

## **Social network externalities and price dispersion in online markets\***

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### **Abstract**

Ample empirical studies in the e-commerce literature have documented that the price dispersion in online markets is 1) as large as that in offline markets, 2) persistent across time, and 3) only partially explained by observed e-retailers' attributes.

Buying on the internet market is risky to consumers. First of all, consumers and the products they purchase are separated in time. There is a delay in time between the time consumers pay and the time they receive the orders. Second, consumers and the products they purchase are separated in space. Consumers cannot physically touch or examine the products at the point of purchase. As such, online markets involve an adoption process based on the interaction of consumers' experiences in the form of references, recommendations, word of mouth, etc. The social network externalities introduced by the interaction of consumer's experiences reduces the risk of seller choice and allows some sellers to charge higher prices for even homogeneous products.

This research aims to study online market price dispersion from the social network externalities perspective. Our model posits that consumers are risk averse and assess the risk of having a satisfactory transaction from a seller based on the two dimensions of the seller's social network externalities: quantity externality (i.e., the size of the seller's social network) and quality externality (i.e., the satisfactory transaction probability of the seller's social network). We further investigate the moderating effect of product value for

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consumers on the impact of social network externality on online market price dispersion. Our model yields several important propositions which we empirically test using data sets collected from eBay. We found that 1) both quantity externality and quality externality of social network are salient in driving online price dispersion, and 2) the salience of social network externality is stronger for purchase behavior in higher value product categories.

**Keywords:** network externalities, price dispersion, online markets, word of mouth.

### Resumen

Estudios empíricos en comercio electrónico han documentado que la dispersión de precios en estos mercados es 1) de la misma magnitud que en los mercados convencionales, 2) persistente en el tiempo, y 3) sólo parcialmente explicada por los atributos observables de los oferentes en línea.

Comprar en Internet es riesgoso para los consumidores. Primero, los consumidores y los productos están separados temporalmente. Existe un rezago de tiempo entre cuando el consumidor paga por el producto y cuando lo recibe. Segundo, los consumidores y los productos que compraron están separados espacialmente. Es decir, los consumidores no pueden tocar o examinar los productos en el punto de compra. En este sentido, los mercados electrónicos involucran un proceso de adopción basado en la interacción de las experiencias de los consumidores en la forma de referencias y recomendaciones. Las externalidades de redes sociales que emergen de la interacción de las experiencias de los consumidores reduce el riesgo en la selección del vendedor y permite a algunos oferentes en Internet cargar precios mayores que la competencia (premios) aún para productos homogéneos.

Esta investigación busca estudiar la dispersión de precios en mercados electrónicos desde la perspectiva de las externalidades de redes sociales. Nuestro modelo propone que los consumidores aversos al riesgo evalúan el riesgo de tener una transacción satisfactoria en los mercados en línea basados en dos dimensiones de las externalidades de las redes sociales del vendedor: la externalidad de cantidad (i.e., el tamaño de la red social del vendedor) y la externalidad de calidad (i.e., la probabilidad de tener una transacción satisfactoria que se infiere de las opiniones de la red social del vendedor). Adicionalmente, investigamos el efecto moderador del valor del producto para los consumidores en el impacto de las externalidades de redes

sociales en la dispersión de precios en el comercio en línea. De nuestro modelo se deducen proposiciones importantes que probamos empíricamente utilizando información recolectada de eBay. Encontramos que 1) ambas, la externalidad de cantidad como la externalidad de calidad de las redes sociales son importantes factores para explicar la dispersión de precios en el comercio electrónico y 2) la importancia de las externalidades de redes sociales es más fuerte en la conducta de compra en las categorías de productos de mayor valor.

**Palabras Claves:** externalidades de redes, dispersión de precios, mercados en línea, referencias de palabra.

**Clasificación JEL:** L11, L14, L15, L86.

## **Introduction**

Price dispersion for homogeneous products across vendors in online markets has attracted much attention. Several stylized facts on online price dispersion are well documented in the literature:

*Online price dispersion is present in a variety of markets.* Bailey (1998), Brynjolfsson and Smith (2000), Clay, Krishnan and Wolff (2001) and Clay et al (2002) have documented variation coefficients (standard deviation as proportion of the mean) between 20% and 50%. Clemons et al (2002) reported hedonic price regressions in the online travel agencies and concluded that even controlling for all relevant tickets attributes, some sellers can still charge premium prices in the order of 28%. In the European online market of contact lenses, Häring (2003) found dispersion in the range of 60% of the mean. For a broad sample of products, Pan et al (2001) reported moderate price dispersion for several categories in online commerce.

*Online price dispersion is of the same magnitude as offline.* Price dispersion in many offline retailing sectors also ranges from 20% to 30%. For example, Lach (2002) estimated a price dispersion of 25% of the mean in grocery retailing in Israel, a sector subject to frequent sales specials (high-low pricing) and Sorensen (2000) estimated a price dispersion of 22% in the pharmacy business. In direct comparisons, Brynjolfsson and Smith (2000) found that price dispersion was larger for the Internet than conventional retailing in books and CDs. Sholten and Smith (2002) found no significant difference in the price dispersion measures in online and offline vendors in a sample of several merchandises.

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*Online price dispersion is persistent even for homogeneous products.* In other words, there is no sound signal that price dispersion in online markets tends to diminish in time (Lach, 2002). Clay et al (2001) estimated that intertemporal price dispersion is close to zero for a sample of more than one hundred books.

Researchers have made attempts to address why these stylized facts on price dispersion exist in a seemingly frictionless online market. Studies explaining online price dispersion focused on product differentiation, buyer heterogeneity, and seller heterogeneity (e.g., Brynjolfsson and Smith, 2000; Brown and Goolsbee, 2002; Pan et al, 2001, 2002a, 2002b; Smith, 2002; etc.). These studies have made significant progress in understanding the drivers of online price dispersion, but they often leave behind a significant proportion of the variability of online price dispersion unexplained.

In this paper, we attempt to study online price dispersion from the perspective of social network externalities. The idea is that online markets convey a consumer adoption process driven by the interaction of consumers' experiences in the form of references, word of mouth, digital word of mouth or just imitating behavior. If the firms in online markets recognize that consumers understand that their adoption of e-commerce faces risks under which the importance of the network approval is high (e.g., use network based information sources to make judgment on whether they will have a satisfactory online transaction), then the firms' optimal strategy is to invest in building a large consumer base with positive word of mouth in the short run and to enjoy price premiums in return in the long run.

Our idea finds support in anecdotic evidence in the e-commerce industry. Jeffrey Bezos, CEO of Amazon.com, once summarized the key element of the success of Amazon: "Repeated purchases and word of mouth have combined to make Amazon.com the market leader in online industry".<sup>2</sup> Word of mouth, sharing past purchasing experiences, imitating other consumers, and reading the comments other consumers rate the sellers in e-auctions markets (e.g., eBay) or shopbots (e.g., Bizrate) which involve the presence of social network externalities allow firms like Amazon to charge a premium price.

Our idea also finds support in e-commerce literature. "*Winner takes it all*" is a widely accepted e-commerce notion in which sales are often concentrated in a few large e-retailers for a given industry. As such, Goolsbee and Chevalier (2002) using the sales rank measures reported by the major online

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<sup>2</sup> Jeffrey Bezos, CEO of Amazon.com, 1997 letter to shareholders, Annual Report of 1997.

bookstores estimated that Amazon might sell 70% of the online book market whereas B&N might have a market share of 15%. Thus the remaining 15% is shared among more than 7,000 fringe e-retailers suggesting that online markets at large might be as concentrated as conventional retailing, even in commodity markets (such as books).

The study is organized as follows. In Section 1, a review of the related literature on online price dispersion and social network externality is presented. Section 2 presents our modeling framework. We posit that consumers are presented with risk of an unsatisfactory transaction in online markets. Consumers do not know the true probability of a satisfactory transaction from a particular seller and have to rely on estimations they make based on other consumers' word of mouth, digital word of mouth,<sup>3</sup> or behavior. We further derive five testable hypotheses from our modeling framework, concerning both the quantity externality of social network (i.e., the social network size) and quality externality of social network (i.e., the satisfactory transaction probability) for sellers. In section 3, our hypotheses are empirically tested using data collected from e-Bay. Finally, the implications of the study, its limitations and some opportunities for further research are discussed.

## **1. Literature Review**

### *1.1 Drivers of online price dispersion*

#### *Product Differentiation*

One stream of research focuses on how product differentiation dilutes price competition and allows price dispersion. This literature suggests that buying via the Internet might decrease price elasticity if the products are differentiated and the search attributes of the products are important in consumers' choice decisions. The reason is that Internet lowers not only the search costs for price, but also the search costs for other product attributes. As such, the price competition is often counterbalanced by product competition. Using experiments, Lynch and Ariely (2000) found that the lowering search costs makes differentiation on product quality more salient than that on price and hence decrease price sensitivity in electronic markets.

In a broader framework, Degeratu et al (2000) further argue that the counterbalance of product competition on price competition triggered by

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<sup>3</sup> Digital Word of mouth is a recent concept introduced by Dellarocas (2003) referring to consumers comments and feedback about sellers through reputation mechanisms used by the most popular electronic markets such as eBay or shopbots as Bizrate.

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lowering search costs in electronic markets depends on the types of product attributes. They propose that the Internet lowers the search cost of non-sensory attributes (e.g., the content of fat in margarine), but increases the search costs of sensory attributes (e.g., the softness of paper towels). As such, we might expect less intense price competition among brands in electronic markets for products where sensory attributes are important to consumers. In these cases, brand might act as a surrogate of sensory attributes in consumer choice in online markets, which increases market concentration and decreases price sensitivity. Using an online shopping behavior data set from peapod.com, the authors found empirical support for their hypotheses.

A more theoretical treatment was given by Bakos (1997). He built a theoretical model of monopolistic competition in which each producer has a monopoly of one variety, but all varieties are close substitutes. The model suggests that as the Internet reduces the costs of information search about product quality, instead of making the market more competitive, the Internet reinforces the “monopoly” of each seller in its particular variety. As such it decreases price sensitivity of consumers.

This stream of research offers some important insights on why lowering search costs does not necessarily enforce price competition and often allows price dispersion among differentiated products in online markets. However, for homogeneous products, the search for non-price related product attributes (e.g., product quality) does not exist. As such, this literature is short in explaining why price dispersion exists for homogenous products in online market.

### *Buyer Heterogeneity*

A second stream of research on online price dispersion for homogenous products focuses on buyer heterogeneity. This literature suggests that a persistent price dispersion arises if consumers have different search costs (Salop and Stiglitz, 1977), buy different quantities (Salop and Stiglitz, 1982), have different exposures to advertisement (Butters, 1977), or have different awareness (Brynjolfsson and Smith, 2000; Brown and Goosbee, 2001; Smith, 2002).

A well known scenario is when there are two segments of consumers for the homogeneous products: one segment (“shoppers”) has low search costs and the other (“non-shoppers”) has high search costs. A Nash equilibrium in pure strategies occurs with unequal prices for the same product in which shoppers make an exhaustive search and buy at the lowest price and non-shoppers do not engage in this process and buying the same product with a premium. For

price dispersion to be persistent, however, these models require that consumers are amnesic (each period they reset their previous experience), and/or that consumers do not communicate among themselves (to ask references and learn from others). In other words, the market should resemble the one in which new consumers enter with high search costs and others remain with low search costs (e.g., tourists versus locals). However, if consumers communicate with each other, a Nash equilibrium with persistent price dispersion is still sustainable in mixed strategies. The problem was studied initially by Varian (1980) and further generalized by Stahl (1989). The randomness of the mixed strategy makes the communication among consumers ineffective for them to make price judgment for particular sellers.

Brynjolfsson and Smith (2000) suggest consumer awareness heterogeneity as a driver for online price dispersion. Brown and Goolsbee (2002) assume that the consideration set of most of the consumers is restricted to well known insurance vendors, and only a very small proportion of agents are aware of the whole market suppliers. Smith (2002) built a theoretical model for the online book industry, in which three kinds of consumers are identified depending on their awareness level. Segment one is only aware of the branded online retailers in the book industry (Amazon, Barnes & Noble and Borders), segment two is aware of these big players as well as some of the “fringe” online bookstores, and segment three consists of shopbot users who always seek the lowest price alternative. At equilibrium, branded retailers play a cooperative solution in a repeated game framework of posting the same price and fringe retailers play a randomize-price Varian (1980) strategy which precludes consumers to fully be aware of the whole price distribution across vendors. This line of research finds empirical support in some markets. For example, Brown and Goolsbee (2002) present empirical evidence from the insurance industry. They find that after controlling for all relevant variables in a hedonic price regression of insurance policies, a clear tendency of narrowing price premiums and intensifying competition has occurred as a consequence of appearance of insurance prices comparison web sites (a kind of insurance shopbots).

This literature provides an interesting explanation for online price dispersion, but it comes with some important shortcomings. First, intertemporal price dispersions of online markets (i.e., the variation of particular seller’s prices across time) are small, suggesting that randomized high-low price strategies are not a critical determinant of price dispersion. Actually, most of the sellers usually offer the same price for long periods of time. Second, Salop and Stiglitz (1977, 1982) model might explain price dispersion without random-price strategies, but as the proportion of low-cost shoppers increases (e.g. shopbots users), eventually price dispersion should decrease. However, there is no direct evidence about such price convergence process. Third, a no

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concentrated market results from the price dispersion in the Varian (1980) or Salop and Stiglitz (1977, 1982) models, what seems to be a strong stylized fact in online markets experience.

While the Smith model (2002) on consumer awareness is a nice theoretical step in explaining price dispersion, it does not explain how the different levels of awareness were formed in the first place. Moreover it lacks face-validity about the fringe prices, because book prices on the Internet are relatively stable, a fact that contradicts that fringe vendors use random-price strategies. Additionally, Brynjolfsson and Smith's (2000) study of consumer behavior in a particular shopbot showed that even when shopbot consumers are very price sensitive, brand still matters, since 51% of shopbot consumers did not choose the lowest price alternative. Actually, in their study, even when brand sites had the lowest prices only 15% of times, they captured a 27% share of consumer choices.

### *Seller Heterogeneity*

A third stream of research focuses on the attribution of the seller heterogeneity on key attributes such as reliability, trust guarantees, handling and shipping policies, attractiveness of the interface, etc. The argument on seller heterogeneity for online price dispersion is appealing, but the attempts find limited evidence that such measurable attributes explain a significant portion of price dispersion. For example, Brynjolfsson and Smith (2000) found that the coefficients of these measurable attributes in hedonic price regressions are usually neither significantly different from zero nor having the correct signs. Also, Pan et al (2001, 2002a, 2002b) found four factors -- reliability, shopping convenience, product information, shipping and handling -- that synthesize all measurable service attributes of e-retailers. Again, these factors did not explain price variability well in hedonic regressions.

There are several important shortcomings in this line of research. First, the attempts to analyze online price dispersion from sellers' heterogeneity (Brynjolfsson and Smith, 2000; Pan et al, 2002a) lack a theoretical foundation in which the mechanism that the sellers' heterogeneity attributes to consumers' willingness to pay is described. Second, this literature fails to take into account an important endogenous variable that reflects the deviation from pure competition: market concentration. Indeed, price dispersion might be a direct consequence of the fact that online sales are very concentrated in few vendors. For example, in the case of the online bookstore industry, it is evident that Amazon is the undisputable leader. Third, market concentration carries unequal weighting on consumer decision making. For example, consumers may prefer shopping from Amazon.com

than from a fringe retailer even though the two firms have identical average reliability rating. Methodologically, ignoring market concentration implicitly puts equal weight on each seller (e.g., Bizrate.com).

We propose a theoretical framework on price dispersion in which these remedies are addressed from the perspective of social network externalities.

### *1.2 Social Network Externality*

“Network Externality” refers to the change of value a consumer derives from a product when the number of other consumers adopting the same product changes (Katz & Shapiro, 1985).

Network externality can be direct or indirect, depending upon how the consumption value is changed (e.g., Economides, 1996). A direct network externality occurs when the addition of a new consumer to the current consumers of the product (or the network) presents a new potential composite product which can be consumed by and thus changes the consumption value of some consumers in the network. For example, in telephone market, adding a new subscriber to a phone network presents new phone service possibility for the current subscribers and therefore changes the value of subscribers’ using the phone services (e.g., many mobile phone services providers such as Sprint, Nextel etc. market their products by offering unlimited mobile to mobile services). The indirect network externality occurs when the change of value is attributed to sources other than the number of composite products, such as compatibility, quality, learning, diversity etc. For example, consumers might be inclined to use the more popular software packages because they can transfer files with more people (compatibility). Consumers also are more prone to acquire the most purchased software because it is more likely to be updated (quality). In addition, consumers find that it is more convenient to purchase the most popular software because it is easier to find support of experienced users (learning). For example, Brynjolfsson and Kemerer (1996) showed evidence of the presence of indirect network externalities in the use of software packages, because investing time in learning the dominant software is more profitable given the higher probability of being updated compared with less popular software. Also, Goolsbee and Klenow (1999) showed that the diffusion of home computers exhibits strong indirect network externalities as well, mainly through learning but perhaps also because of status-seeking behavior.

Social networks have been widely studied in marketing. Marketing researchers used social network externality to study diffusion of innovations and new products. Bass (1969) assumes that imitators’ utility grows as the

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size of the adopted population (or network size) increases. Although Bass (1969) does not explicitly specify the way the network externality operates, the inference of the model, however, suggests two possible impacts of social network externality for diffusion. First, diffusion requires necessity of communication and exchange of information of the individuals who are linked through a social network (e.g., word of mouth). Bass (1980) and Clarke, Darrough and Heineke's (1982) address the "experience" effects on demand and costs, willingness to pay depends on the learning of all consumers, because "experience" spills across consumers.

Second, the network externalities operate mostly through risk reduction of adoption, particularly in risk-sensitive markets. For example, Oren and Swartz (1988) assume consumers learn in a Bayesian approach. Consumers are heterogeneous in risk bearing. The diffusion process operates through the interaction of the outcome variance of the adopters and the size of adopters. As the higher risk bearing individuals become adopters, they reduce the uncertainty of the rest of the consumers. This consequently allows lower risk bearing consumers to adopt. Roberts and Urban (1988) also imposed Bayesian updating of consumers' beliefs. As the size of the adopters segment grows, the variance of the outcome decreases and the certain equivalent increases. If there is no satiation, then the larger the network size, the higher the expected utility of consumers. Lattin and Roberts (2000) extended Roberts and Urban (1988) model to take into account other possible transmission channels of network externalities, specifically conformism and social pressure. They implemented a practical method of estimating diffusion models to new products just prior to the launch.

In summary, social network externality offers a theoretical foundation in approaching the aggregate on price and market structure when the market has a salient presence of network externalities. Online markets post a strong presence of (indirect) social network externality. For example, in online banking market, Kennickell and Kwast (1997) found that 33% of the consumers admit that their adoption decision was influenced by their friends and family members who had adopted online banking. Some other 27% of the consumers were influenced by financial consultants and brokers. We develop our model along these lines next.

## 2. Modeling Framework and Hypothesis Development

Economides and Siow (1988) and Economides (1993) introduce an indirect network externality in the context of financial markets: the liquidity effect. According to these studies, prices are less volatile in more liquid financial markets (with a high volume of daily transactions) than in thin financial

markets (with a low volume of daily transactions). This is true because high volume of transactions suggests a reduced risk of trading.

We posit that this liquidity proposition happens in online markets and drives the online price dispersion, much the same way as “reputation liquidity” works in financial markets. The risk of a transaction in an online market is high. First, consumers and the products are separated in time. There is a delayed time between the time consumer pays and the time he or she receives the order. Second, consumers and the products are separated in space. Consumers cannot physically touch or examine the products at the point of purchase. Consumers assess seller’s ability to guaranty a satisfactory transaction through word of mouth (comments and evaluations of other consumers to a seller) in online markets. The size and quality of the electronic references about a seller in online markets lower the variance and the risk of buying from a seller and help to build up consumer trust. The built-up sellers’ reputation allows some sellers to charge price premium over others, which attributes to the online price dispersion.

### *2.1 Modeling Framework*

We assume a consumer has utility value  $v$  for a product purchased from an e-retailer if the transaction is satisfactory (i.e., the consumer gets what she wants on time). However, in electronic markets, consumers often involve a risk for unsatisfactory transaction due to poor performance of the e-retailers. An unsatisfactory delivery occurs if consumers do not receive the product on time, receive the wrong product, receive the correct product but in poor condition, or receiving nothing at all. This potential uncertainty of unsatisfactory delivery scales down the expected utility for the customers.

Assume the probability that a satisfactory delivery for the e-retailer is  $\lambda$ . Then the expected utility of the transaction is  $\lambda v$  if the consumer is risk-neutral. The consumer evaluates the e-retailer performance by observing other consumers’ behaviors and feedbacks, and assesses the satisfactory transaction probability  $\lambda$  from the e-retailer. For example, “herd” behavior, in which rumors, fads, and fashion models lead the way (Banerjee, 1992 y 1993) suggests consumers infer the performance of e-retailers by observing where and how many other consumers purchase. On the other hand, digital word-of-mouth coming from reputation mechanisms as the one implemented by the eBay Rating Score, the “stars” rating systems of most of shopbots, and the plain text comments of unknown consumers who had a positive or negative experience with particular e-retailers etc. acts as another important source to consumers’ inferences (Dellarocas, 2003)

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Assume that there are  $M$  references in which  $x$  references are positive. Also assume that the consumer assesses the e-retailer's satisfactory transaction probability  $\lambda$  via the sampling positive reference ratio  $s = x/M$ .  $M$  approximates the consumer's social network size at the e-retailer because it is the estimation consumers often use to infer the true social network size.

It is reasonable to assume that random variable  $s$  follows a binomial distribution with a population proportion  $\lambda$ . For large  $M$ ,  $s$  will be an unbiased estimator of  $\lambda$ . The binomial distribution assumption is convenient for two reasons. First, the binomial distribution is appropriate for the references to the e-retailer because it is restricted to either positive (1) or negative (0). This binary classification of references is the very procedure adopted by the majority of reputation mechanisms in electronic markets such as the eBay Feedback Score. Second, a binomial distribution is a natural choice for facilitating a proportion estimator. As such, for a risk neutral consumer, the estimated expected utility will be  $sv$ .

However, consumers are not risk-neutral, but rather risk averse, whether they shop online or offline. The e-commerce has well documented that one of the biggest problem for consumers to avoid online shopping is the high risk when shopping in online markets. As in standard treatment of uncertainty in economics literature, we assume a risk adjusted utility function as  $U = U(sv)$ . For risk-averse consumers, the utility function is concave and has the properties  $U'(sv) \geq 0$  and  $U''(sv) \leq 0$ . A second degree Taylor expansion of  $U(sv)$  shows:

$$U(sv) \approx U(\lambda v) + (sv - \lambda v)U'(\lambda v) + \frac{(sv - \lambda v)^2}{2}U''(\lambda v) \quad (1)$$

As such, the maximum price  $p$  consumers are willing to pay is equal to the expected risk-adjusted utility, i.e.,

$$p = E[U(sv)] \cong U(\lambda v) + \frac{U''(\lambda v)}{2} E[(s - \lambda)^2] v^2 = U(\lambda v) + \frac{U''(\lambda v)v^2}{2} \left[ \frac{\lambda(1-\lambda)}{M} \right] \quad (2)$$

For large  $M$ , equation (2) is a good estimation for maximum price consumers are willing to pay (Economides and Siow 1988). Since  $U''(\bullet) < 0$ , equation (2) suggests that the expected utility  $E[U(sv)]$  with uncertainty is lower than the expected utility without uncertainty  $U(\lambda v)$ . The difference depends on the risk aversion of consumers (reflected by  $U''(\bullet) < 0$ ) and the

variance of the outcome  $\left(\frac{\lambda(1-\lambda)}{M}\right)$ . We derive some important hypotheses from our modeling framework next.

## 2.2 Hypothesis Development

For the tractability of developing testable hypotheses, we follow the network economy literature (e.g., Economides and Siow, 1988) and use a Cobb-Douglas utility function to capture consumer risk aversion:

$$U(sv) = [sv]^\beta \text{ with } \beta \in (0,1) \quad (3)$$

This specification has the 1<sup>st</sup> and 2<sup>nd</sup> derivatives  $U' = \beta(sv)^{\beta-1}$  and  $U'' = \beta(\beta-1)(sv)^{\beta-2}$  respectively, which satisfy the risk aversion conditions for  $\beta \in (0,1)$ . This specification has some advantages: 1) it simplifies the mathematical derivation; 2) it involves a decreasing absolute risk aversion coefficient that has face validity; and 3) it implies a constant relative risk aversion coefficient that makes empirical analysis more applicable.<sup>4</sup> With specification (3), equation (2) becomes

$$p = E[U(sv)] \cong (\lambda v)^\beta - \frac{1}{2} \beta(1-\beta)(\lambda v)^{\beta-2} v^2 \frac{\lambda(1-\lambda)}{M} \quad (4)$$

We use equation (4) to develop some testable hypotheses regarding the impact on price dispersion from social network externalities and the moderating effect of product value for consumers.

### *Quantity Externality of Social Network*

We first develop hypotheses regarding the quantity impact of seller's social network externality (i.e., the impact of sellers' social network size) on price dispersion. Assume that seller 1 has the same satisfactory transaction probability as seller 2, but larger network size. A consumer's estimate of the satisfactory transaction probability is more precise for seller 1 than for seller 2. Consequently, a consumer is willing to pay a price premium to seller 1. Indeed,

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<sup>4</sup> The Pratt's absolute risk aversion measure is equal to  $\frac{-U''}{U'}$ , which is equal to  $\left(\frac{1-\beta}{sv}\right)$  in the Cobb-Douglas case. The relative risk aversion is the absolute coefficient times the argument, which results simply in  $1-\beta$  for the Cobb-Douglas specification.

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$$\begin{aligned}
 p_1 - p_2 &= -\frac{1}{2} \beta (1 - \beta) v^\beta \lambda^{\beta-1} (1 - \lambda) \left[ \frac{1}{M_1} - \frac{1}{M_2} \right] \\
 &= \frac{1}{2} \beta (1 - \beta) v^\beta \lambda^{\beta-1} (1 - \lambda) \left[ \frac{M_1 - M_2}{M_1 M_2} \right]
 \end{aligned} \tag{5}$$

which is positive because  $\beta \in (0,1)$  and  $M_1 > M_2$ . We have,

*H1: Other things being fixed, having a larger social network allows a seller to charge a higher price premium. As such, the impact of quantity externality of social network is positive on price dispersion.*

The rate at which price premium increases with network size is a decreasing function of the absolute network sizes. In other words, the effect of network sizes on price premiums is diminishing. Regrouping (15), we obtain,

$$\mu = \frac{p_1 - p_2}{M_1 - M_2} = \frac{1}{2} \beta (1 - \beta) v^\beta \lambda^{\beta-1} (1 - \lambda) \left[ \frac{1}{M_1 M_2} \right] \tag{6}$$

which is positive but decreasing in  $M_1$  or  $M_2$ . As such, we have

*H2: Other things being fixed, having a larger social network allows a seller to charge a higher price premium at a diminishing rate. As such, the impact of quantity externality of social network on price dispersion increases at a diminishing rate.*

### Quality Externality of Social Network

We next develop hypotheses regarding the quality impact of sellers' social network externality (i.e., the impact of sellers' satisfactory transaction probability) on price dispersion. If seller 1 has a higher satisfactory transaction probability than seller 2, then the price premium a consumer is willing to pay seller 1 is:

$$\begin{aligned}
 & p_1 - p_2 \\
 &= E[U(s_1, v)] - E[U(s_2, v)] \\
 &= (\lambda_1 v)^\beta - \frac{1}{2} \beta (1 - \beta) (\lambda_1 v)^{\beta-2} v^2 \frac{\lambda_1 (1 - \lambda_1)}{M} - [(\lambda_2 v)^\beta - \frac{1}{2} \beta (1 - \beta) (\lambda_2 v)^{\beta-2} v^2 \frac{\lambda_2 (1 - \lambda_2)}{M}] \tag{7} \\
 &= v^\beta \left[ \lambda_1^\beta - \lambda_2^\beta \right] - \frac{1}{2} \frac{\beta (1 - \beta) v^\beta}{M} \left[ \lambda_1^\beta \left( \frac{1 - \lambda_1}{\lambda_1} \right) - \lambda_2^\beta \left( \frac{1 - \lambda_2}{\lambda_2} \right) \right]
 \end{aligned}$$

The first term in the expression is positive since  $\lambda_1 > \lambda_2$ . The second term is also positive if  $\frac{1-\lambda_2}{1-\lambda_1} > \left[\frac{\lambda_2}{\lambda_1}\right]^{1-\beta}$ , which is true since  $\lambda_1 > \lambda_2$  and  $\lambda_1, \lambda_2 \in (0,1)$ . As such, we have

*H3: Other things being fixed, having a higher satisfactory transaction probability allows a seller to charge a higher price premium. As such, the impact of quality externality of social network is positive on price dispersion.*

*The Moderating Effect of Product Value for Consumers*

Our next two hypotheses address the moderating effect of product value for consumers on the impact of social network externality on price dispersion. Assume A is a high-value product such as an LCD or Plasma TV and B is a low-value product such as a DVD movie, i.e.,  $v_A > v_B$ . The rate of change of price premiums with respect to network sizes for product A and B follows the same expression as in (6). Holding other things constant, the ratio of rates of changes is:

$$\frac{\mu_A}{\mu_B} = \left[\frac{v_A}{v_B}\right]^\beta \quad (8)$$

which is larger than one when  $v_A > v_B$ . The rationale is that an increase in the product value increases the variance of the outcome so that the impact of the network externality on price premiums increases. As such, we have

*H4: Other things being fixed, having a larger social network allows a seller to charge a higher price premium when selling higher valued products. As such, the impact of quantity externality of social network on price dispersion is more salient for higher valued products.*

Let

$$\phi = \frac{p_1 - p_2}{\lambda_1 - \lambda_2} = v^\beta \left(\frac{\lambda_1^\beta - \lambda_2^\beta}{\lambda_1 - \lambda_2}\right) + \frac{1}{2} \beta(1-\beta) \frac{v^\beta}{M} \left(\frac{(\lambda_1^\beta - \lambda_2^\beta) + (\lambda_2^{\beta-1} - \lambda_1^{\beta-1})}{\lambda_1 - \lambda_2}\right) \quad (9)$$

$\phi$  represents the rate of price change with respect to the seller's satisfactory transaction probability change. To compare the rate of change  $\phi$  for different products, we have

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$$\gamma = \frac{\phi_A}{\phi_B} = \frac{v_A^\beta \left\{ \left( \frac{\lambda_1^\beta - \lambda_2^\beta}{\lambda_1 - \lambda_2} \right) + \frac{1}{2} \beta (1 - \beta) \frac{1}{M} \left( \frac{(\lambda_1^\beta - \lambda_2^\beta) + (\lambda_2^{\beta-1} - \lambda_1^{\beta-1})}{\lambda_1 - \lambda_2} \right) \right\}}{v_B^\beta \left\{ \left( \frac{\lambda_1^\beta - \lambda_2^\beta}{\lambda_1 - \lambda_2} \right) + \frac{1}{2} \beta (1 - \beta) \frac{1}{M} \left( \frac{(\lambda_1^\beta - \lambda_2^\beta) + (\lambda_2^{\beta-1} - \lambda_1^{\beta-1})}{\lambda_1 - \lambda_2} \right) \right\}} = \left[ \frac{v_A}{v_B} \right]^\beta \quad (10)$$

$\gamma > 1$  for  $v_A > v_B$ . The rationale of the result is that the expected utility and the variance of a transaction are larger for the high-value product A than for the low-value product B, which allows a larger impact on sellers' satisfactory transaction probability. As such, we have the following hypothesis addressing the moderating effect of product value for consumers regarding the impact of quality externality of social networks on price dispersion:

*H5: Other things being fixed, having a higher satisfactory transaction probability allows a seller to charge higher price premium. As such, the impact of quality externality of social network on price dispersion is more salient for higher-valued products.*

### 3. Empirical Analysis

#### 3.1 Online Market and product selection

We select eBay auction market as the e-market to conduct our empirical analysis. This selection is based on the following important consideration: 1) eBay enforces accurate registrations and hence the feedbacks generated by all operations held by a specific account. This is different from other retailer evaluations reported at shopbots (e.g., epinion.com, Bizrate.com etc.) in which the shopbots only report the results of those who want to complete the evaluation form which often contains the "promotional chat" from marketers (Mayzlin, 2006). 2) eBay auctions are a proper mechanism to reveal demand properties. The supply is fixed (completely inelastic) and consumer bids reveal their willingness to pay since eBay auctions are English auctions and winning bids fully reveal the second highest willingness to pay. 3) eBay Scores or Reputation Mechanisms about sellers, create good proxies for network sizes and satisfaction transaction probability assessment with sufficient variations allowing credible estimations.

We collected two samples of eBay auctions with two considerations. First, product value for consumers, which is operationalized on the total costs consumers incur to acquire the products: product price and product purchase involvement (i.e. the opportunity cost of the time involved in searching, learning, comparing among products and sellers). As such, the low price and

low involvement products are taken as low-value products whereas the high price and high involvement products are taken as high-value products. Second, estimation appropriateness, which is operationalized on selecting products in which products exhibit little differentiation across auctions to minimize the impact of product differentiation on price dispersion and are highly traded to assure a good sample size to minimize the impact on price dispersion of sample bias and errors.

### 3.2 Model Specification

To test our hypotheses, we consider a simple linear specification

$$P_j - \text{Min}(P_j) = \beta_o + \beta_1 \log(N_j) + \beta_2 r_j + u_j \quad (11)$$

where  $P_j$  is the price,  $N_j$  is the quantity externality of social network (i.e., network size) and  $r_j$  is the quality externality of social network (i.e., satisfactory transaction probability) for e-retailer  $j$ , and  $u_j$  is random error with  $E[u_j] = 0$ , constant variance and null serial correlation between any pair of auctions. This specification is appropriate because the dependent variable is exactly the price premium that is commanded by seller  $j$ . A log-linear relationship between price premiums and with network size was assumed to allow for the marginal diminishing effect of network sizes. The model allows other controlling variables such as the end day and hour of the auction, which are omitted for the sake of notation simplicity.

Other alternative specifications such as using the logarithm of the price premium or the traditional double-log specification in most hedonic prices applications<sup>5</sup> can also be applied. However, the rate of change of price premiums to changes in network sizes and satisfactory transaction probability are highly non-linear and depend on the actual values of the variables involved. As such, these alternative specifications make it harder to statically test the hypotheses and are not considered further.

Consider two sellers  $j$  and  $k$  with  $N_j \geq N_k$  and  $r_j \geq r_k$ , then subtracting  $P_k - \text{Min}(P_j)$  from equation (11):

$$E[P_j - P_k] = \beta_1 (\log N_j - \log N_k) + \beta_2 (r_j - r_k) \quad (12)$$

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<sup>5</sup> Specifically the variants are  $\text{Log}(P_j - \text{Min}(P_j)) = \beta_o + \beta_1 \log(N_j) + \beta_2 r_j + u_j$  and  $\text{Log}(P_j) = \beta_o + \beta_1 \log(N_j) + \beta_2 r_j + u_j$

Thus, other things being fixed, the higher the difference in social network sizes, the higher the price premium seller  $j$  can charge above seller  $k$ , as long as  $\beta_1 > 0$  (H1). By the same token, other things being fixed, the higher the difference in the satisfactory transaction probability, the higher the price premium seller  $j$  can charge above seller  $k$ , as long as  $\beta_2 > 0$  (H3).

To examine H2, it is necessary to form the rate of change of price premiums to network sizes. For simplicity, assume both sellers have equal satisfactory transaction probability, differing only in the network sizes. By definition, the rate of change of price premiums to network sizes is:

$$\mu = \frac{E[P_j - P_k]}{N_j - N_k} = \frac{\beta_1(\log N_j - \log N_k)}{N_j - N_k} \quad (13)$$

Take the first derivative of the rate of change of price premiums respect the Network size of the e-retailer  $j$ :

$$\frac{\partial \mu}{\partial N_j} = \frac{\beta_1 \left[ \frac{(N_j - N_k) - (\log N_j - \log N_k)}{N_j} \right]}{(N_j - N_k)^2} = \frac{\beta_1}{(N_j - N_k)^2} \left[ \left( 1 - \frac{N_k}{N_j} \right) - \log \frac{N_k}{N_j} \right] \quad (14)$$

Let  $\Delta(x) = 1 - \frac{N_k}{N_j} - \log \frac{N_j}{N_k} = 1 - x + \log x$ , where  $x = \frac{N_k}{N_j}$  with  $x \in (0,1)$ .

Obviously  $\Delta(1) = 1 - 1 + 0 = 0$ , since  $\frac{\partial \Delta(x)}{\partial x} = -1 + \frac{1}{x} \geq 0$  for  $x \in (0,1)$ , thus

$\Delta(x)$  is an increasing function of  $x$ , i.e.  $\Delta(x) \leq \Delta(1) = 0$  for  $x \in (0,1)$ . Thus, as long as  $\beta_1 > 0$ , we must have  $\frac{\partial \mu}{\partial N_j} < 0$ , i.e.  $\mu$  is a decreasing function of

$N_j$ , which is H2.

H4 and H5 involve the moderating effects of product value for consumers on the impacts of quantity externality and quality externality of social network on price dispersion respectively. Holding constant the network sizes of sellers  $j$  and  $k$  across the product H (high-value) and product L (low-value), equation (13) gives the ratio of the two product rates of change as:

$$\frac{\mu_H}{\mu_L} = \frac{\beta_{1H} \left( \frac{\log N_j - \log N_k}{N_j - N_k} \right)}{\beta_{1L} \left( \frac{\log N_j - \log N_k}{N_j - N_k} \right)} = \frac{\beta_{1H}}{\beta_{1L}} \quad (15)$$

Thus, to be consistent with H4,  $\beta_{1H} > \beta_{1L}$  is required. Similarly, the ratio between the rates of change regarding the satisfactory transaction probability is:

$$\frac{\left( \frac{E[P_{jH} - P_{kH}]}{(r_j - r_k)} \right)}{\left( \frac{E[P_{jL} - P_{kL}]}{(r_j - r_k)} \right)} = \frac{\beta_{2H}}{\beta_{2L}} \quad (16)$$

Hence, in order to be consistent with H5, it is necessary that  $\beta_{2H} > \beta_{2L}$ .

In conclusion, estimations are consistent with the hypotheses H1-H5 if the coefficients of network size and the satisfactory transaction probability are 1) both positive and 2) respectively larger for high-value product than for low-value product.

### *3.3 Description of the products and samples*

We choose the popular T.V. show “Lost” DVD box sets as the low value product. We restrict our product to the 2<sup>nd</sup> season and new sets only. We selected the 4 GB Blue Apple Nano iPod as the high value product. Again, we restrict our product to the new product and in blue color, since it was the most popular by that time, only. Data collection timing is the only different attribute among auctions in these two samples. The TV show sample was collected in October 2006 and April 2007 while the iPod sample was collected in November 2006, January and February 2007.

The TV show sample consisted of 415 auctions. The average final price bid of these auctions was \$27.2 with a standard deviation of \$5.2, meaning a variation coefficient of 19.1%.

The quantity externality of social network for a seller is measured by the seller’s total transactions. Its frequency distribution is asymmetrical, with a long tail to the right, suggesting that few suppliers have high network sizes. The mean of the distribution is close to six thousand transactions but its standard deviation is three times larger than the mean. The quality externality of social network is measured by the ratio of positive customer’s opinions in total transactions. This reputation score is high and shows small dispersions towards the mean. For the TV show sample the mean of positive opinions is 0.99 with a standard deviation of 0.01. The apparent overestimation of the quality of sellers is a stylized fact of eBay’s reputation system that has been discussed in Resnick and Zeckhauser (2002). One explanation is that eBay allows sellers and buyers to leave feedbacks for

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each other for a single auction. As such, buyers may not report negative feedbacks for fear of retaliation (Avery et al, 1999).

The Apple 4 GB Nano iPod sample consists of 147 auctions. The mean price of this equipment was \$183 with a standard deviation of \$19.2 (10.5% of the mean). The quantity externality of social network mean is around two thousand transactions with a large standard deviation equal to 1.5 times of the mean. As in the case of the low value product, the distribution has a salient positive skew. The quality externality of social network is 0.99 with a standard deviation of 0.01. The descriptive statistics of both samples are shown in Table 1.

Table 1  
Descriptive Statistics of the eBay Data Set

		Mean	Std. Deviation
<i>The TV Show Sample</i>			
<b>Control Variables</b>			
	April	0.7133	0.4528
<b>Prices</b>			
	Final Bid Price	27.24	5.24*
	Price Premium	17.29	5.24*
<b>Social Network Externality</b>			
	Quantity	5799.88	16286.2
	Quality	0.9953	0.0116
<i>The Ipod Sample</i>			
<b>Control Variables</b>			
	January	0.2517	0.4355
	February	0.0884	0.2849
<b>Prices</b>			
	Final Bid Price	182.99	19.21*
	Price Premium	87.99	19.21*
<b>Social Network Externality</b>			
	Quantity	2009	3043.84
	Quality	0.9948	0.0118

\*The standard deviations of final bid price and price premium are necessary identical by construction.

### 3.4 Estimation

Since products are homogeneous, there is no control variable for product differentiation. However, to further control the time difference of the samples, we specify time dummies in model estimations.

Table 2 present the ordinary least squares (OLS) estimations of the model (11) for each of the samples separately with the month dummy variables.

The simple linear model fits both samples reasonably well, with goodness-of-fit 0.20 for the TV Show sample and 0.54 for the iPod sample respectively. In both cases, the control variable coefficients for the months are significant at 0.01. The results suggest that the price of second season of the TV Show was \$5.21 lower in April 2007 compared with October 2006. A similar decreasing price trend occurs in the case of the iPods. Prices were \$21.30 lower in January 2007 than in November 2006 and \$24.73 lower in February 2007 than in November 2006. The coefficients of quantity and quality of social network externalities are both positive and significant at 0.01, which suggest that our hypotheses H1, H2, and H3 are again strongly supported.

Table 2  
**OLS Estimation of Price Premiums Equation**

		Coefficient	Std. Error
<i>The TV Show Sample</i>			
<b>Control Variables</b>			
	Constant	-25.53	19.92
	April	-5.21**	0.52
<b>Social Network Externality</b>			
	Quantity $\beta_{1L}$	0.31**	0.1
	Quality $\beta_{2L}$	44.81*	20.03
<b>Goodness-of-Fit</b>			
	R-Square	0.2	
<i>The Ipod Sample</i>			
<b>Control Variables</b>			
	Constant	-176.33	92.68
	January	-21.3**	2.71
	February	-24.73**	4.05
<b>Social Network Externality</b>			
	Quantity $\beta_{1H}$	2.97**	0.57
<b>Goodness-of-Fit</b>			
	R-Square	0.54	

\* Significant at 0.05

\*\* Significant at 0.01

Similarly, a direct observation again shows the face validity of H4 and H5. For example, the seller's social network coefficient of the iPod sample is 9.6

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times (2.97:0.31) the TV show DVD box set coefficient. In addition, every 10% increase on the satisfactory transaction probability for a seller would allow the seller to charge just \$4.45 more for the TV Show ( $44.81 \cdot 0.10$ ) and \$25.47 more for the iPod ( $254.74 \cdot 0.1$ ).

In order to test H4 and H5 directly, a system of equations is employed. We use two approaches: Pooling regression and Seemingly Unrelated Relationships (SUR) Method to control any possible correlation between the residuals for low and high value auctions occasioned by unobserved common factors to all eBay auctions.

The pooled OLS estimates are reported in the first two columns of Table 3. Again, the coefficients of control variables resemble those in the individual sample estimation. The coefficients of quantity externality and quality externality are both positive and significant for the TV Show sample, confirming our hypotheses H1, H2, and H3. Moreover, the estimates show that the impact of quantity externality is more than ten times larger for the iPod sample than for the TV Show sample, and the impact of quality externality is 70% larger for the iPod sample than for the TV Show sample.

The Wald test for the moderating effect on the impact of quantity externality is 50.26, which is significant at 0.01. The Wald test for the moderating effect on the impact of quality externality is 465.47 which is also significant at 0.01. Both tests confirm that the coefficients of quantity and quality externality are indeed larger for the high-value product than that for the low-value product (H4 and H5).

We present the SUR estimates in the final two columns of Table 3. Similar to the pooled OLS estimates, all coefficients are significant at 0.01, and have the expected signs. The magnitudes of the estimates are similar to those of pooled OLS estimates as well. The coefficients of quantity externality are 0.31 and 3 for the low-value and high-value samples respectively, rendering a ratio of approximately 1:10 across samples. The ratio of the quality externality coefficients is 1:2.12 across samples. As the coefficients of both quality and quantity externalities are positive and significant at 0.01, hypotheses H1, H2 and H3 are again supported. The Wald  $\chi^2$  statistic for testing H4 is 22.18 with a  $p < 0.01$ , suggesting that quantity externality is larger for the high value product. The Wald  $\chi^2$  statistic for testing H5 is 200.36, significant at 0.01. Therefore, H5 is strongly supported. In summary, the results suggest that our hypotheses H1 – H5 are strongly supported empirically.

Table 3  
**Pooling and SUR Estimations of Price Premiums Equation**

	Pooled Method		SUR Method	
	Coefficient	Std. Error	Coefficient	Std. Error
<b>Control Variables</b>				
Constant	-66.08*	28.56	-32.5	19.47
April	-5.3**	0.88	-5.23**	0.52
January	-21.27**	1.61	-21.17**	2.68
February	-24.34**	2.4	-24.24**	3.98
<b>Social Network Externality</b>				
Quantity $\beta_{1L}$	0.32*	0.16	0.31**	0.1
Quality $\beta_{2L}$	85.55**	28.71	51.82**	19.57
Quantity $\beta_{1H}$	2.98**	0.34	3.01**	0.56
Quality $\beta_{2H}$	143.81**	28.84	109.87**	20
<b>Goodness-of-Fit</b>				
R-Square (TV Show)	0.2		0.2	
R-Square (Ipod)	0.54		0.53	

\* Significant at 0.05

\*\* Significant at 0.01

### Conclusions

In this research, we attempted to understand the impact of social network externalities on price dispersion in online markets. Buying in the Internet market often involves risks in both space and time: 1) a delayed time between the time consumer pays and the time he or she receives the order (Will I get my product at all? Will I get my product at the expected date?), and 2) the product and the consumers are spatially separated so that a careful product check is often impossible (Will I get what I wanted?)<sup>6</sup> As such,

<sup>6</sup> Degeratu et al, 2000.

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consumers rely on online social interaction such as word-of-mouth, recommendations etc. to reduce the associated risk in their purchase decision making. The heterogeneity of degree of risk reduction results in heterogeneity of price premium paid by consumers, which attributes to the price dispersion in online markets.

In the demand model consumers are uncertain about whether the e-vendors can make a satisfactory transaction. Consumers are risk averse and they try to assess the probability of satisfactory transaction of the web sites through interaction with other e-shoppers. Social network externalities operate through the assessment process in two different ways: the quality externality anchors the location of the assessment and the quantity externality reduces the variance of the assessment. Consumers are willing to pay a higher price premium for those sellers who exhibit higher quality externality as well as higher quantity externality at a diminishing way. However, such willingness to pay is likely to exhibit asymmetric effect for some moderating factors such as consumer product value. The salience of social network externality effect is higher for purchase behavior in higher value product categories, particularly so for the salience of quality externality of social networks.

Our demand model suggests five hypotheses on price dispersion. We tested these five hypotheses using data collected from two products in auction market at eBay: a low value product (the DVD box set of a TV show) and a high-value product (an Apple iPod). We employed three different econometric methods (OLS, Pooled OLS, and SUR) to conduct the testing. The hypotheses are well supported across both products and methods employed.

The salience of quantity externality of social network is statistically significant, but its impact seems to be small. There might be several possibilities to explain the small empirical quantity externality effects in online markets. First, social network advantages may disappear rapidly as the quantity externality grows, a typical diminishing marginal return situation frequently observed in any market. If our empirical observations on network size go beyond a certain threshold, the point estimate of the impact is small. Second, there may be omission of relevant variables. For example, if some type of scale economies are present, making big retailers bear low unit costs (scale and scope economies are rather common facts in retailing), then the absence of a proxy for the unit cost (which is negatively correlated with the quantity externality) underestimates the true quantity externality effect. Future research is needed to investigate these possibilities.

Our research can be extended in several dimensions. First, we may want to test our theory longitudinally across vendors. That is, collecting a sample of

the auctions in which specific e-retailers have participated and then exploring the gains vendors enjoy as their network size increases. Second, we may want to extend our study across country markets. Social network externality may have different impacts in different cultures. Finally, our model posits some interesting propositions regarding the level of risk aversion of consumers. Indeed, if we allow for consumer heterogeneity in the risk aversion dimension we should find a negative price premium for risk lovers and a null premium for risk neutral ones. These predictions can be explored using experiments and non-experimental data.

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