Designing a Social Network Based Electronic Market: Trust, Incentives and Welfare

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Abstract

Using the design science approach we conceptualize a novel IT artifact that embeds a digital social network in an electronic market. We show the buyer's benefit from embedding a social network into marketplace design from reduced search costs, better product fit and lower trading risks. Sellers benefit from the transferability of reputation they may possess in the physical world that the embedded social network facilitates, from a wider range of methods for monetizing established electronic reputation, and may also use the social network to build and compete for buyer loyalty or to cross-sell complementary products. The design we propose is robust, unique, and includes a design of an incentive system that makes such transfers viable, and which is simple enough to implement. We test our design by simulating the seller side social network features and fixing buyer utility based on a lexicographical preference ordering scheme. We find that while giving cash back to the social network lead to more revenue, there comes a point at which it adversely impacts profits. These findings point to several new directions for future analytical and empirical research.

1. Introduction and Motivation

Electronic markets like eBay and Amazon.com account for a significant and growing fraction of commerce in the United States today. Similar electronic marketplaces are emerging in other countries as well, often designed in a manner very similar to these U.S.-based leaders. Each such market generally features an electronic reputation system [Dellarocas (2003), Zeckhauser and Resnick (2002)] which aggregates feedback provided by buyers into an average "score" for each of the market's sellers. In parallel, a number of Internet-based social networking sites like LinkedIn, MySpace and Orkut have grown in popularity over the last couple of years. While many of these sites have millions of members, their current business models rely on revenue obtained from displayed or keyword advertising, and although they have the potential to be rich platforms for commerce, there are no clear designs or models that can guide them in this transition.

In this paper, we use the design science approach [Hevner et al. (2004)] to conceptualize a novel IT artifact, a *social-network based electronic market* (hereafter SNEM) that combines elements of existing marketplaces and social networking sites towards creating what we believe will be a more efficient electronic marketplace design. Briefly, we provide a technical context level view of the external entities and their interactions with the proposed IT artifact, we discuss the benefits that our design can have for both buyers and sellers in an electronic market, and we motivate why an appropriate consideration of incentives needs to be integrated into the design of such an IT-based market. We then test whether the benefits we expect from our design do in fact emerge by running a discrete-event simulation, and using the data it generates to test how key elements of our design affect outcomes in the marketplace.

Our work is motivated by two intuitive observations. First, it is widely accepted that shopping, or buying and selling, is inherently a social activity. Traditional non-digital shopping activity relies heavily on social and tacit information that is transmitted primarily through individuals' local networks of friends and family. Yet, none of the existing large scale digital electronic market platforms are designed from the ground-up to capture, disseminate, and crucially, provide the necessary incentives for sustaining social network activity. Second, as mentioned earlier, despite increasing activity on relationship oriented social networks such as MySpace, and nascent but growing interest on the part of firms, such as Nike's Joga.com for example, in developing their own social networks, it is not clear whether and how such activity can be monetized.

Before we discuss the proposed merits of our approach, we describe how a typical transaction would occur in SNEM, and how it differs from existing electronic market implementations such as eBay and Amazon.

1.1 A Typical SNEM Transaction

Consider the stylized case of a registered[1] buyer *A* entering the SNEM website with a broad objective of buying, say, a "good digital camera." We ask the reader's indulgence here to ignore the significance of actual parameter values, such as the commission levels and active trading period, used in this stylized example. Note that phrases in bold are SNEM constructs, the design of which we discuss later in the paper.

1 The system recognizes the buyer through a cookie, or alternatively she logs in.

We also deal with how these values are set later in the paper. For now, let's imagine buyer *A's* experience with SNEM.

The process gets initiated by either by a search or a menu drill down, at which stage there are several options of digital cameras to choose from. In the design we propose the embedded social network would facilitate a search for friends or relatives of the buyer who may have bought a digital camera in the near past. Assume A's friend *Alpha* shows up as having bought a product in the category of digital cameras in the last month. SNEM will prompt *A* to find out whether she would like to discuss the product's features with *Alpha*, who may or may not respond. Assume *Alpha* does not immediately respond, so *A* continues her search, and finds a system generated top-selling product that she likes. Let's call this product *DC1*. In making her product choice decision she is influenced by a detailed product review by an expert, say *B*. Assume there are 17 different sellers, each with their ratings on a 0-5 scale, selling *DC1* using a mix of posted-price and online auction formats. Assume that it turns out that of these 17, there is one that is a new seller (called *SNew*), who is known to *Beta*, a close friend of *A*. It turns out that just last week, *Beta* bought the same product from *SNew*, and is happy with the product and the transaction. Thus *Beta* is a part of *SNew's* **trading network**. SNEM connects *A* with *Beta* who 'vouches' for *SNew*. Buyer A prefers to work with *SNew* even though there were other higher ranked sellers in play. At the time of checkout, SNEM queries *A* about whether *Alpha, Beta* and B, the professional review writer, were helpful in her decision making. She confirms that *Alpha* was not, but B and *Beta* were. The system designates 1% of it's commission, to be split between *B* and *Beta*, as a part of the **buyer's network cash back incentive**.

Both buyer *A* and seller *SNew* rate each other favorably after the transaction. *SNew* invites A to be a part of her **trading network**. In the next one month, whenever *SNew* sells again to any other buyer, SNEM the system will designate 1% of its commission to be proportionally split between all active members of *SNew's* trading network. Realizing that this is a powerful loyalty-inducing tool, and noting that its competitor *SOld* has a significant market share, *SNew* adds a further 1% **seller network cash back** to compete for the buyer's loyalty.

Two months later *SOld* figures *SNew* is here to play and agree to cross-list products, generate recommendations that get commissions when acted upon, and *SOld* even goes to the extent of **transferring his reputation** to *SNew* by "vouching" for *SNew's* credibility. This causes a sharp increase in *SNew's* feedback rating. By playing according to the rules, and providing buyer's a good product *SNew* is quickly able to get at par with older sellers, who do not feel threatened as long as they benefit from the business *SNew* sends to them.

1.2 SNEM's Theorized Benefits

As is evident from the stylized example above, SNEM's objective is to weave together the formation of trust, the alignment of incentives and monetization of market and non-market activities (such as product reviewing). To achieve this it needs a strong theoretical basis. The theorized welfare benefits of an SNEM are quite intuitive. A key design construct facilitated by combining a social network with an electronic market is that it enables, in the digital world, the sort of reputation and trust transfers that otherwise occur naturally in the physical world. This permits sellers who are new to the electronic market but have existing reputations in the *physical* world to enter the electronic market with reputation levels that are comparable to those they possess offline, provided someone with an established reputation in the electronic market and whom they know is willing to vouch for them. A second (ancillary) benefit of our design is that it allows a seller who establishes a positive reputation in the electronic market to monetize this reputation in ways that go beyond simply being able to charge a higher price for its products. This increases the incentive that a seller has to perform its fulfillment and other intangible aspects of its transaction well, thereby increasing marketplace welfare. It also makes the seller more likely to educate new entrants about the tacit aspects of successful electronic market transactions. A third benefit to sellers from our SNEM design is that provides a natural structure for network based loyalty programs, the kind lacking in current electronic market implementations.

For a buyer, a social network based electronic market can have two benefits. First, it can provide the buyer with superior information about products purchased by other buyers, thereby reducing search costs, or alternatively, increasing the "fit" that a product purchased by the buyer has with his or her preferences. Second, it can significantly reduce the trading risks faced by a buyer, relative to existing electronic market designs, by providing the buyer with superior information about the actual effectiveness a seller will have in fulfilling a transaction with a buyer. This information might be obtained from a known buyer who has transacted with this seller in the past, or through a reputation transfer from another seller.

While these benefits are indeed potentially substantial, the SNEM design needs to ensure that the transfers of reputation and payment made across agents are done appropriately. For many of the same reasons that pricing of Internet services [Gupta et al.

1997] are intimately linked to performance guarantees and return on investment, economic market-based incentive alignment and pricing will be critical for social networks to become commercially viable and sustainable. If a seller can simply vouch for any other new seller with no cost in the event of an adverse outcome (or benefit in the case of a positive outcome), it is clear that this “vote of confidence” may not be relied on by buyers (or may not be given at all).

Motivated by the third dimension of information systems design in Ba, Stallaert, and Whinston (2001), and given our electronic market context, we treat the system’s external entities as boundedly rational economic agents [Simon (1990)] whose incentives have to be aligned appropriately for the smooth functioning of the market. We expect our incentive driven design science approach towards formalizing a SNEM to provide key insights into monetizing a variety of social network types. We incorporate this incentive alignment into our design in a manner that is simple and implementable, rather than seeking the globally optimal mechanism for incentive alignment, which might represent an interesting direction for future research. This paper is an initial foray into conceiving and calibrating a large scale field experiment with real buyers and sellers partaking in real economic activity in an actual implementation of our social network based electronic market design.

The specific research questions we address are:

a) How can a social network be meaningfully designed to maximize the welfare of an electronic market setting? Critical to this would be the understanding of:

- The network’s growth and propagation process, and

- The relationship between the social structure (size, location and position of actors) and informational and monetary flows

b) Does the social network play a role in:

- Reducing friction in the marketplace,
- Accelerating growth of the marketplace,
- Inducing market and seller loyalty

c) What measurable impact does the social network have on the market's performance in terms of revenue and social welfare, and on the individual agents' surplus?

2. Background

A wide body of literature suggests that individuals benefit from the social capital [Coleman (1988), Putnam (2000)] that accrues to them from people they know and with whom they are networked with. Feick and Price (1987) find that consumers benefit from research of friends and family. Jaffe et al. (1993) examine patent citations in the contexy of industry innovation and find that the spread of information is often local and thus can depend on social networks and the geography of trade. Mobius and Szeidl (2006) coin the term "social collateral" to capture the trust that is created by the relationships implicit in a social network, a key notion for this paper. They also point out the role of social networks in distributing trust is even more influential in societies where formal contract enforcement is missing or imperfect. Internet usage is rapidly growing in countries like China and India[2], with millions of new users coming online to surf, buy and sell every

2 As of Dec 2005 http://www.internetworldstats.com/asia.htm reports that there are 111,000,000 Internet users in China and 50,600,000 Internet users in India. These numbers correspond to 9.4% and 4.5% percent

year. While both countries have vastly different contract laws, they share the common trait of missing or inadequate contract enforcement.

Even in more Internet-savvy regions such as Europe and North America, the nature of online commerce is such that a cloak of anonymity still shrouds many ecommerce transactions. Dellarocas (2003) and Resnick and Zeckhauser (2002) demonstrate the importance of eBay's voluntary and user driven feedback mechanism towards eliciting good behavior and cooperation among loosely connected and geographically dispersed economic agents. The digital and anonymous nature of these interactions obscures many post-transaction details from the electronic markets view. In fact, Dellarocas and Wood (2006) point out that voluntary self-reporting opens the door to several forms of reporting bias. On eBay often the threat of retaliatory behavior induces participants to strategically misreport or in some cases not report outcomes. Their study indicates that if reporting bias is severe enough, posted feedback provides a distorted view of the risks that are associated with trading in a given market. Our study is motivated in part by these deficiencies in existing reputation systems, since such systems are central to the viability and future effectiveness of electronic markets.

An aspect of current electronic market implementation that is often ignored is that they are not designed to optimize entry, or the seamless introduction of new buyers and sellers into the market. Klemperer (1999) argues that attracting entry is a pillar of good market design. While a wide variety of studies [Ba and Pavlou (2002), Cabral and Hortascu (2005), Ghose, Ipeirotis and Sundararajan (2006)] have shown that reputed sellers attract price premiums, the literature has largely ignored the challenges faced by

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penetration of the population. By way of contrast the same website estimates the total number of users in North AmericaNorth Americato be 227,470,713 reflecting 68.6% population penetration.

new sellers, many of whom already have existing reputations in the physical world, who are either forced to enter electronic markets with no reputation, or who may simply be deterred from entering on account of the lack of transferability of their physical world reputation. Our study conjectures and shows that a digital social network can help mitigate the welfare losses that may be ensuing due to suboptimal entry levels, by facilitating the transferring of reputations that exist in the physical world to the digital world. We expect that by virtue of our SNEM based reputation transfer mechanism, the realized electronic seller reputation will be closer to the actual seller reputation (or the actual capabilities the seller has in fulfilling transactions effectively), relative to other electronic markets that do not use our design.

A further limitation of current electronic market implementations is that they do not provide a platform for sellers to compete on building loyalty. When a buyer searches in a marketplace like eBay for a given product, the system does not 'connect the dots' from a social network perspective. That is, the system is not designed to point out whether there exist sellers in the mix that the buyer herself may have transacted with directly, or sellers who have transacted with people who the buyer knows personally (who are one degree away in the buyer's personal network). Similarly, social capital is not leveraged in electronic markets for finding products amongst a category of products, or for finding related and complementary products and sellers. Yet, in the physical world, it is long established that social capital as defined by Coleman (1990), by virtue or providing trust between two selfish individuals, generates rents to both the agent investing in social links to others as well as to agents connected to her. These findings have been confirmed empirically in the physical world. DiMaggio and Louch (1998), building on the early theoretical work of Katz and Lazarsfeld (1955), find that people who transact with friends and relatives report greater satisfaction with the results than do people who transact with strangers, especially for risk-laden exchanges. Such social capital is clearly valuable in the anonymous world of digital transactions, especially given the international variation in contract law enforcement and contractual completeness, and yet the utilization of social capital in electronic markets is lacking in theoretical practice and practical implementations. Of course, in order to be effectively utilized, the marketplace must be constructed in a manner that recognizes its existence and incorporates it into it's design. This motivates our pursuing a design science based approach towards studying a social network based electronic market.

We have organized the rest of this paper as follows. In the next section we present the design science view of the proposed SNEM. In Section 4 we discuss the issues of incentive alignment and outline some theoretical predictions. Section 5 reports on a discrete-event simulation whose data computationally validates our theoretical propositions. We conclude in Section 6 by presenting directions for future research.

3. A Design Science View of SNEM

3.1 Designing the IT Artifact

As per Hevner et al. (2004) the first step in pursuing the design science approach is to design an IT artifact. Our social network based electronic market is a combination of two IT artifacts, digital social networks and electronic markets, each of which is independently growing in importance. Consider a market operator who is designing, from scratch, a trading platform that provides incentives to attract buyers, sellers and other

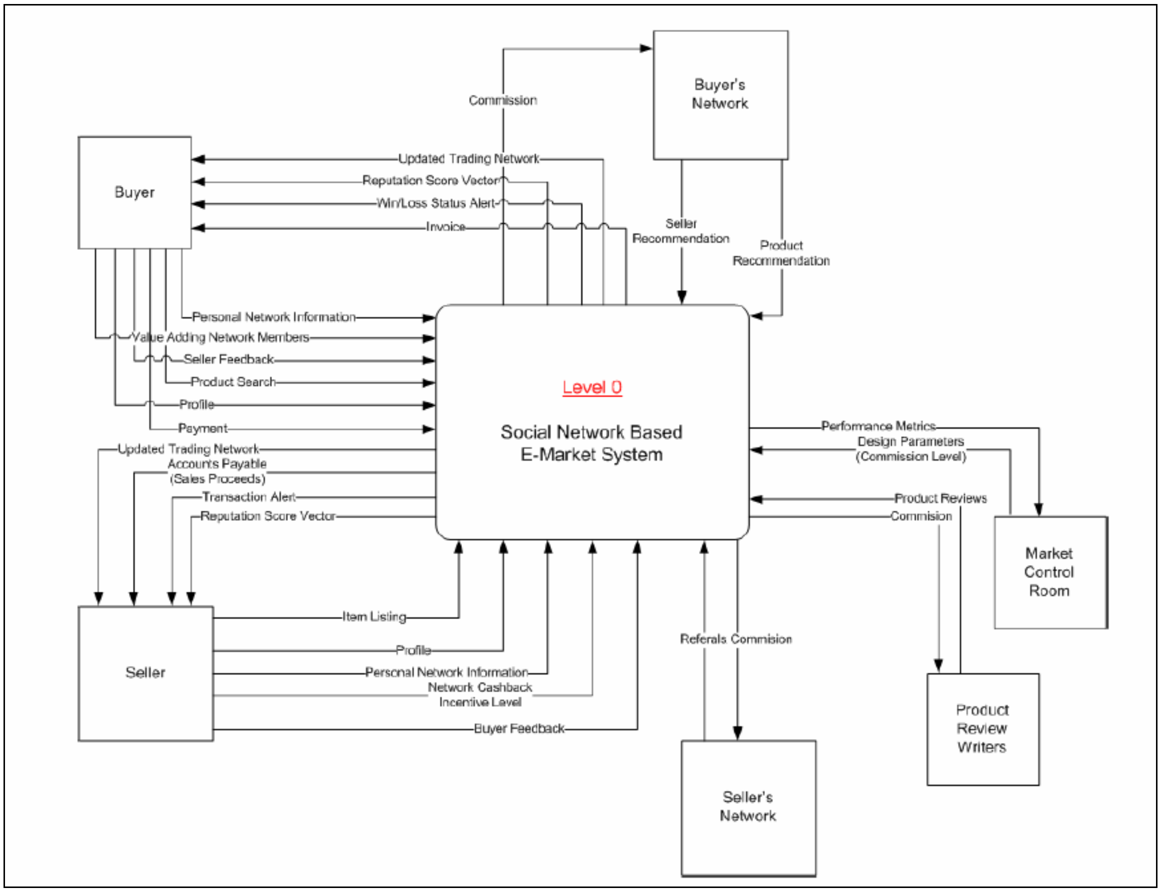

Figure 1 – Context Diagram of a Social Network Based Electronic Market

friction reducing agents such as review writers or product rating specialists to enhance the welfare generated by the electronic market. Using the principles of structured systems analysis and design [Whitten and Bentley (1997)] we present following context diagram to provide a bird's eye view of our proposed design.

From the perspective of the system there are five external entities. On the surface buyers and sellers have their traditional roles that they currently perform in electronic markets. Sellers post items for sale, choose their selling partners, and provide transaction feedback after the transaction is over. Buyers search for products, bid on auctions or accept posted prices, pay the seller either electronically or offline, and rate the seller. In addition to these activities, similar to sites such as LinkedIn.com, SNEM encourages market participants to invite their friends and relatives to join SNEM. Based on the seminal work of Granovetter (1974), we limit our attention to a relatively “small circle of trust” that is empirically shown to matter. Granovetter (1974), in the context of friends recommending friends in the labor market, demonstrated that the circle of trust typically involves no more that three intermediaries. In our first design of the SNEM, we *limit* the reach of the buyer and seller network in potentially impacting a market transaction *to one degree*.

Definition 1: Personal Network Links –Social network links created by a user, who invites her friends and relatives, are defined to constitute a user’s personal network. In addition, as buyers trade with sellers, and both parties are not negative about the transaction, both parties will have the option of including each other as a part of their trading networks.

Definition 2: Trading Network Links –A buyer who has transacted with a given seller, upon both parties reporting non-negative feedback, can include each other in their trading network. Social network links created by users based on non-negative transactions with trading partners are defined to constitute a user’s trading network.

When specifying the design of the seller’s trading network, we take the perspective of a benevolent dictator [Keeney (1976)]. One purpose of the seller’s trading network is to bridge a gap in current electronic market implementations, such as eBay, by building a loyalty mechanism that also accelerates the markets growth. This requires a seller to give a percentage of the transaction revenue back to her *active* trading network. The sellers view the active trading period as an exogenously (by the market maker) set time interval, say one month. All buyers who had transacted with a given seller in the active period, and who did not post a negative feedback rating for the transaction, belong to the seller's active trading network.

> **Definition 3: Seller's Network Cash Back** –Sellers are required to provide a market determined percentage of their revenue from every transaction back to their active trading network. The distribution of such rewards is proportional to the weight of the network members' revenue contributions.

Recall that our SNEM is designed to allow seller's to utilize their social network for transferring their reputations to each other. By letting existing sellers give their "vote of confidence" to new sellers they may personally know, the design facilitates the portability of reputation from the physical world. A key design consideration here is how to make such a reputation transfer scheme incentive compatible, in that recommenders have an incentive to truthfully reveal their ratings of recommendees, and a specific incentive alignment method is embedded into our design.

Also recall that buyers benefit from their social network by reducing search costs, by increasing product fit and by mitigating trading risks. These originate from product and/or seller recommendations buyers get from their personal or trading networks. Buyer interactions, say through system based messaging, with their personal and trading networks are tracked by the system. At the time of checkout, buyers are then given the choice to deem helpful those interactions that they consider worthy. SNEM's design in Figure 1 also shows product review writers as an external entity. While a variety of studies have now examined the impact of product reviews on market performance, generally finding that more positive reviews are associated with greater sales [(Godes and Mayzlin, 2004; Dellarocas et al., 2006, Chevalier and Mayzlin, 2006)], the issue of monetizing the reviewers contributions has not yet been considered. We argue that the role of such market specialists is similar in theory to that of the buyers' network and include them in the potential beneficiaries of the buyer's network cash back.

> **Definition 4: Buyer's Cash Back Network –**. Buyers who have used the system to interact with their network members to learn more about a specific product or a seller, are given the option to tag any or all of these interactions as being helpful. The marker equally distributes a percentage of its commission to reward such helpful participants from the buyer's network. This incentive is also extended to product review writers who are deemed to be helpful by the buyer.

The following three scenarios illustrate how the social network can reduce friction and induce loyalty. Scenarios 1 and 2 show how the buyer's network can provide the buyer with superior information about products purchased by other buyers, thereby reducing search costs, or alternatively, increasing the "fit" that a product purchased by the buyer has with his or her preferences. They also show how SNEM can significantly reduce the trading risks faced by a buyer by providing the buyer with superior information about the actual effectiveness a seller will have in fulfilling a transaction with a buyer.

SCENARIO 1 - Reducing Friction Using a Buyer's Personal Network

Assume a buyer is searching for a Harry Potter book, that John Doe is the buyer's friend (in her personal network) and the seller in question is called "MagicBeans":

<u>Case A</u> – The buyer's friend bought something (not a Harry Potter book but something else) from the seller and both parties rated each other positively (negatively). The system will indicate:

"Your friend John Doe had a good (bad) transaction with seller MagicBeans six months ago. Want to talk to John about this?"

Case B (more specific connection)-- The buyer's friend bought a Harry Potter book (something very close to what the buyer is looking for) from the seller. The system should say:

"Your friend John Doe bought a similar/identical product from seller MagicBeans six months ago. The transaction went well. Want to talk to John about this?"

SCENARIO 2 - Reducing Friction Using a Buyer's Trading Network

Assume a buyer is searching for a Harry Potter book, that Harry Smith is a trading partner (in the buyer's trading network) and the seller in question is called "MagicBeans":

Case A -- The buyer's trading partner bought something (not a Harry Potter book but something else) from the seller and both parties rated each other positively (negatively). The system should say:

"Your trading partner Harry Smith had a good (bad) transaction with seller MagicBeans six months ago. Click here to talk to Harry about this?"

Or

"Your trading partner Harry Smith has placed this seller in his preferred seller list. Click here to buy from this seller."

Case B -- The buyer's trading partner bought a Harry Potter book from the seller

"Your trading partner Harry Smith bought a similar/identical product from seller MagicBeans six months ago. The transaction went well. Click here to talk to John about this?"

Or

> "Your trading partner Harry Smith has placed this seller in his preferred seller list and had bought a similar/identical product from this seller. Click here to buy from this seller."

Scenario 3 takes the seller's perspective, allowing sellers who are new to the electronic market to enter the electronic market with reputation levels that are comparable to those they possess offline, provided someone with an established reputation in the electronic market and whom they know is willing to vouch for them. It also demonstrates how our SNEM design provides a natural structure for network based loyalty programs and for the cross-selling of complementary products.

SCENARIO 3 – Transferring Reputation and Cross-Selling Using Seller's Personal or Trading Network

Case A - Someone who is part of the seller MagicBean's network (regardless of whether the seller is a part of the buyer's network), say John Smith, may be willing to "vouch" for MagicBeans by providing a referral link. The system should say:

> "SNEM member John Smith (reputation score is 5-star, the highest) has provided a referral link to seller MagicBeans. This signals John's trust in MagicBeans. Click here to buy the product based on this referral"

3.2 SNEM's Market Control Room – Parameter Design as Search

An important element of the design science approach is to build in an iterative methodology that searches for gaps between the design objectives and the observed metrics. This is the role of the *market control room* external entity in Figure 1. It takes as input the performance metrics, such as revenues, from the monitoring of the market and sets a variety of system level parameters that are in constant need of "fine tuning." We describe the role and influence of the salient parameters (underlined) next:

Market commission structure and level – Bakos (1998) points out that main function of markets are to match buyers and sellers, facilitate transactions and provide an institutional infrastructure to resolve disputes. The market has, at the minimum to recover its fixed and operating costs incurred in the process of providing the above mentioned key functions. In addition, we assume that a percentage of the market's commission will be apportioned for the buyer's network cash back incentive. These values should, in equilibrium, equate to the benefit in terms of reduced search cost and/or reduced trading risk provided to the buyer by her social network. The market will also take a part of its transaction commission and apportion it towards rewarding the seller's active trading network. The seller's network cash back incentive reward is proportional to the value that a buyer provides, which is proportional to the amount they have bought from the seller in the active period. This is a critical parameter as every time a new buyer buys from a given seller, all other buyers who have bought from the same seller get a slice of the reward, in proportion to their purchases in the seller's network. This feature is designed to induce loyalty towards a given seller. The loyalty inducing scheme is robust in that provides buyers the repurchase incentive from sellers with both small and large networks. In the former case due to higher percentage and in latter due to a higher volume of rewards. However, it is unique in that it provides an attractive tool to new sellers to grow their base, a feature lacking in current electronic market theory and practice. . By virtue of having smaller trading networks, they can be expected to give out larger individual rewards, ceterus paribus. Sellers will also be given the option of making voluntary additional cash back rewards to the buyers. While outside the scope of the market control room, this feature will ensure seller competition in attracting customers. Another important feature that is designed to help new entrants is the ability of existing sellers to transfer their reputations to new sellers.

Seller Reputation Transfer Function – There is growing body of literature that is looking at the relationship between the network structure and the level of trust engendered [see, for example, Mobius and Szeidl (2006)] as a result of the network social capital. The key question here is how much trust can be transfered to a given agent from their network neighborhood. Since we limit ourselves to one network degree of impact, we can rephrase and ask what the "optimal" transfer function is for such reputation transfers. For instance, if existing reputed sellers r_1, r_2 and r_3 are willing to transfer their reputation of 2, 3, 4 (on a 5 scale) respectively to new seller s_1, what is the appropriate functional form of f where:

$$reputation(s_1) = f\,(reputation(r_1),\ reputation(r_2),\ reputation(r_3)) \qquad (1)$$

A key factor in modeling this is to ensure that there are consequences for deviation from truth-telling. In other words, if s_1 does not fulfill his obligations as a seller and gets negative feedback from a buyer, what are the consequences of that on recommenders r_1, r_2 and r_3 ? This can be done via global or a local approach. Kandori (1992) develops a model where deviators are punished by the entire network, where Mobius and Szeidl (2006) use local enforcement. They outline three network statistics that are useful in terms of understanding a social networks trust structure. These are 1) the number of friends of an agent (the size of his neighborhood); 2) the clustering coefficient of an agent, defined as the actual number of connections among his neighbors divided by the maximum potential number of such connections; 3) the number of common friends of two agents. They find that different network structures lead to different trust levels depending on the value of the assets in question. While useful, their results do not directly apply to our setting where we are concerned with determining the optimal transfer function that determines the central node's weight accurately.

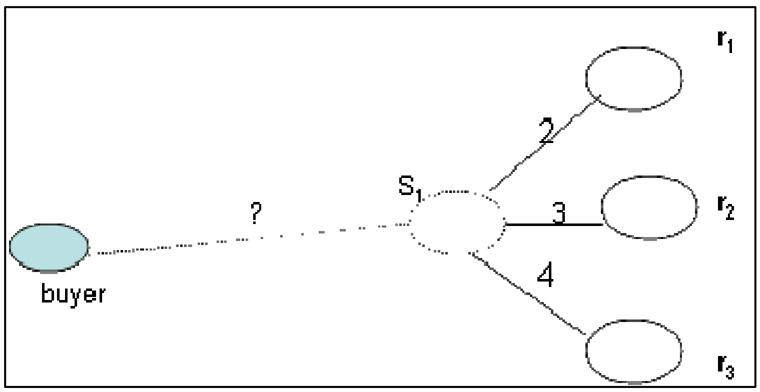

Figure 2- Three reputed sellers "vouch" for new seller s_1. What should be the level of trust between the buyer and the new seller?

Assuming that the votes are noisy, we can take a simplistic view of this transfer function for the initial design of SNEM. Assuming a uniform distribution, we can claim that the recommendation levels are all equally likely to be true and calculate s_1's reputations as a function of her base level (if such a quantity exists, zero otherwise) and random transfer component drawn from U[2, 4]. Other realizations of the transfer function could include the simple average value, or a more conservative *min* function. We expect future analytical and empirical work to pursue this line of research more extensively.

In the next section we consider the impact of SNEM on the individual agents' utilities. This helps us define our theoretical predictions about the nature of the market. In Section 4, we simulate SNEM and test the impact of reputation transfers, the network structure, degree of newness, reputations, and cash back levels on the sellers' revenue and profits.

4. Utility Analysis and Design Evaluation

We begin by analyzing the buyers' utility under SNEM. It is reasonable to assume that

$$\textit{Utility of Buyer} = g(\textit{valuation, price, search cost, risk aversion}) \quad (2)$$

Given that a buyer's valuation for an item is exogenous, keeping price constant, we can examine the impact of SNEM on the buyers search cost and trading risk. Under SNEM , buyers have their personal network and their active trading network, made up of sellers they have had positive experiences in the recent past.

A variety of empirical studies have considered and found evidence in favor of the fact that people gain information from those to whom they are socially linked [Bandiera and Rasul (2001) and Munshi (2004)]. Montgomery (1991) reviews the search patterns of employment seekers and finds that approximately 50 percent of people currently employed found their jobs through friends and relatives. Holzer (1988) analyzes similar search patterns of job seekers and finds that contacting friends and relatives generates a job offer with higher probability and is also inexpensive, compared to the methods. Based on these findings we propose that:

Proposition 1: The SNEM increases a buyer's utility by helping buyers find products that more closely match their preferences and/or finding products that they would not have otherwise found.

The first part of the proposition relies on the fact, that ceterus paribus, buyers by virtue of being able to "discuss" product features with people they know and trust can match their preferences closer than they would have otherwise. The second part of the proposition relies on the seller loyalty aspect of SNEM. By working with the same buyers over a period of time, sellers are better able to cater to their preferences by generating targeted cross-selling type recommendations from their trading network of sellers. Another source of finding products that they would not have otherwise found is through the "see what your friends are buying" feature of SNEM.

The anonymous nature of digital marketplaces introduces high levels of information asymmetry about product and seller quality. As mentioned earlier there is wide support in the literature [Ba and Pavlou (2002), Cabral and Hortascu (2005), Ghose, Ipeirotis and Sundararajan (2006)] that reputed sellers attract price premiums. While the literature has largely ignored the particular challenges faced by new sellers, it is reasonable to assume that, all else being equal, they should be worse off than existing sellers. This allows us to present our first set of hypotheses that relate the attributes of the seller at their **initial state** (original rating and whether they are new or not) to their performance (we consider both total and net profits).

H1a) – An increase in the seller's original rating has a positive impact on her performance.

H1b) – Being a new seller in the market has a negative influence on performance.

Our next set of hypotheses relate to the trust induced by the SNEM, primarily relating to performance uncertainty rather than product uncertainty [Kollock (1994)]. Product uncertainty exists when buyers are unsure about the quality of a product or service; performance uncertainty exists when buyers are unsure about a seller's future performance. According to Internet Fraud Watch, online auction fraud has consistently topped all other types of fraud since 1998. In 2005 it accounted for 42% of all reported Internet related fraud. Thus the extent to which the SNEM in building greater trust by reducing trading risks in the marketplace is paramount to validating the effectiveness of its design. To some extent, the SNEM design partially removes the anonymity that pervades the digital world, since buyers and sellers expose their actions to their network, and are rewarded monetarily for acting in their self-interest. In a sense, what is created is similar to the risk-sharing networks of Bramoullé and Kranton (2005), who and find that efficient risk-sharing networks can (indirectly) connect all individuals within a society and involve full insurance, in situations where risk mitigating insurance markets do not exist. More fundamentally, one can draw from transaction cost economics [Williamson (1985)] that social networks should be used when economic transactions involve high risk and uncertainty. SNEM's built in loyalty schemes should on average increase the frequency of within network exchanges. Thus agents can be expected to be less likely to defraud when engaged in continuing relationship. Generally, when economic exchange involves risk and uncertainty, buyers prefer to (1) transact with sellers they know, or (2) use their social networks to locate dependable and honest businesses. DiMaggio and Louch (1998) call the first strategy "within-network exchange" and the second strategy "search embeddedness." Based on these we hypothesize that the **social network structure** of a seller plays a significant role on her performance. We measure the social network structure using two variables; a) the number of sellers recommending a given seller, and b) the aggregate ratings of the recommenders voting for a given seller. These can be viewed as capturing the quality and the quantity of the seller's social network structure.

H2a) – An increase in the size of a seller's network has a positive impact on her performance.

H2b) – The magnitude of the positive impact from the seller's network is influenced by the ratings of the recommenders.

We also believe that the seller's **actions**, for instance whether she participates in loyalty inducing cash back program, influences her performance.

H3) – Seller participation in the loyalty inducing cash back program has a positive influence on performance.

It should be noted that because the SNEM allows reputation transfers, the realized electronic seller reputation will be closer to the actual seller reputation (or the actual capabilities the seller has in fulfilling transactions effectively), relative to other electronic markets that do not use our design. To summarize, we see SNEM to reduce trading risks by helping buyers find sellers that minimize trading risks, and by being able to discuss seller performance and get seller recommendations from others in their personal and trading network.

5. Testing the Design: A Discrete Event Simulation

To gain better insights into the functioning of SNEM and to test our hypothesis, we design a discrete event simulation that represents an abstraction of the SNEM. We focus our attention on the impact of the seller's network on the market's revenue and the seller's surplus, assuming that buyers' utility is determined according to a lexicographic ordinal preference scheme that we specify in the next paragraph. Recall that sellers give cash back to their trading network to foster loyalty, and also transfer their reputations and give cross-selling product recommendations to the benefit of other sellers in their network. If these treatments are to be beneficial they should either increase seller's profits or market revenues. We use a fairly general model of buyer behavior that is simple to describe, and keeping it constant in the simulation allows us to isolate the impact of the sell side SNEM features. A full blown simulation with varying buyer utility functions and seller heterogeneity in their cash back levels is beyond the scope of this paper. Therefore, we define the buyer's decision process as follows:

> **Definition 4 – Buyers lexicographic ordinal preference (BLOP)**– At any point in the simulation (and the real world market) a buyer may have to choose from many sellers selling an identical product.
>
> Step 1) A recommended seller receives a vote of one if it is recommended by highest number of recommenders, zero otherwise. If two or more receive the same high number of recommendations, everyone with the high number of recommenders receives a score of one.
>
> Step 2) The seller whose recommenders have the highest average rating receives a score of one.
>
> Step 3) The seller who has the highest individual rating receives a one.
>
> Step 4) The seller who has provided the highest amount of cashback to the buyer receives a score of one.
>
> Step 5) We then compute each sellers BLOP by aggregating the scores across these four dimensions and assume that the buyer chooses the seller with the highest BLOP among the competing sellers. Any ties are broken randomly.

Our simulated market consists of 100 products ranging in cost (to the seller) from \$106 to \$482 sold by 20 sellers. Seller ratings are distributed as follows. We assume that each seller sells 10 products and that half the sellers provide additional cash back incentives to the buyers.

	Product cost	Number of Sellers for Each Product	Number of Partners That a Seller Recommends
Mean	301.90	4.00	6.10
Standard Error	10.58	0.16	0.67
Median	309.50	4.00	6.00
Mode	357.00	4.00	10.00
Standard Deviation	105.80	1.61	3.01
Sample Variance	11193.81	2.61	9.04
Kurtosis	-0.84	-0.69	-1.07
Skewness	-0.08	0.13	-0.15
Range	376.00	6.00	9.00
Minimum	106.00	1.00	1.00
Maximum	482.00	7.00	10.00
Sum	30190.00	400.00	122.00
Count	100.00	100.00	20.00

Table 1 – Summary Statistics of the Key Simulation Parameters

In addition half the sellers in the market are considered to be new with initial rating of zero. We simulate 20 transactions per buyer. Table 1 summarizes the seller network structure, and Appendix A provides more details. We assume that products are sold at 5% premiums over cost, and that a cash back levels of 1% is used to reward recommenders. To implement the reputation transfers we assume that the revised rating of the recommended party is computed by taking the lower of the recommender rating and the recommended party rating (call it *minRR*), and adding to that a random value drawn from U[*minRR*, 5], where 5 is the maximum rating in SNEM. Transactions happen between buyers and sellers and both parties leave transaction feedback based on a probabilistic model.

Table 2 sheds light on the impact of SNEM on the evolution of seller's reputation.

Seller	Starting Rating	Ending Rating
0	0	4.499
1	0	4.501
2	0	4.496
3	0	4.499
4	0	4.497
5	4.654	4.541
6	4.701	4.544
7	3.259	3.564
8	3.903	4.137
9	4.306	4.376
10	3.402	3.842
11	4.676	4.542
12	3.672	3.897
13	4.430	4.469
14	3.287	3.721
15	0	4.497
16	0	4.48
17	0	4.498
18	0	4.498
19	0	4.496

Table 2 – Half the sellers are new to start with. Ratings range from 0 to 5. Simulation ending ratings indicate that all new sellers benefit from the network features, but some old sellers tend to drop.

It is evident that while old sellers' reputations are more or less unchanged, although in some cases they drop, the new sellers benefit significantly from the SNEM. New sellers benefit from votes of confidence they get from existing sellers, who in turn get monetary rewards for facilitating reputation transfers. Thus it is useful to see the impact of sellers' initial ratings, their social capital strength and their actions on their revenue and profits. Exploratory data analysis performed on the simulated data suggests that our data is suitable for regression modeling. We fit a regression model to the examine the impact of a) the seller's initial state, as measured by her original rating (**OrigRating)** and whether she is new **(NewSeller?)**, b) her social network structure, as represented by the number of recommender recommending her **(#Recommenders)** and their ratings **(AdjustRecRating)**, and c) by her actions, as measured by whether she gives cash back to induce loyalty to her network or not her **(CashBackProvider?)**. We rely on an exhaustive search model selection procedure and find that the following model, depicted in Table 3, and which includes two interaction terms, best explains the variation in sellers' total profit. The model's R^2 and Adjusted R^2 values are both 0.92. Note that the intercept term has no economic interpretation in a simulated setting and our estimation procedure sets it zero.

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*Lower 95.0%*	*Upper 95.0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
AdjustRecRating	4285.20	590.99	7.25	0.00	3124.51	5445.89	3124.51	5445.89
#Recommeders	-1139.77	121.02	-9.42	0.00	-1377.45	-902.09	-1377.45	-902.09
CashBackProvider?	4330.61	336.52	12.87	0.00	3669.71	4991.52	3669.71	4991.52
NewSeller?	-11826.76	2655.37	-4.45	0.00	-17041.83	-6611.68	-17041.83	-6611.68
OrigRating	9187.56	469.62	19.56	0.00	8265.25	10109.87	8265.25	10109.87
newNumRec	1500.14	157.59	9.52	0.00	1190.63	1809.65	1190.63	1809.65
newRecRating	12082.73	2249.79	5.37	0.00	7664.21	16501.25	7664.21	16501.25

Table 3 – Regression Model Explaining Variation in Sellers <u>Total Profit</u> under SNEM

All the five independent variables, as well the two interaction terms are significant. Consistent with prior literature [Ba and Pavlou (2002)] we find that the seller's original rating has a positive impact on their revenue i.e., hypothesis H1a is supported. Hypothesis H1b is also supported by the regression analysis indicating that a new seller generates lower total profits as compared to an existing seller. , With respect to the impact of a seller's social network, it is interesting to note that while getting reputation transfers from other reputed agents has a positive impact on a sellers' total profit, the density of a seller's social network adversely impacts her. In other words, while hypothesis H2b is supported, hypothesis H2a is reversed. As can be seen in Table 3, the number of recommenders has a significant negative impact on sellers' revenue, a puzzling result at first glance. One possible explanation for this is that the marginal impact of an additional recommender is diminishing, and if this were the case it should be captured in a higher order term involving the number of recommenders. Finally, the cash back scheme seems to work according to hypothesis H3 since, all else being constant, sellers are rewarded for taking part in the social network base cash back scheme and those who do provide cash back make roughly $4330 more in revenue than those who don't.

Furthermore, it is interesting to observer that the interaction term **newNumRec** has a positive sign. This can be interpreted as follows. While new sellers benefit mildy (the net positive gain is roughly $360) from an increase in the number of recommenders, existing sellers do not. The other interaction term **newRecRating** captures the interaction between new sellers and the quality of recommenders transferring their reputations to them. This has a significant and string positive influence on sellers' revenue. Therefore, the hypothesis H2a is partially supported, i.e., the new sellers do benefit from the size of their recommendation network, the existing sellers do not.

Given that some of the profits were given away as cash back by some of the sellers, the net profits figures are different from total profits. We also regressed the net profits on the same independent variables, the results from this exercise are provided in Table 4.

	Coefficients	*Standard Error*	*t Stat*	*P-value*	*Lower 95%*	*Upper 95%*	*ower 95.0%*	*pper 95.0%*
Intercept	0	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
AdjustRecRating	4098.21	420.83	9.74	0.00	3271.72	4924.70	3271.72	4924.70
#Recommeders	-507.45	86.18	-5.89	0.00	-676.70	-338.21	-676.70	-338.21
CashBackProvider?	-1686.34	239.62	-7.04	0.00	-2156.95	-1215.73	-2156.95	-1215.73
NewSeller?	-8434.82	1890.80	-4.46	0.00	-12148.30	-4721.33	-12148.30	-4721.33
OrigRating	6390.19	334.40	19.11	0.00	5733.44	7046.94	5733.44	7046.94
newNumRec	780.87	112.22	6.96	0.00	560.48	1001.26	560.48	1001.26
newRecRating	9501.39	1602.00	5.93	0.00	6355.10	12647.67	6355.10	12647.67

Table 4 – Regression Model Explaining Variation in Sellers <u>Net Profit</u> under SNEM

There is an interesting qualitative change in that the sign of the **CashBackProvider?** variable, which flips to negative. Thus, while giving cash back to the social network lead to higher total profits, there comes a point at which it adversely impacts net profits. This points to an interesting direction for future analytical work that models the buyer and seller behavior to find the optimal cash back levels. We touch upon these and other future research directions in the next section.

5. Research Contributions and Directions for Future Research

We presents a design of a new kind of electronic market, one that combines a traditional outcome-based feedback system with a social networking system which facilitates sharing both the reputation acquired from feedback as well as trust acquired from interaction that is or was external to the electronic market. This is done in a manner that is commonly seen in non-electronic interaction, whereby agents "vouch" for each others' reliability. A key aspect of making this design actually work is an appropriate incentive structure. We validate our theory and design using a discrete-event simulation that assesses the effectiveness of the incentive structure we propose -- it is also designed to be simple to implement.

Our approach has practical applicability. We expect the design science based blueprint of SNEM to be accessible to entrepreneurs interested in developing the next generation (Web 2.0) of electronic markets that leverage the power social networks to reduce friction, accelerate growth and induce loyalty, all while focusing on monetization and incentive alignment. In addition, the issues raised here will resonate with firms trying to understand how they can use digital artifacts such as social networks to meaningfully engage with their stakeholders, whether they be customers, suppliers, bloggers or shareholders. This design is likely to be implemented as a real-world market later this year.

We expect the proposed design to fuel analytical and empirical research that furthers our understanding of how electronic markets, their participants and social networks interact and evolve. We have raised a number of interesting questions regarding the optimization of the parameters used to calibrate the market's performance. Additional empirical questions arise regarding the nature and level of trust that dissipates under varying network structures and densities.

References:

1. Ba, S., and Pavlou, P., "Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior," *MIS Quarterly*, 2002, 26(3): 269-289.
2. Ba, S., Stallaert, J., and Whinston, A. B. "Introducing a third dimension in information systems design: the case for incentive alignment," *Information Systems Research* (12:3), September 2001, pp. 225-239.
3. Bakos, Y., "The Emerging Role of Electronic Marketplace on the Internet," *Communications of the ACM*, Vol. 41, No. 8, August 1998
4. Bandiera, O., Rasul, I., "Social Networks and Technology Adoption in Northern Mozambique," London School of Economics, June 2002.
5. Bapna, R., Goes, P., Gupta, A., and Jin, Y. "User Heterogeneity and Its Impact on Electronic Auction Market Design: An Empirical Exploration," *MIS Quarterly* (28:1) March 2004, pp. 21- 43.
6. Bramoullé, Y., Kranton, R., "Risk Sharing Networks," 2005, working paper of the Department of Economics, Université Laval, Québec, QC, G1K 7P4.
7. Cabral, L., and Hortacsu, A., "The Dynamics of Seller Reputation: Theory and Evidence from eBay," NYU Working Paper (June 2005).
8. Chevalier, J., D. Mayzlin, "The effect of word of mouth online: Online book reviews", *Journal of Marketing Research*, forthcoming, 2006.
9. Coleman, J., S., "Social Capital in the Creation of Human Capital," American Journal of Sociology, **94**, 1988, pp.95-120.

10. Dellarocas, C., The Digitization of Word-of-Mouth: Promise and Challenges of Online Feedback Mechanisms, *Management Science,* **49** (10), 2003, 1407-1424.

11. Dellarocas, C., and Wood, C., “The Sound of Silence in Online Feedback: Estimating Trading Risks in the Presence of Reporting Bias,” presented at the Workshop on Information Systems Economics, UC-Irvine, 2005.

12. Dellarocas, C., N. Awad, M. Zhang, “Using online ratings as a proxy of word-of-mouth in motion picture revenue forecasting”, 2006, Working Paper, University of Maryland.

13. DiMaggio, P., and Louch, H., “Socially Embedded Consumer Transactions: for what kind of Purchases do People Most Often Use Networks?,” *American Sociological Review,* **63**, 1998: 619-637

14. Feick, L., F., and Price, L., L., “The Market Maven: A Diffuser of Marketplace Information,” *Journal of Marketing*, January 1987, 51(1), pp. 83—97.

15. Ford, L., R., Fulkerson, D., R., “Maximal Flow through a Network,” *Canadian Journal of Mathematics*, 1956, pp 399-404.

16. Godes, D., D. Mayzlin, “Using online conversations to study word-of-mouth communication”, *Marketing Science* 23 (4): 545-560.

17. Ghose, A., P. Ipeirotis and A. Sundararajan, “The dimensions of reputation in electronic markets”, Working Paper, New York University.

18. Gupta, A., Stahl, D., O., and Whinston, A. B., "A Stochastic Equilibrium Model of Internet Pricing," *Journal of Economic Dynamics and Control*, **21**, 1997, 697-722.

19. Hevner, A., March, S. T., Park, J., and John, S. “Design Science Research in Information Systems,” *MIS Quarterly* (28:1) March 2004, pp. 75-105.

20. Jaffe, A., B., Trajtenberg, M., and Henderson, R., “Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations,” *Quarterly Journal of Economics*, August 1993, 108(3), pp. 577-598.

21. Kandori, M., “Social Norms and Community Enforcement,” *Review of Economic Studies*, **59**, 1992, 63-80.

22. Katz, E., and Lazarsfeld, P. F., “**Personal Influence**,” 1955, Glencoe, IL: Free Press.

23. Keeney, R., L., “A Group Preference Axiomatization with Cardinal Utility,” *Management Science*, **23**, No. 2., Oct., 1976, pp. 140-145.

24. Kollock, P., “The emergence of exchange structures: an experimental study of uncertainty, commitment, and trust,” *American Journal of Sociology*, **100**, 1994, 313–345.

25. Klemperer, P., “Auction Theory: A Guide to the Literature,” forthcoming in the *Journal of Economic Surveys*, 1999, available at www.paulklemperer.org.

26. Mobius, M., Szeidl, A., “Trust and Cooperation in Social Networks,” Harvard University and NBER UC-Berkeley working paper, 2006, available from http://....pdf

27. Montgomery, J. D., “Social Networks and Labor-Market Outcomes: Toward an Economic Analysis,” *The American Economic Review*, Vol. 81, No. 5. (Dec., 1991), pp. 1408-1418.

28. Munshi, K., “Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution,” *Journal of Development Economics*, 2004, **73**¸ pp.185-213..

29. Simon, H.A. (1990) A mechanism for social selection and successful altruism, *Science* 250 (4988): 1665-1668.

30. Whitten, J., L., Bentley, L. D., **Systems Analysis and Design Methods**, 1997, McGraw-Hill Professional

31. Williamson, O.E.,. **The Economic Institutions of Capitalism**, 1985, Free Press, NY.

32. Zeckhauser, Richard, Paul Resnick. 2002. Trust among strangers in internet transactions: Empirical analysis of ebay's reputation system. Michael Roy Baye, ed., The Economics of the Internet and E-Commerce. Elsevier Science, 127 -157.

Appendix A – Social Network Structure

Details of Recommendation SNLinks of a Seller:

Seller	SNLink1	SNLink2	SNLink3	SNLink4	SNLink5	SNLink6	SNLink7	SNLink8	SNLink9	SNLink10
0	4	15								
1	0	2	6	8	10	13	19			
2	3	4	5	7	8	9	11	15	16	17
3	4	5	6	7	10	13	18	19		
4	1	12								
5	1	4	7	11	15	18				
6	0	1	5	9	11	13	14	15	18	19
7	4	5	9	10	11	14	16			
8	2	3	6	16						
9	2	3	4	8	10	11	12	13	17	19
10	3	4	9							
11	2	3	6	8	9	10	13	14	15	17
12	13	16	17							
13	0	3	8	12	17					
14	1	3	8	9	13	17	18	19		
15	6	10	12							
16	6	8	9	11	13	19				
17	0	2	13							
18	0	8	10	13	15					
19	0	6	9	10	14	15	16	17		

A Sample View of a Given Seller's (Seller 1) Recommendation Matrix for Each Product:

Product	SNLink1	SNLink2	SNLink3	SNLink4	SNLink5	SNLink6	SNLink7	SNLink8	SNLink9	SNLink10
0	Itself									
1	0									
2	13									
3	none									
4	10	11	15							
5	10									
6	none									
7	itself									
8	2									
9	0	2	19							
10	2									
11	itself									
12	none									
13	8									
14	none									
15	Itself									
16	6									
17	6	8	13	19						
18	8	19								
19	None									
20	13									
21	2									
22	None									
23	13	19								
24	none									
…	Seller Recommends Itself									
99	19									