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A Technology Diffusion Model Based on Technology Policy: The Case of Solid-State Lighting Technology Diffusion in the U.S.

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정책변수를 고려한 확산모형의 연구 - 고체조명(Solid-State Lighting : SSL) 기술을 중심으로

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Abstract Technology policy has a substantial impact on the diffusion of a new technology. This paper uses technology policy as a variable in the general epidemic model to quantify the effects of the policy on technology diffusion. The results obtained in this study, using data on solid-state technology diffusion in the U.S. indicate that technology policy plays a positive role in technology diffusion and provide a firm basis for understanding the relationship between technology policy and technology diffusion through the use of quantitative data.

요 약 기술정책은 신기술 확산에 영향을 주는 중요한 요인 중의 하나이다. 본 연구의 목적은 기존의 전염병 확산모형을 기초로 정책변수를 추가한 신기술 확산모형을 구축하고, 미국에서의 이산화탄소 배출 감소에 응용되는 고체조명(Solid-State Lighting) 기술을 사례로 실증연구를 진행하는 것이다. 실험결과, 정책변수는 정(+)의 영향을 미치는 것으로 나타났으며, 기술정책은 신기술의 확산에 추진 작용을 하는 것으로 나타났다. 이는 정책적 역할에 대한 정량적 이해를 도모하는데 있어서 정량적 판단을 위한 자료를 제공하고, 정책변수와 신기술 확산의 정량적 관계를 파악하는데 도움이 될 것이다.

Key Words : Technology Diffusion, Technology Policy, Diffusion Model, Epidemic model

1. Introduction

Rogers (1983)[10] defined the diffusion of innovation as “the process by which an innovation is communicated though certain channels over time among the members of a social system.” There are a number of models for analyzing innovation diffusion, including the S-curve model. According to this model, the use of a new technology follows an S-shaped curve, that is, it is approximately exponential in the initial stages of technology growth and becomes saturated as technology growth slows after the technology reaches maturity.

The epidemic model, the probit model, the competition and legitimation model, the information cascade model, the wine-making model, among others, have been used to explain the S-curve [2]. All these models reflect the same hypothesis in that they all assume a spontaneous process of technology diffusion. In other words, the market is assumed to push users to apply the new technology and complete the diffusion process. However, any technology that cannot directly and immediately enhance productivity, such as environmental protection technology, sewage treatment technology, energy conservation technology, and greenhouse gas reduction technology, cannot fully benefit

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from the technology diffusion process unless it is supported by appropriate technology policy initiatives. Thus, there is a clear need for analyzing and quantifying the effects of technology policy on the innovation diffusion process for developing appropriate technology policy initiatives that could facilitate the effective diffusion of new technologies.

Technology policy guides and promotes the diffusion of new technologies. It is the method by which governments facilitates technology diffusion. Governments often seek to influence technology diffusion directly, by investment in public research and technological development, dissemination of information, and other means[8]. Technology policy involves a wide range of government support for early adopters, including the provision of financial subsidies and tax benefits; the development of network infrastructure; the establishment of industry standards (e.g., standards for high-definition television); and the protection of intellectual property rights. Thus, any innovation diffusion policy should take into account the unique aspects of market behavior toward new technologies and their intertemporal patterns of change.

Lakhani(1975)[7], Oates et al.(1993)[9] and Kerr et al.(2000)[6] analyzed the relationship between technology policy and technology diffusion using the method of building the model. However, few studies have examined the effects of technology policy on innovation diffusion, and such studies have typically provided qualitative analyses. For example, Hosman and Howard (2010)[5] provided a data statistic analysis, Slocum (2005)[11] used different scenarios to represent technology diffusion with policy cannot quantify the policy variable of model, and Blackman (1999)[1] conducted a qualitative analysis of the impact of technology policy on the economy. Thus, there is a need for a quantitative analysis of the impact of technology policy on technology diffusion, which should supplement previous qualitative studies and provide policy makers with quantitative support.

In this paper, we incorporate policy factor into the external epidemic model to quantify the effects of technology policy on technology diffusion, providing a framework for evaluating the effects of the policy. The rest of this paper proceeds as follows: Section 2 presents a technology diffusion model based on technology policy. Section 3 discusses the data. Section 4 estimates and verifies the model parameters, and Section 4 concludes.

2. Technology diffusion model based on technology policy

It is well known that technology policy plays an important role in technology diffusion. Thus, there is a need for quantifying the effects of technology policy on technology diffusion, which can help policy makers to devise and implement better technology policy initiatives. In this section, we describe a technology diffusion model based on technology policy.

This model extends the general epidemic model by using technology policy as a dummy variable in the model. In other words, this study uses technology policy as a key external factor to specifically analyze the effects of technology policy on technology diffusion. The epidemic model is selected for the following reasons: First, there is solid evidence that the diffusion of a new technology typically reflects an S-shaped curve, which the epidemic model can effectively represent. Second, the external epidemic model provides a structural description of external factors influencing technology diffusion. Compared with other models, it is simpler and easier to manipulate. Finally, the epidemic model is more practical than other models because other models are deficient in certain aspects to deal with this kind of problems. For example a return analysis based on assumptions of the probit model is not likely to reflect reality because the threshold limit value may fluctuate. Further, in certain situations, the government may ask firms to adopt a new technology not for competitive purposes but for promoting the speed of technology diffusion without the impact of marketing, which cannot be explained by the competition and legitimation model. In the information cascade model, firms choose a new technology based on spontaneous mechanisms, focusing on the characteristics and superiority of the technology. The wine-making model emphasizes the productivity of a new technology and determines the technology diffusion rate by comparing the efficiency of the new technology with that of the old one. We now introduce the general epidemic model.

Suppose that there are S potential users of a new technology, and that each adopts the technology when he or she is provided with information of that technology. At time t, S(t) users have adopted and {S-S(t)} have not. Suppose further that, in each period, information transmitted from its source, reaching b_1 of the population. Clearly, the range for b_1 is [0,1], and thus, the probability of b_1 showing two extreme values is low. Thus, we can obtain

$$dS(t) = b_1(S - S(t))dt \tag{1}$$

Then it follows that

$$\frac{dS(t)}{dt} = b_1(S - S(t)) \tag{2}$$

We then take the limit of both sides of Equation (2) as follows:

$$\lim \frac{dS(t)}{dt} = b_1(S - S(t)) \tag{3}$$

$$S^{'}(t) = b_1(S - S(t)) \tag{4}$$

Equations (3) and (4) are ordinary differential equations; solutions can be obtained as follows:

$$S(t) = S(1 - \exp(-b_1 t)) \tag{5}$$

Equation (5) is a modified exponential function, where the size of b_1 is proportional to the diffusion speed of the new technology. The higher the rate of technology diffusion, the larger the b_1 is. To quantify the effects of technology policy on the rate of technology diffusion at a certain point in time, we include technology policy in the model as a dummy variable and obtain

$$S(t+1) = S(1 - \exp(-b_{i1}t)) + b_2 D_i + e_i \tag{6}$$

where Di is a dummy variable for technology policy. Here Di equals 1 if the government adopts a policy to promote a new technology and 0 otherwise. The fact that technology policy impacts on technology diffusion is mainly decided by b2 value when the verifying result of b2 is highly significant. The settings for the dummy variable can be found in [12], [14]. Here ei denotes the residual item, and time t is already fixed. In other words, we consider only the data on the horizontal axis, ignore the time effect on the vertical axis. The model is parameterized, that is, we can quantify technology policy as a qualitative index. We then use specific data and an appropriate parameter estimation method to estimate the parameters of the model.

3. The Data

For the analysis, the data were standardized based on solid-state lighting (SSL) technology, which reduces greenhouse gas emissions. SSL technology is an emerging technology that is projected to provide substantial energy savings over conventional lighting sources by 2025. There is growing concern about the consequences of climate change, which is largely attributed to anthropogenic emissions of carbon dioxide (CO2; a greenhouse gas) from fossil fuel combustion [11]. The data, which were drawn mainly from the website of the American Energy Bureau, were analyzed and prepared into a panel data set (see Appendix 1). The data covered 19 periods and 23 states in the U.S. Data of each period represents a state adopted SSL technology (10,000 households). The 1-18-period data sets denotes data with no policy. And among the 19th-period data sets, the first 1-14 states were adopted by policy data, data without policy implied on states 15-23. The dummy variable for technology policy was coded as 1 if the government had a policy promoting SSL technology and 0 otherwise.

4. Estimation of model parameters and validation

The estimation of model parameters consisted of two phases: the estimation of b_{i1} and S using 1-18-period data, and the estimation of b_2 by fixing the time on 19th-period data while known b_{i1} and S value. During the parameter estimation, we used two different methods because this estimation has a considerable impact on the accuracy of the model, that is, different parameter estimation methods are likely to have a significant effect on the model fit. Parameter estimates from the genetic algorithm (GA) are more likely to show good consistency than those from the nonlinear least squares (NLS) method or the ordinary least squares (OLS) method [13], and thus, for the estimation of the b_{i1} process, we used the GA to estimate the parameters as follows:

$$S(t) = S(1 - \exp(-b_{i1}t)) \quad (7)$$

For the estimation of b_2 in the second stage, we used the maximum likelihood estimation (MLE) method because it can better address problems with little constraints and is easy to manipulate. The following briefly introduces the methods used in the parameter estimation process:

First, the GA was introduced by Holland [4] and extended by Goldberg [3]. The GA is used to solve parameter estimation problems involving linear and nonlinear digital filters and has been applied to both feedforward and recurrent neural networks. The GA that we adopted is described as follows:

(a) Create a population of chromosomes of size N.
(b) Calculate the fitness of each chromosome in the group P(t).
(c) If the termination criterion is satisfied, then stop the calculation; otherwise, select a pair of chromosomes for mating.
(d) With the crossover probability PC, exchange parts of the two selected chromosomes and create two offsprings.
(e) With the mutation probability Pm, randomly change the gene values for the two offspring chromosomes.
(f) The group P(t) has been processed from selection, crossover, and mutation operators to be the next group P(t+1).
(g) If the size of the new population equal to N, then terminate the algorithm; otherwise, go to step (a).

Appendix 2 shows the program code that we used to estimate b_{i1} from the GA, and Table 1 shows the estimation results for the parameters b_{i1}.

[Table 1] Estimation from GA for parameters b_{i1}

b11	b21	b31	b41	b51	b61
0.14	0.09	0.06	0.04	0.1	0.14
b71	b81	b91	b101	b111	b121
0.09	0.13	0.14	0	0.02	0.13
b131	b141	b151	b161	b171	b181
0.12	0.14	0.05	0.02	0.08	0.14

Second, the MLE method is typically used to estimate parameters by considering the joint probability. Suppose that residuals of model are independent and obey the same particular distribution. Then the residuals for each sample are multiplied. Further, the corresponding sample data are used in the multiplication to get the maximum or minimum value and its corresponding parameters.

Here we focus on the symbol and value of the coefficient b_2 because it represents whether the technology policy hinders or promotes technology diffusion and indicates the corresponding impact degree on technology diffusion. In this study, the parameter b_2 was 1.79, and the verifying result was also highly significant. Table 2 shows the estimation and verifying results of b2.

[Table 2] Estimation and validation of the parameter b_2

Parameter	Value	P-Value
b_2	1.7945	0.0042
R^2=0.9321		
adjR^2=0.9157		

The results indicate that the model provided a good fit to the data and that it was able to explain the structure of technology diffusion more reliability than others. Also the results suggest that technology policy framed by government plays a positive role in popularizing new technology.

In this study, this model used the SSL technology data in U.S. to examine the effects of technology policy on technology diffusion. In this model, if b_2 is positive, then the policy promotes the diffusion of the new technology, whereas if it is negative, then the policy impedes the diffusion. Therefore, the government can make appropriate and timely adjustments to this model to promote or limit the diffusion of a new technology for industrial restructuring and upgrading purposes.

5. Conclusion

This study contributes to the literature by quantifying the impact of technology policy on technology diffusion. More specifically, this study includes technology policy as a variable in the epidemic model, allowing the model to accurately determine the effects of technology policy on technology diffusion. We then use the data to examine the essential effects of technology policy on technology diffusion. The results of this study have powerful implications for policy makers aiming at facilitating technology diffusion: their decision-making process can now be more scientific, that is, it can be based on quantitative as well as qualitative data. This study has some limitations. In particular, we examine the effects of technology policy in a fixed time. Thus, future research should be on building a dynamic model changing over time. Moreover, we will compare other diffusion models with epidemic model to analyze the effect of technology policy.

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Appendix 1 The data

Time / State	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	Dummy variable
1	3.91	7.31	10.27	12.84	15.08	17.02	18.71	20.18	21.46	22.57	23.54	24.38	25.12	25.75	26.31	26.79	27.21	27.57	30.31	1
2	2.48	4.76	6.85	8.77	10.52	12.14	13.61	14.97	16.22	17.36	18.40	19.36	20.24	21.05	21.79	22.47	23.09	23.67	24.86	1
3	1.83	3.55	5.16	6.68	8.10	9.43	10.69	11.87	12.97	14.01	14.99	15.90	16.76	17.57	18.33	19.04	19.71	20.34	22.72	1
4	1.32	2.59	3.80	4.96	6.06	7.12	8.13	9.09	10.02	10.90	11.74	12.55	13.32	14.05	14.76	15.43	16.07	16.69	16.76	1
5	2.98	5.67	8.08	10.26	12.22	13.99	15.58	17.01	18.31	19.47	20.51	21.46	22.31	23.07	23.76	24.38	24.94	25.44	27.80	1
6	4.03	7.51	10.53	13.15	15.41	17.37	19.06	20.53	21.80	22.90	23.86	24.68	25.39	26.01	26.55	27.01	27.41	27.76	28.14	1
7	2.67	5.10	7.31	9.33	11.17	12.84	14.37	15.76	17.02	18.18	19.23	20.18	21.06	21.85	22.58	23.24	23.84	24.39	24.25	1
8	3.71	6.97	9.82	12.32	14.51	16.42	18.10	19.58	20.87	22.00	22.99	23.86	24.62	25.28	25.87	26.38	26.83	27.22	30.33	1
9	3.95	7.38	10.36	12.95	15.19	17.14	18.84	20.31	21.58	22.69	23.66	24.49	25.22	25.85	26.39	26.87	27.28	27.64	29.10	1
10	0.04	0.09	0.13	0.17	0.22	0.26	0.30	0.35	0.39	0.43	0.48	0.52	0.56	0.61	0.65	0.69	0.73	0.78	2.41	1
11	0.72	1.43	2.11	2.79	3.44	4.08	4.70	5.31	5.91	6.49	7.05	7.61	8.15	8.67	9.19	9.69	10.18	10.65	11.72	1
12	3.67	6.90	9.73	12.21	14.39	16.30	17.98	19.45	20.74	21.88	22.87	23.74	24.51	25.18	25.77	26.29	26.74	27.14	29.54	1
13	3.32	6.28	8.91	11.24	13.32	15.17	16.81	18.27	19.57	20.73	21.75	22.67	23.48	24.20	24.84	25.41	25.92	26.37	27.11	1
14	3.96	7.40	10.38	12.97	15.22	17.17	18.86	20.33	21.61	22.72	23.68	24.51	25.24	25.87	26.41	26.88	27.30	27.65	26.70	1
15	1.42	2.78	4.07	5.29	6.46	7.58	8.64	9.65	10.62	11.54	12.41	13.24	14.04	14.79	15.52	16.20	16.86	17.48	18.18	0
16	0.65	1.29	1.92	2.53	3.13	3.72	4.29	4.85	5.40	5.94	6.46	6.98	7.48	7.97	8.45	8.92	9.38	9.83	12.19	0
17	2.44	4.69	6.75	8.65	10.39	11.98	13.45	14.80	16.04	17.18	18.22	19.18	20.06	20.87	21.62	22.30	22.93	23.50	23.83	0
18	3.81	7.14	10.04	12.58	14.79	16.72	18.41	19.88	21.17	22.29	23.27	24.12	24.87	25.52	26.09	26.59	27.02	27.40	27.21	0
19	0.65	1.28	1.90	2.51	3.11	3.69	4.26	4.81	5.36	5.89	6.41	6.92	7.42	7.91	8.39	8.86	9.31	9.76	9.57	0
20	1.83	3.54	5.15	6.67	8.09	9.42	10.68	11.85	12.96	14.00	14.97	15.89	16.75	17.55	18.31	19.02	19.69	20.32	20.50	0
21	1.58	3.07	4.49	5.83	7.10	8.31	9.45	10.53	11.55	12.52	13.44	14.32	15.14	15.92	16.66	17.36	18.03	18.66	17.66	0
22	3.14	5.96	8.48	10.73	12.75	14.56	16.18	17.63	18.92	20.08	21.12	22.05	22.89	23.63	24.30	24.90	25.43	25.91	25.43	0
23	0.77	1.51	2.24	2.95	3.64	4.32	4.97	5.61	6.24	6.84	7.44	8.01	8.58	9.12	9.66	10.18	10.68	11.18	12.13	0

Appendix 2 The Program Code

```
library(RWinEdt)
library(gafit)
v=list()
for(i in 1:23){

e=expression(sum((S[i,]-30*(1-1/exp(b[i]*(1:17)))^2))
v[[i]]=gafit(e,list(b[i]=1e-6),step=0.1,maxiter=100)

}
v=as.numeric(v)
Y=S[,19]-30*(1-1/exp(v*18))
data1=as.data.frame(cbind(Y,S[,20]))
colnames(data1)=c("y","x")
Regression=lm(y~x,data1)
```