests early buyers' constraint is less influential on consumption rates as prices increases. That is, as prices increase, consumption rates will increase in the presence of less constrained early buyers ( $\beta_{11,4} + \gamma_{11,14} > \beta_{11,4} > 0$ ). Therefore, the results provide support for **H2C-1-ii**.

### **The effects on service level of consumption rate**

As discussed earlier, an important issue in the estimation is the specification of the functional form for  $\varphi(\mathbf{x}, \beta)$ . The estimation proceeded as follows. First, I estimated the PH model (Equation 11a) using the semiparametric partial likelihood procedure suggested by Cox (1975). I then estimated a PH model (Equation 11b) using the penalized partial likelihood approach for fitting shared frailty for clustered data models. Amemiya (1985) and (Lancaster 1990) suggested this approach for treatments of the Cox's partial likelihood estimator, in order to account for the influence of unobserved heterogeneity. Next, I tested different parametric models (equation 12) using the different functional forms listed in Table 11: Weibull, generalized gamma, exponential, lognormal, and log-logistic. I contrasted the results of the parametric models without unobserved heterogeneity with those of models including random effects for unobserved heterogeneity. Finally, I selected the functional form that provided the best model fit.

### **Semiparametric estimation of Cox models**

Table 14 reports the results for the Cox PH model without unobserved heterogeneity (model 1) and the shared frailty model for clustered data with unobserved

heterogeneity (model 2). Notably, the introduction of random effects to account for unobservable heterogeneity in model 2 slightly alters the parameter estimates in model 1. In addition, a Wald chi-square test ( $H_0:\tau=0$ ) suggests that the random effects are significantly different than zero at the .01 level. Moreover, a goodness-of-fit assessment using the likelihood test suggests that model 2 provides a better fit than model 1. This is because the difference between 958.803 (model 1) and 924.738 (model 2),  $\Delta=34.065$ , is greater than the critical value 6.64, the chi-square statistic for 1 degree of freedom (at the .01 level). In all, the results suggest that not accounting for unobserved heterogeneity yields biased parameter estimates. However, the small difference in the magnitude of the parameter estimates between both models is remarkable. Also, the signs direction in model 1 remains unaltered in model 2, when unobservable heterogeneity is accounted for. Thus, I will use the results of model 2 to assess hypothesis **H3**.

Parameter	Cox PH model (Model 1)		Cox PH model with unobserved heterogeneity (Model 2)	
	Estimate <sup>(a)</sup>	Hazard Ratio <sup>(b)</sup>	Estimate <sup>(a)</sup>	Hazard Ratio <sup>(b)</sup>
Initial inventory provision ( $Q$ )	-.085 (.008)**	.919 (.904, .934)	-.091 (.009)**	.914 (.898,.929)
Consumption rate ( $t^*$ )	-.039 (.017)*	.962 (.930, .995)	-.021 (.005)**	.979 (.969,.989)
Wald test ( $H_0:\tau=0$ )			$p < .01$	
-2 Log-likelihood	958.803		924.738	

(a) Standard errors in parentheses.  
(b) 95% Wald confidence limits in parentheses.  
\*  $p < .05$ , \*\*  $p < .01$

**Table 14: Semiparametric estimation of Cox’s models**

In support of **H3**, the result for the consumption rate variable,  $t^*$ , suggests that a faster deal’s consumption rate (i.e. a lower  $t^*$ ) will increase the deal’s stockout likelihood (i.e. decrease its service level). The hazard ratio (i.e. the impact on the hazard of stocking out) estimate from the PH model with unobserved heterogeneity suggests, for instance, that decreasing the tipping point of a deal by 1 second increases its stockout likelihood by

2.1% ( $=e^{[-.021*(-1)]}-1=.021$ ). In turn, decreasing the tipping point by 10 seconds would increase the stockout likelihood by 23.4% ( $=e^{[-.021*(-10)]}-1$ ), while decreasing it by 20 seconds would increase that likelihood by 52.2% ( $=e^{[-.021*(-20)]}-1$ ). Clearly, as the consumption rate increases, the stockout likelihood increases faster. That is, the service level decreases at a faster pace than the consumption rate does.

For better interpretability of results, it may be useful to investigate what happens when the tipping point increases (i.e. the consumption rate decreases). For instance, based on the analysis results, increasing the tipping point of a deal by 1 second would decrease the stockout likelihood by 2.1% ( $.979-1=-.021$ ). In turn, increasing the tipping point by 10 seconds would decrease that likelihood by 23.4% ( $=e^{(-.021*10)}-1$ ), while increasing it by 20 seconds would decrease that likelihood by 34.3% ( $=e^{(-.021*20)}-1$ ). That is, the service level decreases at a slower pace than decreases in the consumption rate.

It is also noticeable the effect of the initial inventory provision on a deal's service level. Recall that the measure is operationalized as a percentage of the size of the network of consumers. Thus, increasing the initial inventory provision by 10% of the network of consumers' size would reduce a deal's stockout likelihood by 59.4% ( $=e^{(-.091*10)}-1$ ). In turn, increasing initial inventory provision by 25% of the network's size would reduce the stockout likelihood by 89.5% ( $=e^{(-.091*25)}-1$ ), while increasing initial inventory provision by 50% of the network's size (which is around the average initial inventory provision in our sample) would reduce that likelihood by 98.9% ( $=e^{(-.091*50)}-1$ ).

### **Parametric estimation of AFT models**

Table 15 reports the results of estimating the parametric models without unobserved heterogeneity, while Table 16 reports the results of the estimation of parametric models with unobserved heterogeneity.

In agreement with the results of the semiparametric estimation, it is notable that the introduction of random effects to account for unobserved heterogeneity slightly modifies the parameter estimates obtained when unobserved heterogeneity is unaccounted for. In addition, a Wald chi-square test ( $H_0:\tau=0$ ) suggests that the random effects are significantly different than zero at the .01 level, irrespective of the chosen distribution. Moreover, a goodness-of-fit assessment using the likelihood test suggests that model 2 provides a better fit than model 1, irrespective of the chosen distribution. For instance, for the generalized gamma distribution, the difference between 560.615 (model 1a) and 552.601 (model 2a),  $\Delta=7.914$ , is greater than the critical value 6.64, the chi-square statistic for 1 degree of freedom at the .01 level. Once again, the results suggest that not accounting for unobserved heterogeneity yields biased parameter estimates. Therefore, the issue here is to choose the model that accounts for unobserved heterogeneity with the “right” distribution to assess hypothesis **H3**.

As described earlier, the generalized gamma model nests several other parametric models and can, therefore, be used to adjudicate between them. However, a limitation of the generalized gamma for adjudicating between parametric models is that it is only helpful for distinguishing between those parametric models that are nested within it. For non-nested parametric models, we might use Akaike’s Information Criterion (AIC) (Akaike 1974) to distinguish between different parametric models. Typically, we would look for a model whose AIC is the smallest.

Based on the results reported in Table 16, it appears that the generalized gamma model is a reasonable model for the data. The likelihood ratio test indicates that the Weibull model is also acceptable, and the exponential model is equally good. However, there are two reasons to take the exponential model as the final model. First, it exhibits

the smallest AIC value among all five models (i.e. 548.771). Second, we cannot reject the hypothesis that both shape and scale parameters in the generalized gamma are equal to 1. The 95% confidence limits for the scale parameter  $\lambda$  are (.633, 1.067), and the 95% confidence limits for the shape parameter  $\gamma$  are (.465, 1.250). Thus, the results for the generalized gamma distribution suggest that the hazard function follows an exponential distribution. Likewise, we cannot reject the hypothesis that the shape parameter  $\gamma$  of the Weibull distribution is equal to 1. Its confidence limits are (.925, 1.228), which also implies the exponential distribution. Therefore, I will use the results of the parametric model on the basis of the exponential distribution with unobserved heterogeneity (model 2c in Table 16) to further assess hypothesis **H3**.



Distribution	Generalized Gamma (Model 1a)	Weibull (Model 1b)	Exponential (Model 1c)	Lognormal (Model 1d)	Log-logistic (Model 1e)
Parameter	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>
Initial inventory provision ( $Q$ )	.083 (.003)**	.084 (.003)**	.085 (.003)**	.095 (.089)**	.088 (.003)**
Consumption rate ( $t^*$ )	.027 (.005)**	.028 (.004)**	.029 (.005)**	.026 (.002)**	.031 (.004)**
Scale parameter	.993 (.102)	.898 (.061)	1.000 (.000)	1.594 (.122)	.740 (.060)
Shape parameter	.867 (.166)	1.113 (.105)	1.000 (.000)	(b)	(b)
-2 Log-likelihood	560.515	561.086	561.828	590.887	562.628

(a) Standard errors in parentheses.

(b) Not provided

\*  $p < .05$ , \*\*  $p < .01$

**Table 15: Parametric estimation of AFT models without unobserved heterogeneity**

Distribution	Generalized Gamma (Model 2a)	Weibull (Model 2b)	Exponential (Model 2c)	Lognormal (Model 2d)	Log-logistic (Model 2e)
Parameter	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>	AFT metric <sup>(a)</sup>
Initial inventory provision ( $Q$ )	.055 (.003)**	.054 (.003)**	.059 (.004)**	.064 (.003)**	.051 (.003)**
Consumption rate ( $t^*$ )	.037 (.004)**	.038 (.005)**	.039 (.005)**	.038 (.002)**	.043 (.005)**
Scale parameter	.821 (.110)	.938 (.068)	1.000 (.000)	1.338 (.107)	.647 (.054)
Shape parameter	.858 (.200)	1.066 (.077)	1.000 (.000)	(b)	(b)
Wald test ( $H_0: \tau=0$ )	$p < .01$	$p < .01$	$p < .01$	$p < .01$	$p < .01$
AIC	560.601	559.030	557.302	579.324	559.970
-2 Log-likelihood	552.601	553.030	553.302	573.324	553.970
$\Delta$	7.914	8.056	8.526	17.563	8.658

(a) Standard errors in parentheses.

(b) Not provided

\*  $p < .05$ , \*\*  $p < .01$

**Table 16: Parametric estimation of AFT models with unobserved heterogeneity**

In further support of **H3**, and in agreement with the results of the semiparametric approach, the result for the consumption rate variable,  $t^*$ , suggests that a faster deal's consumption rate (i.e. a lower  $t^*$ ) will decrease a deal's time to stocking out; i.e. it will decrease its service level. The parameter estimate is significantly different than zero at the .01 level ( $\beta_2 = .039$ ). This result suggests, for instance, that decreasing the tipping point of a deal by 1 second would decrease the expected stockout time to  $\exp[\ln(100)+.039(-1)] = 96.18$  seconds for deals expected to stock out in the 100<sup>th</sup> second. In turn, decreasing the tipping point by 10 seconds would decrease the expected stockout time to  $\exp[\ln(100)+.039*(-10)] = 67.71$  seconds for deals expected to understock in the 100<sup>th</sup> second. To the extent that a deal's consumption rate is a constant, such non-linear decreases in the expected stockout times imply non-linear increases in the stockout likelihood (or, conversely, non-linear decreases in service levels).

The results of model 2c in Table 16 also provide interesting insights into the effects on the service level of initial inventory provision. The results suggest that increasing the initial inventory provision, for instance, to 10% of the network of consumers' size, would increase the expected understocking time to  $\exp[\ln(100)+.059*10] = 180.40$  seconds for deals expected to understock in the 100<sup>th</sup> second. In turn, increasing the initial inventory provision to 25% of the network of consumer's size would increase the expected understocking time to  $\exp[\ln(100)+.059*25] = 437.10$  seconds for deals expected to understock in the 100<sup>th</sup> second.

## Results summary

Table 17 provides a summary of the hypothesis testing. The results suggest that opinion leadership of early buyers, network integration of early buyers, and network constraint of early buyers positively influence consumption rates. Hence, they provide support to **H1A**, **H1B**, and **H1D**. In addition, the results suggest that a product's quality negatively moderates the effects on consumption rates of opinion leadership of early buyers, network integration of early buyers, and network constraint of early buyers. Hence, they provide support to **H2B-i**, **H2B-ii**, and **H2B-iv**. Moreover, the results suggest that a product's price positively moderates the effects on consumption rates of opinion leadership of early buyers, network integration of early buyers, and network constraint of early buyers. Hence, they provide support to **H2C-1-i**, **H2C-1-ii**, and **H2C-1-iv**. Finally, the results suggest that the relationship between consumption rates and service level is non-linear, monotonically increasing. Hence, they provide support to **H3**.

<b>Hypothesis</b>	<b>Hypothesis statement</b>	<b>Supported</b>
<b>H1A</b>	<i>Greater opinion leadership of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.</i>	<b>Yes</b>
<b>H1B</b>	<i>Greater network integration of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.</i>	<b>Yes</b>
<b>H1C</b>	<i>Greater cohesive group membership of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.</i>	No
<b>H1D</b>	<i>Greater network constraint of early buyers of a deal is negatively associated with greater consumption rate in that deal, ceteris paribus.</i>	<b>Yes</b>
<b>H1E</b>	<i>Greater network centrality of early buyers of a deal is positively associated with greater consumption rate in that deal, ceteris paribus.</i>	No
<b>H2A-i</b>	<i>Greater product popularity will negatively moderate the relationship between the consumption rate and opinion leadership of early buyers.</i>	No
<b>H2A-ii</b>	<i>Greater product popularity will negatively moderate the relationship between the consumption rate and network integration of early buyers.</i>	No
<b>H2A-iii</b>	<i>Greater product popularity will negatively moderate the relationship between the consumption rate and cohesive group membership of early buyers.</i>	No
<b>H2A-iv</b>	<i>Greater product popularity will negatively moderate the relationship between the consumption rate and the network constraint of early buyers.</i>	No
<b>H2A-v</b>	<i>Greater product popularity will negatively moderate the relationship between the consumption rate and network centrality of early buyers.</i>	No
<b>H2B-i</b>	<i>Higher product quality will negatively moderate the relationship between the consumption rate and opinion leadership of early buyers.</i>	<b>Yes</b>
<b>H2B-ii</b>	<i>Higher product quality will negatively moderate the relationship between the consumption rate and network integration of early buyers.</i>	<b>Yes</b>
<b>H2B-iii</b>	<i>Higher product quality will negatively moderate the relationship between the consumption rate and cohesive group membership of early buyers.</i>	No
<b>H2B-iv</b>	<i>Higher product quality will negatively moderate the relationship between the consumption rate and the network constraint of early buyers.</i>	<b>Yes</b>
<b>H2B-v</b>	<i>Higher product quality will negatively moderate the relationship between the consumption rate and network centrality of early buyers.</i>	No
<b>H2C-1-i</b>	<i>Greater product price will positively moderate the relationship between the consumption rate and opinion leadership of early buyers.</i>	<b>Yes</b>
<b>H2C-1-ii</b>	<i>Greater product price will positively moderate the relationship between the consumption rate and network integration of early buyers.</i>	<b>Yes</b>
<b>H2C-1-iii</b>	<i>Greater product price will positively moderate the relationship between the consumption rate and cohesive group membership of early buyers.</i>	No
<b>H2C-1-iv</b>	<i>Greater product price will positively moderate the relationship between the consumption rate and the network constraint of early buyers.</i>	<b>Yes</b>
<b>H2C-1-v</b>	<i>Greater product price will positively moderate the relationship between the consumption rate and network centrality of early buyers.</i>	No
<b>H2C-2-i</b>	<i>Greater product price will negatively moderate the relationship between the consumption rate and opinion leadership of early buyers.</i>	No
<b>H2C-2-ii</b>	<i>Greater product price will negatively moderate the relationship between the consumption rate and network integration of early buyers.</i>	No
<b>H2C-2-iii</b>	<i>Greater product price will negatively moderate the relationship between the consumption rate and cohesive group membership of early buyers.</i>	No
<b>H2C-2-iv</b>	<i>Greater product price will negatively moderate the relationship between the consumption rate and the network constraint of early buyers.</i>	No
<b>H2C-2-v</b>	<i>Greater product price will negatively moderate the relationship between the consumption rate and network centrality of early buyers.</i>	No
<b>H3</b>	<i>Increasing the consumption rate in a deal will decrease the service level in the deal, after controlling for initial inventory provision. This relationship is monotonically decreasing.</i>	<b>Yes</b>

**Table 17: Results summary**

## Chapter 6

### DISCUSSION AND CONCLUSION

#### **Discussion of results**

Social shopping revolves around social interactions among consumers in online communities. Both scholars and managers have traditionally assumed that social interactions influence consumption rates in social shopping. As a result, online retailers have made large investments to encourage consumers to join online communities linked to their websites, in the hope that social interactions among those consumers will help foster sales.

This dissertation empirically investigates the mechanisms through which social interactions influence consumption rates in social shopping. Moreover, it theorizes and empirically assesses a moderating role of marketing activity on such an influence. Finally, it challenges the predominant assumption in social interactions studies that increasing consumption rates will always yield desirable business outcomes to online retailers. This is because those studies have largely ignored common knowledge in the operations management literature, which posits that deals that have higher consumption rates are more likely to understock, which is an undesirable inventory performance outcome.

#### **The effects on consumption rates of social interaction mechanisms**

This study uses models of social influence based on the two-step flow of influence principle (Katz 1957; Katz and Lazarsfeld 1955) to theorize relationships between social interaction mechanisms and consumption rates in social shopping. Such models posit that influential consumers occupy “prominent” positions in the social network of consumers. When influential consumers are early buyers of a deal, other

consumers in their social network observe their purchases and thus are more likely to buy that deal, thus increasing consumption rates.

In line with hypothesis **H1A**, the empirical results provide support to the *opinion leadership* model of social influence. Opinion leadership is the most basic model of social influence (Bonacich 1987; Freeman 1979; Marsden 2002). It posits that a deal's purchases by consumers who receive the most nominations in a social network are likely to influence other consumers to purchase that deal (Godes 2011; Iyengar et al. 2011b; Valente and Davis 1999). Most social shopping communities allow consumers to nominate others by "following" or "liking" them. Also, they usually display the number of nominations a consumer receives, and give prominence on their websites to those consumers with the most nominations. For instance, social shopping website *MyITThings.com* features the "top 50" members of its online community (in terms of nominations) on its opening page. So, based on this study's empirical results, we should expect to observe marketing messages aimed at those "top 50" consumers to diffuse through the social network of consumers in *MyITThings.com*'s online community through social interactions. That is, the results suggest that purchases of a deal by members of the "top 50" group at *MYITThings.com* might influence other consumers in its online community to purchase that deal.

In addition, in line with hypothesis **H1B**, the empirical results provide support to the *network integration* model of social influence. This hypothesis posits that a deal's purchases of consumers who are well connected in the network are likely to influence other consumers to purchase that deal. This is a more comprehensive approach than the opinion leadership model, which only characterizes a consumer's immediate environment (Valente and Foreman 1998). This result is important, since it shows that influence flows

through relations beyond first-order ties. Marketing messages directed to consumers with high integration might be more effective than those directed to consumers who only receive more nominations.

Finally, in line with hypothesis **H1D**, the empirical results provide support to the *network constraint* models of social influence based on the principle of structural holes. This hypothesis posits that consumers on either side of a structural hole become exposed to different flows of influence. Consumers filling structural holes have opportunity to broker the flow of influence among consumers. These brokers reach more people indirectly. The diversity of their contacts among separate groups of consumers means that they are responsible for the spread of new ideas and behaviors (Burt 1999). This finding provides an interesting alternative to the predominant use in academia and practice of the opinion leadership model. This is because the constraint model is based on structural, rather than relational, characteristics of influential consumers. In many circumstances, the nature of the relationship between two consumers may not be obvious, or may be erroneously assessed. For instance, I may nominate a close friend of mine in a social shopping community (e.g. by “following” her) without being nominated by her. Even though my purchases in this social shopping community might influence my close friend’s decision making, I would not be considered influential, according to relational models of social influence. Conversely, I would be classified as influential in the constraint model of social influence.

**The effects on the relationship between social interaction mechanisms and consumption rates of marketing activity**

This study builds on the scarcity and information economics literatures to theorize the moderating role played by the marketing activity on the relationship between

social interaction mechanisms and consumption rates. In line with hypotheses **H2B-i**, **H2B-ii**, and **H2B-iv**, the empirical results suggest that *a product's quality* will *negatively* moderate the relationship between social interaction mechanisms and a deal's consumption rate. As discussed in the previous sub-section, a deal's consumption rate will increase when its early buyers will be opinion leaders, integrated, or least constrained. However, when the quality of a product being offered as part of a deal is high, the magnitude of such positive effects on a deal's consumption rate will be smaller than when that quality is low. All things being equal, consumers are less likely to purchase products of inferior quality (Ferguson and Koenigsberg 2007; Morales and Fitzsimons 2007; Subramanian and Subramanyam 2008). However, when an online retailer offers a low-quality product as part of a deal, consumers are more likely to resort to other consumers' purchases to infer the deal's value. As a result, if influential consumers are early buyers of a deal offering a low-quality product, then other consumers are less likely to react negatively to it (i.e. they are more likely to purchase that deal).

Conversely, when an online retailer offers a high-quality product as part of a deal, consumers are less likely to resort to other consumers' purchases to infer the product's value, because quality is a strong screening device (Nelson 1970). Also, high-quality products are usually regarded as scarce (Cialdini 1985; Stock and Balachander 2005). As a result, consumers tend to purchase early a deal of a high-quality product – hence increasing its consumption rate – in order to avoid missing the opportunity to do so later due to a stock out.

The implication of this finding is significant to inventory provisioning and availability. The amount of inventory that online retailers make available during each social shopping deal varies considerably. This is because online retailers source products



that are usually overstocked from other retailers. So, for instance, online retailers may commit to make early sales to influential consumers (Tang et al. 2004) and thus explore social interactions effects in order to sell large amounts of low-quality inventory. In fact, making such commitments is a common approach in social shopping websites that offer overstock fashionable products, including *MYITThings.com*. Such online retailers often allow a select (and small) group of consumers to make purchases in the deals' first hours. Our empirical results suggest that these retailers might be more effective in selling deals of low-quality products if they made early sales to influential consumers (i.e. opinion leaders, integrated, and least constrained).

Interestingly, in line with hypotheses **H2C-1-i**, **H2C-1-ii**, and **H2C-1-iv**, the results suggest that *a product's price* will *positively* moderate the relationship between social interaction mechanisms and a deal's consumption rate. The conceptual framework (Figure 2) put forth theoretical arguments for both positive and negative moderating effects of a product's price on such a relationship. The results of this dissertation imply that consumers will resort less to observing others' purchases to make an informed decision when prices are low. This finding supports the fact that, in social shopping, most consumers are bargain hunters. That is, when online retailers offer low-price products as part of a deal, consumers will tend to purchase that deal irrespective of other consumers' purchases.

Conversely, as prices increase, social interactions become more influential. This is an interesting result, because it shows that online retailers can sell deals of more expensive products by encouraging influential consumers to purchase those deals early. In fact, this is a practice that is becoming increasingly popular. For instance, Magazine Luiza, a leading bricks-and-clicks retailer who explores social shopping in Brazil, offers

rebates to consumers who purchase deals of certain expensive products (usually home appliances) and whose Facebook friends also purchase those deals.

### **The effects on service levels of consumption rate**

This study finds support to hypothesis **H3**, which builds on the behavioral operations management literature to theorize a non-linear, monotonically decreasing relationship between a deal's consumption rate and its service level. This finding is a major contribution of this dissertation. This is because it challenges the predominant notion that increasing consumption rates is always beneficial to online retailers in social shopping. Also, it provides a much better understanding on the sources of demand uncertainty that affect service levels in social shopping.

Analytical models in the economics literature (Economides 1996; Granovetter and Soong 1986) suggest that the inventory outcomes of a social shopping deal become very unpredictable in the presence of social interactions. This is because social interactions induce demand uncertainty. This implies that it becomes harder for online retailers to achieve desired service levels in social shopping as social interactions effects become stronger. Therefore, social interactions are a source of inefficacy in this focused context.

When social interactions are negligible, managers may use the newsvendor model in order to clear markets. This is reasonable, since they may rely on their knowledge of the demand distribution, and hence approximate the optimal inventory quantity and price, according to the newsvendor model (Dana Jr and Petruzzi 2001; Petruzzi and Dada 1999). However, when social interactions are not negligible, it becomes difficult to obtain a nice specification of the demand distribution (Granovetter and Soong 1986). As a result, the basic newsvendor model becomes no longer a useful

tool for inventory provisioning (and pricing) decisions. To cope with bounded rationality, managers should make adjustments in their decision making process – and rely on strong assumptions – in order to approximate the optimal inventory quantity and price (Su 2008). In line with the theoretical argument put forth in the development of **H3**, the results suggest that managers will err by increasingly undersupplying the market as social interactions effects become stronger. That is, the tendency of inventory managers to safeguard from uncertainty by underordering is likely to lead to stockouts when social interactions are at play. And, as our results show, as deals' consumption rates will increase, their service levels will decrease even faster.

### **Academic Contribution**

This dissertation investigates social influence in social shopping above and beyond the effects of word-of-mouth by providing a conceptualization of *social interactions* – i.e. “interdependencies in which consumers’ choices influence others’ choices in a direct and meaningful way”. Also, to the best of my knowledge, this is the first study to empirically assess the effect of *multiple* social interaction mechanisms on consumption rates in tandem. Predominantly, the social interactions literature has assessed whether social interactions are influential, or has limited the investigation to the traditional opinion leadership model of social influence. In this dissertation, I offer a much broader perspective on social interaction mechanisms by assessing both relational and structural models of social influence. Namely, the results of this study suggest that we may use the *opinion leadership*, *integration*, and *constraint* models in tandem to better understand demand management in the focused social shopping context.

In addition, this study disconfirms the predominant view that purports that marketing activity inherently predicts consumption rates. Instead, the statistical results

show that social interaction mechanisms predict consumption rates and that marketing activity is a moderator of such an effect. Besides, the study joins the debate on whether social interactions are indeed significant after one accounts for marketing activity (Aral 2011; Aral and Walker 2011; Godes 2011; Iyengar et al. 2011a, b; Van den Bulte and Iyengar 2011), thus providing a clear slate for future investigations of social influence mechanisms in online retailing context.

Moreover, the study moves one step further in our understanding of the effects of social interaction mechanisms in the social shopping context. This is because it theorizes and empirically assesses the relationship between the outcomes of influence (i.e. increases in consumption rates) to inventory performance outcomes (i.e. decreases in service levels). The study brings together two apparently opposing literatures. While the marketing literature suggests that increasing consumption rates should be a goal, the operations management literature suggests that achieving high service levels should be a goal. However, both goals are often conflicting. This is because increasing consumption rates may lead to stockouts, which are widely recognized as costly inventory outcomes (Anderson et al. 2006; Zinn et al. 2002) in online retailing settings (Jing and Lewis 2011). In doing so, this dissertation answers calls for more research on the interface of the marketing and operations management disciplines (Frankel et al. 2008; Ho and Tang 2004; Karmarkar 1996; Malhotra and Sharma 2002; Mentzer et al. 2008; Rinehart et al. 1989).

Furthermore, the use of experiments and econometrics techniques to empirically assess the conceptual model is a significant contribution to the operations management literature. Researchers in the discipline have been arguing for the use of innovative data sources and statistical techniques (Boyer and Swink 2008; Gattiker and Parente 2007)

that depart from the predominant approach based on surveys and structural equation modeling (Boyer and Swink 2008). In doing so, this dissertation also contributes to the behavioral operations management literature (Bendoly et al. 2006; Knemeyer and Naylor 2012), by investigating how consumer behavior and provisioning decisions affect inventory performance outcomes in social shopping.

### **Managerial implications**

The results of this dissertation support the use of marketing messages hinging on influential consumers exerting above-average social influence on other consumers. This study suggests the existence of influential consumers (1) who are well connected and (2) who are least constrained in the network, hitherto neglected in extant literature. This comes in addition to the more common approach of identifying opinion leaders as influential.

For over seventy years, researchers have attempted to quantify the notions of “stars” or “isolates” that would reflect how influential people are in social networks. More recently, there have been efforts to quantify consumers’ influence in online social networks such as Facebook, LinkedIn, and Twitter (e.g. the Klout score). This study’s evidence indicating the presence of three mechanisms of influence in tandem joins these efforts and is quite novel. As a result, my dissertation equips managers with tools to better manage demand by identifying who the influential consumers are in social shopping.

Moreover, the empirical results go beyond marketing practices to suggest which levers inventory managers might operate to better manage demand in the presence of social interactions. Specifically, social interaction mechanisms will become less

influential as the quality of the product being offered as part of deal increases. In turn, social interaction mechanisms will become more influential as the price increases.

Another relevant implication of my dissertation is that, under some circumstances, increasing consumption rates may be undesirable because this decreases service levels in a non-linear fashion. This challenges the largely held assumption in social interactions studies that selling more by selling faster will always be of interest to online retailer. Here, the issue is: what is the online retailer's inventory management approach? Managers must address whether stockouts are desirable prior to targeting influential consumers, sourcing products according to their quality, and setting prices, because of the implications of stockouts for repeat purchases and long-term consumer relationships.

This implication relates to an emerging debate on inventory availability in online retailing context. Currently, both scholars and managers have been attempting to model and empirically test inventory management practices that would yield high inventory availability in numerous settings. However, such efforts have focused more on sourcing and operations practices than on demand management practices. From this research standpoint, sourcing and demand management go hand in hand. For instance, this study suggests the counter-intuitive tactic of setting high prices for deals offering low-quality products *and having exceedingly high inventory availability*, as long as influential consumers buy those deals early. This is because influence stemming from social interactions might help increase consumption rates. Hence, based on inventory managers' decisions regarding sourcing and pricing, marketers could act to target those influential consumers that would yield superior inventory performance – and consequently higher

profitability, for instance, by providing them financial incentives to buy a deal early or by locating, in a social network, influential consumers who are uninformed.

### **Limitations and Directions for future research**

This dissertation has some limitations and opens up interesting research avenues to be pursued. Generalizability is a concern, since the use of undergraduate students may not adequately represent a population of online consumers. Experiments encompassing a more diverse population might increase the generalizability of the current study. Alternatively, agent-based simulation studies (Fibich and Gibori 2010; Swaminathan et al. 1998) emulating consumer behavior might be useful in the investigation of the phenomenon under inquiry in this research.

Also, our experiments only offered deals of “normal goods”. As such, they constrained the investigation to the positive effects of social interactions on consumption rates (Duesenberry and Stemple 1949; Granovetter and Soong 1986; Leibenstein 1950). Future research might want to investigate the effects of social interaction mechanisms on consumption rates of deals offering different types of products, including “Veblen goods” (Leibenstein 1950; Veblen 1899). Research (Amaldoss and Jain 2005a, b; Bagwell and Bernheim 1996; Tereyagolu and Veeraraghavan 2011) has found that Veblen goods promote conspicuous consumption – that is, there are consumers likely to purchase “exclusive” deals of low consumption. In such case, we should expect to observe opposite results to the ones obtained in this study, since social interactions should lead to decreases in consumption rates of exclusive deals.

Since social shopping attempts to use technology to mimic the social interactions found in offline retailing, another interesting line of inquiry would be to investigate social interactions effects and inventory management practices according to different types of

technology, including tablets, cell phones, and personal computers. It also might be fruitful to make such distinction according to the demographics of the technology users. This might provide a fine grained understanding on the channels of influence among different groups of consumers in social shopping.

One notable limitation in this study is the limited definition of product quality as low (remanufactured) or high (“mint in box”). Future research might attempt to operationalize quality as a multidimensional construct, or measure quality according to a continuum scale rather than treating it as binary. Besides, it might be fruitful to investigate the effects of social interaction mechanisms on the inventory outcomes of those deals offering products in a specific life cycle stage (i.e. introduction, growth, maturity and decline). It would also be interesting to contrast such effects for products in transition (Li et al. 2010).

Moreover, it would be valuable to contrast the effects on consumption of social interaction mechanisms with consumers’ reactions to their awareness of inventory availability (Yin et al. 2009). Another interesting avenue of inquiry is to investigate how inventory location and inventory ownership (Rungtusanatham et al. 2007; Wallin et al. 2006) might interfere with the results of the current research. This is because online retailers might promise different service levels and charge consumers differently depending on (1) inventory location in the supply chain and (2) who owned inventory (e.g. whether the online retailer sells in consignment) (Rabinovich and Bailey 2004; Rabinovich et al. 2003; Rabinovich et al. 2008b).

In addition, future research might integrate the downstream-facing perspective of this study with both internal- and upstream-facing perspectives of operations in this research context. For instance, the incredibly fast turnaround time for vast numbers of



items represents a burden for warehouse operations in several aspects (e.g. storing, picking, packaging, and shipping). Studies building on this research might assess warehouse management and inventory control approaches (including implementation of information and other systems) of online retailers who invest in social shopping. An integrated conceptual framework might assess the drivers and outcomes of inventory record inaccuracy in distribution centers (Barratt et al. 2011; Fleisch and Tellkamp 2005; Kull et al. 2011) in social shopping. Also, sourcing practices (e.g. supplier selection, negotiation, quality assurance, inbound transportation) appear to be crucial for the success of online retailers in this focused context. In a similar vein, future research could explore the return practices of online retailers in social shopping.

Furthermore, an emerging body of literature (Chen et al. 2009; Chen et al. 2010; Kauffman and Wang 2001; Kauffman et al. 2010a; Kauffman et al. 2010b; Kauffman and Wang 2002; Netessine and Tang 2009) has investigated price-setting and price discrimination in related contexts. In line with Whitin's (1955) groundbreaking idea, it might be interesting to integrate two streams of literature, namely revenue management and inventory control (Elmaghraby et al. 2009, 2010) in social shopping.

Finally, Walmart and Facebook recently announced (Reuters 2011) and have been strengthening (Reuters 2012) a partnership. This initiative might provide an interesting case study for investigation of changes in business practices in general, and supply chain management in particular, as traditional retailers such as Walmart enter social shopping and adopt social interactions in large social networking websites as a selling mechanism.

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## APPENDIX A

### SEMIPARAMETRIC ESTIMATION LIKELIHOOD FUNCTION

Cox (1975) (see also Kalbfleisch and Prentice, 1980) provide a partial likelihood estimator for semiparametric hazard models that accommodate right-censored data, such as those used in this study.

Suppose that the baseline hazard  $h_0(t)$  in equations (11a) and (11b) is arbitrary, and recall from those equations that we want to estimate  $\beta^{10}$ . Cox argues that no information can be contributed about  $\beta$  by time intervals in which no failures (i.e. understocking) occur, because the baseline hazard  $h_0(t)$  might conceivably be identically zero in such intervals. Hence, we make the argument conditionally on the set  $\{t_i\}$  of instants at which failures occur.

For the particular failure at time  $t_i$ , conditionally on the set of deals that are at “risk” of failing at that time,  $\mathfrak{R}(t_i)$ , the probability that the failure is on the deal as observed is

$$\prod_{i=1}^N \exp\{x_i\beta\} / \sum_{l \in \mathfrak{R}(t_i)} \exp\{x_l\beta\}$$

where  $x_i$  are the covariates and indicators correspond to the ordering of times ( $t_1 < t_2 < \dots < t_N$ ) of both censored and uncensored observations. Each failure contributes a factor of this nature. Thus, the conditional likelihood function is

$$\mathcal{L}_1 = \sum_{i=1}^N x_i\beta - \sum_{i=1}^N \log \left[ \sum_{l \in \mathfrak{R}(t_i)} \exp\{x_l\beta\} \right] \quad (13)$$

and we obtain the estimation of  $\beta$  in a iterative way.

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<sup>10</sup> Cox claims that the loss of information of the parameter estimates  $\beta$  arising from leaving the baseline hazard arbitrary is usually slight – and consequently, the procedure put forth by him is justifiable as a reasonably cautious approach to the study of  $\beta$  (p. 190).

## APPENDIX B

### PARAMETRIC ESTIMATION LIKELIHOOD FUNCTION

Lancaster (1990) provides a maximum likelihood estimator for parametric hazard models that accommodate right-censored data, such as those used in this study.

Consider the hazard function,  $h(t)$ , defined as  $f(t)/[1-F(t)]$ . Then,

$$1 - F(t) = \exp\left\{-\int_0^t h(u)du\right\} \quad (14)$$

Equation (14) is the fundamental relation connecting a specification of the probabilities of failure (i.e. understocking) with the distribution of time to understocking. Then, the expected time to understocking is

$$\int_0^{\infty} 1 - F(t)dt = \int_0^{\infty} \exp\left\{-\int_0^t h(u)du\right\} dt \quad (15)$$

In the simplest case in which we have the completed durations of deals (i.e. all deals sold out), the likelihood function is:

$$\mathcal{L}_1 = \prod_{i=1}^N g_i(t_i) \quad (16)$$

where, from equation (14),

$$g_i(t_i) = h_i(t_i)\exp\left\{-\int_0^{t_i} h_i(z)dz\right\} \quad (17)$$

A second situation arises when we have completed durations of some deals only. That is, others reach their deadlines without selling out. Consider a deal  $i$  that has not sold out at time  $t$  ( $t < d$ ), where  $d$  is the deadline of a deal (in the case of our experiment, the deadline  $d$  is 3 minutes). Let  $c = d - t$ . The event that a deal has not sold out at time  $d$  has probability

$$\frac{1 - F_i(t_i + c)}{1 - F_i(t_i)}$$

which is the conditional probability that a deal that has not sold out at time  $t$  fails to sell out in the subsequent  $c$  periods of time. Conversely, the event that a deal  $i$  does sell out at, say,  $t+s$  ( $0 < s < c$ ) has probability

$$\frac{f_i(t_i + s_i)}{1 - F_i(t_i)}$$

If  $N_U$  of the deals will not sell out at time  $d$  and  $N_O$  will, then the likelihood function is

$$\mathcal{L}_2 = \prod_{i=1}^{N_U} \left\{ \frac{1 - F_i(t_i + c)}{1 - F_i(t_i)} \right\} \prod_{j=1}^{N_E} \left\{ \frac{f_j(t_j + s_j)}{1 - F_j(t_j)} \right\} \quad (18)$$

Finally, of course, to complete the likelihood functions in equations (16) and (18), we need to provide a specification of  $F$ , or equivalently of  $h$ . In this research, I provide five specifications of  $h$ : Weibull, generalized gamma, exponential, lognormal, and log-logistic.