Differences between European Regional Innovation Systems in Terms of Technological and Economic Characteristics

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Abstract
This study aims to identify different types of regional innovation systems (RISs) and explain regional dynamic changes, in terms of technological specialization and economic characteristics, between periods. We firstly collect various variables on regional level from EPO (European Patent Office) and REGIO database to extract and construct regional characteristics. Secondly, these characteristics are used to distinguish the differences between RISs, e.g. high-tech RISs and low specialization RISs. According to our empirical results, we find that some regional characteristics, such as high-tech specialization and high innovativeness, have highly close relationship within RISs. Furthermore, the comparison between periods shows us different characteristics in technological specializations in early stage lead RISs toward different RISs in economic performance, technological development and innovativeness.

Keywords: Regional innovation systems; technological specialization; regional characteristics; innovation;

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1. Introduction

This study aims to explore whether or not different types of regional innovation systems exist among European regions, based on the economic characteristics and technological specialization patterns. The theoretical motivation of the study lies in the theory of economic growth, which underlines the importance of technological change and innovation for growth, and the innovation systems literature. Furthermore, due to that the developments of regional innovation systems (RISs) are characterized by specific economic phenomena and technological specializations, the concept of 'regional club' has been showed in Europe (Verspagen, 1998). This study further aim to identify the differences of specific characteristics between "clubs" and show their dynamic changes cross time.

We start with constructing different characteristics from various indicators, and then focus on identifying the differences and changes between regional innovation systems in terms of different characteristics. Most of the economics literature on regional development, only a single or a few indicators are used, and we cannot observe the overall pattern of regional development. The overlap and distinction between the various indicators are also paid less attention. Although economics research indeed points to the role of specific indicators, there if often no agreement on which indicators are the best. For the purpose of explaining regional development this study applies an integrated picture of economic and technological indicators from various regional indicators. In addition, in order to find out if different types of innovation systems can be identified among European regions, the crucial economic and technological indicators are used to identify the differences between regions. From the specific combinations of technological and economic indicators in different types of innovation systems, we hope to learn how specific economic and technological characteristics interplay within innovation system.

The aim of the paper is not to test any theoretical frameworks explaining regional economic growth or otherwise. The aim is rather to take stock of the variety and commonalities in European regional experience, and the role of technology and innovation in this. Specifically, we aim to find a taxonomy of different types of regional innovation systems, and combinations of specific economic and technological characteristics within these systems. For example, we are interested in the role of innovativeness in high-tech technological development, which we seek to illustrate by means of comparisons between two clusters analyses of regions. The different types of innovation systems also provide one of the reasons that some European regions perform better than others do, which is why we include economic performance variables in the taxonomical analysis. Furthermore, from a more dynamic viewpoint, we aim to observe changes between the 1980s and 1990s, hoping to provide insight into how initial characteristics lead the region to develop.

The main results of this study show that it is meaningful to use technological and economic characteristics to taxonomize regional innovation systems. We find there exist different types of innovation systems among European regions, such as high-tech activities combined with high economic performance, or natural resource based activities combined with low growth. The high-tech, high innovative, and "mid-high" economic performance pattern is found in metropolitan regions, and low specialization and low economic performance regions are mostly found in south Europe. The comparisons between technological clusters in the two periods shows that the technological base in the initial period is strongly related to further technological development.

In the second section, we discuss the relevant past research, and, based on this theoretical background, we try to identify the relevant regional indicators. From research in economic growth theory, innovation systems, and international business theory, we summarize how to explain regional development from a holistic view. The third section describes the database, the definition of each research variable, and the methodology that we apply in this study. The fourth section presents the empirical results, which includes factor analysis and cluster analysis in different periods, and some discussion. Finally, in the last section, we summarize our conclusions, point out some limitations of this study and further research directions.

2. Literature Review

For discussing regional development, we briefly survey the literature from different theoretical backgrounds. The research on economics growth, innovation systems, and international business guides us to identify the crucial regional characteristics for our analysis, including economic and technological dimensions.

2.1 Theoretical background

From past literature on regional economic growth, we find that the crucial dimensions for explaining regional development include technological characteristics and economic characteristics. The economic growth literature shows the inseparable relationship between technological progress and economic phenomena (e.g., Solow, 1956, Verspagen). These two dimensions seem to express how a specific region or country develops. Integrating interactive and dynamic characteristics from the literature of innovation systems (e.g., Lundvall, 1992; Cooke, 2000), we conclude to apply different regional characteristics, including input or output indicators. We also include the concepts of knowledge interaction and learning effect into our research model. In addition, some concepts from recent research on international R&D activities lead us to include specific regional characteristics of economic and technological dimensions (e.g., Patel and Vega, 1999).

- **Economic Growth theory**

The economics literature has discussed the inseparable relationship between technological development and economic performance for several decades, and these results mostly show a positive relationship between technological progress and economic growth. Although traditional growth theory (Solow, 1956) and new growth theory (Romer, 1990) concludes out that the growth path of each country or region will converge (unconditional or conditional) to each other, the economists continuously emphasizes the role of technological changes in the process of economic growth. A recent "Schumpterian" literature, on the other hand, argues that technology is a strong disequilibriating factor for economic growth and raises the possibility for regional divergence. Verspagen (1998) summarized these different theories about regional technological changes and applied the concepts from economic geography and spatial technology spillovers to identify European economic and technological 'clubs' of regions, In addition, Dalum, Laursen and Verspagen (1999) examine the relationship between technological development and economic growth and show that specialization in specific technologies and sectors indeed matters for economic growth. In summary, the economics literature shows us that the characteristics in technological development and economic phenomenon are crucial for understanding regional development.

- **Role of Specialization**

Specialization patterns in specific regions show the preference and capability in particular technology as well as the development of regional innovation systems. According the economics results, we find that some evidences show the importance of specialization which brings regional economic growth (Dalum, Laursen and Verspagen, 1999) whereas some controversial argument proposed that diversity rather than specialization is operative mechanism for economic growth (Jacob, 1969). In addition, some research focuses on explaining whether or not technological specialization leads regions to perform better in innovative activities (Feldman & Audretsch, 1999). Although the different results exist in various studies, all of them show us the integrating of knowledge and innovative activities should be concerned together with specialization, so that the phenomenon of regional development could be explained completely.

- **Innovation systems**

According to the literature in innovation systems, we learn that the roles of interactions, knowledge embodied in human resources, and its learning procedures are important for regional development. The concept of an innovation system emphasizes, especially on economic issues, that the trajectory of firms in terms of learning and innovating is the consequence of social interactions. Cooke et al., (2000: 21-24) applied this concept and proposed that these interactions move beyond just the business sphere and reach the public sphere of universities, research labs, technology transfer and training agencies. In other words, under a regional innovation system, the knowledge flows through networks of innovators that are operating in proximity, backed by regional policy and institutions. In addition, these characteristics, including both knowledge itself and knowledge interaction mechanisms, are accumulated from specific regional human capital as the knowledge base for further technological development (Lundvall, 1992: pp.8-9; Breschi & Lissoni, 2001; Johnson, 1992: p.28). From a dynamic and systematic view, human resource in knowledge input/output becomes the innovativeness characteristic crucially linked to the capability of the region with regard to innovative activities.

- **International Business View: Motivation of MNEs' R&D activities**

Recent research starts to address issues around foreign R&D investment and identifies how these MNEs invest in suitable locations (Verspagen & Schoenmakers, 2002; Patel and Vega, 1999; LeBas & Sierra, 2002; Zedwitz & Gassmann, 2002). MNEs invest in different locations that are fit for their different goals of foreign investment, and technological resources play a crucial role in this. This recent research points out that MNEs' behaviors may be motivated by two goals, asset-seeking and asset-exploiting (Dunning and Narula, 1995; Le Bas & Sierra, 2002), which identify different preferences on the technological characteristics and economic potential within a region. The local technological knowledge base is the main determinant of the choice to invest in R&D activities in local place whereas those which look for potential markets concern economic characteristics. From the point of view, MNEs' locational decision cannot ignore the understanding of economic and technological characteristics of RISs.

2.2 Characteristics

Economic static vs. dynamic characteristics: We distinguish static (e.g., levels of income) as well as dynamic economic performance (e.g., growth rates) variables. This is particularly important because growth rates may be different between rich and poor countries. Poor regions with low static economic performance might create high growth as a result of high technological resource infusion. The dynamic and static perspectives in economic characteristics thus provide a complete picture of economic characteristics to classify regions.

Furthermore, the regional ***labor force*** shows the regional endowment that is a crucial input factor for regional development. In neoclassical economics, labor is a necessary factor in the production function, while in the innovation system literature regional knowledge embedded in human resource is indispensable in the innovation process. For example, the prosperity of the labour market, indicated, e.g., by the employment rate, shows how abundant the labour input is within the region and how the fit between labor supply and demand evolves. Therefore, besides economic static and dynamic characteristics, the labour market phenomenon also provides some explanation for regional development.

Innovativeness: We learn from the innovation systems literature that innovative characteristics are accumulated from specific regional human capital as the knowledge base for further development (Lundvall, 1992: pp.8-9; Breschi & Lissoni, 2001). Skilled labors, such as R&D personnel involved in science and technology research, interact with relevant actors, and create knowledge, inventions or patents, and thus shape the innovativeness and technological capability of the regions. Breschi & Malebra (2001) concluded that potential of local technological capability, such as the skilled labor and successful cluster, is an important factor for regional development. Locational connections to technological and market opportunity are often driven by a well-established skilled labor network, leading to an innovative advantage. Fageberg and Verspagen (2002) show the importance of innovation in economic growth and regional development. In summary, we look at human resources in science and technology or R&D, as well as patent as an output indicator of technology for understanding regional development patterns.

Technological specialization: The kind of (technological or economic) activity is often argued to be of importance for the growth potential. Some sectors have a higher growth potential than others, or might generate more spillovers. Here a choice is between a simplified classification such as high-tech / no high-tech (Verspagen, 1998), or a comprehesive view on specialization taking into account abroad range of sectors. The advantage of the latter is that the economic impacts of each single specific sectoral technology can be examined. If we focus only on the distinction high-tech/non-high-tech, the contributions of other technological developments, such as traditional technology or natural resource related industrial technology, might be ignored. It is obvious, for example, that some regions in Italy are famous and prosperous because of their development of traditional technologies, such as clothes design or leather products (Breschi, 2000). Therefore, this study focuses mainly on a broad view of technological specializationin order to explain how regions evolve differently with regard to technological development and how specific technological characteristics are related to economic development.

2.3 Clustering: differences and similarities between regions

Before discussing the relationships between regions, we have to clarify the definition of "cluster" in our study. Many contributions use the term "cluster theory" or "industrial cluster phenomenon" (Porter, 1991; Longhi & Keeble, 2000, etc.) to describe inter-firms interactions and regional agglomeration phenomena. However, the term "cluster" in this study does not mean any industrial cluster or any agglomeration of firms in this sense. What our "cluster" means is a specific group of regions that show roughly the same pattern of development and technological performance, in other words, have similar regional innovation systems. The regions classified into the same cluster are more similar to the regions within same cluster than to the regions that have been classified in other clusters. This concept of cluster or specific type of innovation system is similar to "regional clubs" (Verspagen, 1998), although a difference is the way in which regional characteristics are measured and conceptualized.

In the existing literature, few contributions consider both technological and economic characteristics *jointly* to observe the differences between regions, although both dimensions are highly related and crucial for regional development. Verspagen (1998) has applied different indicators, such as GDP per capita, productivity, and high-tech sectoral specialization, from the two dimensions (economic and technological dimensions) to identify European "regional clubs" and explain the differences between European regions. Although this result shows the high linkage between high-tech development and economic performance, the way to frame out "regional clubs", classified by only economic or only technological factors, cannot show the specific combinations of economic and technological characteristics within a club. This method thus ignores the interplay between economic and technological characteristics within a club. By extending the concepts of "regional clubs", our study includes both economic and technological characteristics jointly to classify regions into clusters (different types of innovation systems). The interactive relationship between technological and economic characteristics is examined from the specific combinations of the variables observed within specific clusters.

An interpretation of regional innovation systems similar to the one used here has been proposed in past research. Cantwell & Janne (1999) argue that each innovation system has different characteristics, and identify a hierarchical relationship between these systems, showing that some nations have more advantages in some specific technological development than others. By distinguishing two types of economic agglomeration effects, (Cantwell & Noonan, 2002: pp.203-204), general external economies and localization economies, and the interactions between these two agglomeration forces, Cantwell and Iammarino (1998) identify the existence of higher-order and lower-order centers in technological development. In other words, we can imagine that the characteristics for clustering regions used here also explain the hierarchy of regional innovation systems.

3. Data and Methodology

3.1 Data

The databases that we use in our analysis are from two sources. The first one is from the **REGIO** database that is collected by EuroStat. The database includes various indicators, such as economic indicators, demographic data, and S & T (Science and Technology) indicators. The database collects regional information from 1979 to 2001 so that we can select the data of different periods to show the dynamic phenomenon. The second database is the patent database from the European Patent Office. This database includes the information of inventors and applicants during two periods, 1986-1988 and 1996-1998. The NUTS (nomenclature of statistical territorial units) classification is used to define regions in both databases. From these two databases, we use multiple variables to measure the regional characteristics.

In order to have enough observations to allow for acceptable and stable results from the multivariate factor analysis, we have to keep our sample size as large as possible. The sample includes 129 regions, and missing values for some regions are replaced by the data in nearby years if we have these data in the database. For example, one Spanish region has no value for high-tech patent number in 1999 so we apply the data of 1998 to replace the null value. However, some regions, such as in Norway and Switzerland, have no data for economic information since these regions are not included in the REGIO database. In all cases, the sample size is more than one hundred, which is suitable to run multivariate analysis.

3.2 Variable Definitions

3.2.1 Economic characteristics:

Economic indicators about short-term static factors, long-term dynamic changes and employment phenomena are included. Economic indicators about growth rate, including GDP growth rate, GDP per capita growth rate and productivity growth rate, are expected to show the dynamic economic phenomena. Indicators such as GDP per capita and productivity levels, express the regional static economic performance. On the labor side, sectoral employment shares as well as the employment and unemployment rates are included. Finally, population density is included. The definitions of each indicator are described in table 1.

Table 1. Economic indicators

Indicators	Definition	Proxy
GDP per capita (GDPp)	GDP / population (based on price index 1995)	Static
GDP growth(GDP_GR)	$(GDP_t – GDP_{t-1}) / GDP_{t-1}$	Dynamic
GDP per capita growth(GDPp _GR)	$(GDP^p_t – GDP^p_{t-1}) / GDP^p_{t-1}$	Dynamic
Employment rate(EM_R) / Unemployment rate (Uem_R)	Persons in employment are those, aged 15 years and over and living in private households, who during the reference week did any work for pay or profit for at least one hour, or were not working but had jobs from which they were temporarily absent. Family workers are also included[1].	Labor market
	For counting average employment/unemployment rate, we use geometric mean that is more suitable for counting ratio data.	
Sectoral employment ratio	Ratio of Agriculture sector: Employed person in Agriculture sectors / all employed person Ratio of Industrial sector: Employed person in industrial sectors / all employed person Ratio of Service sector: Employed person in service sectors / all employed person	
Population density	Population/the measure of region	
Productivity (PRt)	PR=GDP / employed person	Static
Productivity growth rate (PR_Rt)	$PR\_R_{t2} =(PR_{t2} / PR_{t1})^{(t1-t2)}-1$	Dynamic

3.2.2 Regional Innovativeness & Technological characteristics

- Innovativeness and R&D capability:

Innovativeness characteristics represent the knowledge base that plays a crucial role

[1] Eurostat (1996) gives the definition for the variable in REGIO database.

in various interactions within a system (Lundvall, 1992: pp.8-9; Breschi & Lissoni, 2001). We include input indicators, such as human resource in S&T (science and technology) and employment rate of high tech sectors, and output indicators, i.e. patent inventor output, to show the innovativeness of region.

- Technological Specialization Index

  The specialization index is calculated by patent applications in European regions. The data we applied to calculate the specialization index including 129 regions are classified by NUTS region in Europe, and 22 manufacturing sectors, which are broadly compatible with the STAN database classification. We count the MCRCA index in (2), which is based on RCA index in (1), so that the range of MCRCA is between –1 and +1. A positive/negative value means positive/negative specialization. We include specialization indices for all 22 manufacturing sectors.

RCA = (Share sector in patents of region)/(Share sector in patents in all regions) ---(1)

MCRCA = (RCA-1)/(RCA+1) --(2)

For explaining the time-period that we apply in our analysis, some points should be mentioned. The reason that we collect the data since 1986 but not earlier is that the patent registration was underestimated in the early 80s. The European patent came into existence in 1979, and it took a while before firms fully used this way of obtaining patents. Another point is that we include for both periods three years, with the purpose of preventing a significant influence of random fluctuations in a specific single year.

Table 2. Innovativeness &Technological indicators

Indicators	Definition	Proxy
Human resource in Science and Technology (HRST)	The data represents the people who fulfill one or other of the following conditions, (1) successfully completed education at the third level in an S&T (Science & Technology) filed of study, (2) not formally qualified as above but employed in a S&T occupation where the above qualification are normally required [2] ♦ HRST = numbers of human resource in S&T / total labor force	Innovativeness (input view)
Employment in high tech sector (Em_hitech)	♦ Em_hitech = The number of employed person in high tech sector / total number of employed person	Innovativeness (Processing view)
Patent inventor ratio (Pat_R)	Basing on the data of inventor, differing from innovation adoption indicators calculated from applicant data, we calculate patent numbers of each region, to show the knowledge-based resource of the region. ♦ Pat_R = Patent numbers / total labor force	Innovativeness (output view)
R&D input ratio[3]	R&D personnel ratio (in business units)= R&D personnel / all employee (in business units)	Innovativeness (input view)
Sectoral specialization (MCRCA)	22 manufacturing specialization index are applied to construct technological characteristics. ♦ RCA = (Share sector in patents of region)/(Share sector in patents in all regions) ♦ MCRCA = (RCA-1)/(RCA+1)	Technological characteristics (Output view)

[2] The definition is from "Manual on the measurement of human resources devoted to S&T" of OECD/GD, (95) 77, 1995, p. 2, 16.
[3] Because of no data for some region, we only include R&D personnel ratio to confirm its high factor loadings in the construct of innovativeness but not use the factor score, including R&D ratio, to run cluster analysis. This procedure shows us innovativeness characteristics are highly related to human capital and R&D capability.

3.3 Methodology

Multivariate Analysis Methodology is applied in our study for extracting factors and clustering the regions. Factor Analysis is a useful method to reduce various and diverse items into integrated factors, whereas the cluster analysis is practical for grouping large samples into different clusters, in which the regions have similar characteristics. The dataset that we use for this analysis includes many economic and technological indicators. Different indicators expressing similar regional phenomenon will construct a specific factor measuring regional characteristics. For example, the indicators expressing dynamic economic phenomenon, such as GDP growth and productivity growth, are expected to have high factor loadings in the same factor. After getting the regional characteristics from factor analysis, in order to figure out if different types of innovation system exist among European regions, cluster analysis helps to classify the regions into clusters, which are characterized by technological and economic characteristics. Finally, based on different time period data, the cluster analysis also helps us to understand the role of initial technological specialization base for future development.

Because of including various indicators in the factor analysis model, the procedures that we have done should be explained before showing the results. During the process of factor analysis, when we put all indicators into one factor analysis, the results show that economic and technological indicators indeed are separated into different factors. However, due to the large numbers of indicators in our dataset, each factor is linked to all indicators, including many irrelevant indicators with low factor loadings. This introduces noise into the measurement of the factors, and in order to avoid this, we perform two separate factor analysis models, one only for the technological specialization indicators from 22 sectors and the other for economic related indicators and other indicators.

Another point is about the method of cluster analysis. The method we used for classifying regions is K-means cluster analysis, rather than the more conventional hierarchical cluster analysis. The former method, K-means cluster analysis, requires the analyzers to specify the number of cluster beforehand, whereas in hierarchical cluster analysis the number of cluster can be chosen after finishing clustering procedure. One of the reasons that we choose K-means Cluster Analysis is that our sample size is more than 100, in which case the sample size is too large to apply hierarchical cluster procedure (SPSS 10.0 Application guide, p.293). The other reason is that K-means cluster analysis allows us to specify the number of clusters so that we can set the suitable numbers that are helpful to understand the comparisons among the regions. Although there are some methods, such as CCC (Cubic Clustering Criterion), for determining the number of clusters, no standard and objective methods have been found to be substantially better in determining the numbers of cluster (Hair, et. al, 1998: p. 477-479; 499). Some articles in organizational strategy or international business literature (Roth & Morrison, 1990; Taggart, 1997) follow the method that the best number of cluster should fall between[4] n/50 ~ n/30, but they also mentioned that the decision for the number of cluster should fit explanation for the sample. In other words, researchers should complement the empirical judgment with any conceptualization of theoretical relationships and suggest a natural number of clusters that are more manageable and easier to analyze the empirical results. The most useful way that the researchers could concern is that the overall model test of cluster analysis should be significant and that is helpful to decide the number of clusters.

4. Results

4.1 Factor analysis – Constructing regional characteristics

From the indicators that we have discussed above, we extract economic, innovativeness (Table 3), and technological characteristics (Table 4a & Table 4b). The factors are extracted by maximum likelihood method. The tests of goodness-of-fit show that the results of the factor analysis are acceptable. The number of factor is determined by the rule that eigenvalues must be higher than one. In addition, in order to find out the uniqueness of each characteristic, a factor rotated matrix from Varimax method is used to get the factor loadings and identify the representative of each indicators in each factor. Indicators with high factor loadings (higher than 0.4) within a factor are used to broadly determine the label of the factor. The values shown in the tables are those values that are higher than 0.3 in rotated factor matrix, which can help to distinguish the differences between factors.

4.1.1 Characteristics in economic phenomenon

For economic characteristics, there are four factors coming out of the factor analysis. The first economic factor is related to economic static performance, and includes GDP per capita and productivity levels. Secondly, economic dynamic characteristics (growth) are extracted as another factor, represented by GDP growth, GDP per capita growth and productivity growth. The differences between static and dynamic characteristics are so distinct that static economic performance and dynamic economic performance are established as separate factors, among various other variables. The third economic factor represents labor market phenomena, including employment and unemployment rates. The last factor is related to innovativeness and has high loadings on human resource in science and technology, employment in high-tech sectors and the patent ratio.

From table 3, we also see that some indicators have high factor loadings in more than one factor and some have low factor loadings in all factors. Firstly, sectoral employment shares in industrial sectors has low loadings in all factors, while the sectoral employment share in agricultural sectors has high and negative loadings in both the factors for economic static performance (-0.426) and innovativeness (-0.460), which shows employment in agriculture sectors does not correlate positively with high economic performance and

[4] "n" means the numbers of sample.

innovation. Secondly, the indicator from calculating patent number (in per million employee) shows high factor loadings in both economic performance and innovativeness. This implies that regional patent output is always highly related to regional economic performance and other innovativeness characteristics, such as human resource input.

Table 3. Economic and innovativeness characteristics

Indicators \ Characteristics	Economic performance (EP)	Labor employment (EM)	Innovativeness and R&D (Inno)	Economic growth (EG)
	Component			
Productivity (1999)	**0.970**			
GDP per capita (1997)	**0.865**			
Unemployment 2001-1999		**-0.905**		
Employment 2001-1999		**0.891**		
HRST 2000			**0.834**	
Patent number (in per million employee) 1996-1998	*0.407*		**0.514**	
Patent number in high sector (in per million labour force) 1999			**0.482**	
Sectoral employment ratio _ agriculture sector	*-0.426*		**-.0460**	
Population density			**0.453**	
GDP per capita growth (2000-1997)				**0.939**
GDP growth (2000-1996)				**0.785**
Productivity growth (1999-1997)				**0.330**

Notes: (1) The blank cells here do not mean there are no values for these cells but these values are just tiny enough to ignore when we construct these characteristics. (2) Method: Maximum Likelihood (3) Indicator of industrial sectoral employment ratio is included in the factor analysis model but the factor loadings are lower than 0.3 in all four factors.

4.1.2 Technological specialization patterns in 90s and 80s

As to technological specialization, we extract six factors from the specialization index of 22 manufacturing sectors in the 1990s and five technological characteristics in the 1980s.The goodness of fit test of both factor analysis models (80s and 90s) shows that the model is satisfactory. The result for the 1990s includes the following factors: (1) traditional technological industrial related factor, (2) bio-chemical technological factor, (3) ICT-related (computer and electronics) factor, (4) basic metal factor, (5) transportation-related factor and (6) natural-resource-based factor (Table 4a). Meanwhile, the technological specialization factors in the 1980s include (1) ICT & transportation-related factor, (2) natural-resource-based technological factor, (3) bio-chemical technological factor, (4) basic metal factor, and (5) motor vehicles factor (Table 4b).

The comparison between technological specialization factors in the 1980s and 1990s indicate the similarities and differences in technological development patterns between two periods. For example, the bio-chemical technological specialization factor, represented by sectors such as pharmaceuticals and chemical technologies, as well as the basic metal factor, represented by ferrous and non-ferrous basic metal sectors, are extracted in both periods. However, we also find that some differences exist in the factors between the two periods. . For instance, we find that motor vehicles specialization is prominent in the 1980s and is extracted as a distinct technological factor. In contrast, the sector of motor vehicles in the 1990s is combined into a transportation-related technological specialization factor. In addition, the different combinations of sectoral technologies within factors in two periods imply that the relationships between sectoral technologies have changed over time. For example, ICT-related technological specialization in the 1990s has been represented mostly only by computer, electronics, and instrument sectors, but electrical machinery and transportation-related technologies are also included in ICT-related technological development in 1980s. It implies that the developments of both transportation-related technologies and ICT-related technologies in 1980s might be in the start-up stage, so that these technologies were not mature enough to become a distinct technological characteristic. In the 1990s, the rapid development in ICT technologies has made ICT-related technological characteristic so distinct that this characteristic is extracted separately in the 1990s.

Table 4a: 90s Technological Characteristics

Indicators \ Characteristics	Traditional industrial-related	Bio-chemical related	ICT related	Basic metal technologies	Transportation related	Natural resource base technological related
Wood and products	0.693					
Other manufacturing	0.667					
Simple metal products	0.621					
Textiles	0.494					
Non-electrical	0.479					
Plastic and rubber	*0.334*					
Pharmaceuticals		0.884				
Chemicals		0.693				
Food products		0.609				
Refined oil etc		*0.378*				
Computers and office			0.798			
Electronics			0.735			
Instruments			0.467			
Ships and boats			*0.331*			
Ferrous basic metals				0.849		
Non-ferrous basic metals				0.764		
Motor vehicles					0.761	
Other transport					0.642	
Electrical machinery					*0.379*	
Aerospace					*0.302*	
Paper and printing						0.565
Non-metallic minerals						0.547

Table 4b: 80s Technological Characteristics

Indicators \ Characteristics	ICT related and high tech transportation	Natural resource base technological related	Bio-chemical related	Basic metal technologies	Motor vehicles
Computer and office machines	0.671				
Electronics	0.625				
Instruments	0.618				
Food products	0.588				
Electrical machinery	0.577				
Aerospace	0.519				
Other transport	0.505				
Ships and boats	0.437				
Wood and product		0.635			
Simple metal products		0.604			
Other manufacturing		0.593			
Non-metallic minerals		0.579			
Paper and printing		0.521			
Non-electrical machinery		0.514			
Chemicals			0.838		
Pharmaceuticals			0.688		
Refined oil etc			0.487		
Textiles			*0.346*		
Non-ferrous basic metals				0.883	
Ferrous basic metals				0.687	
Plastic and rubber				0.412	
Motor vehicles					0.470

4.2 Cluster analysis

Cluster analysis is applied to classify all the European regions into a suitable cluster, in which regions have similar technological and economic characteristics. We use the factor scores on the factors obtained above to carry out the clustering exercise. By including four economic factors and six technological specialization factors in the 1990s, we obtain four clusters/ types of innovation system. From the results, we may derive conclusions on the links between regional conditions, technological specialization and resources, and economic performance (static and dynamic). For example, the regions specialized in natural-resource-based sectors do not perform well in dynamic growth.

Secondly, we link the four types of innovation systems to 1980s technological specialization clusters. Consequently, the importance of 80s technological base is illustrated by observing the distributions of regions in 1980s' technological cluster and 1990s' innovation system.

As to the determination of the numbers of cluster, we set this to four after several examining procedures. Since we mentioned above that there exists no best method to decide the numbers of cluster, the best number for any analysis is the number that can help us to communicate between the results and realities. The results of five or six clusters make the differences between clusters become insignificant while the results based on three clusters mix too complicated characteristics within a cluster. The same procedures have been applied when we look for the pure technological clusters in the 1980s.

4.2.1 Clustering by multiple characteristics

Distinct characteristics in innovation system

Based on all factors that came out from the factor analysis, we classify European regions into four clusters, i.e. four types of innovation systems. These clusters are (1) high-innovativeness & high-tech development system, (2) low-innovativeness/low economic performance & low specialization, (3) high employment & traditional & basic metal industrial system, and (4) low growth & natural-resource-based technology system. The descriptive statistics (Table 5) and the significance of the difference in factors between clusters (Table 6) illustrate the main differences between the four regional systems.

Cluster one is characterized by ICT-related, bio-chemical tech, and high innovativeness characteristics. The factor scores related to these characteristics are significantly higher than some other clusters. The descriptive statistics of economic indicators (Table 5) are all positive and high values, which show the high economic performance of this cluster. In contrast, cluster two has significantly lower scores in innovativeness, economic performance, and most technological specialization factors than the other clusters. However, although cluster two has a relatively low value in static economic indicators, such as productivity, the highest value (3.006%, Table 5) in growth rate in GDP per capita among all clusters is observed for this cluster. In other words, the coexistence of low economic performance and high growth in specific regions, especially in poor region, seems to confirm the idea of technological diffusion from rich to poor countries. As to cluster three, it has all high and all positive economic performance, similar to cluster one (high-tech cluster), but its indicators about innovativeness, such as HRST (159.69 vs. 266.67), are quite lower than first cluster. The most outstanding and significant specialization factor for this cluster is traditional industrial technology. However, this cluster is also characterized by specialization in multiple technologies (mixed specialization pattern) characteristics. This cluster develops many kinds of technologies, including traditional, transportation-related and basic metal technologies, where other clusters focus more on specific technologies. At last, the most distinct characteristics in cluster four are its high involvement in natural-resource-based related technologies and its low economic growth, which are both significantly different from other clusters.

Table 5. The Differences in Economic Performance between Clusters

Cluster[5] / Economic indicators	Positive economic outcome, innovativeness/ high tech	Low innovativeness, performance /low tech	high employment/ traditional & basic metal technology	Low growth/ Natural resource-based technology	total
N	(n=35)	(n=18)	(n=50)	(n=13)	(n=116)
Employment rate	65.8794*	60.7546	63.8092	57.4437	63.2465
(% annual)[a]	(7.8323)**	(10.0301)	(4.6441)	(10.5464)	(7.7994)
Unemployment rate	8.8212	10.2085	6.9190	11.6234	8.5307
(% annual)	(4.9535)	(7.1940)	(3.0950)	(6.0393)	(5.0468)
GDP growth	2.3234	2.4760	1.6910	0.76824	1.9002
(% annual)	(2.2303)	(1.6222)	(1.2367)	(1.4614)	(1.7333)
Productivity growth rate	0.8987	-1.5352	0.5161	-1.2091	0.1199
(% annual)	(2.0528)	(2.4887)	(1.6905)	(1.3205)	(2.1077)
GDP per capita growth rate (%	2.8761	3.006	2.5522	0.5274	2.4935
annual)	(1.6116)	(1.9276)	(1.8872)	(2.0877)	(1.9529)
Productivity (1999) (ln)	3.7889	3.5278	3.8245	3.6715	3.7506
	(0.2718)	(0.2563)	(0.1678)	(0.1582)	(0.2397)
GDP per capita (ln)	2.8849	2.5197	2.8819	2.6701	2.8029
	(0.2530)	(0.2011)	(0.1899)	(0.1486)	(0.2487)
Population density (population	565.59	93.89	165.06	140.00	272.06
per Km²)	(1147.32)	(79.94)	(122.52)	(107.83)	(660.21)
Sectoral ratio in employment	3.2864	11.3573	4.3731	7.9443	5.5292
(% Of Agriculture)	(2.2371)	(6.3682)	(2.3833)	(5.804)	(4.6366)
Sectoral ratio in employment	24.77	27.1512	30.8754	25.6683	27.8715
(% of Industry)	(5.8699)	(7.0611)	(5.3179)	(2.6003)	(6.1478)
Patent number per mil.	10.8857	1.0222	6.7660	2.400	6.6285
Employee (1995-97)	(12.29)	(1.7397)	(4.9357)	(2.4593)	(8.2815)
High tech patent number per	9.2634	0.2872	2.0257	0.9164	3.8154
million labor force	(10.305)	(0.6353)	1.9729)	0.8689)	(6.8205)
HRST 2000	226.675	116.5326	159.6908	145.8731	171.6561
	(52.4326)	(51.184965)	(31.8776)	(49.0431)	(58.4666)
Ratio of R&D personnel (%)	*71.52*	*6.133*	*47.57*	*24.49*	*42.21*
	(46.63)	*(3.268)*	*(29.11)*	*(23.36)*	*(38.52)*
	n=26	*n=17*	*n=46*	*n=11*	*n=100*

Note: [a]: unit of each indicator;
* : value without parenthesis is the mean;
** : value inside parenthesis is the standard deviation;

5 Each cluster is named by the economic and technological characteristics, which are significantly different from other clusters.

Higher vs. lower innovation system

It seems to be possible to relate the four clusters / innovation systems to the notion of higher or lower order innovation system. Each type has its specific technological and economic characteristics, being distinguishable among the four types, especially the distinct classification between cluster one and cluster two. The former is characterized by high-tech and high economic performance while the later is characterized by low specialization and low economic performance. These two extreme types show that higher / lower order or hierarchical relationship exists between clusters. Higher order innovation systems, showing its high-tech technological characteristics with high innovativeness and R&D capability, have more advantages in regional conditions to develop high-tech advanced technologies. Lower order innovation systems, in contrast, lack R&D capability to develop new technologies and consequently induce poor economic performance. This hierarchical ordering in terms of technological and economic development patterns, and leading to different regional advantages, is in correspondence with past literature (such as Cantwell & Janne, 1999; Cantwell &. Iammarino, 2001).

The combinations of technological and economic characteristics

From the four types of innovation systems, not only the relationship between technological characteristics and economic characteristics but also the linkage between the technological development and geographical area are interesting. We firstly discuss the technological and economic characteristics within each innovation system. First of all, the relationship between high-tech technological development and economic static performance is found from cluster one and cluster two. Cluster one is characterized by high-tech and high economic outcome while cluster two is characterized by low specialization and low economic performance. Although different results in Feldman & Audretsch (1999) show that the specialization in telecommunication, instrument, or pharmaceutical sectors does not bring higher innovativeness on firm level, our explanation, on regional level, is that the development of specialization in regions brings more spillovers effects for other firms and thus encourages the regional innovative development.

Secondly, high innovativeness in human resource is an indispensable characteristic in technological development, especially in high-tech related technologies. When we compare the first two clusters, high innovativeness in high-tech cluster and low innovativeness in low specialization cluster imply that development in high-tech technologies always needs the support from human resources invested in science and technology, which low specialization regions do not seem to possess. In addition, we find that innovativeness is more important in high-tech development than other technological development when comparing cluster one and cluster three. While both cluster one and cluster three have strong economic and technological bases[6], we can easily compare the importance of innovativeness in different technological development patterns. We find that both clusters attain strong economic outcomes, but the high-tech system needs more innovativeness and human resource than the traditional technological system.

Table 6 Factor Significance between Clusters

I \ J	1	2	3	4
1		EP (+) Inno (+) Tech1 (+) Tech3 (+)	Inno (+) Tech1 (-) Tech2 (+) Tech3 (+)	Inno (+) EG (+) Tech3 (+) Tech6 (-)
2			EP (-) Inno (-) Tech1 (-) Tech3 (-) Tech4 (-) Tech5 (-)	EG (+) Tech3 (-) Tech6 (-)
3				EG (+) EM (+) Tech1 (+) Tech4 (+) Tech5 (+) Tech6 (-)
4				

Notes:
"+" or " – "means the sign after(I cluster)– (J cluster)
EP: economic static performance;
EG: economic dynamic growth;
Inno: Innovativeness in human resource;
EM: employment in labor market;
Tech1: traditional-related technological characteristic
Tech2: bio-chemical technological characteristic
Tech3: ICT-related technological characteristic
Tech4: Basic metal technological characteristic
Tech5: transportation-related technological characteristic
Tech6: traditional nature-resource-based technological characteristic

Thirdly, in the third cluster, the combination of positive economic performance, stable employment, and traditional technological specialization shows that strong economic outcome might be related not only by high-tech development but also other traditional technological development. This result seem to be in correspondence with the phenomenon in some area of north Italy (Breschi, 2000), which creates wealth by specializing in traditional technological development in such as dressing design. In addition, as we find in Table 6, cluster three actually is involved in many kinds of technological development, including traditional, basic metal and transportation related technologies. That this multiple technological characteristics provides more job opportunities for labors in cluster three might be the reason for explaining the strong economic performance and stable & high employment in the labor.

Finally, the worst dynamic growth phenomenon is found in the fourth cluster, focusing on developing natural-resource-based technologies, with also the lowest employment rate and lowest growth among the four types of innovation systems. It is imaginable that when the

[6] Both cluster one and cluster three have all positive economic performance and both involve in developing specific technologies (Cluster one focus on developing ICT-related and bio-chemical high-tech technologies and cluster three focuses on traditional and basic metal technologies.)

regions within the fourth cluster are not able to extend natural resources to develop related technologies, such as bio-tech in agriculture or unique furniture design in wood, the growth will come to a standstill. In addition, under the limited development in natural resource technology but ongoing technological progress in other industrial technologies, further automation can easily replace the low-skilled labor and cause unemployment. Furthermore, since these regions invest much in developing natural-resource technologies, the systemic lock-in effect (Narula, 2002, pp.808-813) might block higher growth. In contrast, although this cluster performs not well in economic static terms, dynamic growth is outstanding among these four types of innovation system. The regions in the low specialization cluster may just start from a relative under-developed stage so that they have more room to progress and show dynamic growth.

The geographical distribution of technological specialization

A second issue raised from the four types innovation systems is the relationship between technological specialization and geographical spread (Table 7 and Figure 1). Firstly, the crucial role of population density has been found in cluster one (high-innovativeness and high-tech development). This cluster includes the regions in which many European metropolises, including Paris, Berlin, London, Brussels, Amsterdam, Madrid, Rome, Helsinki and Stockholm, are located.

Secondly, the different technological characteristics seem to show different preferences or technological specialization between the south and north part of Europe. The regions in the low specialization cluster are mostly located in south Europe (Spain, Portugal, and Greece), whereas the regions in the high-tech cluster are mostly located in north Europe. In other words, the development of high-tech technologies, such as ICT-related or bio-chemical technologies, is stronger in the north part than in south part of Europe. In mid-south Europe, such as France, Germany, and Austria, there are many regions classified into the third cluster, which is characterized by traditional industrial specialization and high employment.

Table 7. Regions in 90s' Innovation System with multiple characteristics

Cluster	Regions	Description
1	BE1 DE2 DE3 DE4 DE6_F DE8 DED DEE DEG ES3 ES51 FR1 FR52 FR62 FR71 FR82 IT6 ITA NL31 NL32 NL33 NL41 NL42 SE01_02 SE03_04 SE05 SE08 UK4 UK5 UK6 UK8 UKA FI11_2 FI15 IE	High-tech & high innovativeness / high economic performance
2	AT11 ES11 ES12_3 ES41 ES42 ES43 ES61 ES62 ES7 FR83 GR4 NL23 PT11 PT12 PT13 PT14 PT15 FI2	Low specialization & low economic performance.
3	AT12_3 AT21 AT22 AT31 AT32 AT33_4 BE2 DE1 DE5_9 DE7 DEA DEB_C ES21_2_3 ES24 ES52 FR21 FR22 FR23 FR24 FR25 FR26 FR3 FR41 FR42 FR43 FR51 FR53 FR61 FR63 FR72 FR81 IT1 IT2 IT31 IT32 IT33 IT4 IT51 IT52 IT53 NL21 NL22 SE06 SE07 UK1 UK2 UK3 UK7 UK9 LU	Traditional-related & high employment
4	BE3 ES53 GR1 GR2_3 IT7 IT8 IT9 ITB NL1 NL34 UKB FI13 FI14	Natural-resource-based technological specialization & low economic growth

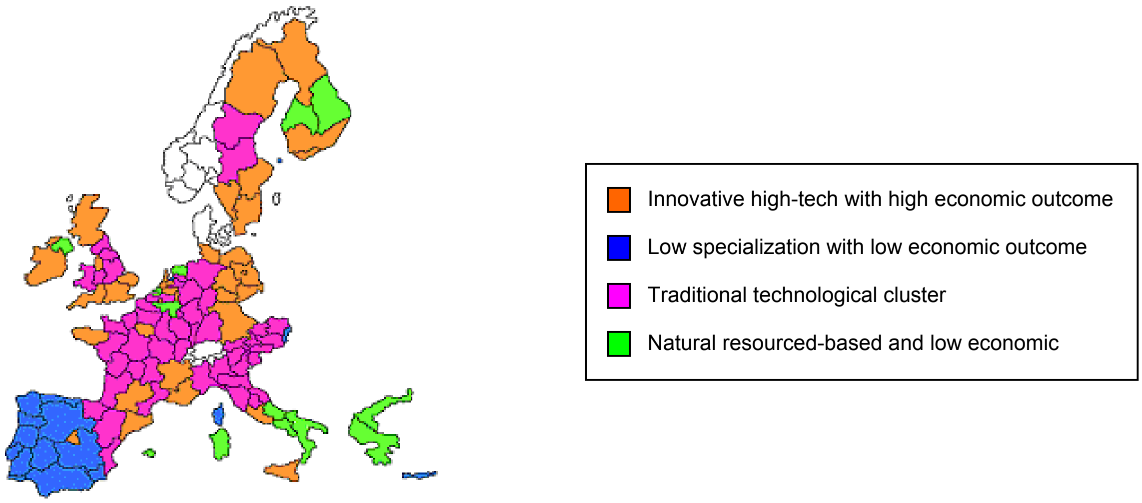

Figure 1 Distribution of different types of RISs (classified by multiple characteristics)

Thirdly, the regions in the natural-resource-based cluster with low growth rate have been found mostly in Greece, Spain, and Italy, and have much lower economic growth than other regions within the same cluster, such as regions in the Netherlands, Belgium, and Finland.

4.3 The linkage between 80s technological cluster and 90s innovation system

Technological characteristics in the 1980s are the base for the further development in related technologies in the 1990s. In Table 8, two dimensions, 1980s technological specialization clusters and 1990s innovation systems clusters (the latter as discussed above), are significantly related (chi-square test with p-value<0.001). On the one hand, the technological specialization in the initial period seems to be the base for technological development in later periods. We find slightly more than 50% of the regions in the 1990s high-tech cluster are from the 1980s ICT or bio-chemical clusters, while 58.3% regions in the 1990s natural resource cluster are from the natural resource based & traditional cluster in the 1980s. In addition, 1990s low specialization cluster regions are mostly (83.3%) from the 1980s low specialization cluster, and the 1990s traditional cluster has more than 50% regions from the 1980s basic metal and natural-resource-based & traditional clusters.

On the other hand, the development in 90s is not so determinately caused by 80s technological characteristics but it depends on whether specific region has capability of utilizing this regional resource. As we know from the four types of innovation system, specialization in natural resource technologies and low economic growth emerge as correlated. However, regions in the 1980s natural resource cluster are not destined to stay in this low-growth cluster. Many regions in the 1980s natural resource and traditional cluster turn to develop multiple specializations or high-tech specializations in the 1990s.

Another finding from table 8 is that the regions with some specific technological specialization characteristics in the 1980s have a higher probability to attain better economic outcomes in the 1990s, or become a higher order innovation system, such as a high-tech innovation system or a traditional & multiple technological cluster (both have strong economic outcomes and significant technological specialization). For example, we find that the regions in the 1980s' natural resource and traditional cluster (28.6%+52.4%), basic metal cluster (100%), or bio-chemical cluster (25%+70%) have a higher chance of becoming a higher-order innovation system than the regions in the low specialization cluster (35.7%+7.1%). In other words, specific technological characteristics, whichever the technological characteristics are, are helpful for regional progress.

Table 8 The Relationship between 80s"technological clusters and 90s' innovation system

		80s tech cluster[7]					
		Low specialization	Basic metal	ICT and motor oriented	Bio-chemical & basic Metal	Natural-resource-based and traditional industrial	Total
90s innovation systems	High Inno, high performance/high tech	5		13	5	12	35
	% within 90s' cluster	14.3%	-	37.1%	14.3%	34.3%	100.0%
	% within 80s'cluster	**35.7%**		56.5%	25.0%	**28.6%**	34.0%
	% of total	4.9%		12.6%	4.9%	11.7%	34.0%
	Low Inno, l /low tech cluster	5				1	6
	% within 90s' cluster	**83.3%**	-	-	-	15.7%	100%
	% within 80s'cluster	35.7%				2.4%	5.8%
	% of total	4.9%				1.0%	5.8%
	Traditional /high employment cluster	1	4	9	14	22	50
	% within 90s' cluster	2.0%	8.0%	18.0%	28.0%	44.0%	100%
	% within 80s'cluster	**7.1%**	100%	39.1%	70.0%	**52.4%**	48.5%
	% of total	1.0%	3.9%	8.7%	13.6%	21.4%	48.5%
	Natural resource/ low growth cluster	3		1	1	7	12
	% within 90s' cluster	25%	-	8.3%	8.3%	58.3%	100%
	% within 80s'cluster	21.4%		4.3%	5%	16.7%	11.7%
	% total	2.9%		1.0%	1.0%	6.8%	11.7%
	Total	14	4	23	20	42	103
		13.6%	3.9%	22.3%	19.4%	40.8%	100%
		100%	100%	100.0%	100.0%	100%	100%
		13.6%	3.9%	22.3%	19.4%	40.8%	100%

<u>Some unexpected results caused by methodology</u>

Because a different numbers of clusters may lead to different results, cluster analysis always shows us a general trend but not the perfect classification that tells all stories and fits all realities. In our study, we apply multiple characteristics to find out what types of innovation system exist among all the regions and we find some specific regions classified into the clusters that are out of our expectations. For example, the regions in Germany, such as Sachen, Mecklenburg-Vorpommern, or Sachsen-Anhalt, change from the high-tech cluster (with high innovativeness and strong economic outcomes) to the natural resource cluster (with high innovativeness and low economic performance) when the number of cluster turns from four to five. Another reason is that because we apply multiple dimensions to classify these regions, for each region, the cluster classification might be dominated by the most outstanding factor within the region or relative special factors. For example, Sicilia in Italy, with quite a high value in ICT-related technological characteristic and insignificant value in bio-chemical characteristic, is classified into the high-tech cluster, characterized by both ICT-related and bio-chemical technological characteristics, because there is no cluster characterized only by ICT-related characteristics. In addition, as the above regions in

[7] See appendix I – table A.

Germany, when observing the details of these regions, we find that both Sachsen-Anhalt and Mecklenburg-Vorpommern show very high score in innovativeness factor, which is outstanding among all regions. The high score in innovativeness might dominate these regions to be in the high-tech cluster when the number of cluster is four[8]. Although realty seems to be more correspondence with the results of five clusters, two of the five clusters are so similar that we are not able to distinguish between them.

5. Conclusions and discussion

The main purposes of this article include constructing crucial characteristics to describe regional differences, examining different types of regional innovation system by clustering regions on the basis of these crucial characteristics, and analyzing the dynamic changes in regional development over time. Firstly, the crucial characteristics, including economic and technological dimensions, are extracted from various indicators. In economic characteristics, economic static characteristic and economic dynamic characteristic are distinctly extracted to yield different economic factors. Innovativeness characteristic, which expresses regional R&D capability and knowledge base, and labor market employment, which shows regional labor phenomenon, are both constructed to explain the role of regional human resource. In addition, technological specialization factors are constructed from 22 manufacturing sectors. Technological characteristics are not classified to just high-tech / low-tech technological characteristics, but several distinct characteristics, including such as ICT-related technological, traditional technological and natural resource related technological characteristics, emerged from the analysis.

Secondly, we apply these crucial dimensions to find out different types of innovation systems among European regions and figure out the characteristics within each innovation system. Four types of innovation systems, high-innovativeness & high-tech development system, low-innovativeness/low economic performance & low specialization, high employment & traditional & basic metal industrial system, and low growth & natural-resource-based technology system, are found among all regions. From the specific combinations of economic and technological characteristics within these clusters / systems, we find that high innovativeness, showing regional R&D capabilities and skilled labor resource, is necessary for technological development, especially in high-tech technological development. For attaining better economic performance, both high-tech technological development and multiple technological developments, such as traditional technologies and basic metal, correlate with positive economic outcomes. Furthermore, we find that the dynamic growth performs is worst not in the low specialization cluster but in the natural-resource-based cluster.

[8] We have discussed the way to determine the numbers of clusters has been discussed in methodology section. After comparing different results, the final number of cluster is determined to be four. Further information of different results could be found in appendix I - table B.

The technological characteristics in the 1980s are the base for further development in the 1990s. We firstly find that previous technological characteristics lead the region toward to related technological development in later periods. For example, regions specializing in high-tech technological development have more advantages toward high-tech innovation systems. Secondly, the technological base implies the advantages or disadvantages towards to a higher-order regional innovation system. As we find, the regions in the 1980s natural resource & technological cluster or in the 1980s high-tech clusters have a higher chance to be in a higher-order innovation system, such the 1990s high-tech cluster or traditional& multiple cluster, than the regions in the 1980s low specialization cluster.

Our analysis still has some limitations that should be solved in further research work. The first limitation is the problem caused by availability of our data that we cannot include all variables for all regions in both the 1980s and the 1990s. Therefore, the economic data of the 1980s cannot be used to construct economic factors since there exist too many missing data in many regions. The shortcomings of lacking 1980s' economic dimensions keep us from identifying types of innovation system in the 1980s as was done for the 1990s. In addition, we are not able to explain whether the economic performance and dynamic growth could be another resource base for region to develop technological characteristics. If these crucial indicators could be applied in further analysis, the comparisons between two periods explain more the changes of regional development.

Secondly, a more robust methodology should be applied to the relationships between characteristics and changes between periods. We only apply cross-tabs statistics to show the dependency between the two dimensions. With more complete data , the relationships between some specific economic and technological characteristics can be explained from two-way relationships, not only examining the influence from technological progress on economic development, but also testing the influence of economic base on technological development and for view of longer period. We also suggest that confirmatory factor constructing methodology should be applied to clarify out these different characteristics so that the path analysis (PA) or structural equation model (SEM) could be used to find out if there exists causal-effect relationship between characteristics.

Finally, we still have to admit that there are some unsolvable quantitative problems existing in the procedure of cluster analysis. Because cluster analysis just shows us the existence of main categories or clusters among all samples, some samples, such as with significantly higher or lower values in some variables, could not perfectly be classified into the clusters that we expect. Although some limitations in sample or methodology exist, our analysis helps to construct the crucial regional characteristics, find out the different types of innovation systems, examines the relationship between specific characteristics, and shows the role of initial technological characteristics.

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Appendix I: Tables of Region distribution

Table A: 80s'Technological Clusters

80s' Cluster	Region
Low specialization	AT11 DE8 DED DEE DEG ES12_3 ES24 ES53 ES61 FR83 ITB NL34 PT13 DK3 NO6 FI15
Basic metal	AT33_4 FR41 IT33 SE06 NO2 NO4 NO5
ICT and motor oriented	AT21 DE1 DE2 DE3 DE4 DE5_9 DE6_F FR1 FR25 FR26 FR43 FR52 FR82 GR2_3 IT1 IT2 NL41 SE01_02 UK4 UK5 UK6 UK7 UKA
Bio-chemical and basic metal	AT22 AT31 BE1 BE2 BE3 DE7 DEA DEB_C FR22 FR23 FR3 FR71 FR72 IT6 NL32 UK1 UK2 UK8 UK9 CH1 CH2 CH3
Natural resource-based and traditional industrial	AT12_3 AT32 ES21_2_3 ES3 ES51 ES52 FR21 FR24 FR42 FR51 FR53 FR61 FR62 FR63 FR81 IT31 IT32 IT4 IT51 IT52 IT53 IT7 IT8 IT9 ITA NL1 NL21 NL22 NL23 NL31 NL33 NL42 SE03_04 SE05 SE07 SE08 UK3 UKB DK1 DK2 NO1 NO3 FI11_2 FI13 FI14 IE

Table B1: Types of Innovation system in 90s (5 clusters)

90s' Innovation system	Region
Low specialization/low innovativeness, low employment	ES12_3 ES24 ES42 ES43 ES61 ES7 FR63 FR81 FR83 IT8 IT9 ITA FI2
High-tech and high innovativeness, high growth	BE1 DE2 DE3 DE6_F ES3 ES51 FR1 FR52 FR62 FR71 FR82 NL31 NL32 NL33 NL41 SE01_02 SE03_04 SE05 UK4 UK5 UK6 UKA FI11_2 FI15 IE
Traditional and transportation / high economic performance	AT12_3 AT21 AT22 AT31 AT32 AT33_4 BE2 DE1 DE5_9 DE7 DEA DEB_C ES21_2_3 ES52 FR21 FR22 FR23 FR24 FR25 FR26 FR3 FR41 FR42 FR43 FR51 FR53 FR61 FR72 IT1 IT2 IT31 IT32 IT33 IT4 IT51 IT52 IT53 IT6 NL21 NL22 SE06 SE07 SE08 UK1 UK2 UK3 UK7 UK9 LU
Natural resource / low growth	BE3 DE4 DE8 DED DEE DEG ES53 GR1 GR2_3 IT7 ITB NL1 NL34 NL42 UK8 UKB FI13 FI14
Low specialization and low innovativeness	AT11 ES11 ES41 ES62 GR4 NL23 PT11 PT12 PT13 PT14 PT15

Table B2: Types of Innovation system in 90s (6 clusters)

90s' Innovation system (6 clusters)	Region
Low specialization / low innovativeness and low economic performance	AT11 ES11 ES12_3 ES41 ES42 ES43 ES62 ES7 FR83 GR4 PT11 PT12 PT13 PT14 PT15 FI2
Natural resource/low growth	BE3 ES53 GR1 GR2_3 IT7 IT8 ITB NL34 UKB FI13 FI14
ICT-related and high innovativeness	DE2 DE3 DE4 DE6_F DE8 DED DEE DEG ES51 FR62 FR82 ITA NL31 NL33 NL41 NL42 SE01_02 SE03_04 SE08 UK4 UK5 UK6 UK8 UKA FI11_2 FI15 IE
Traditional and transportation / low innovativeness	AT32 AT33_4 DE1 DE5_9 DE7 DEB_C ES24 ES3 ES52 ES61 FR21 FR22 FR23 FR24 FR25 FR42 FR43 FR51 FR52 FR53 FR61 FR63 FR72 FR81 IT1 IT32 IT4 IT51 IT53 IT9 NL1 NL21 NL22 NL23 SE05 SE07 UK7 UK9
Traditional and basic metal / high economic performance	AT12_3 AT21 AT22 AT31 BE2 DEA ES21_2_3 FR26 FR3 FR41 FR71 IT2 IT31 IT33 IT52 IT6 NL32 SE06 UK1 UK2 UK3 LU
Bio-chemical / mid innovativeness & economic performance	BE1 FR1

Appendix II. The regions

For the following countries/regions, the NUTS classification has been used:

Austria		**France**	
AT11	Burgenland	FR1	Ile De France
AT12+AT13	Niederösterreich	FR21	Champagne-Ardenne
AT21	Kärnten	FR22	Picardie
AT22	Steiermark	FR23	Haute-Normandie
AT31	Oberösterreich	FR24	Centre
AT32	Salzburg	FR25	Basse-Normandie
AT33+AT34	Tirol And Vorarlberg	FR26	Bourgogne
		FR3	Nord-Pas-De-Calais
Belgium		FR41	Lorraine
BE1	Brussels Hfdst.Gew	FR42	Alsace
BE2	Vlaams Gewest	FR43	Franche-Comte
BE3	Region Wallonne	FR51	Pays De La Loire
		FR52	Bretagne
Germany		FR53	Poitou-Charentes
DE1	Baden-Württemberg	FR61	Aquitaine
DE2	Bayern	FR62	Midi-Pyrenees
DE3	Berlin	FR63	Limousin
DE4	Brandenburg	FR71	Rhone-Alpes
DE5+DE9	Bremen And Niedersachsen	FR72	Auvergne
DE6+DEF	Hamburg And Schleswig-Holstein	FR81	Languedoc-Roussillon
D E7	Hessen	FR82	Provence-Alpes-Cote D'azur
DE8	Mecklenburg-Vorpommern	FR83	Corse
DEA	Nordrhein-Westfalen		
DEB+DEC	Rheinland-Pfalz And Saarland	**Greece**	
DED	Sachsen	GR1	Voreia Ellada
DEE	Sachsen-Anhalt	GR2+GR3	Kentriki Ellada And Attiki
DEG	Thüringen	GR4	Nisia Aigaiou, Kriti
Spain		**Italy**	
ES11	Galicia	IT1	Nord Ovest
ES12+ES13	Asturias And Cantabria	IT2	Lombardia
ES21+ES22 +ES23	Pais Vasco, Navarra And Rioja	IT31	Trentino-Alto Adige
ES24	Aragon	IT32	Veneto
ES3	Madrid	IT33	Friuli-Venezia Giulia
ES41	Castilla-Leon	IT4	Emilia-Romagna
ES42	Castilla-La Mancha	IT51	Toscana
ES43	Extremadura	IT52	Umbria
ES51	Cataluna	IT53	Marche
ES52	Valenciana	IT6	Lazio
ES53	Baleares	IT7	Abruzzo-Molise
ES61	Andalucia	IT8	Campania
ES62	Murcia	IT9	Sud
ES7	Canarias	ITA	Sicilia
		ITB	Sardegna
Netherlands			
NL1	Noord-Nederland	**United Kingdom**	
NL21	Overijssel	UK1	North
NL22	Gelderland	UK2	Yorkshire And Humberside
NL23	Flevoland	UK3	East Midlands
NL31	Utrecht	UK4	East Anglia
NL32	Noord-Holland	UK5	South East
NL33	Zuid-Holland	UK6	South West
NL34	Zeeland	UK7	West Midlands

NL41	Noord-Brabant	UK8	North West
NL42	Limburg	UK9	Wales
		UKA	Scotland
Portugal		UKB	Northern Ireland
PT11	Norte		
PT12	Centro		
PT13	Lisboa E Vale Do Tejo		
PT14	Alentejo		
PT15	Algarve		
Sweden			
SE01+SE02	Stockholm And Östra Mellansverige		
SE03+SE04	Småland And Sydsverige		
SE05	Västsverige		
SE06	Norra Mellansverige		
SE07	Mellersta Norrland		
SE08	Övre Norrland		

For the following countries, a national classification has been used:

Norway Based on Fylken	
NO1	Akershus, Oslo
NO2	Hedmark, Oppland
NO3	Østfold, Busekrud, Vestfold, Telemark
NO4	Aust-Agder, Vest-Agder, Rogaland
NO5	Hordaland, Sogn og Fjordane, Møre of Romsdal
NO6	Sør-Trøndelag, Nord-Trøndelag
NO7	Nordland, Troms, Finnmark
Switzerland Based on Cantons	
CH1	Jura, Neuchâtel, Fribourg, Vaud, Geneva
CH2	Argovia, Appenzell Inner-Rhodes, Appenzell Outer-Rhodes, Basel-Country-Basel-Town, Berne, Glarus, Lucerne, Nidwalden, Obwalden, St. Gallen, Schaffhausen, Schwyz, Solothurn, Thurgovia, Uri, Zug, Zurich
CH3	Valais, Ticino, Grisons
Denmark Based on postal regions	
DK1	Hillerød, Helsingør, København
DK2	Fyn, Sjaelland ex. Hillerød, Helsingør, København
DK3	Jylland
Finland Based on postal regions	
FI11_12	Uusimaa, Etelä-Suomi
FI13	Itä-Sumoi
FI14	Väli-Suomi
FI15	Pohjois-Suomi
FI2	Ahvenanmaa/Åland

The following countries have been included as a single region:

Ireland
Luxemburg

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