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DYNAMICS OF KNOWLEDGE ACCUMULATION IN TECHNOLOGY FOLLOWER COUNTRIES: A SYSTEM DYNAMICS APPROACH

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Abstract

In this paper the process of knowledge accumulation for a particular technology is studied. Two countries, say the technology follower and the technology frontier, are considered. The frontier's knowledge growth is determined by its R&D efforts on the technology. The level of knowledge stock for the follower country is augmented by its R&D activities for the technology and absorbing some of the external knowledge through spillover from the frontier. The extent to which the follower is able to exploit the external knowledge depends on technological gap, absorptive capacity, absorption time and degree of spillover. New concepts such as natural and enhanced degree of spillover, background and innovative knowledge and absorption speed are introduced in the present work to deeply explore the process of knowledge spillover. The factors influencing the knowledge development in the long term are simultaneously studied in an integrated structure provided by the System Dynamics approach. This framework shows the responses to the changes and provides the basis for examining the interactions among the variables over time.

Keywords: Knowledge spillover, technology follower, absorptive capacity, absorption speed, knowledge complexity, system dynamics

1. Introduction

In recent decades, knowledge has been introduced as the most strategic resource for production and it is widely recognized as a key factor in economic progress. It enhances the productivity of input factors; however, it is inherently different from the traditional factors of production (Arrow 1962).

According to the endogenous growth theory (Aghion & Howitt 1992, 1998, Grossman & Helpman 1994, Romer 1990), knowledge is non-rival in character in that it can be used by others without diminishing the amount of knowledge available to the original user or inventor. It also shows some degree of non-excludability (i.e. the owner cannot prevent others from using it) depending on the nature of the specific knowledge and the legal system to protect property rights. However, a part of any knowledge is tacit in nature, which cannot be transferred easily. In addition, acquisition of the codified part of knowledge requires that recipients of the knowledge have the ability to learn, apply and use it.

Due to these properties, large externalities may arise in the production of knowledge, which is referred to as knowledge or R&D spillovers. Empirical studies show that spillovers from R&D are prevalent, their magnitude may be quite large and social rates of return remain significantly above private rates (Griliches 1992).

Due to existence of externalities inherent in the production of knowledge, it is clearly important to understand the role of spillover and the process from which knowledge arises. Spillovers may occur in many directions: vertical spillovers in a value chain for a single product, horizontally between firms within an industry, among different industries and across countries (Kohler et al. 2006).

The diffusion of knowledge occurs both in space and time domains. Nevertheless, traditional diffusion theories do not consider space variables and focus on knowledge diffusion over time. These studies were deepened by technology gap literature at macro-level. Technology gap models investigate the knowledge spillover with geographical and technological distance (Caniëls & Verspagen 2001, Keller 1996, Verspagen 1991). However, the dynamics of knowledge diffusion and accumulation in this line of research has been considered as a black box and since knowledge spillover is not only a geographical phenomenon, there is need to identify the relationship among different factors determining the direction and intensity of spillovers.

At the firm level, the seminal works of Cohen & Levinthal (1989, 1990) provide a basis for the flow of technological and scientific knowledge, which raises the firm's stock of knowledge. They introduced a second face of R&D. Traditionally, R&D has been thought of as a generator of new information, but by introducing the concept of absorptive capacity, it was argued that R&D enhances the firm's ability to assimilate and exploit existing information.

Following Cohen and Levinthal, many empirical and theoretical works have been devoted to studying the absorptive capacity. The use of the concept of absorptive capacity has not been limited to the firm level and it has been widely employed at the regional and national level (see e.g. Jaffe et al. 1993, Maurseth and Verspagen 2002, Doring & Schnellenbach 2006, Mowery & Oxley 1995, Criscuolo & Narula 2008, Narula 2004, Kneller 2005, Kneller & Stevens 2006, Griffith et al. 2003, 2004). More extensive reviews on absorptive capacity have been presented by Daghfous (2004), Doring & Schnellenbach (2006), Schmidt (2005), Van Den Bosch et al. (2003) and Zahra & George (2002).

In the literature of international technology diffusion, some studies investigate the role of absorptive capacity in knowledge spillover. For instance, Keller (2004) in his survey of international knowledge spillovers showed that an R&D effort is needed to absorb the international knowledge. Kneller (2005), by means of an empirical analysis of spillovers across OECD manufacturing industries, found that absorptive capacity, rather than physical distance, plays an important role in determining the amount of knowledge transfers at the international level. In this line of research, Falvey et al. (2007) used panel data to investigate North–South trade-related knowledge spillovers. They found that absorptive capacity increases the benefits of knowledge spillovers, and that spillovers have the least impact on countries closest to and farthest from the technological frontier.

At the national level, some studies have been done to examine the determinants of a country's absorptive capacity, its relationship with national R&D activities and the general characteristics of the international technological environment (Criscuolo & Narula 2008, Narula 2004, Wamae 2006). By aggregating upwards from firm level, Criscuolo & Narula (2008) specified the relationship between the ability of a country to absorb foreign knowledge and its stages of technological development.

The factors that are relevant to knowledge accumulation, as they have been presented in the literature, create a complex net. The complex interactions in the process of knowledge accumulation are difficult to model with conventional approaches. This difficulty often leads analysts to use models much simpler than reality or to use descriptive models. For this reason, this paper is aimed at developing a comprehensive framework for describing, formalizing, and investigating the influence of different parameters on the process of knowledge accumulation. The paper tries to provide a new perspective and a methodological approach to shed light on the dynamics of knowledge accumulation in technology Follower countries.

The present paper has two main objectives. First, a better understanding of the spillover phenomenon is pursued by exploring inside the spillover's black box. For this purpose, we focus on the key factors which shape it and we will attempt to present some quantitative measures for them.

The second objective of this paper is to investigate the interactions among the factors influencing the knowledge spillover and technology development in medium or long term. For this purpose, we construct a System-Dynamics framework that shows how these factors influence each other. The approach leads to a representation of knowledge spillover taking into account both the complexity of the interactions and feedback loops. The methodological approach chosen is able to deal with a large number of variables and to see the interactions at work during the simulations. What this analytical tool attempts to do is to understand the basic structure of the spillover system and thus to understand the behavior it can generate.

For such purpose, based on the concept introduced by Cohen & Levinthal (1989, 1990) and following Criscuolo & Narula (2008), a dynamic model of knowledge accumulation is developed. The major difference is that knowledge stock for a particular technology, e.g. solar photovoltaic technology, at aggregated national (or regional) level is here focused rather than studying individual firms or total national knowledge stock.

In order to do so, the paper is organized as follows. In Section 2 we discuss the theoretical foundations for the knowledge spillover and we explicitly focus on the role of degree of spillover, absorptive capacity, absorption speed and knowledge complexity. In fact, in this section we present the preliminary assumptions of our analysis. Section 3 introduces the System Dynamics model for studying the process of knowledge accumulation. An illustrative example is described in Section 4 and the simulation results are presented. Finally, section 5 is devoted to the conclusions and recommendations on further research.

2. Theoretical Foundations

Cohen & Levinthal (1989, 1990) introduced the following well-known model for the flow of technological and scientific knowledge, which raises the firm's stock of knowledge:

$$Z_i = R_i + \gamma_i(\theta \sum_{j \neq i} R'_j + U) \qquad (1)$$

where:

Z_i: Flow of knowledge accumulation for firm i.

R_i: Firm's own investment in R&D.

γ_i: Firm's absorptive capacity ($0 \le \gamma_i \le 1$).

R'_j: The other firms' R&D investment.

θ: The degree the other firms would share the knowledge with the firm i ($0 \le \theta \le 1$).

U : Extra-industry knowledge generated by public R&D laboratories or universities.

According to equation (1), firms invest in knowledge development to both generate new knowledge and assimilate and exploit the existing information. What a firm can learn from spillovers is a function of both the absorptive capacity of the firm and the amount of knowledge available to be learned.

In order to study the flow of technological and scientific knowledge for a particular type of technology at the macro level, one may consider two regions. It may be assumed that there is one technologically advanced region and the other is technically backward (called hereafter frontier and follower respectively). In general, the follower's knowledge stock may be expanded through three simultaneous options:

1. The follower invests in R&D for the technology under consideration
2. The follower implements a process of absorbing knowledge generated abroad by the frontier for the technology under consideration
3. Absorption of knowledge accumulated for the other similar technologies, which may be located inside or outside the follower's country

According to De Feber et al. (2002), *similar technologies* may be defined as a group of technologies sharing a common essential component. For simplicity and limiting the scope of the paper, the spillovers across different technologies are not considered here. Anyway, there is a need to provide preliminary assumptions for analysis. It is also necessary to redefine and re-conceptualize the key factors associated with the knowledge spillover process. Detailed characteristics of these factors and their interrelationships are presented in the following sections.

2.1 Degree of Spillover

Based on Cohen & Levinthal (1990), one may define the degree of spillover for each technology, $\theta_{\tau,t}$, as the degree to which the generated knowledge for the technology may spill over to a pool of knowledge potentially available to others. $\theta_{\tau,t}$ is limited between 0 and 1. The low values of $\theta_{\tau,t}$ mean that the developed knowledge is more appropriated by the one who is conducting the R&D. If $\theta_{\tau,t}$ equals one, all the knowledge developed by the technology frontier enters the common pool of knowledge. If $\theta_{\tau,t}$ equals zero, no knowledge is spilt over. Either technology frontier implements no knowledge creation or it would be well protected by patent or other legal safeguards and, thus, there would be perfect knowledge appropriability (Dreyfus 2005). Therefore, one can consider $\theta_{\tau,t}$ as the level of technology appropriability which is shaped by external factors such as patent policy (Cohen & Levinthal 1990).

Coefficient $\theta_{\tau,t}$ can be decomposed into two components: natural (or voluntary) spillover and enhanced spillover degree which together form total potential spillover degree.

Natural degree of spillover ($\hat{\theta}_{\tau,t}$) is defined as a fraction of the knowledge stock which is potentially exploited costless (or nearly costless and relatively cheap) by the technology follower. But enhanced spillover degree (i.e. $1-\hat{\theta}_{\tau,t}$) is a fraction of the knowledge stock that shall not be shared costless and it may take place as a result of two conditions: first, the technology frontier is willing to share its knowledge by choosing different patent or technology policies and second, the follower undertakes its own R&D (e.g. by assigning high qualified researchers) to expand the pool of knowledge potentially available to absorb.

Based on the above arguments, we can specify the functional form of $\theta_{\tau,t}$ as the following:

$$\theta_{\tau,t} = \theta(\hat{\theta}_{\tau,t}\ ,\ \mu_{\tau,t}\ ,\ R_{\tau,t})\ ,\ \mu_{\tau,t} > 0 \qquad (2)$$

where:

$\hat{\theta}_{\tau,t}$: Natural or minimum level of the spillover degree for technology τ at time *t*.

$R_{\tau,t}$: R&D activities by the follower for technology τ at time *t*.

$\mu_{\tau,t}$: A parameter that reflects the effects of patent or technology policies undertaken by the technology frontier for the new technology τ at time t.

In this framework, any additional natural spillover always raises the potential degree of spillover ($\partial\theta/\partial\hat{\theta} > 0$). R&D has also a positive impact on the potential spillover degree ($\partial\theta/\partial R > 0$), though at a decreasing rate ($\partial^2\theta/\partial R^2 < 0$). It is also assumed that increasing $\mu_{\tau,t}$ by change in the effective factors such as a shift towards an open technology policy, helps the technology follower to reach to a higher degree of spillover at a lower level of own R&D.

In order to estimate the degree of spillover, the following exponential function can be proposed, which satisfies all the above conditions:

$$\theta_{\tau,t} = 1-(1-\hat{\theta}_{\tau,t})\cdot\exp(-\mu_{\tau,t}\cdot R_{\tau,t}) \qquad (3)$$

In fact, in this equation, $\mu_{\tau,t}$ is a scaling factor that determines the marginal impact of R&D on $\theta_{\tau,t}$. Figure 1 provides an illustrative representation of the proposed equation.

2.2 Knowledge Complexity

The difficulty of learning the spilt knowledge and the characteristics of the technological environment influence the knowledge spillover. These factors influence the ability to assimilate external knowledge and Cohen and Levinthal (1990) represented them by a parameter that reflects the degree of complexity and specificity of knowledge. In order to clarify the main properties of knowledge complexity, first, we define some primary concepts that will be useful in elaborating it deeply.

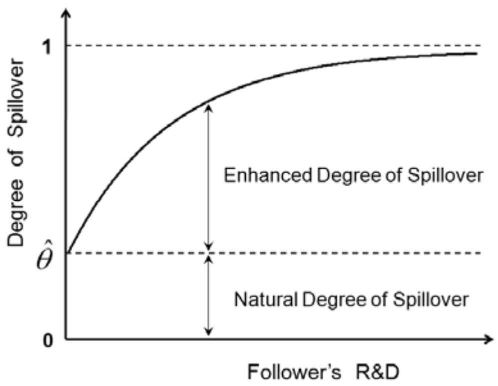

Figure 1 Potential degree of spillover

2.2.1 Defining the Concepts

2.2.1.1 National Innovation Capacity

National innovation capacity is the ability of a country to produce and commercialize a flow of innovative technology over the long term (Furman et al. 2002). Based on Furman et al. (2002), national innovation capacity depends on the strength of a nation's common innovation infrastructure, the environment for innovation in a nation's industrial clusters and the strength of linkages between these two. In other words, national innovation capacity is related to the systems of innovation and the networks and linkages among all agents in economy including firms, organizations, government agencies and consumers that have roles to play in the adoption and diffusion of knowledge. Therefore, it is influenced by the existence and the efficiency of institutions, the degree of openness and the availability of an educated and specialized labor force able to evaluate and assimilate new technologies (Wamae 2006, Criscuolo & Narula 2008).

We assume that the follower's innovation capacity is a dimensionless index limited between 0 and 1. One can argue that it might be enhanced over time by expanding R&D or reducing technological gap. However, national innovation capacity includes a complicated set of factors that are related to the intrinsic learning capability of the follower country. Therefore, in this study, it is assumed that it is exogenously determined by the characteristics of knowledge and the technological environment.

2.2.1.2 Background and Innovative Knowledge at the Frontier

It is assumed that accumulated knowledge at the frontier includes two components: innovative knowledge and background knowledge. Innovative knowledge is generated by the recent innovative activities and it is intrinsically close to the knowledge frontier. It shows a high degree of complexity due to difficulties and huge uncertainties associated with its development process. To represent a measure of frontier's innovative knowledge stock, we use the following equation:

$$KN^*_{\tau,t} = \max\left\{ s_{\tau,t} \times K^*_{\tau,t} \ , \ \sum_{t=t-h}^{t} R^*_{\tau,t} \right\} \qquad (4)$$

where:

$KN^*_{\tau,t}$: Frontier's innovative knowledge stock for technology τ at time t.

$K^*_{\tau,t}$: Frontier's total knowledge stock for technology τ at time t.

$R^*_{\tau,t}$: Frontier's R&D for technology τ at time

t .

h : Number of time points taken into account near the present time.

$s_{\tau,t}$: An exogenous parameter that determines the minimum level of innovative knowledge as a fraction of the total knowledge stock.

According to equation (4), if the total amount of R&D undertaken during the time periods near the present is more than $s_{\tau,t} \times K^*_{\tau,t}$, then it will be the determinant of the level of innovative knowledge.

Background knowledge is the other part of the total knowledge stock that is developed during the earlier stages of knowledge development. In fact, this type of knowledge may be interpreted as a set of basic information and prerequisites that the frontier country has learned during the previous periods. This knowledge provides the basis for new opportunities and innovative knowledge developments. In other words, background knowledge constructs the foundations of total knowledge stock and supports the frontier to enhance its knowledge level. Under these assumptions, we use the following equation to model the frontier's background knowledge:

$$KB^*_{\tau,t} = \min\left\{(1-s_{\tau,t})K^*_{\tau,t}\ ,\ K^*_{\tau,t} - \sum_{t=t-h}^{t} R^*_{\tau,t}\right\} \quad (5)$$

Finally, with the help of equation (4), it can be written as:

$$KB^*_{\tau,t} = K^*_{\tau,t} - KN^*_{\tau,t} \quad (6)$$

2.2.1.3 Background and Innovative Knowledge for the Follower

Background and innovative knowledge for the follower are defined as the same as those of the frontier. However, it is clear that a different approach should be applied to estimate them for the follower. Based on the level of background knowledge at the frontier, equation (7) represents the follower's background knowledge:

$$KB_{\tau,t} = \min\left(K_{\tau,t}\ ,\ KB^*_{\tau,t}\right) \quad (7)$$

This equation states that if the follower's knowledge stock is less than the frontier's background knowledge, then the amounts of total knowledge stock and background knowledge for the follower will be the same. In other words, the knowledge development for the follower stems completely from the frontier's background knowledge and, hence, the level of innovative knowledge for the follower will be zero.

If the follower can enhance its knowledge stock up to the level of frontier's background knowledge, development of the innovative knowledge will be started for the follower. The following equation helps us to estimate the follower's innovative knowledge level:

$$KN_{\tau,t} = \max(0, K_{\tau,t} - KB^*_{\tau,t}) \quad (8)$$

2.2.2 Modeling Knowledge Complexity

It is assumed that the knowledge complexity index for a technology in the follower country is a dimensionless index and limited between 0 and 1. This index is considered as a function of three dimensionless indices:

1. Relative background knowledge
2. Relative innovative knowledge
3. Follower's innovation capacity

Relative background knowledge is defined as the ratio of the follower's background knowledge to the frontier's background knowledge. Relative innovative knowledge is the ratio of the follower's innovative knowledge to the frontier's innovative knowledge.

When the technological gap is too high, information is not quite large and the follower does not know much about what the frontier possesses. Thus, the follower will not be able to learn easily and to keep pace with the frontier. Therefore, the larger the technological gap, the more complex is the knowledge. In this situation, relative background knowledge will be the dominant determinant of the knowledge complexity. At the high level of technological gap, the relative innovative knowledge is zero, the relative background knowledge is too low and thus the available knowledge for absorption has a high degree of complexity. As an extreme case, it may be assumed that the complexity index approaches one when the relative background knowledge approaches zero.

On the other hand, as the follower approaches the frontier, there is not much new to learn and the follower must rely merely on its own R&D. Therefore, because of the difficulties and uncertainties associated with the knowledge development, the knowledge complexity will be increased. In this situation, relative innovative knowledge will be the dominant determinant of the knowledge complexity: the more the relative innovative knowledge, the more is the degree of complexity. As an extreme case, it can be assumed that the complexity index approaches one when the relative innovative knowledge approaches one.

Based on the above arguments, for a knowledge gap in between, complexity must reach a minimum level. Around this point, the follower has enough level of prior knowledge to learn and there is also still enough distance to the frontier.

Follower's innovation capacity is the other factor which can influence the complexity of the knowledge to be absorbed. At a given level of technological gap, it is reasonable that an increase in the follower's innovation capacity reduces the complexity. Furthermore, increase in the innovation capacity will help the follower to reach the minimum level of complexity at a considerable distance from the frontier. Under these assumptions, improvement of the follower's innovation capacity will cause the complexity vs. knowledge gap curve to shift down and the minimum of the curve to shift to the right.

It is assumed in a specific extreme case that if the follower's innovation capacity approaches one (i.e. the highest value), the minimum of the complexity curve approaches zero. In the case where follower's innovation capacity approaches zero, the follower has no preamble capabilities to deal with the new knowledge and hence the complexity will remain at its maximum level (i.e. 1).

In summary, one can characterize two distinct sources of the changes in knowledge complexity: changes in background and innovative complexity. Based on the above arguments, the innovative complexity rises at an increasing rate with the relative innovative knowledge. Hence, a simple functional form of the innovative complexity change can be written as following:

$$\beta^{i}_{\tau,t} = \omega_{\tau,t} \times \left(\frac{KN_{\tau,t}}{KN^{*}_{\tau,t}} \right)^{n} \quad , n > 1 \tag{9}$$

where:

$\beta^i_{\tau,t}$: Innovative knowledge complexity change for technology τ at time t.

$\omega_{\tau,t}$: Follower's innovation capacity for technology τ at time t.

$KN_{\tau,t} / KN^*_{\tau,t}$: Relative innovative knowledge for technology τ at time t.

The background complexity change is considered as a linear function of the relative background knowledge:

$$\beta^b_{\tau,t} = \omega_{\tau,t} \times \frac{KB_{\tau,t}}{KB^*_{\tau,t}} \tag{10}$$

where:

$\beta^b_{\tau,t}$: Background knowledge complexity change for technology τ at time t.

$KB_{\tau,t} / KB^*_{\tau,t}$: Relative background knowledge for technology τ at time t.

Finally, setting the maximum knowledge complexity to 1 would yield the following functional form to evaluate the knowledge complexity:

$$\beta_{\tau,t} = 1 - \beta^b_{\tau,t} + \beta^i_{\tau,t} \tag{11}$$

With the help of equations (9) and (10), the above relation can be rewritten as:

$$\beta_{\tau,t} = 1 - \omega_{\tau,t} \times \left(\frac{KB_{\tau,t}}{KB^*_{\tau,t}} - \left(\frac{KN_{\tau,t}}{KN^*_{\tau,t}} \right)^n \right) \;,\; n > 1 \tag{12}$$

The above formula has been derived by combining the two functions, which can separately describe the change in complexity at the low and high level of knowledge gap. To avoid the sharp discontinuities in the above relationship, one may smooth the background complexity change, the innovative complexity change or both of them. The application, operation and rationale behind this formula shall be clear after presentation of the System Dynamics model in Section 3.

2.3 Absorptive Capacity

Cohen & Levinthal (1989, 1990) emphasized that while R&D generates innovations, it also develops the ability to exploit the available external knowledge sources. They called this ability as absorptive capacity (γ) and defined it as the fraction of knowledge in the public domain that a firm is able to assimilate and exploit. In fact, absorptive capacity is the ratio of usable to available external knowledge stock (Leahy & Neary, 2007), and it is assumed $0 \le \gamma \le 1$. If γ equals zero, the firm has no absorptive capacity and learns only by doing its own R&D activities. If γ has the value of one, the firm learns everything that is spilt over.

Cohen & Levinthal assumed that the firm's absorptive capacity depends on two factors: the firm's R&D activities and the degree of complexity of external knowledge. However, the empirical operationalization and construction of the good measures of absorptive capacity from the available information has been more of a challenge. Some determinants and empirical measures of the absorptive capacity concept in various fields and at various levels of analysis have been reported in the literature (see Schmidt (2005) for an overview).

At the macro level, Bosetti et al. (2008), assumed that absorptive capacity is a function of distance of R&D capital accumulated in a region with respect to the technological frontier. They used the ratio of one country's knowledge stock to the technological frontier as an indicator of this distance. Criscuolo & Narula (2008) extended the seminal work of Cohen & Levinthal to the macro-level specification of absorptive capacity by interpreting complexity as a measure of the technology gap. They considered national absorptive capacity as a function of three factors: country R&D expenditures, distance to the technological frontier and innovation system context that determines the diffusion of knowledge within the country and across countries.

In this study, based on Cohen & Levinthal's seminal work and also Criscuolo & Narula's idea of national absorptive capacity, we propose a dynamic model of absorptive capacity for a particular type of technology at national or regional level.

First, we consider the follower's absorptive capacity for a technology as a function of two factors:

$$\gamma_{\tau,t} = \gamma(R_{\tau,t}, \beta_{\tau,t}) \tag{13}$$

where $R_{\tau,t}$ is the follower's R&D efforts on technology type τ and $\beta_{\tau,t}$ is the complexity of knowledge to be assimilated for technology type τ. It is assumed that $\beta_{\tau,t}$ increases with the complexity of knowledge and $\partial\gamma / \partial R > 0$, $\partial^2\gamma / \partial R^2 < 0$, $\partial\gamma / \partial\beta < 0$, $\partial^2\gamma / \partial\beta\partial R > 0$, $\lim\limits_{R\to\infty} \gamma = 1$, $\lim\limits_{\beta\to 0} \gamma = 1$ and $\lim\limits_{\substack{R\to 0\\ \beta\to 1}} \gamma = 0$.

These conditions imply that the absorptive capacity increases at a decreasing rate with R, decreases with β and the marginal impact of R&D on absorptive capacity is increasing with β. Namely, an increase in β makes R&D more critical to assimilate the outside knowledge. Also as β approaches zero, γ is less responsive to R and it approaches one and for a huge increase in R&D spending, γ approaches one. On the other hand, for a high degree of complexity, γ approaches zero if there is no R&D.

An exponential functional form may be assumed for absorptive capacity, which can satisfy the aforementioned conditions:

$$\gamma_{\tau,t} = 1 - \beta_{\tau,t} \cdot \exp(-b_\tau \frac{R_{\tau,t}}{\beta_{\tau,t}}) \tag{14}$$

where $b_\tau > 0$ is a scaling parameter that determines the marginal impact of R&D on absorptive capacity. Figure 2 shows the graphical representation of the proposed relationship.

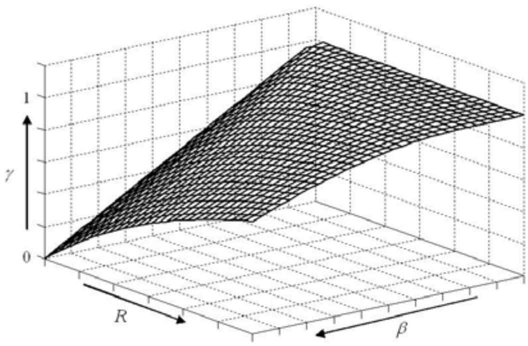

Figure 2 Absorptive capacity as a function of R&D efforts and knowledge complexity

Since the technological environment is dynamic and evolutionary in nature, past investments in knowledge development are not enough to maintain and enhance the absorptive capacity. For this reason, the follower's absorptive capacity is explicitly written as a function of only current-period R&D and the effects of the follower's historic knowledge and, thus, the past R&D activities are reflected through the knowledge complexity in the model.

As already mentioned, national innovation capacity plays an important role in influencing the overall technical efficiency of an economy and the ability to identify, evaluate and assimilate the foreign knowledge.

We assumed that it facilitates the learning through reducing the degree of knowledge complexity. According to equations 11 and 12, it is implicitly assumed that complexity is a function of national innovation capacity and technological gap. These two variables determine the state of the system and, thus, knowledge complexity has been used to determine the cumulative nature of absorptive capacity. In other words, it is assumed that the knowledge complexity, representing the characteristics of technological environment, influences the development of absorptive capacity by affecting the marginal impact of R&D.

2.4 Absorption Speed

Absorptive capacity has been studied as the fraction of the external knowledge that is exploitable. But, the role and importance of the length of time which is necessary for internalizing this part of knowledge has not been addressed. We, therefore, generalize and extend the absorptive capacity concept by introducing a new concept called *absorption speed*. At the macro level, this concept allows us to study the ability of a country to internalize the exploitable knowledge per unit time. In other words, absorption speed determines the speed of knowledge spillover and, therefore, it can be illustrated as:

$$\lambda_{\tau,t} = \frac{\gamma_{\tau,t}}{\phi_{\tau,t}} \tag{15}$$

where:

$\gamma_{\tau,t}$: Absorptive capacity.

$\phi_{\tau,t}$: Absorption time.

$\lambda_{\tau,t}$: Absorption speed (absorptive capacity per unit time).

Absorption time can be formalized separately or may be included within the primary concept of absorptive capacity to derive a comprehensive concept. We leave it to the future research to determine the properties of the absorption time and, hence, we specify it here as an exogenous parameter. If the follower could absorb the exploitable knowledge in one year, absorption speed would reach its maximum level.

2.5 Modeling the Knowledge Flow

The growth rate of knowledge stock for the follower country is determined by the growth rate of the knowledge resulting from its own R&D and a diffusion or spillover term, reflecting the opportunity to absorb the knowledge from the frontier. During the time periods of analysis, frontier's knowledge growth is determined only by its R&D efforts and the follower can dynamically track it.

To state the model for the flow of knowledge, assume that the time period is given by t, which is started at a given base year. Suppose that the knowledge stock of technology type τ for the follower and the frontier are $K_{\tau,t}$ and $K^*_{\tau,t}$ respectively. It is assumed that the frontier's innovative knowledge and, hence, its total knowledge can be accessible with some delays. In other words, there is a lag-time between the time at which the innovative knowledge is generated by the frontier and the time at which it can be accessible by the follower. Hence, if Δ is the lag-time, then

$K^*_{\tau,t-\Delta} - K_{\tau,t}$ will be the amount of knowledge potentially accessible to the follower at time point t. The interaction between absorption speed and spillover degree determines the follower's ability to absorb this knowledge at time t. Hence, for the follower, the flow of knowledge for technology τ at time point t is written as:

$$Z_{\tau,t} = R_{\tau,t-m} + \lambda_{\tau,t} \cdot \theta_{\tau,t} \cdot (K^*_{\tau,t-\Delta} - K_{\tau,t}) \quad (16)$$

where:

$Z_{\tau,t}$: Flow of knowledge for technology τ at time point t.

$R_{\tau,t-m}$: Follower R&D activities for technology type τ at time point $t-m$.

m: Lag between the time at which R&D takes place and the time at which its results are materialized and become a part of the knowledge stock.

$\lambda_{\tau,t}$: Absorption speed of the follower country for technology type τ at time point t.

$\theta_{\tau,t}$: Degree of spillover for technology type τ at time point t.

With the help of the above equation, it is now possible to illustrate the knowledge stock as a function of the flow of technological and scientific knowledge that takes into account the depreciation:

$$K_{\tau,t} = (1-\overline{\delta}_\tau) \cdot K_{\tau,t-1} + Z_{\tau,t} \quad (17)$$

where $\overline{\delta}_\tau$ is the knowledge depreciation rate. According to equations (16) and (17), the level of knowledge stock for each technology is augmented not only by carrying out R&D for this technology but also by acquiring some of the external knowledge through technological spillovers.

3. System Dynamics Model Configuration

According to the previous sections, the process of knowledge spillover can be described by a set of nonlinear and complex equations. In general, due to the high order nonlinearities, it is not possible to solve even small models analytically. Moreover, multiple feedback loops and time delays produce system behavior not seen in the simpler systems and, hence, unexpected behavior may be resulted. Therefore, we integrate the concepts and relations, discussed in the previous sections, together to develop a dynamic framework for studying the accumulation of knowledge using the System Dynamics approach. System Dynamics is a methodology for studying and managing complex feedback systems. System Dynamics uses the concept of feedback to explain how systems behave over time. Causal loops provide the mechanisms for feedback within the system, where outcomes influence inputs. It is a computer-aided approach and one can carry out many simulations and, hence, many future development paths can be evaluated.

System Dynamics modeling is here used to simulate the behavior of the knowledge development for a technology over time in response to changes in some variables or key parameters. System Dynamics looks at the process of knowledge development as a whole and facilitates understanding the interactions of many phenomena in this complex system.

Figure 3 shows a stock and flow diagram of the follower's knowledge development for a technology. It represents the main feedbacks mechanisms that influence the long-term development of the technology. The model has

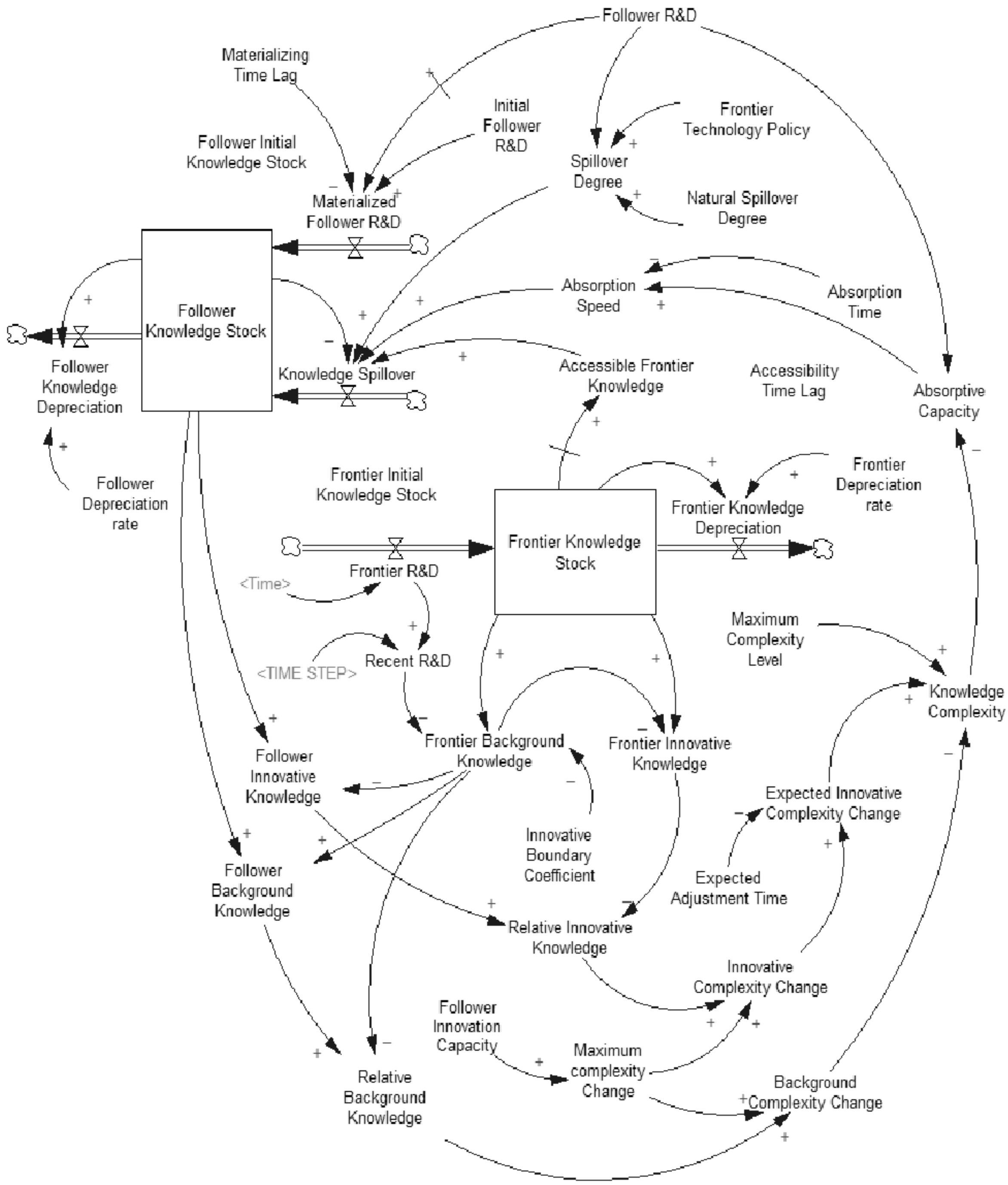

Figure 3 Stock and flow diagram of the follower's knowledge development

been implemented with the standard System Dynamics software Vensim-PLE where the rectangles represent levels, arrows represent flows, and each flow is controlled by the valves. The clouds represent sources and sinks outside the system that are thought to be infinite or unimportant for the system of interest.

According to Figure 3 there are two main stock variables in the model: the follower's knowledge stock and the frontier's knowledge stock. The follower's knowledge stock may be improved as a consequence of the knowledge acquired through spillover and its own materialized R&D. On the other hand, knowledge depreciates proportionally with the knowledge stock. There is a time lag between the follower's R&D and its direct impact on the knowledge stock. For this purpose, an exponential delay is assumed between the time at which the R&D takes place and the time at which its results are materialized and become the part of the knowledge stock.

Knowledge spillover is estimated according to equation (16). The frontier's innovative knowledge and, hence, its total knowledge can be available with some delays. A fixed delay is assumed between the time at which the innovative knowledge is generated and the time at which it can be accessed by the follower. Spillover degree, absorptive capacity and absorption speed are the variables that affect the knowledge spillover. The corresponding causal links for them have been constructed on the basis of equations (3), (14) and (15) respectively.

The level of the frontier's knowledge stock is controlled by the input flow of the frontier's R&D, which is exogenously determined at each time point, and the output flow of knowledge depreciation, which reduces the knowledge in time at a constant rate.

The causal links for the frontier's background knowledge, the frontier's innovative knowledge, the follower's background knowledge and the follower's innovative knowledge have been represented on the basis of equations (4)-(8).

It is assumed that the maximum change in complexity shall be determined according to the follower's innovation capacity. The variation of the complexity for the background knowledge (i.e. background complexity change) is directly a function of the relative background knowledge and the maximum complexity change. The innovative complexity change is affected by the relative innovative knowledge and the maximum complexity change. The innovative complexity change has been smoothed to avoid sharp discontinuities. The expected change in innovative complexity is the smoothed function that is derived by assuming an expected adjustment time. Finally, the knowledge complexity is affected by the change in background complexity, the expected change in innovative complexity and the maximum level of complexity (i.e. 1). In summary, the above relationships are mathematically determined with the help of equations (9)-(12).

One might argue that some factors such as innovation activities, human capital or cumulative experience can enhance national innovation capacity. However, as mentioned before, national innovation capacity includes a complicated set of factors that are related to the intrinsic learning capability of the follower country to develop a technology and, thus, incorporating such influences necessitates extending the boundary of the model. Therefore, in this model, it is assumed that the innovation capacity is exogenously determined by the type of technology and the technological environment. More exhaustive studies could provide an endogenous analysis of national innovation capacity. This could definitely be the next step.

In order to study the main feedbacks of the model, Figure 4 summarizes the overall causal structure of the model. It shows a causal loop diagram with the key feedback loops associated with the follower's knowledge development. The important loops are highlighted by the loop identifiers, which show whether the loops are Balancing (B) or Reinforcing (R).

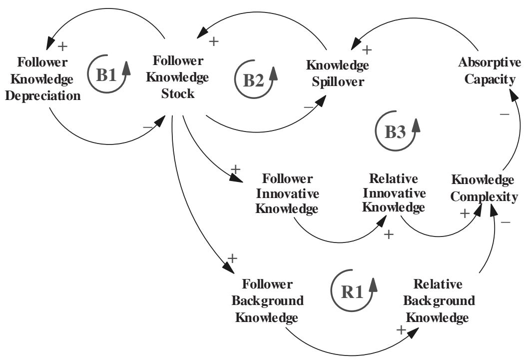

Figure 4 Main feedback loops influencing the follower's knowledge development

There are three balancing feedbacks (i.e. B1, B2 and B3) and one reinforcing feedback (i.e. R1) in the model. The loops read as follows:

Balancing loop B1: The knowledge depreciation, which intrinsically has a negative impact on the knowledge stock, is increased proportional to the knowledge stock. In other words, according to equation (17), knowledge depreciates at a constant rate over time. It means that an increase in the level of knowledge leads to an increase in the amount of depreciation. An increase in the knowledge depreciation, on the other hand, reduces the knowledge stock.

Balancing loop B2: An increase in the flow of spillover leads to increase in the level of knowledge stock. On the other hand, increasing the follower's knowledge stock through spillover reduces the technological gap between the follower and the frontier. Hence, the potential for the knowledge spillover is decreased.

Balancing loop B3: The follower's knowledge development improves the relative innovative knowledge, which in turn increases the knowledge complexity. Increase in the knowledge complexity leads to reduction in the absorptive capacity. As a result of this, the knowledge spillover and, thus, the rate of knowledge accumulation are diminished.

Reinforcing loop R1: Further development of the follower's knowledge enhances the relative background knowledge, which in turn negatively affects the knowledge complexity. Decrease in the knowledge complexity results in increase in the absorptive capacity. Enhanced absorptive capacity augments the knowledge spillover and hence the follower's knowledge stock is increased.

Unlike the conventional mathematical models, which study the spillover process by breaking it up into smaller pieces, the presented model can also look at this process as a whole. The objects in the system interact through feedback loops, where a change in one variable influences other variables over time, which in turn influences the original variable, and so on. What this analytical tool attempts to do is to understand the basic structure of the spillover system and, thus, to understand the behavior it can generate. Therefore, this methodology could be used to analyze and communicate innovation theory and the factors that influence knowledge spillover phenomena.

The proposed framework takes advantage of the fact that a computer model can be of much greater complexity and carry out more simultaneous calculations than mental or descriptive models. It focuses on computer simulation modeling, using special software programs to figure out how a system's behavior might play out over time if certain changes are applied.

The analytical tool can easily show which parameters in a system have enough ability to influence the whole system so that by changing them one can alter the system behavior. In addition, there is the ability to study the impact of delays on systemic behavior. In general, the presented system dynamics model may change the way we look upon the technology development process. The model is a powerful tool, which can be used to analyze this process both qualitatively and quantitatively.

The model can be used by managers or policy makers to provide a general understanding of the relations among the different factors that form a spillover system. The details of each factor could give us the ability to study all the elements involved in an innovation system and to analyze the influences they exert.

4. Simulation Results

The results obtained from application of the System Dynamics model are presented in this section. We have chosen Photovoltaic technology for our analysis. Photovoltaic is a solar power technology that uses solar cells to convert light from the sun directly into electricity and it has been considered as one of the most promising energy technologies of the 21^{st} century.

The time horizon of the model is 40 years, beginning in 2010 and continuing until 2050. The knowledge stock for this technology in year 2000 was almost \$15000 million in 1998 dollars (Barreto 2001). Hence, the level of \$18000 million is assumed for the frontier's initial knowledge stock in year 2010. In fact, for the Frontier's initial knowledge stock, the global level of knowledge for solar photovoltaic technology has been considered. This value has been derived based on the cumulative global R&D expenditures in the past.

Also the level of \$500 million is assumed for the follower's initial knowledge stock. This value is an assumption of the simulation for an imaginary follower country.

Follower's R&D, frontier's R&D, follower's innovation capacity and absorption time are the most important exogenous factors, which drive the model behavior. We set the absorption time to 1 year. Frontier's R&D has been chosen as the time series data based on MERGE-ETL database (Bahn & Kypreos 2003). To review the effects of the follower's R&D on the knowledge development, we have chosen it as a RAMP function that is linearly increasing from 0 in year 2010 to \$40 million in year 2050. Details of formulations, the values of parameters and calibration coefficients have been listed in the Appendix.

Three scenarios have been considered that are related to the follower's innovation capacity:

1. Low (weak) innovation capacity (0.2)
2. Medium innovation capacity (0.5)
3. High (strong) innovation capacity (0.8)

The medium innovation capacity scenario has been selected as the reference one. The results of the reference scenario are provided as an interpretation of the simulation, showing the main aspects of the model behavior. The subsequent runs show some selected responses to the variations of innovation capacity.

Figure 5 presents the behavior of the knowledge development for both follower and frontier in the reference scenario. Different types of knowledge, which introduced in the paper, have been illustrated in this figure. The frontier's knowledge stock is increasing corresponding to the amount of the frontier's R&D. The hatched area shows the knowledge gap, which is initially too high and it is gradually reduced by the follower's knowledge development. For the follower's knowledge stock, an S-shaped growth pattern has been observed, where its carrying capacity is increased corresponding to the level of frontier's knowledge stock.

Because of huge technological gap and insignificant R&D in the initial stage of development, knowledge has a high degree of complexity and hence the absorptive capacity will be very low (see Figures 6 and 7). As a result, the follower's knowledge has a slow growth in early stages. Gradually, increased R&D efforts and reduced knowledge gap provide foundation for overcoming the initial slow growth stage that is then followed by a rapid growth stage. The process of growth continues until the positive feedback loop of the background knowledge development, i.e. R1 in Figure 4, is dominant, causing reduction in the knowledge complexity, enhancing the absorptive capacity which leads to rapid growth of the follower's knowledge stock.

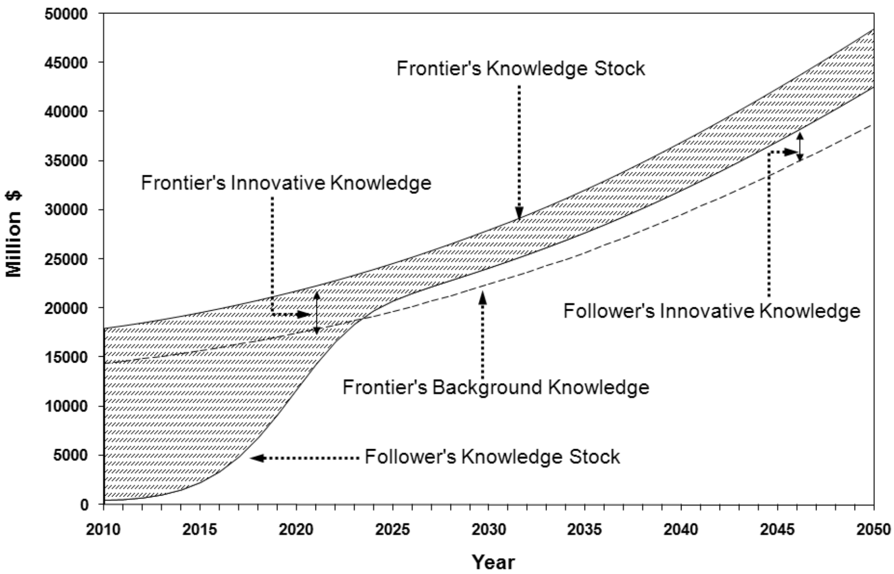

Figure 5 Behavior of the knowledge development over time

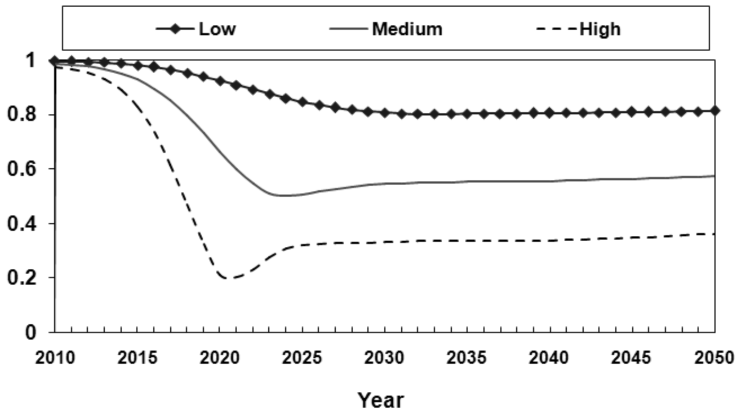

Figure 6 Knowledge complexity in different scenarios

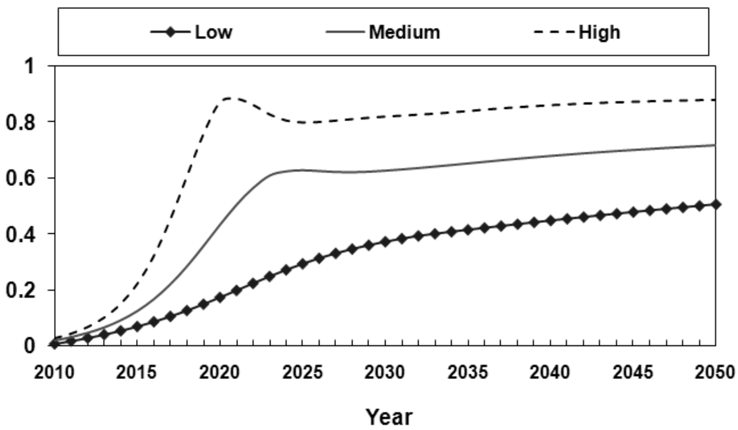

Figure 7 Absorptive capacity in different scenarios

As the follower's knowledge stock is increased and the knowledge gap is reduced, the balancing effects of the negative feedback loop of knowledge spillover, i.e. B2 in Figure 4, slow down the follower's growth. Furthermore, as soon as the frontier's background knowledge is completely absorbed, the follower's innovative knowledge starts to increase. Hereafter, the negative feedback loop of the innovative knowledge development, i.e. B3 in Figure 4, becomes more dominant than the positive feedback loop and the follower's knowledge stock begins rising by a smaller amount each period. However, it will not reach a fixed stationary equilibrium and it dynamically tracks the trend of frontier's knowledge development with a relatively fixed gap.

Figures 6 and 7 show an overview of knowledge complexity and absorptive capacity in different scenarios. During the first stages of the development, increase in the follower's background knowledge reduces the knowledge complexity, which leads the knowledge complexity to reach its minimum level. Further development of the follower's knowledge improves the relative innovative knowledge which in turn increases the knowledge complexity. It can be seen that increase in the innovation capacity shifts down the complexity curve and helps the follower to reach the minimum level of complexity at an earlier stage. After the follower approaches to the frontier, the knowledge gap remains relatively fixed over time. It leads to a relatively fixed level of knowledge complexity in these periods. The behavior of absorptive capacity is inversely related to the behavior of knowledge complexity; however, it is also enhanced by the increasing amount of the follower's R&D.

Figure 8 shows the behavior of the follower's knowledge development in different scenarios. This figure shows how follower's knowledge development is influenced by changes in the follower's innovation capacity. An increase in the follower's innovation capacity leads to the shift up of the curve describing the knowledge accumulation process and it also brings forward the time of the maximum growth (i.e. the time of the inflection point).

Figure 9 compares the total amount of knowledge spillover in different scenarios. Criscuolo & Narula (2008) and Verspagen (1991) have previously shown a bell-shaped knowledge spillover. However, the results of simulation show a tilted bell-shaped curve for knowledge spillover. The maximum value of this curve corresponds to the time at which the maximum growth rate of the follower's knowledge takes place.

At the high level of technological gap, the available knowledge for absorption has a high degree of complexity. Development of the follower's background knowledge reduces the knowledge complexity and, thus, enhances the absorptive capacity. Enhancing the absorptive capacity augments the knowledge spillover to reach a maximum level. Then, as the follower approaches the frontier, the complexity is increased and the quantity of the knowledge that

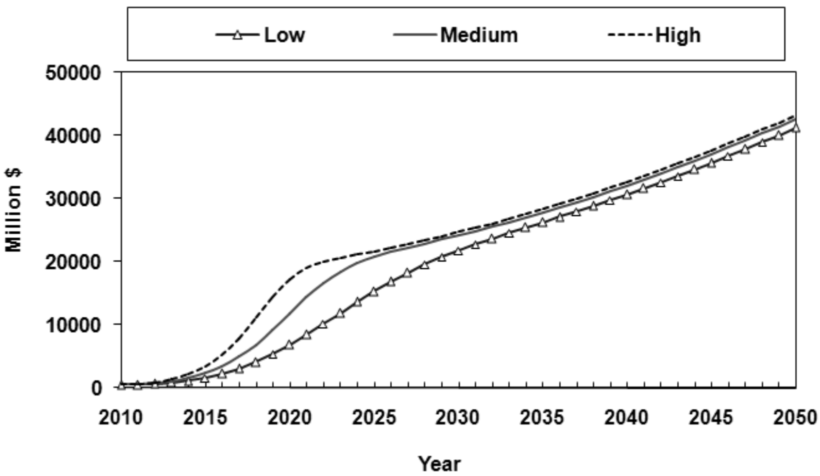

Figure 8 Comparison of the follower's knowledge development in different scenarios

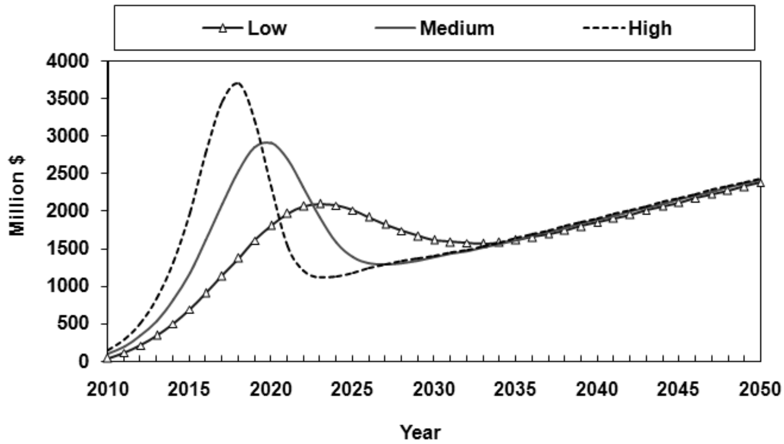

Figure 9 Comparison of the knowledge spillover in different scenarios

can be acquired is diminished. Therefore, the assimilation of the external knowledge becomes more difficult and, hence, the amount of knowledge spillover is reduced. Finally, the gradual increase in the knowledge spillover during the final stages of development corresponds to the frontier's knowledge growth and the level of absorptive capacity, which has been enhanced by the increasing amount of the follower's R&D. Figure 9 clearly shows that an increase in the follower's innovation capacity leads to a higher maximum level of knowledge spillover, which is reached at an earlier stage.

According to Figures 8 and 9, the simulation results show that knowledge development and, specially, knowledge spillover based on the three innovative capacity scenarios tend to become less different from about 2035 onwards. This is despite substantial differences in the three scenarios for knowledge complexity (Figure 6) and absorptive capacity (Figure 7). The reason is that for the high innovation capacity, the follower's knowledge tends to accumulate faster than in the case of low innovation capacity. It means that the amount of knowledge potentially accessible to the follower (i.e. knowledge gap) in the High scenario would be more reduced than that of the Low scenario. Therefore, the knowledge gap would be wider in the case of low innovation capacity. For example, the ratio of knowledge gap in High scenario to that of Low scenario in the years 2025, 2030, 2035, 2040, 2045 and 2050 are 0.215, 0.394, 0.499, 0.535, 0.561 and 0.586 respectively.

On the other hand, according to Figure 7, the corresponding ratios for absorptive capacity in the abovementioned years are 2.73, 2.21, 2.03, 1.93, 1.83 and 1.75 respectively. Hence, the corresponding ratio for the interaction term $\lambda_{\tau,t} \cdot (K^{*}_{\tau,t-\Delta} - K_{\tau,t})$ in equation (16) would be near unity for 2035 onwards. Since this interaction between absorptive capacity and knowledge gap determines the amount of spillover, knowledge spillover based on the three innovative capacity scenarios converge to the same level.

Figure 10 illustrates the trend of follower's innovative knowledge development in different scenarios. The stronger innovation capacity helps the follower to develop extensive innovative knowledge. It is observed in the high scenario that the startup time to achieve the innovative knowledge is delayed till 2020. However, the Low scenario postpones the achievement time by almost 12 years.

Finally, Figures 11 and 12 are presented for the Medium scenario to explain the relative significance of different components that contribute to knowledge creation for the follower at various stages of development. To give a sense of the degree to which spillovers are important vs. own R&D at a particular point in time, the share of knowledge spillover in total flow of knowledge (i.e. the sum of knowledge spillover and internal R&D) has been demonstrated in Figure 11. According to this figure, the R&D undertaken by the follower country is really insignificant compared to the knowledge absorbed from the frontier. In fact, the main role of R&D undertaken by the follower country is to enhance the knowledge spillovers through increasing the absorptive capacity. This would allow taking advantage of the positive externalities of innovation and spillover processes such that long-term economic benefits can be derived. It may imply that cooperation between industrialized and developing countries may enable developing countries to profit from the experience of the industrialized countries and have access to new technologies at lower costs.

Figure 12 shows the relative significance of different components of knowledge spillover. For such purpose, the components of knowledge spillover in equation (16) are decomposed as following:

- Knowledge gap (i.e. the term $K^*_{\tau,t-\Delta} - K_{\tau,t}$ in equation 16).
- Available external knowledge (i.e. the term $\theta_{\tau,t} \cdot (K^*_{\tau,t-\Delta} - K_{\tau,t})$ in equation 16).
- Absorbed knowledge (i.e. the term $\lambda_{\tau,t} \cdot \theta_{\tau,t} \cdot (K^*_{\tau,t-\Delta} - K_{\tau,t})$ in equation 16).

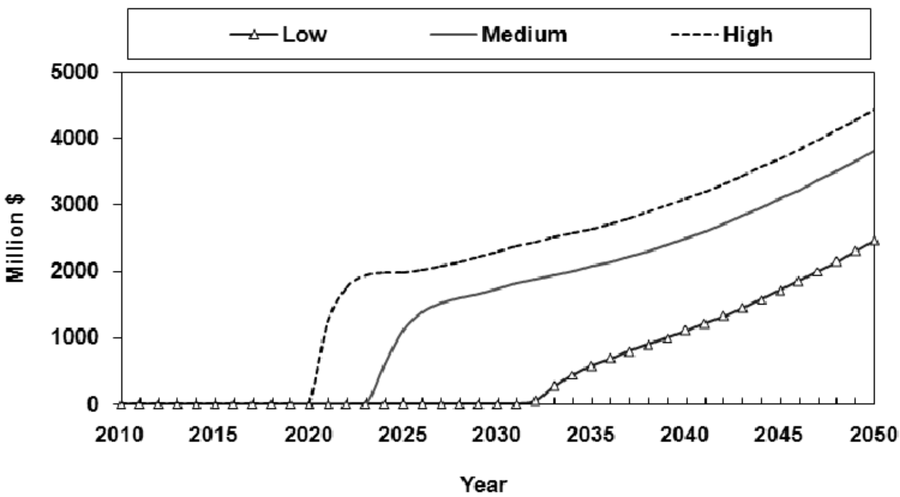

Figure 10 Follower's innovative knowledge development in different scenarios

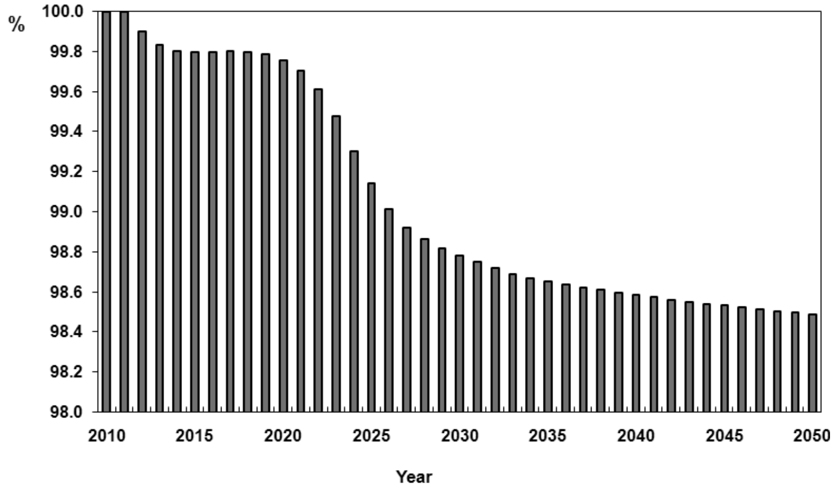

Figure 11 Share of knowledge spillover in the flow of knowledge over time

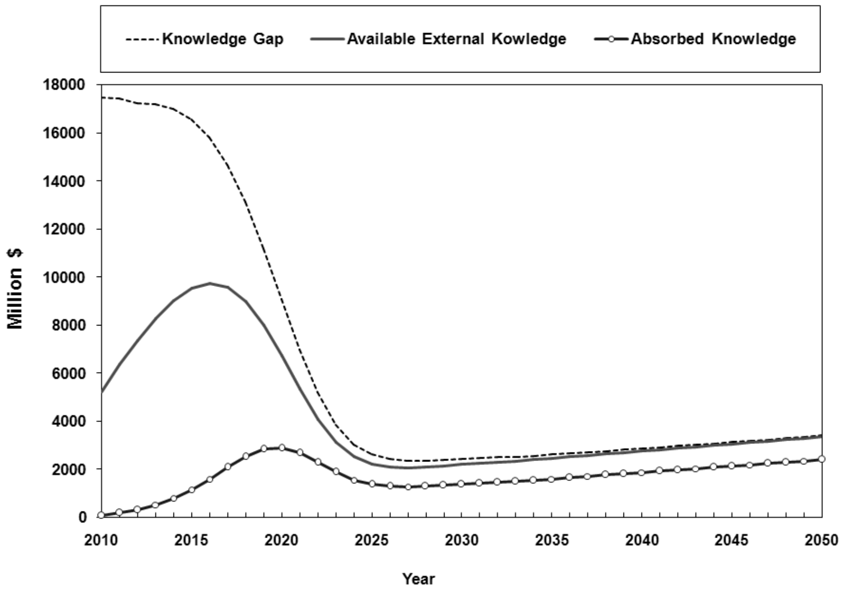

Figure 12 Trend of the components of knowledge spillover over time

5. Conclusions and Prospects for Future Research

The process of knowledge accumulation for a particular technology has been studied in the present research in the context of a leader and a follower country/region. In this framework, the frontier's knowledge growth is determined by its R&D efforts. The level of knowledge stock for the follower is augmented by its R&D activities for the technology and acquiring some of the external knowledge through spillover from the frontier country. The extent to which the follower is able to exploit the external sources of knowledge depends on the technological gap, the absorptive capacity, the absorption time and the degree of spillover.

New concepts introduced in the present work allow us to deeply explore the impact of spillover phenomenon on the development of a technology. The study has focused on the key factors that influence the knowledge spillover and a detailed mathematical formulation of interaction among factors has been presented. Different factors influencing the knowledge spillover and technology development in the long term have been studied simultaneously in the form of an integrated structure provided by the System-Dynamics approach. This framework shows the response to the changes and provides a basis for examining the effects of follower's innovative activities, knowledge development at the frontier, existence of time delays, feedbacks structure and interactions among the variables over time. The constructed framework allows us to simultaneously determine the knowledge stock, the amount of spillover, the knowledge complexity and the absorptive capacity.

System dynamics modeling and simulation can be used as an analytical tool in scenario analysis to understand the influence of uncertainty and time delays on the sequential decisions of the follower and frontier countries. By simulating illustrative alternative scenarios, the model helps to develop a deeper understanding of the underlying dynamics and the impact of timing of decisions on value creation and decay.

The approach leads to a representation of knowledge spillover taking into account both the complexity of the interactions and feedback loops. The methodological approach is able to deal with a large number of variables and to see the interactions at work during the simulations. These interactions are difficult to model with more conventional approaches. This difficulty often leads analysts to use the models much simpler than reality or to use descriptive models. Ability of the methodology to handle both quantitative and qualitative variables is the other advantage. Therefore, compared to the existing literatures on the knowledge spillover, the detailed System-Dynamics model of knowledge spillover presented in this study provides us with a better understanding of the dynamics and feedback mechanisms governing the knowledge accumulation process in a technology follower country.

The complex knowledge accumulation process has been codified to create a model that includes the most important aspects that academia or policy-makers need to consider around innovation activities. The model may be a theoretical tool for academia to be used to study and communicate innovation theories and knowledge spillover process. The analytical tool is capable of providing a better understanding of the root mechanisms of technological change and technological improvement. Additionally, it can help to improve the decision making of managers and policy-makers when innovation is concerned, through the analysis of the spillover process and its related factors.

The dynamic model can be used to show how the strategies and decisions made by the technology frontier influence the follower's knowledge accumulation by altering the technology policies such as patent policy or degree of appropriability. For example, a frontier technology policy measure can be modeled as a change in a parameter, and the resulting system's behavior reflects the effects of such policy. On the other hand, the impact of the follower's internal R&D and national innovation capacity on the rate of knowledge spillover can be studied.

Finally, the specifications of functional forms and stages of development have been kept as simple as possible and, hence, the proposed model has several restrictions. Nevertheless, the structural form of the model can be improved along various aspects. The boundary of the model can be expanded or contracted depending on the purpose of using this formal model. However, one should always bear in mind that increasing the complexity of models makes it more difficult to understand. Further researches should be performed to extend the model and to collect data from the real cases of technology spillover. We therefore suggest the followings for the future developments of the model:

- Analyzing R&D and knowledge spillovers among different technology types.
- Endogenizing the dynamics of the frontier's knowledge development.
- Analyzing the reverse spillover from the follower to the frontier and evaluating its impact on the knowledge development.
- Clarifying the main properties of the concept of absorption speed.
- Scrutinizing the role and structure of the exogenous parameters and coefficients such as follower's innovation capacity, natural degree of spillover, frontier's technology policy and innovative boundary coefficient.
- Endogenizing the absorptive capacity in the System Dynamics' causal loop diagram as an autonomous process (for testing purposes) rather than specifying a single nonlinear function.
- Providing a basis for a real empirical study using country or regional level data.

6. Appendix: Detailed Model Formulations

(1) Absorption Speed = Absorptive Capacity / Absorption Time
Units: 1/Year

(2) Absorption Time = 1
Units: Year

(3) Absorptive Capacity = 1− 1 * Knowledge Complexity * exp (−0.01 * "Follower R&D" / Knowledge Complexity)
Units: Dmnl

(4) Accessibility Time Lag = 2
Units: Year

(5) Accessible Frontier Knowledge = DELAY FIXED (Frontier Knowledge Stock, Accessibility Time Lag, 18000)
Units: M$

(6) Background Complexity Change = Maximum complexity Change * Relative Background Knowledge
Units: Dmnl

(7) Expected Adjustment Time = 2
Units: Year

(8) Expected Innovative Complexity Change = SMOOTH (Innovative Complexity Change, Expected Adjustment Time)
Units: Dmnl

(9) FINAL TIME = 2050
Units: Year

The final time for the simulation.

(10) Follower Background Knowledge = MIN (Follower Knowledge Stock, Frontier Background Knowledge)

Units: M$

(11) Follower Depreciation rate = 0.03

Units: 1/Year

(12) Follower Initial Knowledge Stock = 500

Units: M$

(13) Follower Innovative Knowledge = MAX (0, Follower Knowledge Stock − Frontier Background Knowledge)

Units: M$

(14) Follower Innovation Capacity = 0.5

Units: Dmnl

(15) Follower Knowledge Depreciation = Follower Depreciation rate * Follower Knowledge Stock

Units: M$/Year

(16) Follower Knowledge Stock = INTEG (“Materialized Follower R&D” + Knowledge Spillover-Follower Knowledge Depreciation, Follower Initial Knowledge Stock)

Units: M$

(17) “Follower R&D” = RAMP(1, 2010, 2050)

Units: M$/Year

(18) Frontier Background Knowledge = MIN (Frontier Knowledge Stock – “Recent R&D”, (1−Innovative Boundary Coefficient) * Frontier Knowledge Stock)

Units: M$

(19) Frontier Depreciation rate = 0.03

Units: 1/Year

(20) Frontier Initial Knowledge Stock = 18000

Units: M$

(21) Frontier Innovative Knowledge = Frontier Knowledge Stock − Frontier Background Knowledge

Units: M$

(22) Frontier Knowledge Depreciation = Frontier Depreciation rate * Frontier Knowledge Stock

Units: M$/Year

(23) Frontier Knowledge Stock = INTEG (“Frontier R&D” − Frontier Knowledge Depreciation, Frontier Initial Knowledge Stock)

Units: M$

(24) “Frontier R&D” = WITH LOOKUP (Time, ([(2010,0) − (2050,3000)], (2005,745), (2010, 810), (2020,1160), (2030,1590), (2040,2160), (2050,2720)))

Units: M$/Year

(25) Frontier Technology Policy = 0.1

Units: Year/M$

(26) “Initial Follower R&D” = INITIAL (“Follower R&D”)

Units: M$/Year

(27) INITIAL TIME = 2010

Units: Year

The initial time for the simulation.

(28) Innovative Boundary Coefficient = 0.2

Units: Dmnl

(29) Innovative Complexity Change = Maximum complexity Change * (Relative Innovative Knowledge^2)

Units: Dmnl

(30) Knowledge Complexity = Maximum Complexity Level - Background Complexity Change + Expected Innovative Complexity Change

Units: Dmnl

(31) Knowledge Spillover = Absorption Speed * Spillover Degree * (Accessible Frontier Knowledge – Follower Knowledge Stock)

Units: M$/Year

(32) "Materialized Follower R&D" = DELAY1I ("Follower R&D", Materializing Time Lag, "Initial Follower R&D")

Units: M$/Year

(33) Materializing Time Lag = 3

Units: Year

(34) Maximum complexity Change = Follower Innovation Capacity

Units: Dmnl

(35) Maximum Complexity Level = 1

Units: Dmnl

(36) Natural Spillover Degree = 0.3

Units: Dmnl

(37) "Recent R&D" = TIME STEP * "Frontier R&D"

Units: M$

(38) Relative Background Knowledge = Follower Background Knowledge / Frontier Background Knowledge

Units: Dmnl

(39) Relative Innovative Knowledge = Follower Innovative Knowledge / Frontier Innovative Knowledge

Units: Dmnl

(40) Spillover Degree = 1− (1−Natural Spillover Degree) * exp (−Frontier Technology Policy * "Follower R&D")

Units: Dmnl

(41) TIME STEP = 1

Units: Year

The time step for the simulation.

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