Value Model of Knowledge Diffusion in High Technology Innovation Networks

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Abstract. To measure the influence of knowledge diffusion and information exchange between enterprises on high-tech innovation networks' production and operation, a production model and innovation model based on a network diffusion process are introduced. The knowledge diffusion process treated as an learning-by-observing process in a random network are influenced both by network's structure and non-structure properties. We analyze the influence of diffusion process theoretically and find that, if given the precondition that initial belief and belief elasticity follow a normal distribution, an increase in mean of initial belief would lead to increase in PV and IV; otherwise, mean of belief elasticity would have a opposite effect on PV and IV under some different conditions. Finally, we give the condition to compare knowledge diffusions in two high-tech networks with same mean degree but different variance.

Keywords: High-tech innovation networks, Social learning, Knowledge diffusion, Diffusion value, Degree distribution

1 Introduction

For high-tech enterprises, continuous technological innovation is one of key factors to maintain their core competitiveness. Technological innovation depends largely on the partnerships they coordinate with other companies within the industry [1].

As a substrate of knowledge transferring between high-tech enterprises, high-tech innovation network has an important impact on the dissemination process of knowledge between enterprises[2]. For example, Uzzi (2005) found that large-scale structure of the network has a significant effect on musicians' creativity, art of music composed and profitability[3]. Schilling (2007) found that structure of inter-enterprise cooperation networks influence their knowledge creation and that enterprises cooperative networks in which have a higher clustering coefficient and less redundant links would have higher knowledge creation capability[4]. Phelps (2010) found that structure and composition of alliance networks have a significant impact on the ability of enterprises to explore innovation, corporate partners' technical diversity has a positive influence on its ability to explore new knowledge, while the density of network structure plays as regulatory role[5]. These empirical findings provide new reference for companies to acquire knowledge and set off a wave of knowledge diffusion research of high-tech innovative networks.

With above empirical findings and the rise of complex network studies[6][7][8], a large number of scholars have focused on dynamic characteristics of large-scale network structure and knowledge emergence properties in these networks. Cowan (2004) examined the relationship between network structure and diffusion performance, and concluded that knowledge diffusion in small-world networks with different structure properties have great difference[9]. These studies have used simulation to explore knowledge diffusion process, but did not analyze the impact of such knowledge diffusion on the overall economy of high-tech innovation networks. In this paper, we define knowledge as a group of technical knowledge which would have a positive impact on production, operation and business activities (or reduce production costs and improve product quality). Although technical cooperation network can accumulate knowledge and innovate technologies, thus increase the whole profit, the implementation of these activities may bring risks and costs, so companies will evaluate the risk and decide whether to absorb new knowledge or not. Based on this consideration, this paper, which is different from previous studies, treat knowledge dissemination process as a learning process, companies will observe business-to-business alliances' adoption of new knowledge in return each period, and then evaluate the impact of new knowledge on their production and management, and finally decide whether to adopt new knowledge.

We build high-tech innovation network with mean-field approximation[10][11][12], with the aim to discuss the heterogeneity of degree distribution on knowledge diffusion. In addition, this article focuses on the overall impact of knowledge diffusion on the high-tech innovation network. Based on knowledge diffusion models, we also construct knowledge diffusion production value model and inter-enterprises impact value model. This article focuses on answering these questions: How is the impact of cost and actual knowledge value on adoption rate, production value (short for PV) and influence value (short for IV) in high-tech innovation network? How is the impact of initial belief of knowledge value and elasticity of evaluating of knowledge value on adoption rate, PV and IV? What about the heterogeneity of degree distribution's regulated role in these relationships?

2 Assumptions and Individual-level Model

We regard knowledge dissemination process in the high-tech innovation network as a process of enterprises' evaluating benefit of adopting new knowledge. The transmission of knowledge isn't the same that of information or viral, but is an active behavior of knowledge acceptors. In this process, high-tech enterprises evaluate knowledge value repeatedly, combine together adoption cost and adoption risk of knowledge, and then decide whether to adopt new knowledge or not.

To simplify the process, we firstly make the following assumptions: 1) each period enterprise i can observe new knowledge adoption behavior of other k_i enterprises, a_i of which have adopted new knowledge; 2) For those enterprises who have adopted new knowledge, they produce a unit of information about the adoption of return every period which are independent from each other, the value return follows a normal distribution $I \sim N(m s^2)$; 3) Enterprise has a neutral risk preferences, information obtained in each period is independent with each other; 4) enterprises have the same cost c and value return of using knowledge; 5)the diffusion process follows a mean-field approximation process.

2.1 High-tech Innovation Networks

The high-tech innovation network is represented as $DG = (V, E)$. The enterprises in the network are represented as node set $V = \{1, 2, ..., n\}$, and their relationship is represented as edge set $E = \{e_{ij}; i, j = 1, 2, ..., n\}$. If enterprise i observes the production return of enterprise j, and then there is a relationship between them, in other words $e_{ijt} = 1$; if not, then $e_{ijt} = 0$. This relationship between nodes is not fixed, but each node observes fixed number of other nodes across different period; the number k_i is featured as the degree of that node. Further, this relationship is unidirectional observation. In other words, $e_{ij} = 1$ doesn't mean $e_{ji} = 1$. To facilitate the analysis, we assume in_degree equals to out_degree. The proportion of node with degree k in the network is represented as $p(k)$, so the degree distribution could be represented as $P(k) = \{p(k); k = 1, 2, ..., k_{\max}\}$.

2.2 Knowledge Adoption Rules Based on Learning from Observation

If enterprises have complete information of knowledge value, and $m > c$, then all would adopt the knowledge at the initial stage. In reality, Enterprises actually don't, however, know that kind of information. But they have a prior belief of the knowledge value, which is represented as v_{i0}. With the accumulation of information about knowledge value, they would also update their belief about knowledge value. When the posterior belief b_{it} at stage t is strong enough, enterprise i would decide to adopt the knowledge. Here we use a standard normal-normal belief updating rule[16][17].

At the initial stage, enterprise i's initial belief of knowledge value is v_{i0}. A low v_{i0} means that enterprise i has a negative attitude towards that knowledge. t_i represents the elasticity of enterprise i's belief updating. As time goes, enterprises get information from its neighbors, and then update their belief. At t period, if there are a_i adopted neighbors, enterprise i would obtain a_i units of information. For that information is independent from each other, we can get the mean of knowledge value $\bar{I}_{it} \sim N(m \frac{s^2}{a_{it}})$. Followed as standard norm-norm updating rules, enterprise i's bayesian posterior belief can be expressed as the weighted average of prior valuation and the information obtained

$$v_{it} = \frac{\tau_i}{\alpha_{it} + \tau_i} \cdot v_{i0} + \frac{\alpha_{it}}{\alpha_{it} + \tau_i} \cdot \bar{I}_{it}$$

When $v_{it} > c$, enterprise i will adopt the knowledge.

3 A knowledge Diffusion Dynamic Model in Random Network

Each stage, suppose that enterprise i selects k_i enterprises randomly from the network to get information about knowledge usage. In the initial period, enterprises who meet the condition $v_{i0} > c$ would adopt knowledge and then create information for others next stages. Meanwhile, those adopted enterprises would, if their belief of knowledge value is larger than cost, give up using new knowledge.

We use $\rho_k(t)$ to represent knowledge adoption rate of sub-class featured with degree k in t period, and $\rho(t)$ to represent knowledge adoption rate of innovation network. Obviously, we have

$$\rho(t) = \sum_k \rho_k(t) p(k) \tag{1}$$

in which $0 \le \rho_k(t), \rho(t) \le 1$. Since enterprises may get several other enterprises' information, the probability of enterprise's observing an adopted counterpart is represented as

$$\theta(t) = \frac{\sum_k k p(k) \rho_k(t)}{\langle k \rangle} \tag{2}$$

in which $\langle k \rangle = \sum_k k p(k)$ is mean degree of the network. Thus, expected amount of information of enterprise i could be represented as

$$\begin{aligned} I_k(\theta(t)) &= \sum_{a=0}^{k} C_k^a \theta(t)^a (1 - \theta(t))^{k-a} a \\ &= k \cdot \theta(t) \end{aligned} \tag{3}$$

For enterprise i, the bayesian posterior belief of knowledge value at stage t is

$$v_{it} = \frac{\tau_i}{k_i\theta(t) + \tau_i} \cdot v_{i0} + \frac{k_i\theta(t)}{k_i\theta(t) + \tau_i} \cdot \bar{I}_{it} \tag{4}$$

, in which $\bar{I}_{it} \sim N(\mu, \frac{\sigma^2}{k_i\theta(t)})$. When $v_{it} > c$, enterprise i would adopt knowledge, and then we have $\frac{\tau_i v_{i0} + k_i\theta(t) \cdot \bar{I}_{it}}{k_i\theta(t) + \tau_i} > c$. Suppose $X \sim N(0,1)$, then

$$(\tau_i v_{i0} + k_i\theta(t)) \cdot \mu + \frac{(\tau_i v_{i0} + k_i\theta(t))\sigma}{\sqrt{k_i\theta(t)}} \cdot X > (k_i\theta(t) + \tau_i) \cdot c$$

which implies

$$\theta(t) > \frac{\tau_i(C-\mu v_{i0})}{k_i(\mu-C)} - \frac{(\tau_i v_{i0}+k_i\theta(t))\sigma}{(\mu-C)\cdot\sqrt{k_i\theta(t)}}\cdot X$$

Now we can define the expected information level for enterprise i adopting knowledge

$$\theta_i = \frac{\tau_i(c-\mu v_{i0})}{k_i(\mu-c)} \tag{5}$$

when $\theta(t) > \theta_i$, enterprise i would be inclined to adopt knowledge. Without lose of generality, suppose that when $\theta(t) > \theta_i$, enterprise i will adopt knowledge. For sub-class k, we have：

$$Z(\tau_i, v_{i0}; k) = \frac{\tau_i(c-\mu v_{i0})}{k(\mu-c)} \tag{6}$$

Suppose it's a continuous process, then the growth of adoption rate of sub-class k could be characterized as

$$\dot{\rho}_k(t) = F(\theta(t);\tau_i, v_{i0}, k) - \rho_k(t) \tag{7}$$

$$\dot{\theta}(t) = R(\theta(t)) - \theta(t) \tag{8}$$

$$\dot{\rho}(t) = \sum_k p(k)F(\theta(t);\tau_i, v_{i0}, k) - \rho(t) \tag{9}$$

$$R(\theta(t)) = \frac{\sum_k kp(k)F(\theta(t);\tau_i, v_{i0}, k)}{\langle k\rangle} \tag{10}$$

When $R(\theta(t)) = \theta(t)$, equilibrium state is reached. Recall that the transitive from adopted to non-adopted is always possible. Hence, the equilibrium only refers to the value of $\rho(t)$ and $\theta(t)$.

4 Knowledge Diffusion Value for High-tech Innovation Network

After modeling knowledge dynamics in high-tech innovation network, a following question would come as 'How is this diffusion's impact on the whole high-tech network?', and 'what's the role of the interaction between enterprises?'. Most literatures didn't, however, discuss these questions. For an analytical purpose, we construct a PV model and IV model, which is similar as customer value and influence value in Ho(2012). PV measures accumulated value from all enterprises' using new knowledge, and IV measures value raised from the interaction among enterprises, both of which are influenced by network structure.

Firstly we introduce discount coefficient r and valid period of knowledge. For a particular adopted enterprise, suppose that its PV each period is equal to μ. If enterprise i adopts knowledge at t, its PV could be represented as

$$PV_i = \sum_{s=t}^{T} \mu e^{-rs} \tag{11}$$

Except adopters in the initial stage, all new added adopters are influenced by earlier adopters whose influences are related to their degree. Thus, accumulated IV of adopted enterprise i with degree k_i could be represented as

$$\begin{aligned} IV_i &= \int_t^T \omega \frac{k_i}{n \cdot \langle k \rangle \theta(s)} \cdot n \cdot \dot{\rho}(s) \cdot \mu e^{-rs} ds \\ &= \frac{k_i \omega \mu}{\langle k \rangle} \int_t^T \frac{\dot{\rho}(s) \cdot e^{-rs}}{\theta(s)} ds \end{aligned} \tag{12}$$

in which $0 < \omega < 1$ and $\tau \geq 1$. ω is coefficient of IV. Thus, PV and IV of knowledge in its life cycle could be represented as

$$PV = n\mu \int_0^T \int_t^T e^{-rs} \dot{\rho}(s) ds dt \tag{13}$$

$$IV = \frac{n\mu\omega}{\langle k \rangle} \int_0^T e^{-rt} \dot{\rho}(t) dt \tag{14}$$

PV characterizes the direct influence of knowledge on enterprises' production and operation, and is also influenced by the shape of knowledge adoption curve. Obviously, for two knowledge diffusion processes who have the same final adoption rate, the one having a higher initial adoption rate would also have a larger PV and a smaller IV. On the contrary, the rate of IV to PV mirrors the characteristics of diffusion curve. In this view, knowledge payoff, cost, enterprises' characteristics, and structure of high-tech innovation network all influence the shape of diffusion curve, would in turn influence PV and IV.

5 Theoretical Analysis

The diffusion process is influenced not only by knowledge payoff and cost, but also by distribution of initial belief b_0 and of elasticity τ and by degree distribution $P(k)$. If $\max\{v_{1,0}, v_{2,0}, ..., v_{i,0}, ..., v_{n,0}\} < c$, all enterprises would not adopt that knowledge at initial stage, which in turn lead to no information for next stage and finally to the failure of knowledge diffusion. This phenomenon could be found in practice— some technologies or knowledge are too expensive or revolutionary, giving enterprises a sense of risk, and thus all enterprises are waiting. As for this case, if $\mu > c$, the creator of knowledge could take some measures to handle with, such as giving discount to initial adopted enterprises or signing an agreement about sharing risky. Then, we have proposition 1.

Proposition 1: If all enterprises' initial belief of knowledge payoffs are lower than cost, or actual knowledge payoff is lower that cost, knowledge would fail to diffusion in the high-tech network.

For the sake of deeply understanding the model, we suppose that v_0 and τ follow a normal distribution. And also we will take the discrete version of this model.

Proposition 2: Suppose $v_0 \sim N(\mu_1,\sigma_1^2)$ and $\tau \sim N(\mu_2,\sigma_2^2)$, then

1) an increase in μ_1 would lead to increase in PV and IV,

2) when $c<b\mu$, an increase in μ_2 would lead to increase in PV and IV; when $c>b\mu$, an increase in μ_2 leads to decrease in PV and IV.

Proof. According with equation (6)

$$Z(\tau_i,v_{i0};k)=\frac{c-\mu v_{i0}}{k(\mu-c)}\cdot\tau_i$$

suppose $\tau_i=\tau=0$, then $Z\sim N(\frac{\tau(c-\mu\cdot\mu_1)}{k(\mu-c)},\frac{\tau\mu}{k(\mu-c)}\cdot\sigma_1^2)$, combining with equation (7), we get

$$\theta(t+1)=\frac{\sum_k kp(k)\Phi\left(\frac{k(\mu-c)\theta(t)-c\tau+\tau\mu\mu_1)}{\sigma_1\sqrt{k\tau\mu(\mu-c)}}\right)}{\langle k\rangle}$$

in which $\Phi(\cdot)$ is CDF of normal distribution. Obviously, an increase in μ_1 leads to an increase in knowledge diffusion speed. If the diffusion achieve dynamic equilibrium at θ^*, then

$$\theta^*=\frac{\sum_k kp(k)\Phi\left(\frac{k(\mu-c)\theta^*-c\tau+\tau\mu\mu_1)}{\sigma_1\sqrt{k\tau\mu(\mu-c)}}\right)}{\langle k\rangle}$$

If there is θ^*, at this point, an increase in μ_1, the equilibrium state would be disrupted. Thus, would gain a growth. Combining equations (13) and (14), we can achieve proposition 1).

If b_{i0} equals to b and $b\neq\frac{c}{\mu}$, $Z\sim N(\frac{c-\mu b}{k(\mu-c)}\cdot\mu_2,\left|\frac{c-\mu b}{k(\mu-c)}\right|\cdot\sigma_2^2)$, combined with equation (7), we get

$$\theta(t+1)=\frac{\sum_k kp(k)\Phi\left(\frac{k(\mu-c)\theta(t)-(c-\mu b)\mu_2}{\sigma_2\sqrt{k(\mu-c)|c-\mu b|}}\right)}{\langle k\rangle}$$

Then we can achieve proposition 2) with the same method used for proposition 1).

As in proposition 1, distributions of b_0 and τ have an impact on diffusion curve. b_0's influence is intuitive, τ's is, however, depend on different constrains.

Proposition 3: If there are two high-tech networks: network a with degree distribution $P_a(k)$ depicted by mean $\langle k_a\rangle$ and variance σ_a^2; network b with $P_b(k)$ depicted by $\langle k_b\rangle$ and σ_b^2. Then

1) If $P_a(k)$ FOSD $P_b(k)$ and $F(\theta,k)$ is, for any θ, a non-decreasing function of k, then there is more PV and IV in network a than that in network b.

2) If $P_a(k)$ SOSD $P_b(k)$ and $F(q,k)$ is, for any q, a weak concave function of k, then there is more PV and IV in network a than that in network b.

Proof.

The proposition is easy to achieve with definition of First Order Statistical Dominance (short for FOSD) and Second Order Statistical Dominance (short for SOSD) given by Jackson (2006). $P_a(k)$ FOSD $P_b(k)$ means that $\langle k_a \rangle > \langle k_b \rangle$, then we can conclude that in two random network a and b, if average degree of a is larger than that of b, there would be also a larger PV and IV in high-tech network a. $P_a(k)$ SOSD $P_b(k)$ means that $\langle k_a \rangle$ 3 $\langle k_b \rangle$ and $s_a^2 > s_b^2$, and we can draw the conclusion that in two networks with same average degree and different degree variance, the one with larger variance would also have larger PV and IV. For example, in a scale-free network and a regular network, PV and IV in the former one are larger that those in the later one.

The discount effect of knowledge also has an important influence on PV and IV. If $T \to \infty$, time axis would, for a knowledge diffusion process with a low discount coefficient, have little effect on PV and IV. In this situation, the equilibrium state of knowledge diffusion would have a decisive influence on PV and IV. If, however, a knowledge diffusion process is highly risky, which implies there is a large discount coefficient, then the initial stage of diffusion is vital to determine PV and IV.

6 Conclusion

Knowledge diffusion in high-tech networks is of importance in research area of knowledge management. We construct a knowledge dynamic diffusion model in high-tech networks with degree distribution based on observation learning and mean-field approximate method. In this high-tech network, every enterprise observes fixed amount of knowledge payoff from others, and then updates its belief of knowledge payoff. With mean-field approximation, we elicit a threshold of information level for each enterprise to decide whether to adopt new knowledge or not. Besides, we construct production value model of knowledge for high-tech networks and influence value model of the interaction between enterprises.

The result shows that new knowledge would, if all enterprises have too low belief of knowledge value, fail to diffusion in high-tech networks. If given precondition that initial belief and belief elasticity follow a normal distribution, an increase in mean of initial belief would lead to increase in PV and IV; otherwise, mean of belief elasticity would pose an opposite effect on PV and IV under different conditions. Finally, we give the condition to compare knowledge diffusions in two high-tech networks with same mean degree but different variance. The research in future would construct multiple-agents model to analyze different properties of high-tech on knowledge diffusion, and also on PV and IV.

Acknowledgments. This research is supported by projects: National Natural Science Foundation of China (71271126); research Fund for the Doctoral Program of Higher Education (20120078110002); the 6th graduate innovative fund of Shanghai

University of Finance and Economics (CXJJ-2012-427); the 4th stage of 211 project of Shanghai University of Finance and Economics.

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