The Role of Networks in Durable Goods Technology Adoption

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Abstract. In this paper, we study the role of social networks in the framework of durable technology adoption. We hypothesize that individuals use social networks to develop perceptions of the quality of a product in the absence of complete information. To determine how a firm can choose its optimal price in such situations, we create an agent and firm-based simulation and test various pricing strategies. We find that pricing strategies that encourage gradual adoption earn the highest revenues for the monopolist. These strategies let quality information flow through the network so that agent perceptions of quality rise *before* they purchase the good, allowing the firm to charge a higher price to more individuals.

1 Introduction

In February 2013, Google released early versions of its new wearable computer, called "Google Glass", to some developers and consumers through its Glass Explorer program[9]. Individuals were required to apply to buy the device, and a limited number of buyers were chosen to purchase a test version of the product. Through this strategy, Google was able to sell its new product at a high price ($1,500) to a small number of individuals while generating excitement about the device's future release.

With the rise of social networks, strategies like Google's are much more commonplace. Individuals are more connected than ever before, and firms look to take advantage of built-in social structures in the release of new products. Firms' use of word-of-mouth to market a product provides a new challenge in economic models of technology adoption.

In this paper, we examine the adoption of a new durable technology within the context of a social network. We discuss one important role a social network plays in the technology adoption decision: the sharing of information. When a firm introduces a new technology, buyers may not have complete information about the quality of the product. However, they may construct a perception of quality using the information from their friends, particularly if these friends have prior experience with the new product.

Firms therefore have incentives to increase perceptions of their product by creating high-quality goods and inducing early adoption of connected individuals. We develop a number of pricing strategies and test them in a simulated network of agents to determine how a firm may optimally take advantage of network structure to maximize its profits. We base the agent model on models of technology adoption in cognitive psychology in order to capture the ways in which individual beliefs change through interactions.

Technology adoption, social networks, and durable goods are not new concepts to economics. Network theory has had an increasingly important role in the conceptualization of the market in recent years. Rauch and Watson (2001) [10] discussed the combined contributions of sociology and economics, providing potential frameworks for the introduction of network theory into economic decision making.[1]

Additionally, the concept of network externalities (that is, when the value of a technology depends on the number of individuals who have adopted that technology) has been frequently applied to the adoption of durable goods, notably in Katz and Shapiro (1986) [7]. However, many network effects exist outside the realm of network externalities. In this paper, we consider the impact that a social network may have on expectations about a good when its quality is unknown.

This paper proceeds as follows: first, we consider the problems faced by a durable goods monopolist and how networks may increase profits; second, we describe the various components of the simulation; finally, we discuss the results of the simulation and their implications for firm decision making.

2 The Durable Goods Problem and Information Sharing

As first presented in Coase (1972) [3], durable[2] goods monopolists face an interesting problem. The monopolist has incentives to lower the price after selling the first units of a good, in order to extract surplus from the consumers remaining in the market. However, consumers recognize that the price will fall in later periods, and will wait to purchase the good. In this manner, some firms may lose all of their monopoly power, as consumers wait to buy until price equals marginal cost. Bulow (1982) [2] found that this problem creates incentives for firms to produce less durable products (that is, lower the quality of their good).

In this paper, we model durable goods in the context of technology adoption and social networks. When a new technology is first introduced, consumers are unsure of the actual value of the good. Therefore, they look to their neighbors, who may or may not have actual experience with the product, to develop expectations about quality. These cognitive social networks allow the individuals' expected values to change over time. In this case, an optimizing firm may look to take advantage of information flow through the network to extract additional surplus from consumers.

Consider a two-stage game with two consumers. These consumers believe a product has a single stage value of V^H and V^L, respectively, where $V^H >$

[1] Zuckerman's (2003) [12] discussion of Rauch and Watson provides an excellent commentary on their work and the future of network theory in economics.

[2] A good is "durable," in economic terms, if consumers receive value from it for multiple periods after their initial purchase. [2] [3]

V^L. The profit-maximizing monopolist would like to extract all surplus from both consumers. In the absence of changing expectations, his ideal strategy, as discussed by Coase and Bulow, is to set $P_1 = 2V^H$ and $P_2 = V^L$, selling to consumer 1 in stage 1 and consumer 2 in stage 2. However, the high-valued consumer recognizes that the price will fall in stage 2, allowing him to have positive two-stage surplus of $V^H - V^L > 0$ if he waits to buy the good. Therefore, the firm will be unable to charge a higher price in the first stage; its equilibrium pricing strategy and profits are $(P_1^*, P_2^*) = (V^L, V^L)$ and $\Pi = 2V^L$.

Now suppose that, after purchasing the good, consumer 1 tells consumer 2 that the product's actual value is V^H, causing consumer 2's valuation of the good to change to V^H in stage 2. While the monopolist cannot select the profit-maximizing price schedule of $(P_1, P_2) = (2V^H, V^H)$, it can earn higher profits than the previous case, choosing the equilibrium strategy of $(P_1^*, P_2^*) = (V^H, V^H)$. In this case, its profits are $\Pi = 2V^H > 2V^L$, so the firm is strictly better off from this information sharing.

Of course, in reality, information sharing, network structure, and expectations about future prices are more complex. Consumers may not be able to accurately predict how future prices will change. Additionally, in a many-staged game with a large network of consumers, it is much more difficult to determine the firm's optimal price schedule. Therefore, to determine profit-maximizing pricing for the firm, we experiment with generalized pricing strategies in a simulated technology adoption framework.

3 Simulation Methodology

3.1 Agent Model

On the demand side of the model, 12,000 agents, arranged in one of three network structures, interact in each stage of 12,000 time steps of the game, sharing their beliefs about a given product with their neighbors. In each time step, agents must decide whether or not to purchase this product, a new, durable technology with a price P_t.

The agent interaction model is derived from Mappus, Briscoe, and Hutto (2012) [8], in which individual beliefs are the driving force in technology adoption decisions. In order to combine cognitive network modeling with economic notions of decision making, beliefs become a perceived value of the product to the individual, when the actual value of the product is unknown. Agents then make decisions by comparing the perceived value of the good to the actual price to determine their expected surplus from adoption.

Individual agents interact with their neighbors in the social graph in each time step. An agent's neighbors are those with which he shares cognitive ties, communication links, and social relationships [4]. Neighbors share a single belief, their perception of "quality." Quality encompasses all relevant characteristics of the product, both objective and subjective. At each time step, agents compare their perceived quality to the perceived quality of their neighbors through the social cognitive influence potential (SCIP), a measure of the differences in the beliefs of two individuals. If the SCIP between two individuals is sufficiently large, then the agents will update their beliefs and change their perceived quality.

We translate the individuals' perceived quality into a measure of the expected value the product using a weighted sigmoid function:

$$V_{it}(q_{it}) = \frac{1}{1 + e^{-w_i q_{it}}} \tag{1}$$

where i indexes the individual, t indexes the time period, V_{it} is the expected value of the product in each period, q_{it} is the perceived quality of the good, and w_i is a weight, randomly assigned to the individual. The difference between the perceived valuation of the product and the product's price in a given stage is the expected surplus from adoption in that stage.

Agents decide whether or not they should adopt a product based on the expected surplus they will receive from adoption. However, agents who have decided to adopt the product must also choose the optimal *time* to adopt. If they believe the price will drop significantly in the following stage, then they may receive higher surplus by waiting to adopt. Therefore, the individuals' decisions depend on both the expected surplus today, but also the expected surplus tomorrow.

Agents predict the price in the following stage using information from the previous time step. At each time step, they estimate how the price will change based on the difference between the current price and the previous price. The expected price in the next stage is then $\hat{P}_{t+1} = P_t + (P_t - P_{t-1}) = 2P_t - P_{t-1}$. If the agent decides to adopt today, then his expected surplus today is $V_{it} - P_t$ and his expected surplus[3] tomorrow is V_{it}. If he decides to adopt tomorrow, then his expected surplus today is 0 and his expected surplus tomorrow is $V_{it} - 2P_t + P_{t-1}$. Therefore, an agent will decide to adopt the product in stage t, assuming no time discounting, if and only if $(V_{it} - P_t) + (V_{it}) > (0) + (V_{it} - \hat{P}_{t+1})$, or, more simply:

$$2V_{it} - P_t > V_{it} - 2P_t + P_{t-1} \tag{2}$$

Following adoption, agents are informed of the actual objective quality of the good, updating their perceived quality. They continue interacting with other agents in the network, but these interactions do not change their personal perceptions of quality.

3.2 Firm Model

The supply side of the model consists of a single firm offering a single good for the price P_t subject to a constant marginal production cost of c. In each stage, the firm chooses the price of the product according to one of five strategies. It will follow this strategy for the entire run of the simulation.[4]:

[3] We assume that individuals do not expect their perceptions of quality to change.

[4] These pricing strategies were originally developed in Galloway, Mappus, and Briscoe (2013) [6]

Table 1: Summary Statistics

	Observations	Mean	Std. Dev.	Min	Max
Price	375	0.63	0.24	0.07	1.00
Cumulative Adoption	375	11,684.35	692.44	7,385	12,000
Cumulative Revenue	375	7,610.91	2,901.22	861.72	11,998.19

1. Profit Maximization
2. Normalized Maximum
3. Average
4. Maximum
5. Maximum Connectivity

The profit maximization strategy serves as a control by which we can compare our derived pricing strategies. Here, the firm assumes a linear demand function of $P = a - bQ$ and then chooses P to maximize its single-stage profits. In this strategy, the firm does not take into account the impact of its current price on future profits and sets price equal to $P = \frac{1}{2}(a + c)$. We approximate the P-intercept of the linear demand curve using $\max(V_{it})$, the maximum valuation of all individual in the market. Therefore, the price is:

$$P_t^{PM} = \frac{1}{2}(\max(V_{it}) + c) \tag{3}$$

The remaining four strategies attempt to take into account the way information moves through the network. The firm targets key individuals in the network by "pricing to" them; that is, it chooses a price that induces those individuals' adoption. For "Normalized Maximum", the firm uses W_{it}, the perceived value of the good to individual i, weighted by their (normalized) connectivity, measured in node degree. "Normalized Maximum" sets the price equal to the valuation of the individual with the highest W_{it}. "Average" sets the price equal to the average weighted perceived value.

The normalized maximum strategy targets the individual with the greatest combination of perceived value and connectivity left in the market. By pricing in this way, the firm takes advantage of the diffusion of information through the network while still charging a relatively high price.

"Maximum" and "Maximum Connectivity" also target specific individuals. "Maximum" is essentially the firm's preferred strategy from the durable monopolist's problem; the firm sets the price equal to the maximum valuation of all individuals remaining in the market at a given time period. Of course, rational agents will recognize that prices are trending downward over time, and will prefer to wait to buy the good at a lower price.

"Maximum Connectivity" ignores the magnitude of an individual's valuation of the good and focuses solely on how connected they are to others in the market. It sets the price equal to the price threshold of the individual with the highest degree in the network. Unlike the "maximum" strategy, any upward or downward trend in prices will be, for the most part, random.

Table 2: Regression Results

	(1) All	(2) Small World	(3) Erdős-Rényi	(4) Power Law
Average	-0.11	0.23	-0.56	-0.23
	(0.13)	(0.13)	(0.10)	(0.32)
Maximum	0.36^{***}	0.55^{***}	0.20	0.28
	(0.10)	(0.12)	(0.23)	(0.19)
Maximum Connectivity	0.41^{***}	0.51^{***}	0.33	0.37
	(0.13)	(0.15)	(0.30)	(0.24)
Normalized Maximum	–0.04	0.30	-0.42	-0.19
	(0.13)	(0.14)	(0.33)	(0.24)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors in parentheses.

To examine the effect of various random network structures on the effectiveness of our pricing strategies, we run all pricing strategies over three types of random graphs: small-world[11], Erdős-Rényi[5], and power law[1].

In an Erdős-Rényi random graph, the probability of an edge existing between any two nodes is some constant p. The resulting model is highly random, with limited clustering. Unlike the Erdős-Rényi, a small-world model, in which edges in a regular lattice structure are rearranged with a given probability p, graphs have high clustering. However, their degree distributions (that is, the distribution of the number of connections of individual nodes) do not match those of real-world networks. Degree distributions in real networks tend to follow a power law[5] distribution. We examine all three types of random graphs in our analysis.

4 Results

We run the simulation 10 times for each of the five pricing strategies in the three network structures. Table 1 contains summary statistics for the final time step over all simulations. The revenue in a given stage is defined as the number of buyers in that time step multiplied by price in that stage. Cumulative revenues are the sum of individual stage profits over the entire simulation, up to the given time step. Note that we are analyzing firm *revenue* rather than firm $profits$ (the product of the number of buyers and the marginal revenue $P - c$). Differences in marginal costs, which is randomized in the initial stage of the simulation and remains constant throughout all time steps, will created differences in profits not reflected in revenues. However, because cost does not vary systematically with

[5] $P(k) \sim k^{-\gamma}$, where $P(k)$ is the fraction of nodes with k connections to other nodes and γ is a chosen parameter.

Table 3: Power Law Test

	(1) All	(5) Power Law 1	(6) Power Law 5	(7) Power Law 15
Average	-0.11	0.03	-0.45*	-0.06
	(0.13)	(0.21)	(0.19)	(0.31)
Maximum	0.36***	0.19	0.24	0.31*
	(0.10)	(0.17)	(0.21)	(0.18)
Maximum Connectivity	0.41***	0.33	0.39*	0.38*
	(0.13)	(0.21)	(0.23)	(0.21)
Normalized Maximum	–0.04	-0.35	-0.37	-0.13
	(0.13)	(0.21)	(0.23)	(0.21)

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors in parentheses.

the pricing strategy, using revenues instead of profits is a valid measure of the success of the various strategies.

To estimate the effects of various pricing strategies on cumulative simulation revenues, we estimate generate indicator variables for four of the five pricing strategies: A ("Average"), M ("Maximum"); MC ("Maximum Connectivity"); and NM, ("Normalized Maximum"). We then estimate equation 4 using ordinary least squares:

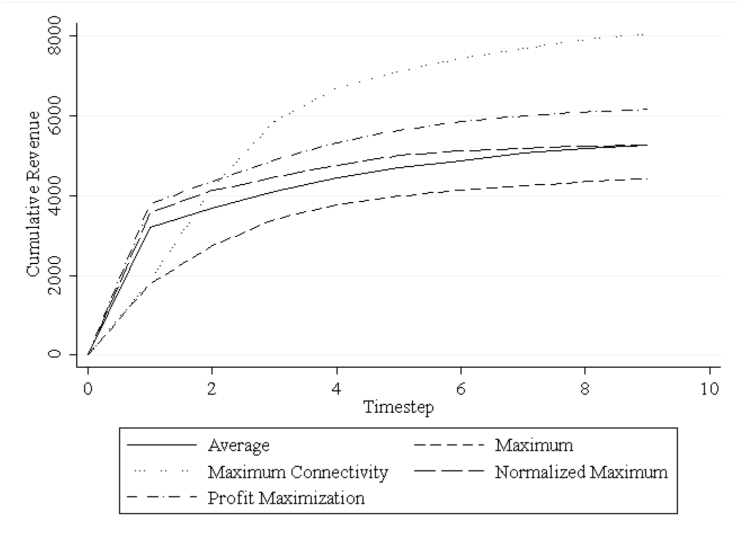
$$\log(CRev_i) = \beta_0 + \beta_1 \cdot A_i \beta_2 \cdot M_i + \beta_3 \cdot MC_i + \beta_4 \cdot NM_i + u_i \qquad (4)$$

where i indexes the run of the simulation, $CRev_i$ is the cumulative revenue, and u_i is random error. Note that all other variables affecting cumulative profits are randomized across pricing strategy conditions; therefore, they are exogenous in this estimation. The coefficients β_1, β_2, β_3, and β_4 represent the percent difference of the given strategy from the omitted strategy; that is, from the profit maximization strategy.

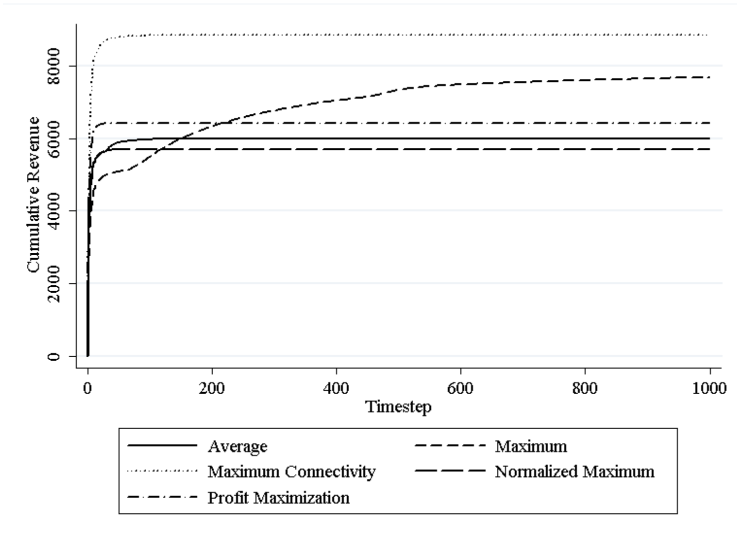
Table 2 contains the results of the estimation of equation 4 for total simulation revenue (that is, cumulative revenues in the final stage of the simulation). We estimate the effects of the various pricing strategies first on cumulative revenues in all simulations (column 1), and then by network type (columns 2, 3, and 4). The power law used in Table 2 has an edge count of 120,000.

First, we consider the regression over all types of networks. The results in column (1) indicate that the maximum and maximum connectivity strategies create revenues 36% and 41%, respectively, than the profit maximization strategy. These strategies also dominate both of the strategies based upon the "normalized" price strategy (average and normalized maximum).

The "maximum" pricing strategy is the monopolist's preferred pricing strategy in the Coase durable goods problem; the firm sells to the individual with



(a) Revenue stream in the short run.



(b) Revenue stream in the long run.

Fig. 1: A comparison of revenue streams across various pricing strategies in the short-run and in the long-run.

the highest valuation of the good who has not already purchased the good. This strategy's success is a product of the limited foresight of the agents in the model. Individuals have imperfect information about the future direction and magnitude of price changes.

The "maximum connectivity" pricing strategy takes into account only how information spreads in the network. By choosing a price that specifically targets the most influential person in the network, the firm ensures that accurate information about the product's value spreads through the network.

Figures 1a and 1b illustrate the key differences between the successful strategies and the alternative strategies. Figure 1a shows the stream of revenues in the first ten timesteps of the simulation. In the average, normalized maximum, and profit maximization strategies, the firm achieves mass adoption at an early stage by choosing a low price. While this may achieve higher revenue in the short-run (notably, the profit maximization strategy has higher profits than the maximum strategy, on average, in the first 200 or so time steps), it does not allow for growth. The firm does not take advantage of the changes in consumer perceptions of the product.

The successful strategies, maximum connectivity and maximum, do not reduce their price in order to attract large initial adoption. They rely on word of mouth to earn high long-run revenues. In the maximum connectivity strategy, information diffusion is more rapid, and the firm reaches higher revenues faster than the maximum strategy. If firms discount future revenues in favor of current revenues[6], than the maximum connectivity strategy clearly dominates.

Table 2 also displays the results of the estimation of equation 4 for each of the three types of random graphs. From columns (2), (3), and (4), it is clear that the small-world network drives the primary result. In the Erdős-Rényi and Power Law networks, no strategy is clearly dominant in the results.

To further investigate this result, we rerun the simulation using only power law random graphs with varying number of edges. Column (1) in table 3 replicates the primary results; columns (5), (6), and (7) assume power law graphs with 12,000, 60,000, and 180,000 edges, respectively.

When the edge count is small, there is no clear difference between the different strategies. However, as the edge count grows to 180,000 (that is, as agents become more connected), the strategies that allow for diffusion of information through the network once again gain an advantage on the other strategies. Therefore, the ability of the maximum and maximum connectivity strategies to achieve higher revenues depends on the degree of connectivity in the network. If an individual does not have many people with whom to share communicate, quality information about the product cannot diffuse through the network.

[6] Future discount rates are common in game theory analysis; however, we make the assumption that both the firm and the agent care equally about current and future income.

5 Conclusions

Interaction with neighbors helps agents build an impression of a product in the absence of complete information about its value. Social networks may allow a durable goods monopolist to retain some of its monopoly power without renting the good or signing a long-term pricing contract. To test this idea, we designed a simulation of technology adoption with agent interactions and experimented with various pricing strategies. We found that strategies that encourage rapid early adoption do not encourage the sharing of quality information before agent adoption and, consequently, result in lower revenues for the firm. The strategy offering the highest revenues for the firm targets highly connected individuals in the network and uses them to build "word of mouth" for the product. Future work will continue to refine the simulation as well as develop more sophisticated pricing strategies to better achieve the firm's optimal profits.

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ABMUSITE: Agent Based Model for Understanding Social Information Transfer and Expression used in ``The Role of Networks in Durable Goods Technology Adoption“

1. Purpose

The Agent Based Model for Understanding Social Information Transfer and Expression (ABMUSITE) is a framework for modeling and simulating interpersonal influence, which uses an agent based model to represent individuals (and other entity agents). Attributes of agents allow for representation of complex intra- and interpersonal psychological aspects of influence. The agents in the model perform realistic information processing and behavioral intention formation within the simulations, which are meant to be informed by human-subject experimentation (in progress). Memes (consisting of beliefs) are evaluated by agents at the time of reception, and are processed (accepted or rejected by degrees) according to the agent's existing set of beliefs, along with consideration of other agent attributes. ABMUSITE links together two theoretical representations - the Cognitive Network Model (CNM), a framework for quantitatively characterizing individuals' belief systems as a network of interrelated proposition nodes, with each node having specified quantitative parameters, and the Socio-Cognitive Network Model (SCNM), which is intended to capture the effects of interpersonal communication and influence on individuals' CNMs during person-to-person interactions. In this instantiation, the agents interact both with each other and exogenous marketers (also referred to as the 'world').

2. Entities, state variables, and scales

The following entities are used in the model for the simulation described in the accompanying paper. The complete model includes more variables that are not described below.

Variable Name	State variables
Consumers	float productBelief (veracity of beliefs related to adopting new technology) productDefense (defense of beliefs related to the adoption of new technology); boolean usedEcommerce, marketedTo; network (Mason) friendshipNetwork
Firm	float productPrice, productQuality

The simulation fixed transactions to 1 round of interactions with immediate neighbors every 2 hours. Given the rate of interaction, total individual simulation time was 2.74 years.

3. Process overview and scheduling

Questions: Who (i.e., what entity) does what, and in what order? When are state variables updated? How is time modeled, as discrete steps or as a continuum over which both continuous processes and discrete events can occur? Except for very simple schedules, one should use pseudo-code to describe the schedule in every detail, so that the model can be re-implemented from this code. Ideally, the pseudo-code corresponds fully to the actual code used in the program implementing the ABM.

There are two types of agents in the simulations: consumers and firms. Consumer agents participate in the social network and make purchasing decisions of a product produced by a firm agent. In each simulation, there are many consumer agents and one firm agent. At each time step (discrete time simulation), consumer agents communicate with their immediate neighbors in the social network and make a purchasing decision based on their price threshold for the product. The firm agent sets the price of the product at each time step. Once consumer agents make a decision to purchase the product, they do not make any more purchasing decisions for the rest of the simulation Further, when consumers purchase, their belief in the product becomes the actual quality of the product.

Consumers are scheduled to interact, update their cognitive state, and make their purchasing decision before the firm adjusts the price in each time step. Consumers are scheduled in a random order in each time step. After consumers are finished, the firm then updates the product price for the next time step.

Consumer agents are initialized with randomly uniform a belief regarding their attitude toward product adoption (based on Venkatesh et al., 2003), all of which range in value from {–infinity..infinity} (single floating point precision). The belief is represented by two variables, veracity and defense, which are initially randomly uniformly set. The firm agent is initialize with a price value of 1.0 and random (uniformly distributed) floating point value of the quality of the product. The quality value does not change in the simulation.

Veracity indicates an agent's level of acceptance or rejection in the ``degree of truth'' of the proposition. Quantitatively, veracity is represented as a value between -infinity and infinity, where -infinity indicates the agent believes the proposition is not true at all (proposition is completely rejected), and inf indicates complete belief in the truth of the proposition (proposition is completely accepted). Defense can be thought of as the degree of resistance to adoption, also with a value between {-infinity…infinity} (single floating point precision).

Consumers are connected in a social graph (small-world, Erdos-Renyi, or power law). Edges represent the cognitive ties (commonly shared beliefs), communication links, and social relationships between the nodes. Within the current context, cognitive ties generally refer to the extent of agreement between the individual beliefs of multiple agents. The strength of the cognitive ties (degree of agreement between agent beliefs) affects the degree to which agents influence and are influenced by one another's beliefs during social interactions. We use this tie-strength concept to regulate influence propagation in the network model according to SCIP values between agents, described below.

The social cognitive influence potential (SCIP) represents the degree to which one agent can successfully influence another agent (i.e. get them to change their propositional belief state). For our demonstration model, SCIP is based on the concept of *cognitive homophily* and is a computed value representing the similarity of beliefs between two agents.

Agents have an adoption threshold derived from their belief value, using a sigmoid transfer function that maps the belief value domain to the {0..1} range. Friendship networks are created as communication networks for the agent using the JUNG graph library. Small-world networks (edu.uci.ics.jung.algorithms.generators.random.KleinbergSmallWorldGenerator) use a cluster exponent of 0.8. Erdos-Renyi networks (edu.uci.ics.jung.algorithms.generators.random.ErdosRenyiGenerator) use a connection probability value of 0.025. Power law networks (edu.uci.ics.jung.algorithms.EppsteinPowerLawGenerator) use the number of edges as 10 times the number of nodes, and 10000 iterations to form the network.

After every interaction (with other agents and marketers/world), the agents' beliefs are updated according to the veracity and defense of each belief, and the SCIP (S) between the two agents, according to the formula below.

In this simulation, we are primarily concerned with cognitive centrality (or overlap in beliefs (Kameda, 2003)), therefore here the SCIP is determined only by the 'distance' between the beliefs of the interacting agents.

Figure 1: Process of interactions and belief updates arising from marketers targeting agents in a social network where the agents and their interactions are modeled using ABMUSITE

4. Design concepts

Basic Principles: The theory that is tested in this model is how product price and social interaction network types interact to inform firms on pricing strategies. Our submodels include the beliefs at the agent level, or the Cognitive Network Model (CNM), a framework for quantitatively characterizing individuals' belief systems as a network of interrelated proposition nodes, with each node having specified quantitative parameters. This takes into the account the notion of belief networks (Venketesh et al., 2003) relevant toward technology adoption. At the group level, Socio-Cognitive Network Model (SCNM), is built on the notion of cognitive centrality (Kameda), intended to capture the effects of interpersonal communication and influence on individuals' Belief Networks (BNs) during person-to-person interactions.

Emergence. The agents are expected to change their beliefs in accordance with the beliefs of the involving beliefs of their social network. Structural properties often result in emergent factions linked by ties of varying strength.

Adaptation. The agents adapt their beliefs in accordance with those that they encounter within their social network and their interactions with the world (here, marketers).

Objectives. By situating the agents within social networks with real-world properties, we are able to understand how adoption behavior may be optimized in light of cognitive and structural properties. This is especially true in the case of the cliques that are formed through small-world networks, where we expect that targeting on centrality measures will be less successful that targeting on cognitive and centrality metrics. All adoption decisions are collected from the agent population.

Observation. Observations from the simulation include the adoption index of the agents, their centrality measures (degree and betweeness), and the SCIP values between all agents.

5. Initialization

Agents are initialized with uniformly distributed random belief and defense regarding their attitude toward a product. Firms have a uniformly distributed random quality of the product. Friendship networks are created as communication networks for the consumer agents – which are small-world, Erdos-Renyi, or power law networks (using the JUNG functionality), with a clustering exponent of .8, a conection probability of 0.025, or edge count of 10 times the number of nodes and 10000 iteration generation in the small-world, Erdos-Renyi, and power law networks respectively.

7. Submodels

ABMUSITE links together two submodels - the Cognitive Network Model (CNM), a framework for quantitatively characterizing individuals' belief systems as a network of interrelated proposition nodes, with each node having specified quantitative parameters, and the Socio-Cognitive Network Model (SCNM), which is intended to capture the effects of interpersonal communication and influence on individuals' Belief Networks (BNs) during person-to-person interactions.

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