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Abstract

In the past China's rural areas, home to 70% of its population, suffered energy shortages. China's indigenous energy resources are limited, with the exception of coal. The widespread use of coal requires large investments in production and transport –making it costly-, and degrades the environment. As a result the Chinese government has implemented an energy policy that aims at the use of renewable energy resources and increasing energy efficiency. For this the Chinese government has reorganised its institutional framework, which now aims at learning and improving profitability to diffuse technologies. Simultaneously the decision to use a technology has been shifted from officials to the consumers and profitability of a technology has become the main decision criterion. This paper analyses the effect of learning and profitability in technology diffusion and looks at the effectiveness of the institutional efforts.

Keywords: technology diffusion, learning, institutional framework, government policy

JEL: Q42, Q48, O32, C99.

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1. Introduction

With the majority of China's population living in rural areas, sufficient and adequate energy supply for these areas is a major issue for the Chinese government. China's rural areas suffered fuel shortages for cooking and heating for a long time. It is estimated that in the late 1970s and the early 1980s 70% of rural households suffered fuel shortages, and 47% of rural households lacked fuel for more than three months each year. Fuel shortages lead to the direct burning of a huge amount of crop residues, a major contributor to the organic matter loss in soil, and to over-cutting of forest, among others leading to erosion. Reducing the fuel shortages is not an easy task. China's main indigenous source of energy is coal, the use of which leads to local (particles), regional (SO_2), and global (CO_2, NO_X) environmental problems. Furthermore, the distribution of coal to rural areas is costly.

To stop the soil degradation process and to limit the widespread use of coal the Chinese government invested in the R&D of energy technologies. The Chinese government wants every region to utilise as much as possible its, preferably renewable, resources to produce energy, before importing commercial fuels. For this China has developed and/or adjusted renewable and non-renewable energy technologies. Examples are family-size and large bio-digesters, various solar and wind technologies, and improved stoves; see Smith et al. (1993), and Gu et al. (1995). Furthermore, the Chinese government has adapted its original institutional framework to support the diffusion of these technologies (Deng Keyun, 1994). The diffusion of the improved energy technologies is regarded a key measure in the alleviation of the fuel shortage and the protection of the environment in rural China.

Technology diffusion is the final part of the process of technological change, encompassing invention (the generation of new ideas), innovation (the development of those ideas through to the first marketing or use of a technology), and diffusion (the spread of new technology across its potential market) (Stoneman and Diederen, 1994). Technology diffusion commonly refers to the acceptance and spread of a new technology in a market or user community; that is, the adoption of innovations by others (Norberg-Bohm, 1999).

The diffusion of energy technologies involves a number of institutions[2], and much depends on the structure and ability of these institutions to successfully implement energy programmes. In the light of economic reforms in countries like China and India, institutional issues in energy systems diffusion have become more important than under the command and control approach of the past (Monga, 1997). No efforts, however, have so far been taken to empirically test or measure effectiveness of the institutional structure involved in diffusion of energy technologies in developing countries. Our research, thus, is an effort to fill this gap.

The Chinese diffusion efforts rest on two pillars, R&D to improve the profitability of energy technologies and an adequate institutional framework to diffuse technologies. The R&D effort improves profitability through (i) increased energy efficiency, and (ii) developing production techniques that reduce the cost of production and can be used locally. Because of the cultural and climatic differences within China, technologies are also adjusted to local conditions and culture.

An example is the efficient stove program. Within this program improved wood and coal stoves (mainly for cooking) have been designed that increased the efficiency of the biomass stoves from 6-12% to 20-25% and of coal stoves from 16-18% to 30-35%. The general principles and prototypes were developed in national research institutes (among them Tsinghua University), which were then introduced to research institutes at the provincial level that developed stoves for their regions. The latter worked together with regional energy offices to adjust the stoves to local habits in stove usage, such as, its role in every day life and the fuels available. Furthermore, the production technology had to be such that the stoves can be produced and repaired locally. The same principles have been used for other technologies, with the exception of large and medium size bio digesters (more than 50 m^3 in size) that require the support of skilled technicians.

The institutional framework changed from the ‘command and control’ approach used in the past, when government officials decided, to a framework that is based on market oriented decision making, that is, the energy user decides based on profitability. The new institutional framework tries to initiate and promote learning to

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[2] Here institutions comprise all non-market, non-profit organisations, public agencies, universities, etc. In the literature a broader definition is used also, comprising all forms of organisations, conventions, and repeated and established behaviours that are not directly mediated through the market (Dosi and Orsenigo, 1988)

reduce consumer uncertainty about the new technologies, and to improve the profitability of the technologies.

For the Chinese government it is important to know whether or not its R&D and institutional efforts are useful. This is the question we want to answer in this paper. For this we first develop a theoretical model to describe the diffusion process of rural energy technologies based on learning and profitability, and look at an application. In traditional diffusion models (Bewley and Feibig, 1988) the diffusion coefficient has no economic meaning. The diffusion model developed here differs from this traditional diffusion model by linking the diffusion coefficient to economic reasoning. Next we quantify the effects the R&D-profitability efforts and the learning efforts have on investments in rural energy.

This paper is organised as follows. In Section 2 the Chinese institutional framework is briefly discussed. In Section 3 a theoretical diffusion model is developed and simulation results for the Chinese stove program are reviewed. The effect the R&D efforts and the new institutional framework have on investments in rural energy technologies is tested empirically in Section 4. Section 5 contains conclusions.

2. China's institutional framework

Before 1978 the institutional framework to diffuse technologies was based on command and control. Between 1978 and 1989 the existing institutional framework was adjusted to the new main principle in rural energy planning: market-oriented decision-making, which is the Chinese term used for profitability. Under the command and control policy diffusion targets, set by the government, had to be achieved, often at the expense of quality. The main example is the family-size bio-digester program. This program started in 1973 and seemed very successful reaching over 718 thousand installed digesters by 1978. However, the quality of many digesters was such that they did not function properly and often digesters were installed where they were not needed. As a result the number of digesters used quickly decreased after the policy changes in the late 70s to 392 thousand in 1983. After 1983 the number of digesters started rising again, because new improved bio-digesters were marketed, and consumers could decide whether or not they wanted one. The government energy offices only showed them the advantages of the bio-digester in a rural farming. (See

FAO (1994) for an extensive discussion of the role bio-digesters can play in farming.)

FIGURE 1 ABOUT HERE

China's institutional rural energy technology diffusion system is shown in Figure 1. Five ministries, two state commissions (a kind of super ministry), and the State Power Company (SPC) (the former ministry of power) are involved. They have different roles. Basically the State Council (not depicted in Figure 1) funds all programs, but the participating government bodies also supply funds for programs in which they have a specific interest. The State Development Planning Commission (SDPC) co-ordinates all efforts (which goes beyond rural energy) and acts as chair. The Ministry of Agriculture (MOA) executes the rural energy program, because they have an administration that is present in all counties. (China is divided into 2,166 counties, which are again divided into townships and villages.) The left-hand side of Figure 1 shows the provincial rural energy R&D institutions; often these are universities and other government funded research institutes. (R&D on the national level is of a more fundamental nature and is (mostly) in support of the provincial R&D.) The provincial rural energy R&D institutions work with the county R&D institutions[3], which are normally physically located within the county Rural Energy Office. Together they adjust the general technologies to meet the local conditions and execute field programs.

The learning diffusion efforts are concentrated in the Rural Energy Offices (REOs) in the centre of Figure 1; all REOs in the national diffusion system, from the provincial to the township level, are semi-government organisations. Initially a learning program is designed for a limited number of townships and villages in a few counties that are willing to co-operate. Within each county one or more technologies that have shown their adequacy in field experiments, are introduced in demonstration projects. These demonstration projects are never fully subsidised. The technology users have to pay part of the cost. For some technologies the county gets, however, a subsidy. For example, within the stove program initially 25,000 Chinese Yuan (about U$ 5,000) was paid to a county that volunteered. When the people in the

[3] A county R&D institution consists of one or more people that assist in the applied

demonstration counties have some experience with the new technology and are satisfied with it, consumers and officials of other counties are invited to come and evaluate the new technology for themselves, and speak to the users. Once there are sufficient initial adopters, the subsidy stops, and the county and township rural energy offices only disseminate information to potential new users, and help local craftsmen and workshops to learn the skills required. If a technology proves to be successful, the MOA organises lager county programs through the REOs at county and township level. For example, after several projects in a limited number of counties and incorporating the experiences in these counties into the technology designs, the One-Hundred-County Rural Energy Development Program was initiated during the 1991-1995 five year plan (the biggest renewable and energy efficient technology diffusion program in rural China). Total expenditures for this program by governments at different levels was 174.8 million Yuan[4] while the users' investments were 5.73 billion Yuan (Zhang, 1997). A second 100 county program followed in the 1995-2000 five year plan. Since all these activities aim at providing more information to potential adopters, thus, accelerating the learning process, REOs can be regarded as information-based institutions that initiate and promote learning.

In two ways the Chinese government tries to improve the profitability of a technology. First, through R&D efforts in the Rural Energy R&D Institutes (RERDIs), which are on the left-hand side of Figure 1. The RERDIs at the provincial level (each province the size of a medium sized country) develop the new technologies further and/or improve the performance of existing technologies to suit the local conditions and RERDIs at the county level help to adapt the technologies even further. Although at different levels, both RERDIs aim at improving the profitability of technologies by improving the performance.

Second, through the development and introduction of (improved) production methods by educating labour and local manufacturers the cost of production are reduced. This is indicated on the right-hand side of Figure 1 as Energy Service Companies (ESCs). Examples are the introduction of the construction of solar water heaters to metal shops and teaching craftsmen to build family size bio-digesters. Simultaneously a sales and service organisation is build. Often this means that

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research of the higher level R&D institutions.

[4] Which covered the direct subsidies, 100 million Yuan, loan interest rate subsidies, 5.5 million, and the expenditure of program offices at different levels, 69.3 million.

existing outlets for related products are helped to introduce new products into the market and to be able to do repair work.

It is clear that the Rural Energy Offices (REOs), the Rural Energy Research and Development Institutes (RERDIs), and the Energy Service Companies (ESCs) are vital institutions in the diffusion process. They are responsible for the improvement of a technology's profitability and the learning process of adopters. In the next section the diffusion process is modelled as function of profitability and learning. After that we will quantify the role of the REOs, RERDIs, and ESCs in China's rural energy technology diffusion.

3. Technology diffusion

We treat technology diffusion as a process of selection under an evolutionary environment. Let N denote the entire population of adopters and potential adopters and $n(t)$ that of adopters at time t, and assume that all potential adopters are rational and pursue profit maximisation. Then, at time t the decision-making problem of potential adopter i ($i \in N$) can be expressed as:

$$\underset{I_i(t)}{Max} \ \Pi^i(t) = I_i(t)[\int_0^{\infty} \delta_i(t) \cdot B(t) \cdot e^{-r_i(t)\tau} d\tau - C(t)] \ , \qquad (1)$$

or

$$\underset{I_i(t)}{Max} \ \Pi^i(t) = I_i(t)[\frac{\delta_i(t)B(t)}{r_i(t)} - C(t)] . \qquad (2)$$

$\Pi^i(t)$ is the profit function of potential adopter i; $I_i(t)$ is an indicator function, $I_i(t) = 1$ if potential adopter i decides to adopt the technology and $I_i(t) = 0$ otherwise. $B(t)$ is the annualized net benefit of the technology and $C(t)$ is the initial investment requirement or the price of the technology. $r_i(t)$ is the implicit discount rate of potential adopter i, and $\delta_i(t)$ is the adopters subjective risk coefficient with respect to the technology.

It is easy to see that the sufficient and necessary condition for potential adopter i to adopt the technology is:

$$\frac{\delta_i(t)B(t)}{r_i(t)} - C(t) > 0\,. \tag{3}$$

With $\lambda_i(t) = \dfrac{r_i(t)}{\delta_i(t)}$ and $b(t) = \dfrac{B(t)}{C(t)}$ Equation (3) can be rewritten as

$$\lambda_i(t) < b(t)\,. \tag{4}$$

This is the simplest condition for technology adoption. $b(t)$ indicates the *profitability of the technology* and the R&D efforts aim at increasing $b(t)$. λ_i *(t)* can be looked upon as *individual i's risk adjusted implicit discount rate for adopting the technology*, which depends on the adopter's time preference and the adopter's attitude towards risk, and parameterises the characteristics of potential adopter i in terms of introducing a technology. The learning efforts in the diffusion activities aim at reducing λ_i *(t)*.

Remark: Jaffe and Stavins (1994) have listed evidence showing that the implicit discount rates of energy-saving technology vary substantially and what may cause these variations. The interpretation and usefulness of results similar to (4) has been the subject of some discussion; see for example Hassett and Metcalf (1993), Howarth and Sandstad (1995), and DeCanio and Laitner (1997). However, all agree that profitability and learning are important factors in technology diffusion, the main argument is about the interpretation of the empirical results and the ways consumers use information.

Suppose that the λ_i *(t)* follows a distribution $f(\lambda)$, then the adoption rate among potential adopters $a(t)$ at time t can be written as:

$$a(t) = \int_0^{b(t)} f[\lambda(t)]d\lambda(t)\,. \tag{5}$$

Using Equation (5), we can reach the following technology diffusion speed model:

$$\frac{dn(t)}{dt} = a(t)[N - n(t)]\,. \tag{6}$$

The solution of Equation (6) can be expressed as (see Appendix A):

$$n(t) = N - \left[N - n(0)\right]e^{-\int_0^t a(\tau)d\tau}\,. \tag{7}$$

Dividing the two sides of Equation (7) by N and defining $\rho(t) = \frac{n(t)}{N}$ and $\rho(0) = \frac{n(0)}{N}$, we can obtain the percentage diffusion model:

$$\rho(t) = 1 - \left[1 - \rho(0)\right]\cdot e^{-\int_0^t a(\tau)d\tau}\,. \tag{8}$$

Equations (6), (7), and (8) are three different forms of our technology diffusion model.

The model differs from the classical epidemic diffusion:

$$\frac{dn(t)}{dt} = \alpha \cdot n(t) \cdot [N - n(t)]\,, \tag{9}$$

where α is the diffusion coefficient. Equation (9) captures the learning mechanism between adopters and potential adopters, that is, the learning by observing the experience of existing adopters. It is simple and has shown a good fit to a variety of phenomena (De Araujo, 1995; DeCanio and Laitner, 1997). It has, however, a number of important deficiencies. One line of criticism has been on the rigidity of (9) and more flexible forms have been developed with α a function of t (Bewley and Feibig, 1988). These more flexible forms give a better fit, but they do not meet two other main points of criticism. First, Equation (9) assumes that all potential adopters are homogenous; which is normally not the case. Second, the diffusion coefficient, α, has no economic meaning, nor is it affected by economic policy; also see Metcalfe (1981). The approach developed here meets these criticisms. In our model, the coefficient $a(t)$ is dynamic and clearly parameterises the economic dynamics of the technology diffusion process. Furthermore, our model captures the adopter heterogeneity. It is also very flexible and allows for the same S-shape curve as (9) if required, but without the mathematical rigor of the traditional model.

In our model the technology diffusion process is an accumulated result of the effects of the two mechanisms: technology profitability, and learning between heterogeneous adopters and heterogeneous potential adopter. The model not only interprets the nature of technology diffusion process, but also provides a framework within which the major variables affecting technology diffusion can be investigated. Next we give an example of the effects of the two mechanisms on the technology diffusion process.

A simulation example: Improved stoves

The effects of technology profitability and learning will be simulated for the diffusion of improved stoves in rural China. In 1983 the Chinese government initiated an improved stove program. Since then tremendous progress has been achieved; see Smith et al. (1993) and Gu et al. (1995). By 1998 approximately 85% of China’s rural households used an improved stove, much more than in other developing countries. Annual data are available on the number of stoves diffused and the total number of households for the time period 1984-1998. Among all energy technologies diffused in rural China, improved stoves are the most successful technology. It is also the only technology for which the diffusion process seems almost completed.

To apply the diffusion model, it is necessary to specify the distribution function of $\lambda(t)$. We assume that $\lambda(t)$ can be approximated by the incomplete Gamma distribution:

$$f(\lambda(t)) = \frac{1}{\Gamma(\mu(t))}(\lambda(t)^{\mu(t)-1}e^{-\lambda(t)}) . \qquad (10)$$

Then, according to Equation (5) we have:

$$a(t) = \frac{1}{\Gamma(\mu(t))}\int_0^{b(t)} \lambda(t)^{\mu(t)-1}e^{-\lambda(t)}d\lambda(t) . \qquad (11)$$

μ (t) is the sole parameter characterising potential adopters. Equation (11) clearly demonstrates how the technology's profitability, $b(t)$, and the characterisation of the distribution of potential adopters, $\mu(t)$, govern the adoption rate of potential adopters, thus, the whole technology diffusion path.

TABLE 1 ABOUT HERE

Unfortunately we do not have time series on fuel prices and stove prices, which determine the profitability $b(t)$. What we do have is a range for profitability, based on a price range for stoves and fuel prices at the start of the program. These were obtained from experts in the field and previous studies; also see ADB (1996). The values correspond with a simple payback time between 6 month and three years. The value range for $\mu(t_0)$ can be calculated based on Equation (11), given the actual initial adoption rate, profitability $b(t_0)$, and distribution function (10). The value-ranges for the parameters $b(t_0)$ and $\mu(t_0)$ are shown in Table 1.

Since profitability and customer attitude (can) change over time, we introduce two change parameters, γ_1 and γ_2, which allow for a fixed annual change in $b(t_0)$ and $\mu(t_0)$ when time progresses; that is, $b(t) = b(t_0)(1+\gamma_1)^{t-t_0}$ and $\mu(t) = \mu(t_0)(1-\gamma_2)^{t-t_0}$. For profitability we assume $\gamma_1 \geq 0$. The reason to do so is that improved production techniques will lower the cost of production, which, in combination with more competition between producers as the use of improved stoves increases, will increase the profitability of the stove for the user. We also assume $\gamma_2 \geq 0$, which implies that the risk-adjusted discount rate does not increase over time. There are two arguments to support this assumption. First, real rural incomes have increased during the simulation period 1984-1998, and second, the learning effect will reduce the perceived risk and thus $\mu(t)$. Initial simulation runs show that γ_1 and γ_2 will certainly be less than 10%, so we assume these parameters will be between 0 and 10%; see Table 1.

TABLE 2 ABOUT HERE

To optimise the simulation result we applied a Monte Carlo search for the best parameter values. The model was simulated one million times in MATLAB using random draws from the four-dimensional parameter hyper cube that constitutes the experimental area. The criterion used was minimising the sum of absolute deviations between the diffusion rate data and the estimated diffusion path. The resulting $\rho(t)_{SIM}$ and the data for $\rho(t)$ are depicted in Figure 2, and the corresponding optimal parameter values are in Table 2.

FIGURE 2 ABOUT HERE

Note that our simulation is a stylised one. We treat a variety of improved stoves, mainly for cooking using biomass, developed for various regions of China as one technology.

Sensitivity Analysis

As mentioned before, Equation (11) in combination with Equation (6) can be used to derive a number of different diffusion patterns. Figure 3 shows a variety of patterns based on some of the extreme points of the experimental area (see Table 3), which lead to different development paths of $\mu(t)$ and $b(t)$.

TABLE 3 ABOUT HERE

Figure 3 clearly shows that the traditional diffusion pattern following from Equation (9) or other related curves can be obtained; also see Bewley and Feibig (1988). We will not discuss all the curves in detail, but highlight some of the main effects.

FIGURE 3 ABOUT HERE

Curve number 1 in Figure 3 is based on $b(t_0)$ low, $\mu(t_0)$ high, and a 10% annual growth in profitability. Even under the considerable growth in profitability the fraction of adopters stays low. Curve 2 shows the effect of a 10% annual decrease in $\mu(t)$, resulting in a decrease in $\lambda_i(t)$, leads to a much stronger increase in the diffusion rate. Curve 3 combines a low initial uncertainty with an increase in profitability. Comparing curves 1 and 3 indicates that reducing uncertainty seems more important then increasing profitability, assuming the parameter ranges are comparable. Curve no. 4 shows the effect a higher initial profitability on the diffusion rate. Curves 5, 6, and 7 show different forms of the familiar S-curve, but with different adoption speeds, whereas Curve 8 looks similar to an exponential growth. Curve 5 is actually close to the results that can be obtained with Equation 9. This analysis shows the advantage of an economic underpinning of the broadly used diffusion model in Equation (9). It provides a wider range of possible diffusion paths than the purely mechanical approach.

Figure 4 shows the changes in the percentage diffused. The changes in the different curves clearly show that the model covers the whole spectrum of increasing diffusion patterns.

FIGURE 4 ABOUT HERE

Although Figures 3 and 4 show a wide range of diffusion patterns, they do not indicate the relative importance of the different parameters. We use the theory of the design of experiments (DOE) in combination with regression meta-modelling to indicate the importance of each of the four parameters. For more details on DOE and meta-modelling in sensitivity analysis of model output we refer to Van Groenendaal and Kleijnen (1997), and Van Groenendaal (1998). This approach is easy to apply and requires only a limited amount number of simulation experiments. For the statistical details we refer to Appendix B.

Since our simulation model is non-linear we want to apply a meta-model of the form:

$$Y_i = \alpha_0 + \sum_{j=1}^{4} \alpha_j X_j + \sum_{j=1}^{4} \sum_{k=1}^{4} \alpha_{j,k} X_j X_k \,. \tag{12}$$

Y_i is the dependent variable indicating the result of experiment *i*, and is defined as the change in the diffusion rate $Y_i = \hat{\rho}_{i,1998} - \hat{\rho}_{i,1983}$. X_j (*j* = 1, … , 4) are explanatory variables, the values of which are a function of the value ranges for the parameters given in Table 1. (See Appendix B for details.) The estimation results are in Table 4 and need some interpretation. The constant indicates the growth in the diffusion rate for the centre point of the experimental area and the other coefficients how this is affected by changes in the parameter values. The main effects, $\alpha_1, \ldots, \alpha_4$ are as expected. For example, an increase in $\mu(t_0)$, indicating a reduction in the subjective risk adjusted discount rate, leads to a decrease in the diffusion rate α_2. This effect is strengthened when we take into account the quadratic effect α_{22}, stressing the importance of learning. The strong main effect of an increase in profitability $b(t_0)$ on the other hand, indicated by α_1 is mitigated by the corresponding quadratic effect α_{11}. This suggests that in our application profitability is less important than learning. The overall-effects of the dynamic parameters γ_1 and γ_2 are small, but statistical testing shows that they cannot be omitted. There is one significant interaction effect, between $b(t_0)$ and γ_2, indicating that a high initial profitability and a high reduction in the adopters risk adjusted discount rate, both resulting in growth of the diffusion rate, mitigate each other.

In summary, with the diffusion model for improved stoves we have demonstrated the dynamics of our approach to the diffusion process of energy technology in rural China. We have found that both *learning*, aiming at a decrease of the risk-adjusted discount rate, and *profitability* play an import role in the diffusion process of improved stoves, but that learning seems more important. Unfortunately we do not have sufficient data on other technologies to apply the model. The only sufficiently long time series available is for family size bio-digesters. However, contrary to the improved stove program, consumers were for many years, especially during the pre 1978 period, coerced into installing a family size bio-digester. So the bio-digester program does not meet the assumption of our model that the consumer decides. Next we analyse if the government efforts to speed up diffusion work.

4. The role of institutions in rural energy technology diffusion

In the previous sections it was demonstrated how profitability and learning can affect the diffusion of technology, and that this approach can be used to describe the diffusion process of rural energy technologies in China. In this section we will analyse what effect China’s institutional diffusion support system actually has on rural energy technologies. Through its rural energy policy the Chinese government wants to influence both sides of inequality (4). The Chinese diffusion efforts aiming at learning want to reduce $\lambda_i(t)$ by showing the potential adopters the quality of the technology. The diffusion efforts aiming at profitability want to increase $b(t)$ through increased efficiency and lower production cost. The empirical relationship between investment in energy systems in rural areas and learning and profitability is the subject of this section.

A problem for our analysis is that the institutional efforts can in general not be assigned to particular technologies. In practice the efforts of the REOs as well as the RERDIs are dedicated to all technologies. As we will see below, also the information on ESCs is only available as a total for all technologies. Furthermore, there will be differences between provinces with respect to the success of the diffusion program.

Another problem is to find data that represent the different variables. The most accurate and detailed data available are published in the *China Rural Energy Yearbook* first published in 1997. The book contains (among others) information on energy technology diffusion based on the yearly statistical reports from the REOs and is regarded the most authoritative source of information.

Available is the total annual investment in rural energy systems per province. Let $I_{i,t}$ denote the total investment in all energy technologies in province *i* in year t.

While expenditures on energy technology diffusion, on R&D, and on production capacity would be the desirable measurement of the activity levels of REOs, RERDIs, and ESCs respectively, only annual expenditure data for REOs' per province are available. We define $REO_{i,t}$ as the sum of all expenditures on the REOs in province *i* in year t at the provincial, county, and township level.

For the RERDIs only the number of R&D staff on the provincial and the county level is available. This is used as a proxy for the activity level of the RERDIs. $RERDI_{i,t}$ denotes the number of R&D staff in province *i* in year t.

ESCs expenditures on capacity are not available, only information on the number of people employed. This will be used as a proxy for this activity level. Let $ESC_{i,t}$ denote the number of people employed to produce the various energy technologies in province *i* in year t.

In the China Rural Energy Yearbook data are available from 1990 to 1998.

However, data on total investments in rural energy technologies per province are only available for 1993-1998. The REO and ESC data are available for 25 provinces. Unfortunately, the RERDI data are missing for quite a number of provinces, limiting the estimation to 10 provinces instead of 25. However, with these data we can perform a panel data analysis.

A panel data analysis has several advantages (Verbeek, 2000, pp 309-25). In general the estimates will be accurate since the data vary over province and time, and the estimators are more robust for incomplete model specification. Because provinces differ the fixed effect model seems the most appropriate. We will, however, use the random effect model and the OLS model with corrected estimator for the standard errors to test the robustness of our results. If the different estimates are of the same order of magnitude, the result obtained is robust.

We assume that the relationship between investments $I_{i,t}$ and the variables indicating the different diffusion activities $REO_{i,t}$, $RERDI_{i,t}$, and $ESC_{i,t}$ is of the log-linear type, which leads to:

$$\ln(I_{i,t}) = \beta_0 + \beta_1 \ln(REO_{i,t}) + \beta_2 \ln(RERDI_{i,t}) + \beta_3 \ln(ESC_{i,t}) + \varepsilon_{i,t}. \qquad (12)$$

$\varepsilon_{i,t}$ is an error term, which is assumed to be i.i.d. over time and province.

The significant estimation results are given in Table 5. The coefficients of the three models (fixed effects, random effects, and OLS) do not differ much, which indicates that the fixed-effects model is a good choice. From the estimation results we can learn the following.

The efforts by the Chinese government that aim at stimulating learning are highly significant. A one percent increase in government spending leads to a 0.9% increase in investments. On average the size of the annual private investments in rural energy systems are about eight times that of the government spending on REO. This shows that these efforts are money well spend.

We also introduced the spending on REO at the provincial ($REO_{i,t}^{P}$), county ($REO_{i,t}^{C}$), and township ($REO_{i,t}^{T}$) level as separate variables. It turns out that all three variables are significant and the corresponding elasticities are $\beta_1^P = 0.182$,

$\beta_1^C = 0.526$, and $\beta_1^T = 0.269$ respectively; so the county institutional level is the most important.

The variable $RERDI_{i,t}$ was not significant, so we have no empirical evidence that the efforts to improve the profitability of technologies through R&D contribute to the diffusion. It is most likely that the effect of the R&D efforts require a much longer estimation period than the six year available to make the effects of the R&D effort visible.

In as far as $ESC_{i,t}$, the number of employees of the service companies per province, is a proxy for profitability by lowering production cost, it has a positive effect ($\beta_3 = 0.351$), be it statistically weak, on the sales of rural energy technologies.

The differences in fixed effects between provinces were analysed also. We investigated if there is a relationship between the poverty level of provinces and the fixed effect. However, no systematic relationship could be detected.

5 Conclusions

For years the Chinese government invests money in its rural energy program. The Chinese efforts to improve the diffusion of renewable and improved energy technology focus at learning and increasing profitability. In this paper a diffusion model was presented in which the diffusion rate is a function of profitability and learning. Furthermore, the relationship between private investments in energy technology and the government efforts on learning and R&D to improve profitability of was tested empirically. It was shown that the government expenditures on learning is money well spend. Only a weak link between investments and the Chinese efforts to lower production costs could be established. A link between R&D efforts aiming at efficiency improvements and private investments could not be established.

The diffusion model developed allows for a wide variety of diffusion patterns. The exact shape (S-curve, exponential growth) of the diffusion function depends on the values of the profitability and learning parameters. The model was applied to the diffusion data of improved stoves in China, using Monte Carlo optimisation to obtain estimates for the parameters. Sensitivity analysis of the applied model, using the design of experiments in combination with regression meta-modelling, showed that both, profitability and learning, play an important role in the diffusion process, although learning seems to be more important.

The relationship between the government efforts on learning and on profitability improvement and private investments in energy systems was analysed through panel data analysis. It was shown that the government expenditures on rural energy offices, which concentrate on learning and the dissemination of information, have a strong and significant positive effect on the private investments in rural energy technology. Profitability is improved in two ways; by R&D to increase the energy efficiency of technologies and by improving production techniques and educating craftsmen to lower the cost of production. No empirical link was found between private investments in rural energy systems and the R&D efforts on efficiency, and only a weak link was established between private investments and the efforts to lower the cost of production. This does not mean that the Chinese efforts to improve profitability through R&D are futile; it means that the limitations of the data set available does not allow us to verify this link.

Appendix A

Proposition: The solution of the Equation (A1) can be expressed by Equation (A2).

$$\frac{dn(t)}{dt} = a(t)[N - n(t)] \qquad \text{(A1)}$$

$$n(t) = N - [N - n(0)] \cdot EXP\left[-\int_0^t a(\tau)d\tau\right] \qquad \text{(A2)}$$

Proof: Rewrite Equation (A1) as

$$\frac{dn(t)}{N - n(t)} = d\left[\int_0^t a(\tau)d\tau\right] \qquad \text{(A3)}$$

Then, we have:

$$d[\ln(N - n(t))] = d\left[-\int_0^t a(\tau)d\tau\right] \qquad \text{(A4)}$$

The generic solution to Equation (A4) can be written as:

$$N - n(t) = C \cdot EXP(-\int_0^t a(\tau)d\tau) \qquad \text{(A5)}$$

Where C is a constant. Let $n(t)\big|_{t=0} = n(0)$, then we have:

$$C = N - n(0) \qquad \text{(A6)}$$

Substituting Equation (A6) into (A5), we obtain Equation (A2).

Appendix B

The variable representing parameter $b(t_0)$ is denoted as X_1, $\mu(t_0)$ as X_2, γ_1 as X_3, and γ_2 as X_4. The value $X_1 = -1$ corresponds to the parameter value $b(t_0) = 0.33$, and the value $X_1 = 1$ corresponds to the parameter value $b(t_0) = 2$; that is the two extreme values of parameter $b(t_0)$ in Table 1. Furthermore, the value $X_1 = 0$ corresponds to $b(t_0) = 1.165$, the value at the center of the experimental area. Similarly the values for X_2, X_3, and X_4 are assigned; that is, the value of parameter *i*, *i* = 2, 3, 4, in Table 1 that leads to a (relative) slow growth in the diffusion rate corresponds to $X_i = -1$ and the other value to $X_i = 1$. To be able to identify all parameters in the regression meta-model (12) we apply a central composite design, which combines a full factorial 2^4 design in combination with a "star" design (Kleijnen and Van Groenendaal, 1992). The full factorial design describes the 16 extreme points of the four-dimensional unit cube. This is augmented with 8 "axial" points $(a,0,0,0)$, $(-a,0,0,0)$, etc., in which the 0 corresponds to the center of the experimental area and $a > 1$, and the central point (0,0,0,0). This enables us to estimate the main effects α_j, *j* = 1,…,4, of changes in the four parameters, possible interactions α_{jk}, $j \neq k$, and quadratic effects α_{jj}, *j* = 1,…,4.

The estimation results of (12) are in Table 4. For the readers convenience we included the parameters of Equation (12) as well as the effect it represents. Two types of t-values are reported, the standard OLS t-values (t_{OLS}) and the t-values based on the White estimator for the standard deviation (t_{White}) (Greene, 1993, p. 391). Because we use extreme points of the parameter space, instead of random points, it is not reasonable to assume that the error term in Equation (12) will be normally distributed. To test normality of the residues we apply the Wald test that combines skewness and kurtosis (Greene, 1993, pp. 309-311). Wald's statistic is χ_2^2 distributed. The value of the statistic is 14.91 ($\chi^2_{2;0.95} = 5.99$) and thus significant, so the assumption of normality of the residues has, as expected, to be rejected. Therefore, we cannot use the normal F-test on model reduction; that is, test the hypothesis $H_0 : R\alpha = 0$.

The next question is: is the regression homo- or heteroscedastic. Although some tests are available, they all have drawbacks and/or require more data than we have available. An indication can be obtained by applying Wald's statistic for model reduction (see below) under both assumptions. If the statistics lead to the same result this is an *indication* for homoscedaticity and if they lead to different results for heteroscedasticity. Experimenting with the model showed that for this application it is reasonable to assume heteroscedasticity.

Let $(e_1^2,...,e_i^2,...,e_m^2)$ be the vector of squared residues, with m the number of observations (in our case study m = 25), and let $\hat{\Omega}$ denote an estimated covariance matrix with $(e_1^2,...,e_i^2,...,e_m^2)$ on the diagonal and zero otherwise. To test for model reduction; we can use the limiting distribution of Wald's statistic $W = (R\hat{\alpha})^T [R(X^T X)^{-1}(X^T \hat{\Omega} X)^{-1}(X^T X)^{-1} R] R\hat{\alpha}$, which converges to a χ^2 distribution with degrees of freedom equal to the rank of the matrix R (Greene, 1993, pp. 391-392). Only the coefficients $\alpha_{12}, \alpha_{13}, \alpha_{14}, \alpha_{23}$ and α_{34} can be assumed to be zero, despite the low t-values for many of the other coefficients. (This, of course, is caused by the non-linear nature of our original model.) This model reduction is accepted: the value of W is 4.64 ($\chi^2_{5;0.95} = 11.07$). Further attempts for model reduction lead to highly significant W-values.

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Table 1: Parameter value-ranges and initial percentage of stoves diffused

Parameter	Description	Value range
$b(t_0)$	Profitability ratio in year t_0	[0.33, 2]
$\mu(t_0)$	mean of incomplete Gamma distribution in t_0	[4.85, 2.85]
γ_1	annual change in profitability $b(t)$	[0, 0.1]
γ_2	annual change in $\mu(t)$	[0, 0.1]
$\rho(t_0)$	percentage diffused in year t_0	13.3%

Table 2: Simulation results

Parameter	Description	Value obtained
$b(t_0)$	Profitability ratio in year t_0	1.8450
$\mu(t_0)$	mean of incomplete Gamma distribution in t_0	4.1702
γ_1	annual change in profitability	0.0012
γ_2	annual change in $\mu(t)$	0.0045

Table 3: Parameter values used to generate Figures 2 and 3

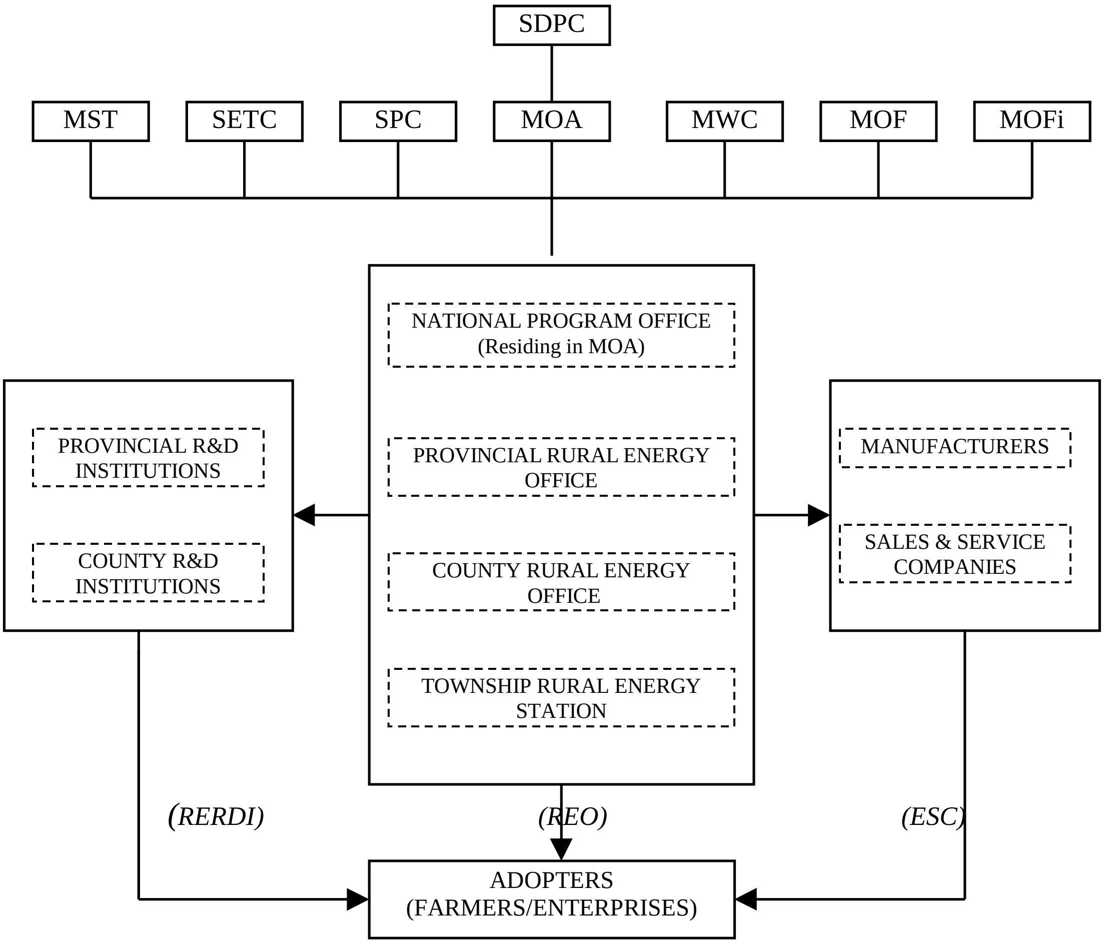
Curve no.	1	2	3	4	5	6	7	8
$b(t_0)$	56	56	56	338	56	56	338	338
$\mu(t_0)$	4.85	4.85	2.85	4.85	4.85	2.85	4.85	2.85
γ_1	0.1	0	0.1	0	0.1	0.1	0.1	0
γ_2	0	0.1	0	0	0.1	0.1	0.1	0

Table 4: Estimation results for the meta-model

Effect of	Parameter	Coefficient	t_{OLS}	t_{White}
Constant	α_0	0.624	14.39	4.03
$b(t_0)$	α_1	0.211	5.12	2.69
$\mu(t_0)$	α_2	-0.116	-2.82	-1.48
γ_1	α_3	0.067	1.62	0.85
γ_2	α_4	0.159	3.86	2.03
$b(t_0)*\gamma_2$	α_{24}	-0.129	-2.89	-1.40
$b(t_0)^2$	α_{11}	-0.136	-1.46	-0.29
$\mu(t_0)^2$	α_{22}	-0.125	-1.35	-0.27
γ_1^2	α_{33}	-0.123	-1.32	-0.26
γ_2^2	α_{44}	-0.123	-1.32	-0.26
R^2_{adj}	0.932			

Table 5: Estimation result panel data

	Fixed Effect Model			Random Effect Model			Least Squares		
Variable	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.	Coefficient	t-Statistic	Prob.
Constant	-			1.234	1.959	0.0523	1.503	3.123	0.0022
Ln(REO)	0.888	15.477	0.0000	0.876	16.243	0.0000	0.849	14.511	0.0000
Ln(ESC)	0.351	1.972	0.0513	0.277	2.691	0.0081	0.264	3.484	0.0007
	Fixed Effect			*Random Effect*					
BEIJING	0.295			-0.518					
TIANJIN	2.279			1.122					
HEBEI	1.610			0.681					
SHANXI	0.776			-0.081					
INNERM	0.972			0.080					
LIAONING	0.294			-0.285					
JINLIN	2.260			0.993					
HELONG	1.095			0.237					
SHANHAI	0.275			-0.392					
JIANGSU	-0.304			-0.652					
ZHEJIANG	0.067			-0.417					
ANHUI	1.276			0.475					
FUJIAN	0.610			-0.096					
JIANGXI	0.429			-0.221					
SHANDONG	0.406			-0.181					
HENAN	0.970			0.219					
HUBEI	0.683			0.059					
HUNAN	1.045			0.297					
GUANGDONG	0.738			0.028					
GUANGXI	1.107			0.292					
HAINAN	0.657			-0.200					
SICHUAN	0.138			-0.311					
GUIZHOU	-0.814			-1.224					
YUNAN	-0.217			-0.696					
SHANNXI	1.119			0.231					
Adjusted R-squared	0.779			0.794			0.708		
S.E. of regression	0.933			0.908			1.073		
F-statistic	470.5			-			154.0		
Prob(F-statistic)	0.000			-			0.000		
D-W statistic	1.759			1.483			1.055		
No. of observations	127			127			127		



Abbreviations:

SDPC	State Development Planning Commission
MST	Ministry of Science & Technology
SETC	State Economics & Trade Commission
MOA	Ministry of Agriculture
SPC	State Power Company
MWC	Ministry of Water Conservancy
MOF	Ministry of Forestry
MOFi	Ministry of Finance

Figure 1: National rural sustainable energy technology diffusion system in China

Figure 2: Monte Carlo result

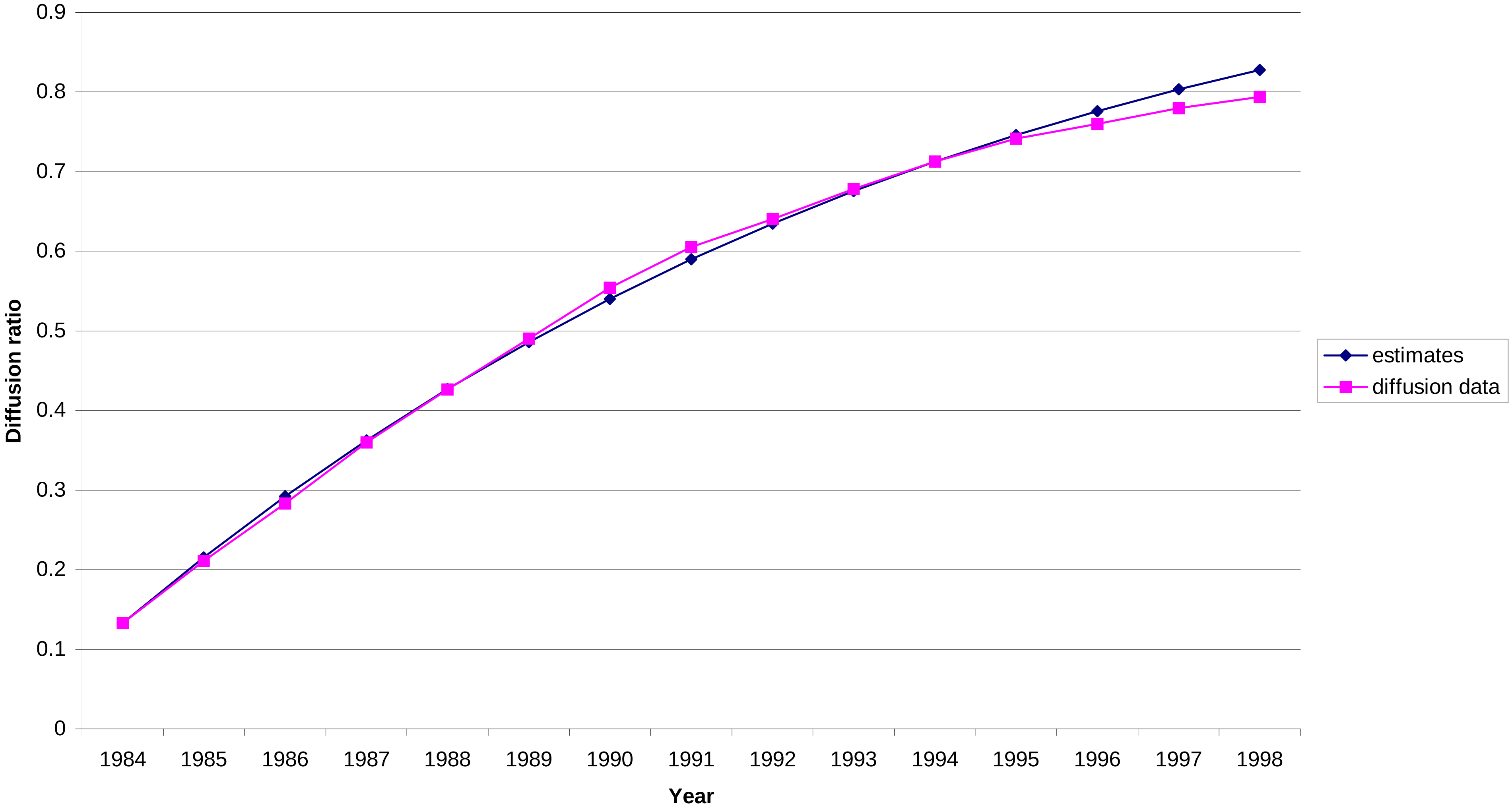


Figure 3: Various diffusion paths

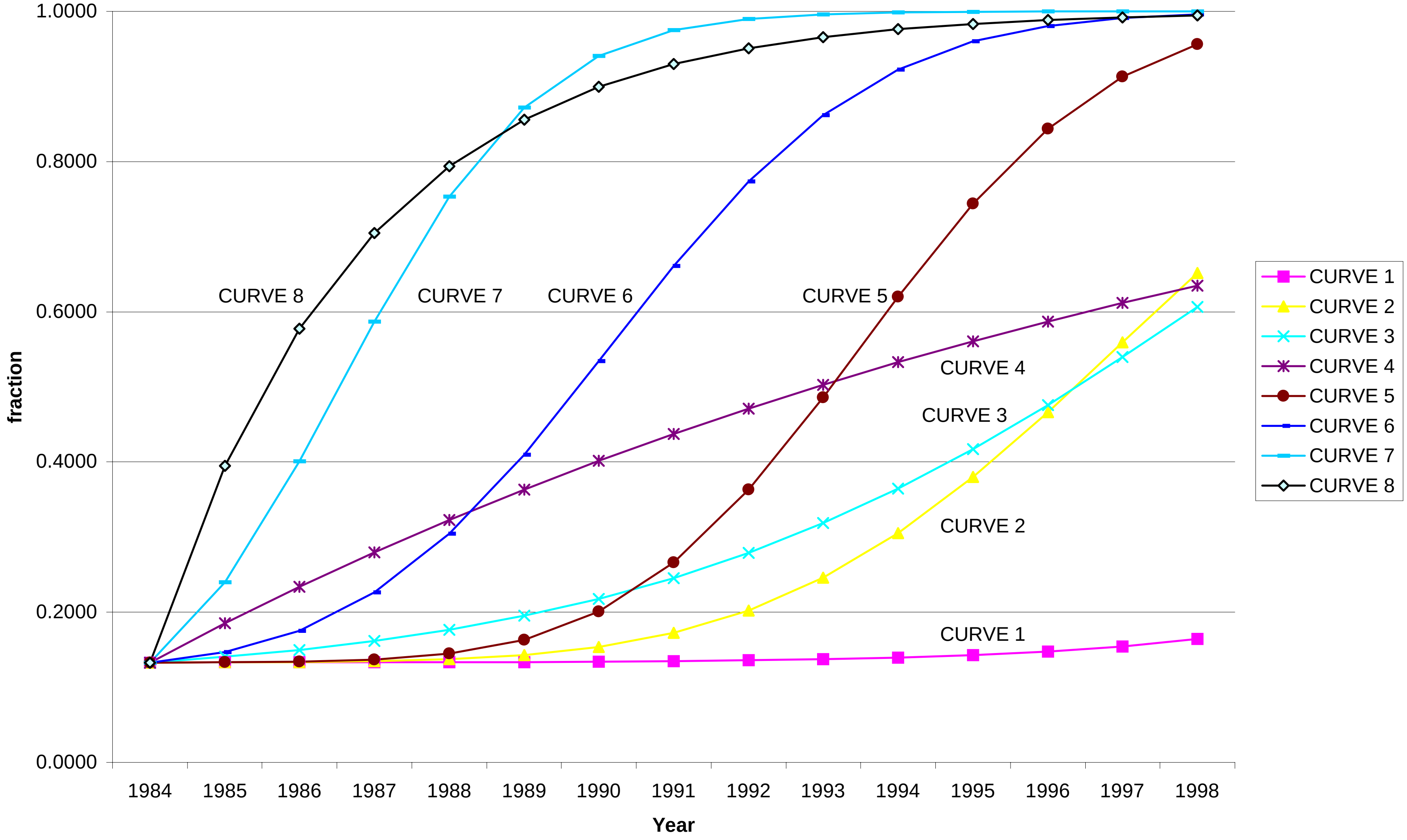


Figure 4: Annual change in diffusion rate