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Technology Incubators as Nodes in Knowledge Networks

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Abstract

Over the last 20 years, there has been a considerable effort to search for a 'new' model of regional economic development. In this respect, the role of small high-technology firms in economic growth and innovation has received a great deal of attention from regional economists, geographers, planners and policy makers. Among the many ways to support the growth of new technology-based firms, perhaps the most captivating one is establishing technology incubators. However, systematic studies of the factors determining the growth of technology incubators are scarce. This paper is written in response to this situation. Using data of incubators in various regions in the developed world, we explore the role of several factors in determining differences in growth. The factors can be categorized into external factors, i.e. regional economic conditions, regional entrepreneurial culture and the degree of stakeholder involvement, and internal factors, i.e. incubation strategy, type of support for start-up firms, and age of the incubator. In our analysis we use a relatively new approach that matches with small (selected) samples and qualitative (and sometimes fuzzy) data i.e. rough set analysis. The findings suggest an explanation of the incubator growth mainly based on the diversity in stakeholder involvement and various internal factors of incubators.

Keywords: knowledge, learning regions, rough set approach, new technology-based firms, technology incubators.

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1. Introduction

Over the last 20 years, there has been a considerable effort to search for a ‘new’ model of regional economic development. Inspired by the economic success of the well-known industrial clusters such as Silicon Valley, California, and Route 128, Boston, many regional economists, geographers, planners and policy makers have attempted to find ways to transform and revitalize the regional economy. In this context, there is a growing recognition that factors determining economic growth are becoming intangible and mobile in nature (e.g. knowledge) and yet their contribution is more significant than traditional economic determinants such as capital and labor (OECD, 1992).

Based on the importance of knowledge in regional economic development, many regional economists have developed a knowledge-based model of territorial innovation (e.g. Lagendijk and Cornford, 2000). In the 1980s, various new concepts emerged, such as the innovative milieu (Aydalot, 1986), the industrial district (Beccatini, 1981, Brusco, 1982), localized production systems (Bouchrara, 1987), and new industrial spaces (Storper and Walker, 1989). More recently, the concepts of regional innovation systems and the ‘learning regions’ have been introduced to refine the model of territorial innovation (Morgan, 1997, Braczyk, 1998). Accordingly, the understanding of knowledge and its role in regional growth has become more enriched and the conceptualization has become more comprehensive. For example, spatial relationships or networks among all economic *agents*, private and public, a specific culture and a shared representation system became heavily stressed in the learning region approach (Lawson, 1999, Aydalot and Keeble, 1988, Camagni, 1991). In this respect, the ‘learning region’ can be acknowledged as a ‘synthesis’ of the predecessor concepts (Moulaert and Sekia, 2003). In this paper, we draw on this learning region concept to analyze activities in supporting growth of new technology-based firms.

With regard to the importance of networks in the growth of firms, a growing body of research has emerged especially in the regional economic field. One may distinguish between two focuses. The first focus points out the importance of networks among firms. Camagni (1991) and Lorenz (1996) recognize information exchange and labor transfers among firms as determinant factors for the growth of firms. The second focus, led by scholars such as Cooke and Morgan, places a greater emphasis on the role of non-firm institutions such as governments, development agencies, universities, etc. (e.g. Cooke, Uranga and Extebarria, 1998; Cooke and Morgan, 1998). Empirically, Keeble et al. (1999) address the role of regional institutions (e.g. university and local government) in enhancing and shaping the development of learning capacity of technology-based SMEs in the Cambridge region. Based on research using both focuses, we may assume that the growth of firms is a result from the combination of networks among firms and interaction with non-firm institutions. In regional policies to support new firms to survive, incubators have been recognized as one of the effective tools (Castells and Hall, 1994). In this respect, incubators may act as a resource gatherer and intermediary agent who provides an environment and networks to new technology based-firms. As an intermediary agent, incubators create favorable conditions by establishing networks among firms, as well as with non-firm institutions.

Although the contribution of incubators has been recognized in the conceptual frameworks of the learning region (Morgan, 1997), little attention has been given by geographers, regional economists and policy makers to the factors that contribute to the development of incubators. Scholars from the management and entrepreneurship field have given more attention to this area. However, they focus mainly on internal factors of incubators, such as selection criteria, incubator expertise, access to network and capital. It seems that the influence of external factors, namely characteristics of the regions where incubators are located, is neglected. Furthermore, many studies on the development of incubators rely heavily on using qualitative (case study) methods (Mian, 1997), studies that approach the development of incubators quantitatively and in a systematic way are scarce.

In response to above situation, this paper intends to combine a focus on internal and external factors that underlie the growth of incubators. Moreover, it aims to identify these factors in a quantitative and systematic way. To this purpose, we develop a causal model and test it by applying rough sets theory. Based on this background, the following question will be addressed:

> *What factors determine the growth of incubators, particularly which factors are internal and external to the incubators?*

The paper is organized in the following manner. First, we take a closer look on internal and external factors that may determine the growth of incubators based on a study of the literature. This part leads to various hypotheses. In the next section, we discuss the research design of this study including rough set theory and a step-wise approach that will be employed to increase the validity of the results. This is followed by the empirical results and conclusions following from hypotheses testing. Finally, we will discuss directions for further research and some implication for policy making.

2. Growth of Incubators

An increased awareness has grown among scholars, policy makers and practioners that knowledge and learning (or the capability to learn) are critical to the competitive advantage of firms, regions, and nations (Amin and Thrift, 1994, Reich, 1991). Historically, philosophers such as Ryle (1949) and Polanyi (1958) were among the earliest scholars who had expressed an interest in knowledge. Since then, the number of studies on knowledge has been growing rapidly with much recent attention focused on the importance of 'tacit knowledge' for sustaining competitiveness, and its role in learning and innovation. Tacit knowledge refers to the knowledge that cannot be easily articulated or transferred because it is un-codified and its understanding is influenced by a specifics social context. With these characteristics, tacit knowledge is the most important basis for innovation-based value creation (Gertler, 2003). Protection, exchange (transfer) and use of tacit knowledge tend to be difficult task. Lambooy (1997) and Camagni (1991) argue that geographical conditions are considered to be important in this process. It is because a short distance and socio-cultural similarities among *agents* will facilitate knowledge and information sharing (Boschma, 1999, Maskell and Malmberg, 1999). Lundvall (1988) for example, states that *agents* learn and adapt to 'best practice' through close interactions with other *agents* in their close environment. The existence of universities, government research institutes and industrial clusters at a close distance together with support from the regional government and other institutions influence the learning process of *agents*.

As an *organization*, incubators aim to accelerate the development of start-ups by providing an array of targeted resources and services. Incubators act as a mediator of knowledge transfer and support firms in building their networks. Incubators can be seen as an exemplar of the network among university, industry and government, which is popular under the concept of Triple Helix (Etzkovitz, 2002). Incubators traditionally merge the concept of fostering new business development with the concept of technology transfer and commercialization (Phillips, 2002). They can be seen as entrepreneurial (non-profit) organizations in performing a bridging function between promising spin-offs and resources required by these spin-offs while protecting them against any potential failure (Hackett and Dilts, 2004). Incubators may also act as a link between start-ups and other stakeholders that provide resources, such as governments, financial institutions, and business networks. In fact, incubators perform as a mechanism for a wide range of networking while encouraging the development of small businesses.

Many incubators employ large buildings, in which they offer customized rooms and supporting services. However, there are also examples of decentralized facilities, e.g. rooms spreading over different faculty buildings of the university. Generally, incubators support start-ups only on a temporary basis, e.g. three or four years, after which the start-ups are forced to leave the incubator and support will end. However, in practice this time limit is often used in a flexible way. Based on the above-indicated features, we conceptualize the process of incubation as a transformation of initial start-ups to viable firms that have survived the first few years.

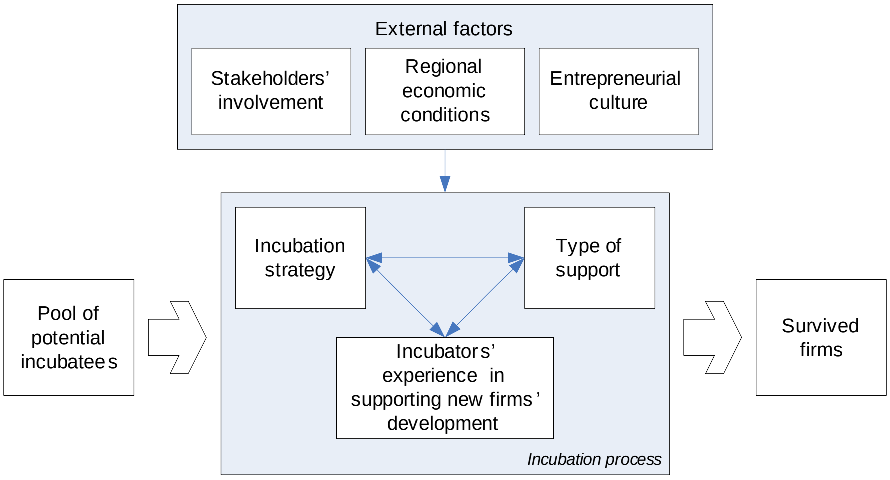

Figure 1. Simplified model of the incubation process

In this paper we develop a model that perceives the incubation process as a function of several knowledge-related factors, both external and internal to the incubators (Figure 1). External factors represent major characteristics addressed in the learning region approach, including the involvement of stakeholders, regional economic conditions and entrepreneurial culture. Internal factors refer to various qualities of incubator organizations themselves in managing resources to support start-ups, including selection procedures of candidates, tailor-made support, capability of monitoring and business coaching, and exit assessment. Quite recently, a new form of incubator has been addressed in the strategy adopted by particular incubators, namely through the extent in which profit-seeking plays a role and brings in start-up companies from outside universities (Clarysee et al, 2003). In the remaining section, we will discuss the above factors in more detail, starting with external factors, and summarize our expectations in hypotheses.

2.1 External factors

According to Camagni (1991), in the concept of the learning region, knowledge can spread effectively through a set of territorial relationships of production systems, which include economic actors (e.g. firms, chambers of commerce) and social actors (e.g. government at different levels, university, cultural institutes). The participation of actors in networks and their regional context will shape the networks and determine the quality of learning region (Knight, 1995). These networks, sometimes defined as 'untraded interdependencies' (Storper, 1995), are localized in regions and stimulate a process of dynamic learning which is essential to the growth of firms. Cooke and Morgan (1998) show the evidence in Baden Wurttemberg where the close interaction among the actors in the local networks support the growth of the local firms. Florida (1995) raises analogous themes in his argument that economic growth is endorsed by knowledge transfer through integrated networks of supplier and product development activities. Accordingly, the bigger the network the bigger the chance of firms to acquire knowledge and enhance their learning capacity that matches with heir specific needs. Lawson and Lorenz (1999) show that learning is a cycle, which involves a strong interaction among actors in Minneapolis, the US and Cambridge, the UK.

Based on the above consideration, it is important for incubators to receive support from different kinds of stakeholders, thus avoiding being solely dependent upon their own university (Monck et al., 1988). In principle, the involvement of different stakeholders means a potential access to a larger variety of resources and networking possibility. It means increasing the capability of incubators to grow, particularly responding to heterogeneity among incubated start-ups (Druilhe and Garnsey, 2004). We assume that this factor affects the incubators' growth, and therefore we propose the following hypothesis (1): *the involvement of many stakeholders stimulates incubators to have a more dynamic development than the involvement of a single stakeholder*.

Our next hypothesis is concerned with the geographical concentration of human capital. In order to grow and to be competitive, regions must have a human infrastructure – a labor market from which firms draw skilled and creative workers (Glaeser et al., 1995). Jacobs (1961) draws attention to the role of metropolitan cities in attracting and mobilizing talented and creative people. Lucas (1988) has argued that regional development is gaining from the clustering of talented people or human capital. In line with this, a growing stream of research focuses on the factors that attract talented people (Glaeser et al., 2001; Lloyd, 2001). This has led to the understanding that metropolitan cities which can provide more diversity in amenities, entertainment and lifestyle, have important advantages to attract talented and creative people. Based on the previous ideas, we may assume that incubators located in metropolitan cities benefit from various advantages, like attracting talented people and a large flow of new entrepreneurs. Moreover, in metropolitan cities incubators will obtain benefits from knowledge spillovers, information, proximity to suppliers and customers, and cheap access to facilities. These external economies refer to cost savings of both incubators and incubated firms. On the contrary, incubators in rural areas and peripheral regions at a distance from metropolitan cities seem to be less competitive and thus less attractive for new business activities. Therefore we propose the following hypothesis (2): *regions within the large metropolitan areas face a more dynamic incubator development than regions outside large metropolitan areas*.

Our next hypothesis is built on the theory of national culture by Hofstede (1991). His framework originally consists of four dimensions that describe the key aspects of national culture, which are power distance, individualism, masculinity, long-term orientation and uncertainty avoidance. With refer to with the adoption of innovation, Van Everdingen and Waarts (2003) put an emphasis on the latter, namely uncertainty avoidance. Firms in countries facing high levels of uncertainty avoidance generally show characteristics such as resistance to enter new avenues and avoid risks. A strong entrepreneurial culture is also believed to endorse incubators to be active in searching for new possibilities of supporting their tenants including new networks. Hence, we hypothesize as follows (3): *countries with lower levels of uncertainty avoidance face a more dynamic incubator development than countries with higher levels of uncertainty avoidance.*

2.2 Internal factors

The first hypothesis on the internal factors refers to the nature of support provided by incubators. The nature of support varies to a certain extent, depending on up the perceived needs of start-ups and upon the competence and resources of incubators. Conventional support is oriented towards the provision of tangible assets, e.g. room, laboratory facilities and financial support. However, there has been an important evolution in the kinds of support, from conventional to added-value support; the latter includes connecting the start-ups to various networks and new methods in business mentoring. In the learning regions model, where interaction among knowledge actors is intense and learning processes become prevalent, incubators respond to the fast changing needs of start-up firms by employing added-value support. Added-value support such as network building aims at increasing the capability of start-ups to survive and become independent. Assuming that an emphasis on added-value support will enhance the growth of incubated start-ups and decrease their nurturing time in incubators, we propose the following hypothesis (4): *incubators employing the added-value model of support face a more dynamic development than incubators offering conventional support.*

An important component of incubation strategies are the selection procedure of candidate incubates and the assessment for their exit. Hannon and Chaplin (2003) identify two strategies among UK incubators, i.e. pure incubators and flagship models. The pure incubators are traditionally established by universities and seek to exploit university potentials by producing firms that commercialize university research result. The flagship model, on the contrary, originates mainly from local or regional governments, or real estate developers, and tends to be more profit-oriented. In this model, significant investment is required to initiate the project and revenue stream are necessary to support the running costs. In the pure or traditional incubators, founders of start-ups originate from universities; particularly faculties of a technical signature and most of them lack the necessary entrepreneurial knowledge and skills. By contrast, the profit-oriented strategy urges incubators to attract as many new start-ups as possible. Today we see that the two types of incubators' strategy (traditional and profit-oriented) are adopted from the start of the incubators. However, as a result of the learning process, incubators also evolve from traditional incubators into profit-oriented ones, opening their doors to attract potential entrepreneurs from outside universities. The new type of incubator is expected to grow faster than a traditional type, as it has a larger capacity to absorb new entrants and develop new and diversified networks. Accordingly, we propose the following hypothesis (5): *incubators employing a profit-oriented strategy face a more dynamic development than incubators focusing on research commercialization in a traditional fashion.*

In managing an incubator, experience and professionalism in the selection, monitoring and coaching of start-ups seem to be critical (Smilor et al., 1988). A study by the Business Incubation Association (NBIA) in the US shows that it takes several years for incubators to become mature, in terms of gaining the capability to organize themselves and to produce independent firms on a continuous basis. Apparently, climbing on the learning curve improves the management's capability to meet objectives effectively and efficiently, like to have identified the most adequate networks and to participate in them in the most adequate way. Although learning is not a linear process, it increases with age. Therefore, we use age as an indicator for this improving capability. These considerations lead to the following hypothesis (6): *older incubators face a more dynamic development than younger ones.*

3. Nature of the Empirical Research

3.1 Selection of incubators and data validity issues

The empirical work of this study drew upon a relatively small, *selected* sample of incubators in various developed countries. The selection of incubators was based upon the above-discussed (theoretical) factors determining incubator development. The main data sources for this selection were paper journals, conference proceedings, annual reports of incubators, and incubators' websites. In the refinement of the selection, we imposed some specific requirements on the incubators:

1. To be a technology-related incubator. This type of incubators supports mainly technology-based firms and employs institutional links with and/or is located close to a university or research center.
2. To face particular characteristics in one (or more) of the six determining factors of incubator development. This served to gain a substantial degree of variance in the scores on these factors and to avoid that a particular characteristic is dominant in the sample of incubators.
3. To perform in the same time-frame. Studies concerning the 1980s cannot be compared with those concerning the 1990s, simply because of the potential influence of different macro-economic factors. To avoid the influence of changes in macro-economic conditions we have limited ourselves to one period: the years 1998 to 2002.

An additional criterion for selection stemmed from the meta-analysis nature of our study, as it is based on existing outcomes of previous studies. Therefore, we selected incubators supported by more than one source of literature and presented in a scientific and relatively objective way. Accordingly, we can ensure that every single incubator has a reference of comparison to increase the validity of the data. Nevertheless, we have encountered various validity problems, namely:

- Bias due to subjectivity
- Missing information
- Mismatch between data needed and data available.

We particularly encountered the problem of a lack of empirical data about small and less successful incubators, since reports tend to be published on success stories of incubator development. Annual reports produced by incubator organizations tend to mention successful incubates and firms that failed are not mentioned. Besides, reports and comments from incubator managers are potentially biased because of the self-reported nature. We could not solve the previous validity problems directly but we could decrease them by using more than one data source.

As a result of the selection process, we arrived at a sample size of 40 incubators. In selecting an indicator representing the dynamic development of the incubators we had to make a choice between growth of the number of entrant firms and growth of the number of exit firms. Therefore, we have checked the similarity between the two frequency distributions concerned, and used a Wilcoxon's signed-rank test. The results showed that there is no difference between the two growth indicators, meaning that we could use the number of entrants as well as the number of exits (Appendix 1). The number of new entrants per year varies between – 3.0 and + 7.0 (Figure 2). We divided the incubators into two classes, those experiencing a strong growth and those experiencing a weak growth, based on the median (+1.25).

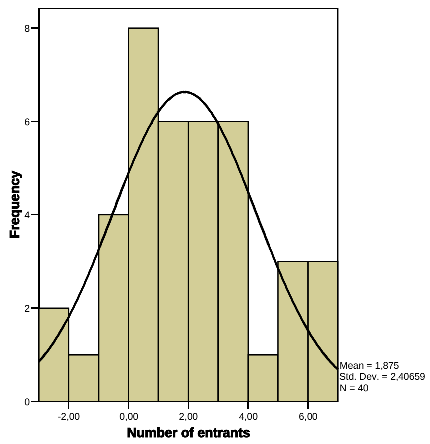

Figure 2. Growth (entrants) of the selected incubators (1998-2002)

3.2 Rough set analysis

Our study deals with qualitative and quantitative information and is based on a relatively small sample of incubators. Therefore we employed rough set analysis to identify and disentangle causal relations (Pawlak, 1991). This approach enables the transformation of an imprecise or incomplete (fuzzy) collection of data, both quantitative and qualitative, into structured knowledge. Unlike other conventional methods that are based on statistical assumptions, this analysis makes only one assumption in that the value of the determining factors can be categorized. In particular, rough set analysis is able to incorporate different measurement scales and different degrees of measurement accuracy, known as granularity in the classified experiments.

In the past few years various studies have proved to be successful in using rough set as a tool of analysis, among others concerning sustainable development (Nijkamp et al., 2002), travel demand analysis (Goh and Law, 2003) and fiscal policies (Nijkamp and Poot, 2004). Despite various strong points, rough set analysis has also potential weaknesses. As the rough set is based on deterministic calculation, it is always capable of producing a result even with a fuzzy input, but it usually does not provide a reliable indication of the quality of the results. Moreover, if a small number of data containing highly diverse characteristics is processed, rough set will produce many rules with a small number of supporting cases. In addressing this problem, we make use of a step-wise procedure (Figure 3), including some tests to ensure the quality of the results. The procedure has several advantages, such as:

- More solid and simpler decision rules.
- A higher quality of results (by using remaining data to test the accuracy of rules).
- More comprehensive results (the role of each factor and combinations of factors).

In our study, the rough set estimations were conducted using ROSE2 software. ROSE2 is a modular system implementing the basic elements of the rough set theory and the decision rules (Predki and Wilk, 1999).

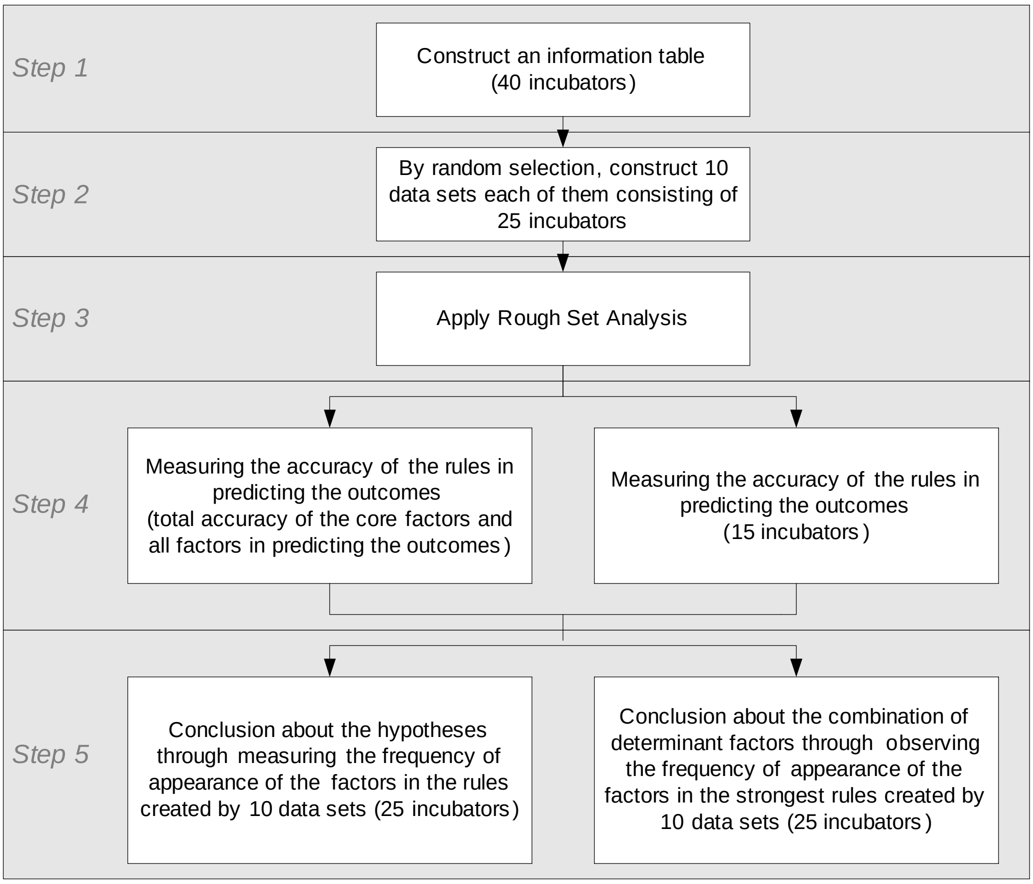

Figure 3. Step-wise procedure

The steps are briefly explained below:

Step 1) Collect initial data and create an information table consisting of 40 incubators (Table 1), including condition attributes (C) and decision attributes (D). The condition attributes are the determinant factors of the growth of incubators, whereas the decision attribute is the incubators' growth.

Step 2) By using a random selection, construct 10 data sets for further analysis with the rough set. Each data set consists of 25 incubators (appendix 2).

Step 3) Apply rough set analysis on 10 data sets (appendix 3). Through this process, redundant attributes are removed. The results of this step are *reduct*, *core*, and *decision rules*. A *reduct* is all combinations of factors, which completely determine the variance in the incubators' growth without other explanatory variables. A *core* is the intersection of all *reducts*. The factors listed in the *core,* have the strongest explanatory power. After employing the attribute reduction process, the procedure will generate the decision rules. The rules are presented in an ‘‘IF *condition(s)* THEN *decision(s)*’’ format.

Step 4) Measure the accuracy of the rules. In this step, the measurement is conducted using two approaches. The first approach is based on the value of the core and factors’ accuracy in predicting the outcomes. Based on the data set (25 incubators), the procedure produces the value that indicates how accurate the core and other factors are in predicting the outcomes. In the second approach, we use the remaining data set (15 incubators) to test the accuracy of the prediction of the decision rules. Since we have 10 data sets, this procedure will be repeated 10 times. The result of this step indicates how accurate the rules are in predicting the outcomes.

Step 5) In this final step, we draw a conclusion about the factors that determine the outcomes. The result of the previous steps is decision rules produced by each data set. To identify the role of each factor, whether they support or reject the hypotheses, we measure the number of factors appearing in the rules which support the hypotheses divided by the number of growth classes (in this case we have a class of strong and a class of weak growth for 10 data sets, therefore in total there are 20 growth classes). If this value is sufficiently high (70%), the hypotheses can be accepted. On the contrary, if the value is low, then the hypotheses need to be rejected. In this step, we also analyze the combination of factors appearing in the strongest rules produced by each data set.

Table 1. Information table

Object	Name of incubator region	Determinant Factors (condition variables)						Growth (decision variable)
		C1	**C2**	**C3**	**C4**	**C5**	**C6**	**D**
1	Texas, US	1	2	1	2	1	2	2
2	Ohio, US	2	1	1	1	2	2	2
3	Atlanta, US	1	1	1	1	1	2	1
4	Charlotte, US	2	1	1	2	1	2	1
5	Evaston, US	1	1	1	2	1	2	2
6	Illinois, US	1	1	1	2	1	1	1
7	Quebec, Canada	2	1	1	2	1	1	1
8	Surrey, UK	1	1	1	1	2	2	1
9	Cambridge, UK	1	1	1	2	1	2	2
10	Leuven, Belgium	2	1	2	2	1	2	1
11	München, Germany	2	1	2	2	1	1	2
12	Chemnitz, Germany	2	1	2	2	2	1	2
13	Enschede, The Netherlands	2	2	2	1	2	2	2
14	Delft, The Netherlands	1	1	2	1	1	1	1
15	Århus, Denmark	1	1	1	2	2	1	1
16	Oeiras, Portugal	2	1	2	2	2	1	1
17	Bordeaux, France	2	2	2	1	2	1	2
18	Trondheim, Norway	2	2	1	1	2	1	2
19	Vaxjo, Finland	1	2	1	2	1	2	2
20	Helsinki, Finland	1	1	1	1	1	1	1
21	Salzburg, Austria	2	2	2	1	2	2	2
22	Styre, Austria	2	2	2	1	2	2	1
23	Zürich, Switzerland	2	1	2	1	2	1	2
24	Gothenburg, Sweden	1	2	1	1	2	1	2
25	Skone, Sweden	2	2	1	1	2	2	2
26	Linköping, Sweden	2	1	1	1	2	2	2
27	St. Petersburg, Rusia	1	1	2	1	1	2	1
28	Baia Mare, Romania	1	2	2	1	2	1	1
29	Budapest, Hungary	2	1	2	1	1	2	1
30	Crete, Greece	1	2	2	1	1	2	1
31	Tartu, Estonia	1	2	2	2	1	1	1
32	Hsinchu, Taiwan	2	1	2	1	2	2	2
33	Singapore, Singapore	2	1	1	1	2	1	1
34	Taedok, South Korea	2	1	2	1	1	2	2
35	Kawasaki, Japan	2	1	2	1	2	2	2
36	Shanghai, China	2	1	2	1	2	1	2
37	Haifa, Israel	2	1	2	1	1	1	1
38	New South Wales, Australia	1	1	2	1	2	1	2
39	Queensland, Australia	1	1	2	1	2	1	1
40	Perth, Australia	2	1	2	1	1	2	2

Determining factors
C1 : Stakeholders' involvement (1: single stakeholder involvement; 2: multiple stakeholder involvement)
C2 : Regional economic conditions (1: agglomerated areas 2: non-agglomerated areas)
C3 : Uncertainty avoiding attitude (index) (1: low; 2: high)
C4 : Type of support provided by incubators (1: conventional; 2: value added)
C5 : Incubation strategy (1: research commercialization; 2: profit-focused)
C6 : Age of the incubator (1: < 5 years old; 2: ≥ 5 years old)
Growth indicator
D : Average annual growth of entrants / exits (1: weak (≤ 1.25); 2: strong (>1.25))

4. Results

The complete results in terms of the factors' appearance in the decision rules for 10 data sets are presented in Table 2.

Table 2. Decision rules created by 10 data sets

	T1		T2		T3		T4		T5		T6		T7		T8		T9		T10	
	W	S	W	S	W	S	W	S	W	S	W	S	W	S	W	S	W	S	W	S
C1	1	2	1	-	1	2	1	2	1	2	1	-	-	2	1	2	1	2	-	2
C2	-	-	1	2	-	2	1	2	1	2	1	2	1	2	1	2	-	-	1	2
C3	2	2	2	1	2	1	2	1	2	2	2	2	-	1	2	1	2	2		1
C4	-	2	-	-	1	2	1	2	1	2	1	2	1	-	1	-	-	2	1	2
C5	1	2	1	2	1	-	-	-	1	2	1	2	1	2	-	2	1	2	1	-
C6	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
Core accuracy [a)]	0.800		0.680		0.640		0.720		0.680		0.800		0.800		0.760		0.800		0.800	
All factors accuracy [b)]	0.800		0.680		0.640		0.720		0.680		0.800		0.800		0.840		0.800		0.800	
Prediction accuracy [c)]	0.800		0.667		0.600		0.667		0.667		0.800		0.733		0.800		0.800		0.733	

Note: sign '-' means that the factors did not show up on the rules
[a)] The accuracy of core factors in predicting the outcomes (25 incubators)
[b)] The accuracy of all factors in predicting the outcomes (25 incubators)
[c)] The accuracy of rules measured by remaining data (15 incubators)
T1-T10: 10 data sets of incubators showing the class of growth (W: Weak and S: Strong)
C1 : Stakeholders' involvement (1: single stakeholder involvement; 2: multiple stakeholder involvement)
C2 : Regional economic conditions (1: agglomerated areas 2: non-agglomerated areas)
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C6 : Age of the incubator (1: < 5 years old; 2: ≥ 5 years old)

4.1 Summary of hypotheses testing

Since the nature of rough set analysis is based on deterministic calculation, the decision to accept or reject a hypothesis is more complicated than using other statistical methods. We decided to accept or reject a hypothesis based on the number of the factors' appearance in the decision rules (see figure 3). A factor that appears in the rules can both support and reject the hypotheses. For instance, a factor such as the involvement of many stakeholders supports the hypotheses if this factor appears in the rules explaining a strong growth and rejects the hypotheses if this factor appears in the rules explaining a weak growth (hypothesis 1). In some cases, it is also possible that the factor does not show up in the rules explaining both growth classes, or showed up in the rules explaining both growth classes but could not explain the differences in both growth classes. We then divided the number of each factor's appearance by the total number of classes (20). We have taken 70 % as a basis to accept or reject the hypotheses. Partly accepted/rejected refers to the situation in which at the same time, a hypothesis is supported and rejected by the factors in both classes.

Table 3. Appearance of factors in the decision rules

	C1	C2	C3	C4	C5	C6
Total number of classes [a] (A)	20	20	20	20	20	20
Frequency of a factor's appearance that support the hypotheses (B)	16	0	13	14	15	20
Frequency of a factor's appearance that reject the hypotheses (C)	0	15	5	0	0	0
Percentage of a factor's appearance that support the hypotheses (B/A) (%)	80	0	65	70	75	100
Percentage of a factor's appearance that reject the hypotheses (C/A) (%)	0	75	25	0	0	0
Conclusion	Accepted	Rejected	Partly Accepted	Accepted	Accepted	Accepted

C1-C6 : The determinant factors (stakeholders' involvement, regional economic conditions, uncertainty avoiding attitude, type of support provided by incubators, incubation strategy, and age of incubators)

[a] We apply the rough set analysis on 10 data sets in which there are 2 outcomes of the decision variables (weak and strong growth); as a result there are 20 classes of the decision variable.

Based on Table 3 we will now discuss our hypotheses. The role of stakeholders' involvement turns out to confirm our hypothesis (1). Incubators supported by different stakeholders tend to experience a relatively strong growth; and the incubators supported by single stakeholders (universities) tend to experience a relatively weak growth. This result indicates that incubators that follow the learning region concept, being placed in a web of networking organizations besides the university tend to be more vital and dynamic. With regard to hypothesis (2) the decision rules indicate that strong growing incubators tend to be located in non-agglomerated regions and the weak ones in agglomerated regions. This can be seen as a rejection of our hypothesis. There are three potential explanations for this unexpected result; first, in particular metropolitan areas, agglomeration economies may have turned into agglomeration diseconomies, like road congestion, high land and real estate prices, labor market shortages, etc., whereas, rural areas and peripheral areas (at least in Europe) receive targeted assistance in regional development and innovation from the EU and the country, through which incubators become more competitive. Secondly, in agglomerated areas the situation may be such that the incubation process works spontaneously, thereby reducing the role of incubators and causing a less dynamic development. Another explanation is that talented people who actually are the potential technology entrepreneurs increasingly move to regions that face better knowledge resources, related opportunities and better established living environment than the metropolitan cities (Florida, 2002). Regarding hypothesis (3) our findings suggest a partial confirmation. Entrepreneurial culture seems only to influence strong growth. Incubators located in a nation/country facing a low uncertainty avoidance tend to perform better than those located in a nation/country facing a higher uncertainty avoidance. However, low uncertainty avoidance also appears in the rules which explain weak growth. Further, with regard to hypothesis (4) the decision rules suggest that incubators providing added-value support tend to have a strong growth while others tend to perform weaker. It seems that incubators which match their support with the changing needs of their tenants, in term of networking and business coaching, experience a relatively strong growth. Concerning hypothesis (5) the decision rules suggest that the profit-focused incubation strategy tends to cause a stronger growth than the strategy of merely commercializing university research. This can be seen as a confirmation of the hypothesis. Finally, the decision rules also suggest a positive influence of age on the growth of incubators (hypothesis 6). Apparently, the older incubator benefits from advantages of learning to large extent the younger incubator.

In the next step, we analyze the combination of the factors in explaining the growth of incubators by using the strongest rules created by each data set. The strongest rule means that the largest number of cases in their set supports the rule. Usually, there is only one strongest rule but if there are two rules with the same strength, we consider both in our analysis. The analysis is made for each growth class (weak and strong growth). In total, there are seven strongest rules for the class weak growth and five rules for the class strong growth. For each factor, we then determine the number of the factors' appearance in the rules and divide it by the total number of strongest rules. For example, with regard to weak growth, the factor stakeholders' involvement appears three times and the total number of the strongest rules in this class is seven, then the percentage of the factors' appearance is 43% ($3/7 * 100\%$). Table 4 shows the outcomes of the calculation.

Table 4. Factors' appearance in the strongest rules (10 data sets)

Weak growth	C1	C2	C3	C4	C5	C6
Frequency of a factor's appearance (A)	3	2	3	4	3	1
Total number of rules in the class (B)	7	7	7	7	7	7
Percentage of a factor's appearance (A/B)(%)	43	29	43	57	43	14

Strong growth	C1	C2	C3	C4	C5	C6
Frequency of a factor's appearance (A)	3	3	1	0	2	1
Total number of rules in the class (B)	5	5	5	5	5	5
Percentage of a factor's appearance (A/B)(%)	60	60	20	0	40	20

C1-C6 : The determinant factors (stakeholders' involvement, regional economic conditions, uncertainty avoiding attitude, type of support provided by incubators, incubation strategy, and age of incubators)

We may conclude that a combination of factors strongly determines the incubators' performance. These factors, including a single stakeholder's involvement, high uncertainty avoidance, conventional support and a university research commercialization oriented strategy, lead to a relatively weak growth. On the other hand, a strong growth performance is caused by only two factors, which are differentiated stakeholders' involvement and location in non-agglomerated regions. The appearance of these two factors shows a relatively higher value that that of the other factors, witness 60% versus a range from 0 to 40%.

4.2 Quality of the analysis

The decision rules can be interpreted straightforwardly, but we need to objectively quantify the quality of the results. To this purpose, we used two different assessments in quality measurement, explained below:

- The first quality assessment is the result from the rough set calculation on 10 data sets (25 incubators). The mean of the accuracy of the core factors is 74.8 and the mean of the accuracy of all factors is 75.6. Based on these values, we may conclude that the determinant factors can satisfactorily predict the growth of incubators.
- In the second assessment, we evaluated how well the decision rules produced by each data set predict the growth of incubators. We decided to conduct an accuracy test by using the remaining data in each set (15 incubators). Each data set produced a set of rules. Using these rules, we predicted the outcomes of the remaining data in each set. In total, the results indicate that the decision rules perform well in predicting the growth of the incubators (72.6).

Table 5. Accuracy of the analysis [a)]

	Mean (percentage)
Accuracy of core factors (10 data sets–25 incubators)	74.8
Accuracy of all factors (10 data sets–25 incubators)	75.6
Accuracy of rules produced by each data set in predicting the outcomes (10 data sets–15 incubators)	72.6

[a)] The highest value: 100.00

Based on the above satisfactory results, we may conclude that the use of the decision rules is indeed justified in our investigation.

5. Concluding Remarks

In this paper we applied a relatively new methodology, namely rough set analysis, to explore a causal model of growth of incubators. The results of this approach in the form of decision rules appeared to be straightforward in predicting the influence of factors or combinations of factors. In addition, in our investigation using a step-wise rough set procedure, the decision rules produced by 10 data sets proved to be sufficiently robust. Based on these decision rules, some preliminary conclusions can be made:

1. In the concept of the learning region, incubators operate as a node in knowledge networks. Accordingly, incubators play an important role in establishing networks among firms and other non-firm institutions such as governments, industry and universities. The findings show that the differentiation in stakeholders' involvement appears to be a relatively strong determining factor in the growth of incubators. Accordingly, fast growing incubators tend to be supported by diverse stakeholders, including universities. Apparently, this situation causes more variation in the networks and the resources that can be disclosed using the networks. In this situation, incubators and firms benefit from receiving more new knowledge in a quick fashion, which is critically important for their growth. ITRI incubator at Hsinchu Science Park, in Taiwan exemplifies such a situation.
2. With regard to the regional conditions, incubators experiencing a strong growth tend to be found in non-agglomerated (peripheral/rural) regions while those experiencing a weak growth tend to be found in large metropolitan areas. This pattern may suggest that the policy to enhance economic growth of peripheral (rural) regions by facilitating the creation of high-technology firms through incubators works well. The TOP incubator of University Twente in the Netherlands provides a good example of this evidence. Located relatively far from the metropolitan area of the Randstad, this incubator successfully

increases the number of new entrants per year. The same evidence is given by the incubator in Trondheim, Norway. In addition, the findings also suggest that strong entrepreneurship in the sense of a low risk avoiding attitude adds to the success of incubators. However, this finding is partially true, since a low risk avoiding attitude is also observed among some incubators with a relatively weak growth.

3. Furthermore, concerning internal factors of incubators, the decision rules suggest that incubators employing a profit-oriented strategy grow faster compared to those solely focusing on the commercialization of research from university. This difference may point to one of the new developments of incubators in which incubators are evolving from the conventional type that focuses on research commercialization to a profit generator. We may assume that this action is forced by the learning process of incubators. In addition, incubators that provide added value support, including participation in various knowledge networks, face a more dynamic growth. Another confirmation about the role of learning comes from the influence of age on the growth of incubators. Apparently, older incubators have benefit from a longer time of learning.

Overall, we may conclude that the learning region produces a dynamic development of incubators when a differentiated stakeholder involvement is combined with various internal factors of incubators.

Despite the appealing results, we acknowledge that there are limitations to our rough set study. The analysis is based on a model including one-way relationships in the incubation process. By using this model, we might have missed a part of the complexity, particularly the feedback effects such as between the growth of incubators and the stakeholders' involvement. Such relations could not be described in our simplified model. Furthermore, this study is a first broad exploration of determinant factors of incubator development. It can be extended in further research to include more refined notions concerning the factors about which our expectation were partially wrong, i.e. the attitude to avoid uncertainty, regional economic conditions. Finally, we can conclude that the rough set analysis using a step-wise procedure has successfully produced a structure in terms of decision rules that explain a different development of incubators at a sufficient level of accuracy.

Appendix 1. The Wilcoxon Signed Ranks Test

The Wilcoxon test aims to test the difference between the two samples of performance indicator (number of entrants and number of exist).

	Indicator 1[a)] – indicator 2[b)]
Z	-.813[c)]
Asymp. Sig (2-tailed)	.416

a) Average annual growth of entrants
b) Average annual growth of exits (graduated firms)
c) Based on positive ranks

The result indicates that there is no difference between the two samples (z = -.813; p-value = 0.416)

Appendix 2. Determine the sample size

There are two different approaches in determining the sample size. The first approach is based on statistical equations. The common formula for the sample size necessary to produce accurate result with regard to a specified confidence and margin of error is:

$$n = \left[\frac{z_{\alpha/2}\sigma}{E} \right]^2$$

where:

$z_{\alpha/2}$ is the critical value
σ is the population standard deviation.
n is the sample size.
E is the margin error

In our case, with a 95% degree of confidence, the formula determines the sample size : 19,6. It means that we need to take a sample at least 20 incubators. The second approach is based on a rule of thumb (Neuman, 2003). In order to be accurate, the smaller the population, the bigger the sample size. For small populations, a large sampling ratio is needed, about 30 percent of the total population. However, based on our past experience on using rough set, we double the sample size to 60 percent. With a population of 40 incubators, we select a sample size of least 24 incubators.

Appendix 3. Decision rules created by one data set (example)

Rules	**Factors**	**Growth**	**Strength**
1	C4='1' & C5='1'	Weak	41.67
2	C2='1' & C6='1'	Weak	38.46
3	C1='2' & C2='2'	Strong	41.67
4	C2='2' & C3='1'	Strong	33.33
5	C5='2' & C6='2'	Strong	41.67

C1 : Stakeholders' involvement (1: single stakeholder involvement; 2: multiple stakeholder involvement)
C2 : Regional economic conditions (1: agglomerated areas 2: non-agglomerated areas)
C3 : Uncertainty avoiding attitude (index) (1: low; 2: medium; 3: high)
C4 : Type of support provided by incubators (1: conventional; 2: value added)
C5 : Incubation strategy (1: research commercialization; 2: profit-focused)
C6 : Age of the incubator (1: < 5 years old; 2: ≥ 5 years old)

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