

PRIVATE AND PUBLIC SECTOR R&D EFFORTS, KNOWLEDGE SPILLOVERS
AND REGIONAL GROWTH IN EUROPE

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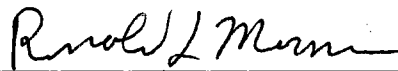
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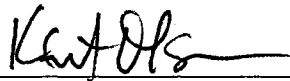
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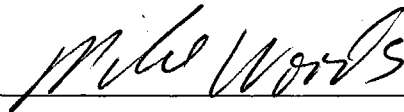
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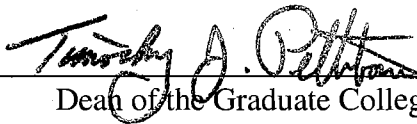


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PREFACE

The primary objective of this dissertation is to empirically measure and test the influence of R&D personnel (employed by business enterprise sector and government sector, respectively) and knowledge spillovers of both types of R&D efforts on the European regional performance in labor productivity. Recently, the further European integration process has brought about a dynamism regarding regional development, that also raises crucial concerns. A central one is whether it will aggravate the underlying regional disparities in economic well-being and productivity performance. In this respect, it is tremendously pertinent to understand whether regional R&D efforts and knowledge spillovers across regions have a significant impact on their performance, how the effects emerge, and how they take place across locations. Available data from EUROSTAT and Cambridge Econometrics limits the study area to 57 regions at the NUTS 2 level from three contiguous members of the EU (France, Italy and Spain) and to the period between 1985-95. Even though this issue has recently received a great deal of attention, only a few empirical studies have carefully specified the EU regional development process. In a different way from most of the earlier empirical work, we spatially specify Romer's (1990) growth model in the light of Caniels (2000) and Magrini (1997) for EU regional development in this research. Hence, we can interpret the empirical findings along with the mainstream economic growth theory, which receives too little attention in the earlier empirical literature.

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TABLE OF CONTENTS

Chapter	Page
I. INTRODUCTION	1
1. Overview of the Subject	1
2. Statement of the Problem.....	3
3. Objectives of the Study	6
4. Major Contributions of the Study	6
II. R&D EFFORTS, KNOWLEDGE SPILLOVERS, REGIONAL DEVELOPMENT AND INTEGRATION IN EUROPE	9
1. The European Integration Process	10
2. European Regional Development Policy and Structural Funds	12
3. European Integration, Regional Economic Development and Convergence	19
3.1. The impact of the integration on growth of overall EU income	19
3.2. The cross-regional economic impact of the integration	21
3.2.1. Barro-type empirical studies on regional convergence	22
3.2.2. Quah-type empirical studies on regional convergence	25
3.2.3. Krugman-type analyses of European regional economic development	31

Chapter	Page
4. R&D Activities, Knowledge Spillovers and European Regional Development	36
4.1. The theory of localized knowledge spillovers	37
4.2. The geographical distribution of R&D activities	39
4.3. The empirical studies of knowledge spillovers and regional development	39
4.3.1. The empirical evidence from the studies of knowledge production function	40
<i>The evidence from the European regional data</i>	42
<i>Criticism of the empirical studies of knowledge production function</i>	43
4.3.2. Empirical evidence from the studies of output production function	45
<i>The evidence from the OECD countries data</i>	46
<i>The evidence from the European regional data</i>	48
4.4. The importance of public sector R&D in the regional development	55
 III. TECHNOLOGICAL KNOWLEDGE FOR ECONOMIC DEVELOPMENT: THEORETICAL CONSIDERATION	 58
1 The Schumpeterian Patterns of Innovation Process	59
2. Technological Progress in the Neoclassical Theory of Economic Growth	64
3. Regional Economic Convergence	70
4. The Technology Gap Approach	82
5. The New Endogenous Growth Theory	85

Chapter	Page
IV. THE THEORETICAL MODEL AND ECONOMETRIC SPECIFICATION FOR THE EUROPEAN REGIONAL DEVELOPMENT	99
1. Derivation of the Theoretical Framework	99
2. Econometric Specification for the European Regional Development	112
<i>The spatial autocorrelation problem</i>	120
3. The Variables, Hypotheses and Data	125
3.1. The variables	125
3.2. The hypotheses	135
<i>The main hypothesis</i>	137
3.3. The data	139
V. ANALYSIS OF THE EMPIRICAL RESULTS	143
1. Preliminary Evaluation of the Regional Distribution of the Primary Indicators	144
2. Important Econometric Issues on the Estimation Method	150
3. Empirical Results from the 1985-95 Data Set	151
4. Empirical Results from the 1988-95 Data Set	164
<i>Evidence from government sector R&D and knowledge spillovers</i>	170
5. Empirical Results from the Region Specific Effects	175
VI. CONCLUSIONS	191
1. Summary of the Study	191
2. Empirical Conclusions	196

Chapter	Page
3. Implications of the Study	203
4. Limitations of the Study	206
5. Suggestions for Further Research	207
 BIBLIOGRAPHY	 209
 APPENDIXES: Tables for the Summary Statistics of the Variables and Indicators	 218

LIST OF TABLES

Table	Page
I. The definition of variables and notations in the theoretical model	111
II. The definition of variables employed in the regional specifications	132
III. Descriptive statistics on the averages of primary indicators in the period between 1988 and 1995	146
IV. Pearson correlation coefficients across the averages of primary indicators in the period between 1988 and 1995	149
V. Estimates for testing the impact of the variables interacted with <i>investment share</i> in the proxy vector on the marginal product of capital from the 1985-95 data	155
VI. Estimates for testing the impact of the variables interacted with <i>investment share</i> in the proxy vector on the marginal product of capital by including the interacted variable separately from the 1985-95 data	156
VII. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on <i>labor productivity growth</i> from the 1985-95 data	159
VIII. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on <i>labor productivity growth</i> from the 1985-95 data	160
XI. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on <i>labor productivity growth</i> from the 1988-95 data	166
X. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on <i>labor productivity growth</i> from the 1988-95 data	167

Table	Page
XI. Estimates for testing the impacts of one-way and two-way knowledge spillovers associated with government sector R&D efforts and gaps across regions on <i>labor productivity growth</i> from the 1988-95 data	172
XII. Estimates for testing the impacts of one-way knowledge spillovers associated with private and government sector R&D gaps across regions on <i>labor productivity growth</i> from the 1988-95 data	173
XIII. Basic statistics on the estimates of cross-region fixed-effects from various specifications of LSDV estimator and on particular demographic variables for the period between 1985 and 1995	177
XIV. Basic statistics on the estimates of cross-region fixed-effects from various specifications of LSDV estimator and on particular demographic variables for the period between 1988 and 1995	178
XV. Pearson correlation coefficients across the estimated variables of cross-region fixed-effects for the period between 1985 and 1995	179
XVI. Pearson correlation coefficients across the estimated variables of cross-region fixed-effects for the period between 1988 and 1995	180
XVII. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on <i>regional effects</i> from the 1985-95 data	184
XVIII. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on <i>regional effects</i> from the 1985-95 data	185
XIX. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on <i>regional effects</i> from the 1988-95 data	186
XX. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on <i>regional effects</i> from the 1988-95 data	187
XXI. Estimates for testing the impact of two-way knowledge spillovers across regions associated with government sector R&D efforts on <i>regional effects</i> from the 1988-95 data	188

Table	Page
APPENDIXES: Tables for the Summary Statistics of the Variables and Indicators	218
AI. Descriptive statistics of particular indicators for the period between 1985 and 1995	218
AII. Descriptive statistics of the variables for the period between 1985 and 1995	219
AIII. Pearson correlation coefficients across the variables for the period between 1985 and 1995	220
AIV. Descriptive statistics of particular indicators for the period between 1988 and 1995	223
AV. Descriptive statistics of the variables for the period between 1988 and 1995	224
AVI. Pearson correlation coefficients across variables for the period between 1988 and 1995	225
AVII. Pearson correlation coefficients across the variables employed in OLS estimates of cross-region fixed-effects for the period between 1985 and 1995	229
AVIII. Pearson correlation coefficients across the variables employed in OLS estimates of cross-region fixed-effects for the period between 1988 and 1995	231
AIX. Cross-regional averages of R&D and patent data for the period between 1988 and 1995	233
AX. Cross-region fixed effects (with LSDV estimator) for the period between 1988 and 1995	234
AXI. Cross-region fixed effects (with LSDV estimator) for the period between 1985 and 1995	236
AXII. Names of the regions and their most populated urban centers	237
AXIII. Names of Sectors	239

CHAPTER I

INTRODUCTION

1. Overview of the Subject

The European Union (EU) has taken courageous steps toward a unified system of relations among its members. However, large interregional disparities in long-run unemployment rates, per capita income, industrial structure and economic performance are fundamental problems of the EU that receive much attention. There is a disagreement about whether further EU integration will diminish or increase discrepancies in economic well being across the EU regions. There is also a concern that regional economic differentials will be a drag on further unification of the EU as well as a concern that the further EU integration could increase economic differentials.

One of the crucial aims of the European Community has been a more equal distribution of economic well being across its member nations and regions. The financial resources allocated to relatively less developed regions from the budget of European Community have increased tremendously since 1988. At the same time, the targeting of these resources to regional development policies has been improved. Despite these developments in financial funds and regional policy, economic disparities have not declined across the EU regions. In general, the EU nations displayed good economic

performance in 1960s and in the first half of 1970s, and regional disparities in economic well being were shrinking until the early 1980s. The weaker EU economic performance after the mid-1970s is associated with a stagnation of regional economic discrepancies.

The observed disparate regional growth process over the EU geography is not completely understood. Particular spatial patterns with regard to the distribution of R&D efforts, innovative and economic activities, and labor force exist over the European geography. Recently, the importance of technological knowledge, knowledge spillovers, and increasing returns to scale in explaining the regional development process has been highly emphasized. In this regard, Fagerberg (1999) argues that the EU competitiveness and growth require innovation-based industries. However, the rapid growth of innovation-based industries is likely to aggravate regional discrepancies further across the EU territory because most poor regions do not have an infrastructure to supportive of knowledge diffusion. Nevertheless, the influence and role of the innovative and R&D activities on the differential EU regional growth have not been exhaustively researched.

Therefore, we specify a spatial economic growth model, which is consistent with the observed situation over the European regions. To do so, we start with the intuition of Romer's endogenous technological growth theory. We then model the knowledge accumulation process in any location as a consequence of its own investment and personnel employed in R&D activities and knowledge spillovers from other regions, based upon its own capability, own fixed characteristics, geographical distance, technological distance and economic distance relative to other locations. Furthermore, the role and influence of R&D personnel employed in government sector, and industrial structure on the regional development will be tested. Thus, with accounting for these

location dynamics and location-specific amenities, we may expect to predict and understand the effect of R&D on the disparate regional growth process for the controversial EU case.

2. Statement of the Problem

The role and influence of R&D efforts on the disparate regional economic performance have not been studied adequately so far for the European case. Firms, on one hand, for private interest and the local or central governments, on the other hand, for social interest have devoted substantial resources to R&D activities, but have done so differentially across regions. Moreover, innovations, R&D intensity, economic activities, population, and industrial composition are distributed unevenly by region. Innovations and R&D activities, however, are much more regionally concentrated than economic activities and population, and they are clustered within particular sectors and locations. (see, for instance, Caniels 1997; Bottazzi and Peri 1999; Verspagen 1999; Paci and Usai 2000). This fact indicates the presence of substantial technological knowledge gaps across regions, and hence implies a significant potential for knowledge spillovers across regions.

The regional variation in economic growth, however, is not tied strictly to regional variation in R&D intensity. Fast-growth regions with low R&D efforts exist as do slow-growth regions with high R&D efforts. These patterns demonstrate that regions have invested in R&D activity both to create new products or processes and to implement or imitate innovations from the innovative regions. The knowledge spillovers and the diffusion of knowledge across regions and within regions are important elements of

regional performance. Regional performance depends both on the region's specific characteristics, including industrial structure, and on the region's geographical location with regard to innovative activity and economic activity in other regions. Understanding the role of regional spillovers is crucial in understanding the regional dynamics of growth process. In other words, economic and innovative performances of regions are interconnected over the geography with the spatial, technological knowledge and economic distances to each other (Verspagen 1999).

On the other hand, the capability of any location or region to generate new technological knowledge inside and to implement or imitate those from outside is not uniquely tied to the magnitude of local resources invested in R&D. In other words, the transition from R&D investments to innovations or technological knowledge and in turn eventually to output or productivity growth is not a smooth process. It substantially differs by localities and regions. As a matter of fact, there are many factors beside economic conditions that affect the innovative capability of a location or region (Rodriguez-Pose 1999).

Roughly one half of R&D activities over the world are funded by the government sector. The importance of this source of funding varies across nations and particularly across regions. R&D activities of government and higher education sectors are implemented for different objectives than those of the private enterprise sector. The government and higher education sectors have in general performed the R&D projects that take a long time, are highly risky, involve basic science, and generate high technological knowledge spillovers. Those are the R&D activities to which private sector may not devote adequate resources. Moreover, government and higher education sectors

tend to publish the findings, rather than hiding them for own use as in the private sector. So, the R&D activities of these sectors is likely to help the diffusion of technological knowledge within a location and across regions as well as to support the private sector R&D (Rodriguez-Pose 1999).

Furthermore, industrial structure and its change over time are other sources of differential regional growth in the EU. The regional distribution of industrial structure is very diverse and changing significantly over time. The productivity of sectors within a region and the productivity of regions within a sector are rather different. A major contribution to regional growth comes from the shift of labor from low productive agriculture to high productive industry and especially services. Also, within sector productivity has increased differently by sectors and regions. Moreover, another view is that some sectors have benefited from knowledge spillovers beyond the extent of their technological intensity (Paci and Pigliaru 1999).

A number of empirical studies have been implemented with the goal of understanding the role of R&D and innovations in EU regional performance. They have, however, been limited by data availability. Available European regional data allowed some econometric studies to emerge in the mid-1990s (in particular, Cheshire and Carbonaro 1996; Fagerberg et al. 1997; Rodriguez-Pose 1999; Bottazzi and Peri 1999; Caniels 2000; Cappelen et. al 2000). Although these studies provide a good start, they leave unanswered questions. Few of them have econometrically specified the regional growth process properly in a spatial context. In particular, the regions cannot be treated as units independent of each other. Two issues have not been adequately tested and evaluated within the underlying spatial context. One is the effect of R&D activities

implemented or funded by private sector and especially by government sector on EU regional performance. The other is the role of variation in industrial composition.

Thus, the principle question addressed in this research is what is the impact of technological knowledge accumulation on the disparate regional economic performance over the EU geography? More specifically, what are the role and influence of regional R&D personnel employed in private and government sectors, respectively, and industrial structure on differential EU regional economic growth through the disparate cross-regional knowledge accumulation process?

3. Objectives of the Study

The main objective of this study is to empirically measure and test the impact of regional R&D personnel employed in private and government sectors and associated cross-regional knowledge spillovers, respectively, on the differential growth rates in per labor gross value added across the EU regions through a linear regression technique within the context of a spatial econometric specification of the Romer model.

Another objective is to test whether these R&D efforts and associated cross-regional knowledge spillovers as well as particular economic structure variables and social-demographic factors have a significant influence on the cross-regional variation in productive efficiency, by implementing the panel data approach with the least squares dummy variable (LSDV) estimator.

4. Major Contributions of the Study

The advancing European integration process has brought about a dynamism regarding regional development that also raises crucial concerns. A central one is whether it aggravates underlying regional disparities in economic well being and productivity performance. In this respect, it is enormously relevant to know whether regional R&D efforts and associated knowledge spillovers across them have a significant impact on regional performance and how these effects emerge, and how they take place across locations. Even though the issue has recently received much attention, only a few empirical studies have carefully specified a model of EU regional development process. Therefore, in a way different from the earlier empirical work, we spatially specify Romer's (1990) growth model in the light of Caniels (2000) and Magrini (1997) for EU regional development. Hence, we can interpret the empirical findings in the mainstream of economic growth theory, something to which the earlier empirical literature pays little attention.

Two types of variables measuring cross-regional knowledge spillovers due to regional R&D efforts are constructed by assuming that their regional influences decay by distance and across regional boundaries. While one accounts for only regional R&D efforts in and immediately surrounding the region, the other accounts for all regional R&D efforts for a region as a potential knowledge spillover force.

Third, the influences of government sector R&D efforts and associated cross-regional knowledge spillovers on labor productivity growth are also tested using the same specification.

Fourth, within the underlying empirical specification of the relevant mainstream theory, crucial economic structure variables for the EU regional development process are

also included. In this regard, spatial dependencies across first and second order contiguous regions regarding the dependent variable are also dealt with by employing a spatially lagged dependent variable as a regressor in the specification.

Finally, we test whether regional R&D efforts and associated cross-regional knowledge spillovers as well as particular economic structure variables and social-demographic factors have significant influences on cross-regional variation in productive efficiencies by implementing the panel data approach with the LSDV estimator.

The rest of the study is organized as follows: a literature on R&D efforts, knowledge spillovers and European regional development along with the integration process is reviewed in Chapter II. The role of technological knowledge for economic development in theory is explained in great part in the mainstream tradition and then regarding the concepts of technology gap approach in Chapter III. The theoretical model and econometric specification for the EU regional development process are presented in Chapter IV. The empirical results are analyzed in Chapter V. Finally, conclusions of the study are discussed in Chapter VI.

CHAPTER II

R&D EFFORTS, KNOWLEDGE SPILLOVERS, REGIONAL DEVELOPMENT AND INTEGRATION IN EUROPE

The dynamic phenomenon of European regional development or growth cannot be properly analyzed without accounting for crucial economic implications of the European integration process. This chapter therefore starts with basic background about the EU integration process in section one, and the evolution of its institutions with regard to the regional economic development in section two. The EU disparate interregional development process and the influence of the integration process on interregional development are reviewed based on the recently popular alternative approaches in section three. In this regard, the findings of prominent empirical studies that tend to test the neoclassical hypothesis of convergence in per capita income across regions are surveyed in section three. Next, the findings and implications of the important empirical studies on the regional income distribution dynamics are presented. To conclude section three, the results and implications of analyses based on the approach of the new economic geography are submitted. Section four critically analyzes the findings, implications and methods of the empirical studies of the influences of the R&D efforts and knowledge spillovers on cross-sectional economic development, specifically on EU differential regional economic performance. Furthermore, we might suggest that the reader, who is

interested directly in the specific problem of this dissertation and has a basic knowledge about the EU integration process and the evolution of its institutions, may omit the first three sections, skipping to section four.

1. The European Integration Process

The unification of European nations has been a long run gradual process involving three broad categories: economic, political, and social. After experiencing the brutal outcomes of two world wars, European nations decided to pursue economic and political unification. Thereby, instead of the conflicting interests of national sovereignties in the past, they would build their future on common interests so that instability in interstate relations would be eliminated. This also could cause the economies of European nations to become more competitive both within and out of the Community, and enable them to take a more powerful policy stand in foreign affairs (Leonardi 1995, p. 9-10).

The integration process started with the treaty of Paris, establishing the first European Community (EC) --the European Coal and Steel Community (ECSC)--, which was agreed on by France, Germany, Italy, the Netherlands, Belgium and Luxembourg in 1951. Since then, the eventual target of the Community has been the building of a united Europe. Next, the treaty of Rome that established the European Economic Community (EEC) in 1957 set up institutions and a common ground to compromise between the national demands and the Community's decision (EC 1997).

The next step in the integration process was the inclusion of other European countries because the fundamental objective was to cover all the European territory along

with deeper integration. The first wave of involvement in the EC came from Denmark, Ireland and the United Kingdom in 1973. Later, Greece in 1981, Spain and Portugal in 1986, and East Germany in 1990 were admitted. In 1995 Austria, Finland and Sweden entered the Community. Hence the number of member countries in the European Union (EU) has reached fifteen. Finally, a number of mostly eastern and central European countries are expecting to be qualified to enter the EU in the near future (EC 1999, 1997).

Two fundamental modifications to the treaty of Rome with regard to the unification of the EU have been made in the last two decades, one of which is economic, the other political. The social content has also developed alongside the economic and political integration (EC 1997, Leonardi 1995 and Monti 1997). The abolition of custom duties following the treaty of Rome in 1957 promoted a tremendous increase in trade and average gross national product (GDP) in the EEC through the mid-1970s. However, it was recognized that big hidden obstacles to the flows of commodities, services and capital across national borders had been maintained. Consequently potential benefits remained that free flows of goods and labor could generate. To promote this, the Single European Act was signed in 1986 between the existing twelve members of the EU. It set up a time schedule to eliminate barriers to the free flows of goods, capital and labor across the national borders of the EU members: a genuine, fully unified internal market was to be established by 1993.

While satisfactory economic integration was established culminating in the Single European Act, the political foundations of the EU were developed with the treaty on EU signed at the Maastricht summit in 1992. It was effective at the beginning of 1993. Political unification implies the formal transfer of power from the national to the

supranational level. The Maastricht treaty also defines a common foreign and security policy, which will eventually lead to a common defense policy. Because economic integration did not guarantee political unification, integration had to be accompanied by political unification.

“Otherwise a change in economic conditions or a national political climate might easily reverse the process and undo all the achievements and benefits gained from the initial stages of economic integration” (Leonardi 1995 p. 23).

The last objective achieved by the EU is the creation of the European Monetary Union (EMU), which a subset of countries have created. Several countries have rejected the EMU, and others did not qualify. A single currency, the European currency of unit (ECU), (EC 1997, p. 8) has been accepted in transactions by central banks of all included countries since the beginning of 1999. The currency unit, the Euro, has been accepted in all transactions by all markets in the EMU territory since the beginning of 2002. The ECU will provide more secure transactions with low cost and without any hesitation of uncertainty due to currency fluctuations or crisis across the member nations. The fluctuations in currencies across the European nations have led to substantial conflicts in the past (Einaudi 2000). Thus the existence of such a common unit of currency will increase the trust and all the transactions across the national borders of the EU members.

2. European Regional Development Policy and Structural Funds

The EC has long perceived the large regional economic differentials as a substantial obstacle to the further economic and politic integration. However, the EC had a passive regional development policy until the beginning of 1970s, because the regional economic differentials were viewed as temporary and expected to be eliminated by

market forces in the short- or mid-term as a consequence of integration. Nevertheless, regional economic and social convergence did not develop as expected during the 1960s and the beginning of 1970s. It was decided that regional economic policy would be necessary to realize convergence. By establishing the European Regional Development Fund in 1974, the EC initiated an active regional development policy in support of national development programs (EC 1992, 1997; Begg et al. 1995; and Leonardi 1995).

Moreover, along with the discussions of the Single European Act during the 1980s, three relatively poor countries of Greece, Portugal and Spain were admitted as members in the community. This expansion was accompanied by a more dynamic and effective regional development policy. A radical reform in 1988 brought a substantial surge in the amount of financial resources allocated to the regional development policies. Efficient use of those resources would, it was thought, require regional planning of specific programs for a particular time and region, and coordination of 'the structural funds'. The EU regional development policy has been supported by a number of these so-called 'structural funds'. Hence, EC initiated a regional development policy based on regional dynamics. In particular, interregional convergence would require the intensive and effective support of the least developed localities, rather than simply a social policy relying on wealth transfers from rich to poor locations. Targeted development programs rather than permanent subsidies could enable the less developed localities to build their sustained economic development structures (EC 1992, 1997; Batchler 1998; and Leonardi 1995).

“For it is the regions that must take the lead in meeting these challenges. It is their ideas which will ultimately determine the success of EC-backed policies to improve their local economies” (EC 1992, p.1).

It was anticipated by many observers, following the European Single Act, that an accelerated integration process would lead to the problems of structural adjustment in lagging regions. As the EU became an increasingly integrated market, the core regions were expected to benefit relatively more than the peripheral ones. In addition, because the European Commission wished its members to be involved in the EMU as rapidly as possible, they had to satisfy particular economic and monetary convergence criteria in a quite short period. This meant that the relatively poor member countries had to discipline their government budgets, and hence could not spend adequately for regional infrastructure and other development policies. Therefore, in 1988 the EU decided to gradually double the financial resources devoted to the structural funds from the EU general budget for the regional development policy during the period 1989-1993. Later, at the Edinburg summit in 1992, in addition to sustaining the regional development budget for the planning period 1993-1999, the principle aim was to focus the resources on the poorest regions and on the structural adjustment of declining industrial areas (EC 1994; Begg et al. 1995).

In addition to the structural funds, a Cohesion Fund was created at the 1992 Edinburg meeting in order to finance principle state projects related to environment and transport infrastructure. An ECU 16,223 million budget in 1994 prices was made available for the Cohesion Fund for the planning period of 1993-1999 to support those stated projects of the less developed countries of the EU. Greece, Ireland, Portugal and Spain are automatically qualified to take aid from this fund, because their per capita income levels have been less than 90 % of the EU average. The purpose of this fund was to enable all these member states to join the EMU as soon as possible, and in contrast to

that of the structural funds, to eliminate the economic discrepancies across nations rather than across regions (EC 1994; Danson 1999).

In this regard, since the beginning of the 1980s the expenditure from the EU budget has increased from 1.7 to 2.5 % of the aggregate public expenditure of the member countries, which corresponds to 1.26 % of the average 1996 GDP. The budget devoted to structural funds from the general EU budget is ECU 172,505 million in 1994 prices for the planning period of 1994-1999. From 1989 to 1993 the share of structural operations in the budget surged from around 18 % to 31 %, and that of research from approximately 2 % to 4 %. Around 2.5 % of the budget is disbursed to the other internal policies. The major portion of this part of the budget goes to the trans-European transport, energy and tele-communication networks, so as to support the missing links across the member states. Roughly another 6 % of the budget is given to the external issues, and about one fourth is spent for economic restructuring and preparation of central and east Europe for admission to the EU (EC 1996). Further, the share of the EU budget spent on regional development objectives has risen from the below 30 % in the 1989-1993 planning period to above 35 % in the 1994-1999 one (Braunerhjelm et al. 2000, p.63).

The general budget of the EU is financed with revenue received from the member states. The size of these resources is limited by the member states with a ceiling, which was 1.20 % of the EU's GNP in 1996 and 1.27 % in 1999. Approximately 18 % of the total revenue in 1996 came from customs duties and agricultural duties or charges levied on products imported from outside the EU. The VAT provides 48.9 % of total revenue. Also, 32.9 % of total revenue is obtained from each state based on its ability to pay, that is, its GNP level in the EU (EC 1996).

Following the 1988 reform, the European Commission has determined particular target areas, and hence the structural funds have financed particular objectives. With regard to the regional development (EC 1992), the objective 1 regions consist of the less developed locations with per capita GDP levels lower than 75 % of the EU average. The objective 2 regions are made up of the industrial declining regions. Structural changes or other global shocks such as technological progress and innovations in the economy have hit more severely regions specialized heavily in basic industries. The specialized skills developed in those traditional sectors could not easily be transformed to skills required in the new environment. Therefore these sorts of regions have faced high unemployment rates and low per capita incomes. Objective 5b regions are rural and less populated areas with relatively low levels of per capita income in the EU.

For objective 1 regions, the structural funds focus on the creation of a sound infrastructure. Transport and communication links are modernized, energy and water supplies are improved, R&D activities are encouraged, and training and technical help to small businesses are provided. For objective 2 regions, the structural funds primarily finance programs that create jobs, improve the business climate by encouraging new businesses, renovate land and buildings, develop R&D activities and foster networks between universities and industry. For objective 5b regions, the structural funds are devoted to programs that create new jobs outside farming in small businesses and tourism. Transport and basic services are promoted to prevent rural depopulation and to ensure harmony between urban and rural locations of the EU. Objective 1, 2 and 5b regions make up approximately 27 %, 15 % and 5 % respectively of total EU population.

Objective 1 regions receive about 70 %, of the EU regional aid (Braunerhjelm et al. 2000, p.64).

The EC has conditioned aid to those regions on three basic principles to maximize efficiency in use of financial resources (EC 1992). The first requires an active involvement of the relevant authorities with a contribution from every one of the regional, national and community levels. The second points to a clear delegation of decision-making to the local, regional, national or community level to ensure maximum efficiency and responsibility. The third suggests an unambiguous commitment to the funds being used as complement to, rather than substitute for, national funds. Thus,

“a three-stage procedure, closely involving the Community, governments and regions, is used to decide on schemes for EC funding. Priorities first set by regional and local authorities, are carefully constructed into an overall program lasting several years” (EC 1992, p. 8).

Local political and administrative elites and local actors are involved in a Community-wide network of relations and decision-making processes.

“... the course of European integration after 1988 demonstrates that regional elites (and considerations of regional policy) are important actors and vigorous proponents of a new European institutional architecture in which EU organs are in direct contact with sub-national elites” (Leonardi 1995, p. 25). “The EC increasingly insists that countries receiving EU regional aid should give regions more autonomy in order to ensure that expenditures are better targeted on the needs of the region” (Braunerhjelm et al. 2000, p.61).

The regional development policy instruments consist of two general forms. Regional investments are put primarily into physical and human infrastructure to improve regional competitiveness. Because all economic activities can benefit from them in the market equally, they are considered as non-distortionary tools in terms of competition policy. On the other hand, regional incentives are provided to encourage individual economic enterprises in disadvantaged locations. That is, they are firm selective so that

they are potentially distortionary in terms of market competition, and are likely to be distortionary in terms of economic efficiency if the policy tools are used inappropriately. The former instrument is extensively used in the objective 1 regions, and the latter instrument is relatively prominent in the objective 2 regions. While the EC pays considerable attention to the elimination of the regional disparities, it stands strongly against the growing use of regional incentives, in the form of state aids, which are potentially destroying competition within the EU (Braunerhjelm et al. 2000, p.61-66). In other words, any instrument and implementation with regard to regional development policy may not conflict with the competition policy of the EU. The EC first of all considers whether any program or project for a regional development policy destroys the competition across economies. Regional development policy in any economy should be compatible with competition policy of the EU. Otherwise the EC does not support such programs or projects at all (Wishlade 1998).

Finally, the EU at the Berlin summit in 1999 agreed with the Agenda 2000 package of reforms. The main property of these reforms is to consider the enlargement challenge of the EU towards new prospective members because of their relatively poor economic and structural conditions. One challenge is to revitalize the present model of European agricultural funding. The other is to concentrate the structural funds firmly in the local economies that are clearly need of revival. Hence, the EC has determined a very tight financial framework for the planning period of 2000-2006 with only very modest increases in the budget to finance the priorities and the costs of the enlargement. It has reduced the number of priority objectives from seven to three in total, and targeted almost 70 % of total spending on objective 1 regions. Beside Objective 1 and 2 regions,

Objective 3 regions are defined. This new objective will finance education, training, and new jobs creating activities and hence will help people to adapt and prepare for change. It will fund all localities not covered within Objective 1 regions. The Cohesion Fund will keep supporting the environmental and transport infrastructure projects of the same lagging countries until their per capita GDP gets over the 90 % of the EU average (EC 1999).

3. European Integration, Regional Economic Development and Convergence

3.1. The impact of the integration on growth of overall EU income

There is a consensus among economists the full European integration will raise overall real GDP of the EU, but how much it is in question (Hansen and Neilsen 1997, p. 95). The EC initiated a project to evaluate the potential overall impact of completion of the Single European market program on the EU GDP. For this aim, two complementary reports reported overall results: the Cecchini Report, prepared by Paolo Cecchini et al. (1988), and the Emerson Report, prepared by Michael Emerson et al. (1989). These reports estimate an overall impact of the program on the EU GDP in a range of around between 2.5 to 7 % of GDP, depending on expectations of particular parameters and on whether a passive or more active macro economic policy would be implemented. The major cumulative impacts were expected to appear in the medium term, after about 5-6 years.

Richard Baldwin (1989) in an alternative study stresses that the greatest benefit of the single European program should arise from its dynamic effects rather than its static

impact based on larger scale and more efficient allocation of resources. The larger market and more efficient use of resources increase rates of return to investment, and hence leads to an endogenous rise in the steady state capital output ratio. As the economy tends towards the new steady state, income increases indirectly in addition to the initial direct impact and in proportion to that in the medium term. Since the earlier studies ignored these dynamic effects they have severely underestimated the overall impact. More importantly, the program may contribute significantly to the long run growth rate of the EU GDP by 0.2 to 0.9 %. At first glance this may seem small effect, but the cumulative impact is huge in the long term.

Baldwin (1989) calibrates the growth effects of the program assuming that $GDP = \Omega K^\theta K^\alpha L^{1-\alpha}$ where Ω is the efficiency coefficient, K is capital stock, L is labor, the parameter α is capital's share in GDP, and θ stands for scale economies due to the overall size of capital stock in the EU. Thus, the percent change in GDP equals the percent change in Ω (the direct effect) plus $\alpha+\theta$ times the percent change in the steady state capital stock (the indirect effect). The outcome obviously depends on the size of these parameters. As a result, the overall estimated increase in discounted GDP is found to be between 11 to 35 % according to the Romer model ($\alpha+\theta = 1$) and between 13 to 33 % according to the endogenous innovations model.

In other words, most of the gains from the single market program were expected from the improved competitiveness of European firms rather than simply static scale economies. The larger markets would provide new opportunities and dynamism to entrepreneurs and hence force them to innovate more. However, the EU's GDP has increased by only 1 to 1.5 % during the period of 1993-1995. But, since it is only half

time of the regarding medium period, it is likely some effects still left to be realized in the coming half period (Monti 1997, p. 105). Nevertheless, one possible drawback is that the EU may lag Japan and the US in invention and innovation. Evidence for this is that the EU has devoted less of its GDP to R&D, 2 % compared to 2.7 % in the US and Japan, and it has proportionately fewer researchers and engineers than those countries, and the unit cost of patenting in the EU is higher (Monti 1997, p. 95).

Furthermore, the EU had highly competitive, specialized markets, before 1992. Perhaps there was not much room to improve efficiency significantly. Indeed, beyond national regulations, transportation costs and the fixed costs of local distribution are the primary influences on the further integration of the markets. Also, markets in some sectors had been previously integrated, so that 1992 does not provide extra gain. Moreover, 40 % of EU trade is with non-EU nations, so that integration could not substantially expand the aggregate trade volume of the EU simply by a limited degree of improvement in trade among the member nations. The EU also has to improve competitiveness of its markets to raise trade with nations outside the EU. Thus, the integration will affect the growth rate less than the model predicts, and the aggregate production process is perceived with simply modest increasing returns to scale. As a result, the integration may raise the growth rate in the medium term, but it is doubtful if it will do so in the long run (Hansen and Neilsen 1997, p. 87).

3.2. The cross-regional economic impact of the integration

Economists dispute whether the further European integration will raise or decrease the regional economic disparities. According to Braunerhjelm et al. (2000),

“several contradictory concerns exist. Poor regions fear that high-wage increasing-returns activities may agglomerate in the ‘core’. Rich regions fear delocation to lower-wage regions in Europe’s ‘periphery’ and beyond. Most regions fear declining competitiveness, de-industrialization and unemployment. All such fears create political pressures that resist further integration. In response, the EU spends a third of its budget on addressing these concerns, ...” (p. xi).

There are principally two opposing arguments on the regional consequences of European economic integration. On the one side, some economists believe that the free flow of goods, services, labor and capital as a result of the further integration is most likely to bring about regional convergence in factor returns, economic performance and economic structure. The European Commission and some others support this optimistic view. On the other side, some economists stress that the economic integration will increase rather than reduce the regional disparities in income and growth in the EU. Paul Krugman and some others support this pessimistic view (Martin and Sunley 1995, p. 276-280).

A great number of studies have attempted to understand the European regional discrepancies in the economic growth process. Most of the empirical studies have tended to test the neoclassical hypothesis of convergence in per capita income and to examine the evaluation of cross-section dynamics of per capita income distribution. They have raised crucial questions about the regional growth process, its regional patterns, and its plausible determinants. However, they could not measure the right role of crucial factors in explaining the observed regional differentials in economic growth process in the reality. Selected ones are reviewed below.

3.2.1. Barro-type empirical studies on regional convergence

Around a 2 % rate of absolute convergence in per capita income across regions within the EU nations, across regions within other countries, and across homogenous

group of OECD countries, has been found by Barro and Sala-i-Martin (1991, 1992, and 1995, chap. 11), Mankiw et al. (1992), Sala-i-Martin (1996a, 1996b), Barro (1997, chap. 1), among others (see Martin and Sunley 1998). Even though this estimated annual speed of convergence is slow, these findings based on the neoclassical growth framework support the optimistic view of the EC. The EC expects that economic disparities across the regions within the EU nations will diminish even more quickly as the EU integration goes further, if the most disadvantageous regions are supported temporarily for some period of time.

However, Sala-i-Martin (1996a, p. 1342) argues that

“the effect of the government in the process of convergence is minor by observing that the speeds of convergence are surprisingly similar across data sets. Since the degree to which national governments use regional cohesion policies is very different, the fact that the speeds of convergence are very similar across countries suggests that public policy plays a very small role in the overall process of regional convergence”.

Besides, the observed slow rate of convergence has not been stable over time. The dispersion of per capita income across regions within the EU countries has declined, a σ -convergence¹, with an absolute β -convergence² during the 1960s and the first half of the 1970s. In the following years, however, except for a trivial absolute β -convergence rate, disparities in per capita income across regions within European nations have stagnated.

The stagnation is observed in particular across the regions at NUTS2 level rather than at

¹ σ -convergence measures the evolution of standard deviation in real per capita incomes across economies over time. If the standard deviation gets smaller over time, it suggests that the variation in real per capita incomes across economies is declining, or vice versa. However it does not necessarily mean poor economies are catching up with real per capita income levels of relatively rich ones.

² β -convergence measures the average speed of growth rate in real per capita incomes across economies with respect to their initial year per capita income levels. If annual growth rates of cross economies are run only on real per capita income levels at their initial year, and a negative association between them is estimated, then β -convergence is absolute. If other factors of growth process are accounted for, and a negative association between the initial year per capita income and annual growth rate is estimated, then it is conditional one. So, β -convergence does not guarantee that the variation in real per capita incomes across economies declines. That is, β -convergence is necessary, but not sufficient condition of σ -convergence.

NUTS1 level³. The annual speed of convergence for the EU regions has been smaller and has declined significantly, particularly after 1981 (Martin and Sunley 1998).

On the other hand, some empirical studies that have used panel data with fixed effects method have estimated convergence rates much larger than those found in other studies. Particular ones for example have found convergence rates between 4.3-9.3 % across-countries, about 11 % for a sample of OECD countries, and 23 % for European regions. According to de la Fuente (1997), these findings cast some doubts on the traditional neoclassical approach to the convergence hypothesis. These observed rates of convergence in per capita income are too large to be explained simply by decreasing returns to capital accumulation. So other sources and mechanisms, such as technological diffusion, mobility of production factors, and changes in sectoral composition of production process, play substantial roles in the convergence process.

The findings of regional convergence studies and the neoclassical estimation method of them have been also criticized by some regional economists from various points of views (Martin and Sunley 1998, p. 206-207). One is connected with the specified growth process, which simply relates a region's growth to its own history and hence assumes that the convergence generating process is identical across regions, which is an inappropriate assumption. A particular weakness is that this approach fails to consider various interdependencies. Also, the significant clustering of similar growth regions over space implies that spillover effects are geographically localized, which

³ NUTS (nomenclature of territorial units for statistics) are the regions within countries of the EU. The EU15 geography is broken down into 78 regions at level 1 (NUTS1) and 211 regions at level 2 (NUTS2). To make data available and to help in the implementation of regional policies, the NUTS are determined based on the criteria of institutional division. Hence, the regions are in some respects are fairly heterogeneous.

neoclassical theory does not explain. Further, the regional convergence does not appear a smooth process, but varies across space and over time.

3.2.2. Quah-type empirical studies on regional convergence

Alternatively, some approaches do not find any significant evidence of convergence across countries and across regions within nations (Quah 1993a,b; 1996a,c; and Magrini 1999). For instance, by exploiting models of cross-section distribution dynamics such as the Markov chain rule, Quah (1993a,b; 1996a,c) finds a polarization of per capita income distribution across countries. That is, rich countries continue to stay rich while poor countries continue to stay as poor. Some of the middle-income countries, however, switch to the rich pole while others switch to the poor pole with the middle-income class of countries vanishing over time. Besides, Quah (1996b) finds convergence in per capita incomes across regions within clusters that are made up of contiguous groups of regions over the EU physical geography. In other words, when the levels and development over time of per capita incomes of the contiguous regions for each region are interdependently accounted for, rather than considering each region as an independent unit, regional convergence clusters are strongly observed. Regional well being and convergence in per capita incomes are also affected significantly by the economic well being and performance of the host nations, but less than that of the surrounding regions. That is, the regions that are within or closer to the EU core of the rich and fast growth nations have on average grown and converged in per capita income relatively more than the others. However, this fact is much more so for the regions that are surrounded by the rich and fast growth regions rather than the nations. Thus the physical location and spillovers, which are due to both mostly regional and host-nation factors, explain a

substantial part of the inequalities in and distribution dynamics of per capita incomes across the EU regions. Further, Magrini (1999) uses a Quah-type methodology and finds some evidence of divergence across the EU functional urban regions during the period of 1979-1990, using the data set constructed by Cheshire and Carbonara (1996). In particular, growth rates of six developed regions diverge from the rest of the EU regions.

Lopez-Bazo et al. (1999) empirically and spatially analyze the evolution of the EU regional income distribution during the period between 1980-1992 by exploiting an approach analogous to that of Quah and others. The findings suggest that the EU integration process has contributed to the convergence in per labor income, but not in per capita income. This may have happened because the overall liberalization in all markets and the regional policy measures supporting the infrastructure of poor regions as a consequence of the integration process have increased the competitiveness of firms in the poor regions. If not, the firms that could not withstand competition have been eliminated from the market, elevating unemployment levels in poor regions. As a result, the competitiveness of the surviving firms in the market and hence labor productivity in those poor regions has improved. But per capita income in poor regions has declined, because the ratio of employed population to the whole population has diminished. This suggests that cross-regional migration is very weak in responding to wage and unemployment rate differentials in the EU. Furthermore, the geographical location of clusters of regions with high value added production sectors, the traditional core of the EU, has shifted southwards somewhat because new regions have emerged that host new high value-added sectors at the expense of the mature ones in certain regions of the

traditional core. However, not all poor regions have displayed the same performance. Some peripheral regions did not improve their position.

Neven and Gouyette (1995) assess convergence in per capita income across the EU regions for the period between 1975-1990 based on three alternative methodologies: β -convergence, σ -convergence, and Markov chain models. They observe substantial disparities in the convergence patterns across different groups of regions and across different periods. The southern regions of the EU reveal convergence in the first half of the 1980s, while convergence stagnates in the second half of the 1980s. In contrast, the northern regions of the EU experience stagnation in convergence or divergence in the first half of the 1980s, whereas they converge significantly thereafter. Thereby, the northern regions of the EU have adjusted relatively better to the structural changes following the recent acceleration in the European integration process. As a result, this evidence gives support to the pessimistic view that the European unification may increase the disparities across the EU regions.

Cuadrado-Roura et al. (2000) find absolute β -convergence with an annual speed between 2.8-3.5 %, and a much larger conditional β -convergence, (by controlling region-specific effects based on time series and cross section data) around 17 % for the period between 1981-1990. They attribute this difference from earlier studies to controlling region-specific effects. On the other hand, they observe that the evolution of labor productivity has generated considerable regional differences even within relatively homogenous regions, although a global convergence in labor productivity prevails. Conditional β -convergence is found perhaps because of the region-specific effects, but it does not teach us further because of the restrictions of the traditional neoclassical

approach to the convergence hypothesis. In other words, simply finding of a conditional convergence does not explain whether the disparities in per capita incomes across regions are diminishing, and whether poor regions are catching up with per capita income of the rich ones. Indeed, cross regional growth is a multivariate process because many forces determine it eventually, while some of them lead to convergence, others to divergence. Therefore, they suggest that an alternative methodology, beyond the neoclassical approach, can provide us deeper knowledge about this heterogeneous behavior. Their empirical evidence suggests that certain regions are dynamic with high growth rates, but they are not necessarily the most developed ones in the EU. Other regions are characterized by stagnation and much lower growth rates, but they are not necessarily the less developed and peripheral ones. Hence both processes of convergence and divergence have acted simultaneously along side the further EU integration. Regional growth and especially productivity in labor are determined by region-specific factors. A highly complex interplay between technological and structural change, which ranges from the integration of technological change, to the innovation of new products and processes, to the structural change in industrial composition, contribute to the labor productivity. However, some EU regions have had rapid productivity growth at the expense of employment, while others have achieved success in both of them.

Paci and Pigliaru (1999) assess the impact of industrial mix and its change based on the three main sectors on regional economic growth of the EU in the period between 1980 and 1990. They discover that the major contribution to the overall labor productivity growth comes from the service sector. This effect is stronger among the more advanced Northern regions because growth rate of productivity in the service sector

is relatively greater than that of the other regions and the other sectors in these regions. In the Southern regions, in which agriculture still has a relatively large share in economy, a significant contribution arises from the shift of labor from low productive agriculture to higher productive industry and services. The observed overall convergence originates essentially from industrial and service sectors and from the Northern regions. Moreover, the great portion of the convergence originates from the structural change. The convergence among the Southern regions is weaker than among the Northern ones. Sectoral composition varies tremendously across regions of the EU.

The analysis of Paci et al. (2001) shows that sectoral dynamics based on three main sectors explain much of the observed regional disparities in labor productivity and employment performance in the EU. Rich regions with a small agricultural share have grown relatively slowly, while poor regions with a large agricultural share have grown relatively rapidly as their agricultural shares show a fast decline. Hence the observed convergence in aggregate labor productivity arises from the transfer of labor and other resources from agriculture with low productivity and large shares in less developed areas to the other sectors: industry and services. Labor productivity in regions specialized in industry has grown faster relative to that in regions specialized in services (mostly metropolitan or urban centers), while employment rates have grown relatively faster in locations specialized in services relative to locations specialized in industry. Consequently, the growth in aggregate labor productivity has been greater and employment growth less in industry intensive regions as labor shifts from agriculture to industry. In contrast, in services intensive regions the growth in aggregate labor productivity has been smaller, but employment growth faster as labor shifts from

agriculture to services. The other crucial factor that has influenced the convergence process is the intrinsic technological capability of localities to innovate and to imitate innovative economies.

A. Cappelen, J. Fagerberg and B. Verspagen (2000) empirically assess the EU regional growth process and the impact of regional support from the EU or national sources between 1981 and 1997 period with a technology gap model. They observe very small regional convergence within the EU countries. It is essentially originates from the catching up by the Southern nations following their entry into the Union in the 1980s. Regional support to the backward regions contributed to the underlying convergence between nations rather than across regions within countries. In spite of increase in structural funds and new regional policies, this new evidence of policy ineffectiveness has brought new discussion and caution regarding regional policy.

So, the evidence from regional convergence studies based on different approaches appears mixed and controversial for Europe.

On the other hand, recent regional development studies, in contrast to those empirical studies testing regional convergence or divergence, have emphasized geography and location, and accounted for local dynamics, externalities, and increasing returns to scale in explaining the differential growth across regions. The approaches of those studies differ by treating the sources and nature of externalities and increasing returns to the regional economic process. That is, there is a growing literature on new economic geography, localized knowledge accumulation, and knowledge spillovers. One stream of these new approaches takes geographical advantages of certain regions as endogenously determined by the ease of interactions among economic agents. This

approach takes particularly the Marshallian pecuniary externalities as an essential element, but not the Marshallian pure externalities (localized knowledge spillovers), of the geographical agglomeration of economic agents. Long term interactions, and hence the trust between suppliers and manufacturers, allow externalities to occur in a location (Caniels 2000, chap. 1).

3.2.3. Krugman-type analyses of European regional economic development

A different approach to analyzing the regional development problems has been developed by Paul Krugman and his colleagues. Many regional economic analyses of geography and development have been substantially influenced by this approach. Martin and Sunley (1998) explain that Krugman's pessimistic argument relies basically on the work of Blanchard and Katz (1992), which analyzes the patterns of growth across the US states. Their seminal work finds that because states have heterogeneous intrinsic amenities and diverse industrial structures, they respond differently to demand shocks. This leads to permanent change in employment rates across states, while the impact on real wages and unemployment rates decays and they tend to return back their natural rates in a few years. This is so in the US because labor mobility is higher relative to that of plants in responding the wage and unemployment differentials across states. Blanchard and Katz (1992) note that because the EU, unlike the US, does not have an effective interregional transfer system, and because labor mobility is also lower than in the US, the influences of shocks on unemployment will be stronger and last longer. Most Krugman-type studies imply that because certain regions have the advantages of substantial external and agglomeration economies, and path dependency, these leading locations will benefit much more from the overall gains of the further integration. Krugman claims that

the higher levels of regional specialization and factor mobility in the EU are most likely to accelerate the discrepancies in economic growth rates across nations and regions (see Martin and Sunley 1998).

Indeed, the basic argument of this approach relies on a prominent contribution to economic geography by Krugman (1991). He builds a regional clustering model of manufacturing activities in which manufacturing firms tend to locate in the region where the demand is larger. The demand indeed is greater in the location where manufacturing activities are concentrated. This circular causation is driven by pecuniary externalities arising from demand or supply interactions across manufacturing firms within those manufacturing clusters rather than by pure knowledge spillovers. In this version of the monopolistic competition model, a manufacturing firm can always operate with increasing returns to scale in production, given that it is located in a region where manufacturing activities are concentrated, because of external economies to the firm in that location.

However, the interaction among three parameters determines in which location and to what extent regional concentration of manufacturing activity takes place.

“When some index that takes into account transportation costs, economies of scale, and the share of nonagricultural goods in expenditure crosses a critical threshold, population will start to concentrate and regions diverge; once started, this process will feed on itself. ... Also, which regions end up with the population depends sensitively on initial conditions. If one region has slightly more population than another when, say, transportation costs fall below some critical level, that region ends up gaining population at the other’s expense” (Krugman 1991, p. 487).

Krugman and Venables (1996) state that

“... agglomeration has been a more potent force for interregional than for international specialization. Barriers to trade between national economies –both formal barriers such as tariffs and the de facto barriers created by differences in

language and culture, lack of factor mobility, and the sheer nuisance presented by the existence of a border— are often enough to block the expansion of a successful industrial district beyond its national market. For this reason, industries within Europe are in general much less geographically concentrated than their counterparts within the US” (p. 960).

These arguments suggest three plausible outcomes of European integration. First, if the integration does not considerably reduce costs in the EU, linguistic and cultural disparities will still continue to segment national markets, leaving current spatial patterns unchanged. Second, the increased integration can lead markets to be substantially connected, but it may not be sufficient to change the distribution of production over the EU geography. Finally, the accelerated integration of the European markets may lead the existing national industries to concentrate in smaller number of industrial districts in the whole EU. Consequently, the integration will bring about long run gains, but during the adjustment process some locations may suffer as the industrial structure of the EU changes (Krugman and Venables 1996, p. 959-967).

According to Puga (1999), greater European integration may not result in higher concentration of activities and lower income disparities across the EU regions. He expects cross-regional migration to remain at a very low level in responding to interregional differentials in wage and unemployment rates; consequently the tendency of firms to agglomerate will be relatively slow. This fact can lead to a non-monotonic relationship between integration (i.e., decline in transport and transaction costs) and agglomeration. The simple intuition behind this view is that if trade costs are high before the closer integration, industrial activities are spread across regions to meet final consumer demand. As trade costs fall with the further integration, cost and demand connections between various markets in an economy bring about agglomeration in

activities exposed to increasing returns. Some empirical studies support this relationship. The findings support an inverted-U shaped relationship between the extent of regional integration and spatial agglomeration in the EU. Until the regional integration reaches at a mature level, the economic activities are spatially concentrated in particular regions to exploit agglomeration economies. Hence the activities in those regions will be relatively more productive. However, after the mature level of the regional integration, the pecuniary externalities due to the supply and demand relations across various markets will spread over larger geography. Hence, once the EU integration goes far enough, interregional convergence in both real wages and production structure may result, but during the early and intermediate stages of the EU integration it is likely the large real wage disparities across regions will continue.

In a report prepared for the EC, Braunerhjelm et al. (2000, p. 1-27) analyze three possible outcomes that further EU integration may create. First, economic activities could be dispersed broadly over the EU geography with considerable equity while most of regions specialize in something. Second, those activities could strongly concentrate over the geography by high labor mobility. It can lead to migration out of declining regions, but not to large inequality of per capita income or unemployment conditions. Finally, it could result in long run polarization of economic activities over the EU geography. They argue that further European integration will encourage regional specialization of economic activities. Individuals and firms will increasingly shape regional clusters to share their particular knowledge and skill pools. These knowledge and skill pools may be within the same industry or simply share a functional specialization among various industries. This specialization, however, would not necessarily bring about a polarization

of Europe with advanced regions with high incomes and low unemployment on one side, and backward regions with low income and high unemployment on the other.

Braunerhjelm et al. (2000) observe that in some ways the EU is becoming similar to the US economy (for instance, with greater flow of capital across the members), but in other ways it is not (for instance, with lower flow of labor across the nations). In other respects the US provides an illustrative example for the EU. For instance, industries are clustered much more in the US than in the EU. This means that there exist large possible benefits yet to be realized from clustering of activities in the EU. Furthermore, even though economic activities cluster or agglomerate relatively more in the US than in the EU, they are less geographically polarized in the US. So, geographical polarization of economic activities following clustering of them is not an automatic outcome. Apparently certain forces such as scale economies, learning effects, pecuniary and pure externalities result in clustering of activities while other forces such as factor immobility, congestion externalities and intrinsic heterogeneity of preferences lead to dispersion. The overall consequence depends on the balance of these forces and particularly size of the integrated market. At this point, government policy might play significant role in preventing polarization. However, misguided public policies in order to prevent polarization can result in inefficient outcomes.

There are essentially two ways that the market linkages and pure externalities can create agglomerations. First is related to the vertical linkages, which implies the advantages of increasing proximity of markets for intermediate and final goods. It relies on transportation and other distance costs. Second is related to horizontal linkages, such as direct knowledge spillovers between firms and indirect knowledge links through a

common local pool of skilled and specialized labor. Information, telecommunication, and internet technology facilitate easy and cheap communication over long distances, so that it has reduced the agglomeration forces associated with vertical linkages. However, in most cases direct knowledge flows are related to informal and face-to-face local communication. This is why, horizontal linkages are most likely to be more essential than vertical ones as an agglomeration force. Then, functional instead of industrial agglomerations are most likely to occur (Braunerhjelm et al. 2000, p. 26-27).

“Integration not only causes specialization in production, but also increases the rate of diffusion of knowledge between members ...” (Hansen and Neilsen 1997, p. 90).

While the further integration has positive dynamic effects on the entire economy, it may not do so on less dynamic sectors and regions with poor learning capabilities. Because the more dynamic sectors are distributed unevenly over the EU geography, the further integration has affected regions differentially (Hansen and Neilsen 1997, p. 91). The less developed regions are dominated mostly by low technology sectors, and any particular sector in those regions uses less advanced technology than in developed regions. Further integration may make this specialization pattern sharper, and learning effects will make the developed regions stronger. Further integration then brings about divergence. Consequently, they argue that the theoretical analysis does not lead to clear-cut conclusions about the effects of the integration on regional development. In reality the single market process will lead some regions to catch up while others lag even further (Hansen and Neilsen 1997, p. 95).

4. R&D Activities, Knowledge Spillovers and European Regional Development

According to Bozeman (2000, p. 627), technology transfer is a complicated issue to understand for several reasons. First, there is no limit on technology. Second, technological knowledge may be transmitted in many ways, so that defining a pattern of technology transfer is very tough problem. Third, measuring the impact of technological knowledge spillovers is challenging because they can influence so many variables and hence it is not easy to isolate their impact on a particular variable. Even though a huge literature exists, most studies are not empirical. As a result, we know little about how technology and technological knowledge spillovers affect the economic development differently across economies (Bozeman 2000, p. 649-650).

4.1. The theory of localized knowledge spillovers

Another stream of the new approaches to the regional development takes localized knowledge spillovers as the essential force for geographical concentration of economic agents, especially of high-tech firms. The principle reason for this is that communication is easier (informal) and more effective among economic agents within a particular locality than across different communities. On the other hand, because information and telecommunication technologies have lately made rapid progress, people might perceive that economic agents can access distant knowledge at a trivial cost. However, if it can be available to everyone and everywhere with only a trivial cost, it is information instead of knowledge. Knowledge is in a great extent tacit in its character and is embedded in human capital accumulated over time. The diffusion of this kind of knowledge thus requires learning by doing and face-to-face contacts between individuals

and firms, so that the cost of transmitting knowledge increases with distance. That is, tacit knowledge is sticky with firms and geographical location and cannot be transmitted easily and without cost. Then, it is important for individuals and firms to locate close to the knowledge, to make good use of it. Hence, R&D activities and innovations agglomerate in certain regions. That is why, technology disparities across geographic locations are likely to exist (Caniels, chap. 1).

The reasons why R&D activities are locally bounded can be collected under five categories (Caniels 2000, chap. 1): uncertainty, complexity, reliance on basic research, importance of learning-by-doing, and cumulateness. The first two imply that investing in innovations requires taking high risk by individuals or firms because the revenue value of the outcome is uncertain. Individuals or firms interacting closely in space can access more local knowledge, and therefore reduce uncertainty. The third category suggests that innovative activity is strongly connected to basic scientific knowledge such as academic findings generated in universities and R&D funded by government. Firms, by interacting closely with a university environment have advantages in innovation relative to other firms. Private firms benefit more from knowledge spillovers the closer they are to sites of basic research universities and government laboratories. More concentration, experience, and specialization on the same subject will increase productivity of innovativeness. Knowledge generation is a cumulative process in its very nature in the sense that new knowledge is generated based on the existing knowledge, which is built on the earlier knowledge. This aspect of innovative activity can essentially explain the uneven regional distribution and local clusters of innovations.

4.2. The geographical distribution of R&D activities

Several empirical studies on the US and the EU regional data have shown that innovations (number of patents or innovation counts), R&D intensity, economic activities, and population are geographically distributed unevenly across regions and across branches of industries. Certain industries have spatially clustered much more than all manufacturing. Innovations and R&D activities are much more regionally concentrated than other economic activities and population, and they are clustered within certain sectors and locations (Audretsch and Feldman 1996; Feldman and Audretsch 1999; Caniels 1997; Bottazzi and Peri 1999; Verspagen 1999; Paci and Usai 2000; and Caniels 2000, p. 127-128). This fact indicates the presence of substantial technological knowledge gaps across regions, so that it suggests a significant potential for knowledge spillovers across regions.

On the other hand, business sector R&D in the EU is concentrated spatially much more than university R&D in general. This could be attributed to the fact that the governments of most countries have played a role in an equal distribution of universities within their countries. However, when government R&D is considered, the results differ by country. In some countries, like Spain and Italy, the geographical concentration of government R&D is strong. In other countries government R&D is less concentrated spatially than business R&D (Caniels 2000, p. 128).

4.3. The empirical studies on knowledge spillovers and regional development

The role of knowledge diffusion in explaining regional disparities in economic growth has developed in the literature in the last few decades, according to Caniels (2000, p. 5). Caniels suggests that this is particularly due to the domination of neoclassical theories in economics. Furthermore, most of empirical and econometric studies have estimated the size and significance of regional spillovers in different ways. The importance of geographical proximity in benefiting from knowledge spillovers is emphasized in these studies. However, how the knowledge spillovers are geographically clustered and transmitted is not well understood. In addition to geographical proximity, technological proximity to an economically active region is crucial for knowledge spillovers. The empirical studies in this regard can be examined within two broad contexts in terms of methodology. One strand of them has employed a Cobb-Douglas type knowledge production function. The technological knowledge or innovation in a spatial economy is determined by the foreign R&D, university R&D, government R&D and its own domestic R&D. The other strand has attempted to estimate the impact of knowledge spillovers due to the R&D on level or growth of the total factor productivity or labor productivity based on output production functions.

4.3.1. The empirical evidence from the studies of knowledge production function

A couple of key empirical studies using the knowledge production function have found that knowledge spillovers have a significant positive impact on regional innovation and R&D, by both directly increasing innovation productivity per unit of R&D effort and indirectly increasing R&D investments in a region. However, the significant influence of R&D spillovers are geographically bounded by physical distance and the major part of knowledge spillovers across localities takes place within particular sectors. The initial

empirical article using US firms' data by Adam B. Jaffe (1986) has triggered many empirical papers in this field. He reports that the productivity of a firm in producing knowledge (number of patents) is an increasing function of other neighbor firms' investments in R&D in similar technology space.

The next empirical paper by Jaffe (1989) encouraged many empirical studies in the same tradition to measure the localized knowledge spillovers due to the university R&D and government sector R&D. He finds evidence that university research has significantly influenced the private innovations (number of patents), especially in certain-high tech sectors. It has also significant impact on private R&D investments, but the causality is not other way around. However, only weak evidence is found to support spillovers due to the geographical coincidence of universities' research labs within the state. The impact lies more clearly in a sector or technology cluster rather than across the geographic areas within the state. On the other hand, Acs et al. (1991) argue that the number of patented inventions is not a good direct measure of innovative output. An alternative and more direct measure of innovative output is the number of innovations, because each innovation is recorded immediately following its introduction in the market. Also, small new entrepreneurial firms attempt to capture more knowledge spillovers from university R&D relative to large-scale firms. After this alternative measure is used, two substantially different outcomes relative to that of Jaffe (1989) emerge. First, the impact of knowledge spillovers due to university research almost doubles. Second, the knowledge spillovers from geographic proximity of private R&D activities to the university R&D activity are much greater.

The recent studies have emphasized the various specific industries and spatial dimensions in this field. Among the noticeable empirical studies, Anselin et al. (1997) re-estimate the knowledge spillovers between university R&D and high technology innovations at both the state and MSA level. Spatial econometric technique is exploited to account for spatial effects. Jaffe's geographical coincidence index is defined based on the gravity potential and covering indices regarding the distance and interactions across spatial units. They find strong evidence of local spillovers at the state level. The evidence at metropolitan (MSA) level supports knowledge spillovers from university R&D in both respects, directly by affecting private innovation and indirectly by affecting private R&D investments. The spillover impacts of both private sector R&D and university R&D are significant within the concentric distance of 50 miles around the core MSA. In the next study, Anselin et al. (1998) employ a finer divided high-tech sectors data across a larger number of spatial units of MSAs. They benefit from spatial econometric methods that combine spatial dependence and spatial heterogeneity in the form of spatial regimes. The findings confirm the earlier ones that the spillover impacts of university research on innovative productivity are not uniform. Further, they differ substantially across sectors. They also observe regional differences in the innovation process. The spillovers can reach a broader geographical area based on the high-tech sector, but not at aggregate level as found in the earlier work. They suggest that in such an empirical study aggregate data can be misleading and that a proper specification of both sectoral and spatial characteristics is necessary.

The evidence from the European regional data:

Several prominent empirical studies using the knowledge production function have analyzed the European data. Among which, Feldman and Lichtenberg (1997) find evidence that private R&D activities tend to specialize in the same science areas where the universities and public organizations do within a nation. The data also suggests that private sector R&D activity is more sensitive to R&D activity in public organizations than to that in universities. Further, they find that greater ability to communicate research findings, that is, the research that leads to more codifiable knowledge, stimulates less centralized R&D activity. Further, Bottazzi and Peri (1999) construct a demand pull model in which innovations and investment in innovations (R&D) are endogenous. They find that regional heterogeneity in R&D activity explains most of interregional disparities in patenting intensity. The cross-regional spillovers are significant for only the R&D activities of close neighbor regions. They are significant until 400 km geographic distance is reached. Moreover, the interregional knowledge spillovers of neighboring regions are strengthened by the technological similarity of industrial structure of the regions.

Criticism of the empirical studies of knowledge production function:

David and Hall (2000) argue that the large econometric literature (more than 50 papers, mostly quite recent) that measures the interactions between public and private R&D investments and their joint impacts on the economy have reported confusing and mostly conflicting estimates. The results change based on various approaches employed, levels of aggregation, specifications and estimation methods of econometric models. Moreover, the theoretical frameworks of those empirical studies are not usually provided so as to suitably interpret the empirical findings. Only a structural specification can

enable us to observe various channels of effect and to examine their plausible interactions within a more comprehensive equilibrium framework. The econometric literature on this problem has tried to measure without theory; a structural framework is necessary to interpret the empirical findings.

Moreover, Breschi and Lissoni (2001) criticize recent econometric literature on localized knowledge spillovers that relies upon the concepts of tacit and uncodifiable knowledge. The increasing and unconditional acceptance of such econometric evidence and theoretical concepts that support industrial locations, high-tech concentrations, and local innovation clusters of research and development is not well grounded and may lead to conceptual ambiguity. Those concepts might suggest that knowledge transmission among the economic agents is a consequence of the market mechanism and should be thought of as pecuniary externalities rather than pure knowledge spillovers. Economic agents invest intentionally in codification and knowledge transmission process. The marginal cost of investing in codification and knowledge transmission process will equal the marginal benefit from the transmitted new knowledge of rival economic agents. Because of mutual benefits on both sides, they contribute to and exchange their new knowledge through the existing network. Otherwise, mainstream economics does not have tools to explain the complexities that prevail in the market. It may require different analytic tools. Knowledge producers might receive substantial benefit from transmitting their new ideas to their local rivals without any compensation or feedback from them because they also learn of their local rivals' new ideas. Any economic agent may expect always to access new knowledge in an agglomeration without any compensation and without sharing with others.

The recent developments on these concepts claim that the knowledge flows, not the knowledge stocks, are tacit. Codification is both a means of transmitting the knowledge and a powerful tool of exchanging it that appears tacit to outsiders, but is an intentional act of economic agents responding to market incentives. In contrast to the conventional wisdom, this implies a community in which corresponding trust, social bonds, understanding each other and communicating the economic messages do not require living within the same local community. This type of community can be formed with economic agents working on the similar subjects. So, the knowledge is codified for and exchanged among the economic agents even far physical distant within the network, but it is still tacit and un-codified for agents even in the same locality outside the network. Then, the distance does not matter significantly to transmit the knowledge across economic agents. It can be perceived as a club good rather than a local public good. The authors actually do not deny that knowledge spillovers are important agglomeration force and a major part of them takes place in certain locations and regions. They criticize the conventional wisdom, that anyone can access pure knowledge spillovers without any cost in a spatially bounded locality, exploiting the concepts above to explain it.

4.3.2. Empirical evidence from the studies of output production function

The observed data suggests that investments in R&D actually have two objectives to achieve in a market economy. Cohen and Levinthal (1989) argue that a firm invests in R&D to innovate new knowledge and to enhance its ability to identify, assimilate, and exploit the existing knowledge generated by other firms in the economy. Many regional studies have been influenced by this analogy. Some regions are important knowledge

producers, but many other regions exploit knowledge spillovers from the producing regions. Knowledge spillovers increase the productivity per unit R&D effort, and thus increase innovations for given amount of R&D and increase investment in R&D in the innovative regions. Hence the knowledge spillovers are most likely to influence indirectly output production of these types of economies. On the other hand, most economies are non-producers of innovations, have relatively low R&D capital stocks, and are not in the clusters of the regions with high R&D capital stocks or innovations. They use new knowledge or innovations that can be codified and transferred, as an input in output production or as a factor that increases the efficiency of output production process.

The evidence from the OECD countries data:

The other stream of recent empirical studies has attempted to estimate the impact of knowledge and knowledge spillovers due to the R&D on the level or growth of total factor productivity or labor productivity across economies. Given data availability, the pioneer ones have studied the OECD countries. The statistical evidence from these studies indicates fairly strong knowledge spillovers across those countries. They are especially stronger within the same industries, or are due to private sector rather than public sector R&D. They increase with openness to trade and decrease by distance. Among the outstanding ones, Coe and Helpman (1995) find empirical evidence that own country R&D capital stock and foreign R&D capital stock significantly affects TFP. And the impact of foreign R&D capital stock increases by the degree of openness to trade of country. Moreover, own RD efforts enhance a country's benefit from spillovers due to R&D efforts of foreign countries.

Walter G. Park (1995) finds that both domestic and foreign R&D investments have affected growth of a country's TFP. Technological knowledge spillovers across countries due to their R&D efforts are much more effective within the same sectors and less across different sectors. The impact of private sector R&D investments on the growth of a country's TFP is more significant than that of public sector R&D investments. Public sector R&D investments have contributed to TFP growth indirectly by encouraging private sector R&D efforts. Some countries have benefited relatively more from foreign knowledge spillovers than they have contributed, while the other few top ones with respect to R&D capital stock have generated more knowledge spillovers than they benefit. Wolfgang Keller (1997) estimates an elasticity of TFP with respect to own-industry R&D between 0.07-0.17. The elasticity of TFP with respect to foreign R&D within the same industry is between 50-95 percent of that with respect to own-industry R&D. However, the inter-industry knowledge spillovers are less effective, even within a domestic economy, in raising productivity.

Eaton and Kortum (1996) find that more than 50 % of the labor productivity growth in each country is determined by innovations in the US, Germany, and Japan. Again, more than 50 % of the growth in productivity of every OECD country rather than the US is attributable to ideas that originated abroad, the number for all except the five leaders in R&D is higher than 90 %. However, the flow of knowledge across countries decays by distance while it increases by trade relationships and education level in the country. The results suggest quite strong international diffusion. The US contributes the most of any foreign country, and more than the home country in all except Germany. Countries other than top-five innovative ones contribute less than 10 % to their own

growth. Consequently, obstacles to knowledge flows are adequate to lead to significant disparities in productivity across countries.

On the other hand, Eaton et al. (1998) observe that European nations have lower R&D efforts than the US and Japan, perhaps because they have smaller and more fragmented markets, and hence less incentive to innovate. Indeed, their potential research productivity is on average even greater than in the US and Japan. That is, most European countries have an intrinsic capacity to do research, but have a lower overall knowledge base relative to the US and Japan. So, increased R&D efforts in the EU would raise the EU average income, even more than such an increase would do in the US and Japanese economy. Various policy measures to stimulate R&D in the EU would increase productivity not only therein but also in other OECD countries. However, in many cases the country implementing the policy benefits less than the other members of the EU because there is a strong potential for free riding.

The evidence from the European regional data:

Several empirical studies using EU regional data have shed light on the fact that there exists a substantial potential for the knowledge spillovers as a determinant of disparate regional economic performance. The uneven regional distribution of innovative, R&D and economic activities and labor force over the EU geography influence the locational dynamics and disparate regional performances in the EU. Verspagen (1999) stresses that the heterogeneous groups of EU regions differ more from each other in dynamic aspects than in static ones. It is not adequate to classify the regions into just two categories: innovative clusters with high R&D intensity high-performing regional economies and the rest. Investing in R&D is not simply for innovating, but also for

imitating and implementing of innovations from other locations. On the one extreme is the most innovative and rich cluster of regions with high R&D intensity, patenting in high-tech sectors, and modest growth. On the other extreme is the poor cluster of regions with the lowest innovativeness, specialized in low technology with low R&D intensity and the lowest growth. However, between these two extremes, the two different clusters with less R&D intensity relative to the first cluster have grown faster than the most innovative richest cluster. The majority of these regions are located near⁴ technological core regions. Despite their weak technological capabilities to innovate, they may benefit from technology spillovers from the innovative regions.

Rodriguez-Pose (2001) observes that investment in R&D activity in the cluster of the EU core regions with relatively high levels of their R&D activity have on average declined, while those have in general expanded in the periphery regions with relatively low levels of their R&D activity between 1986 and 1996. The decline in the R&D effort of the EU core can be attributed to the economic rationalization following the integration, which may allow a gradual elimination of duplications in R&D activity across countries.

In contrast, Lucas Bretschger (1999) argues that

“the problem for development might not be the lack of trading opportunities, which are still at a very high level, but the incomplete integration in European knowledge networks. ... the cross-border restrictions on the markets for skilled labor harm learning-intensive face-to-face contacts to a certain extent” (p. 265).

All but a few of technologically backward regions have both increased their R&D effort and experienced economic growth faster than the EU average. It is difficult, however, to measure what part of this association between growth and R&D investment in technologically lagging regions is the outcome of technological progress and what part of that is the outcome of other factors. Further, regarding all EU regions, there exists a

weak overall association between the development of R&D expenditure and growth of GDP. There are many plausible reasons for this outcome. One is the relationship between growth and R&D may be conditional on the other factors. A crucial factor may be related to the industrial structure of these regions. Some regions have relatively high share of agriculture or services, or tourism, in their economy. The most plausible explanation may be related to the existence of technological knowledge spillovers and the capacity of regions to assimilate, or free ride on, externally generated ideas within an accelerated economically integrated environment. Since technologically advanced regions have sound R&D infrastructure, they can also receive, adopt and assimilate externally generated innovation, and subsequently they can transform innovation into economic activity (Rodriguez-Pose 2001).

Many of the lagging regions may face difficulties in transforming their improved innovative capacity into economic activity for several reasons. They may not have a Schumpeterian threshold of R&D investment. They may have invested in different types of R&D activity, i.e., in major part in the public sector and basic research, which may cause greater time lags, and limit the capacity to transform the technological progress into innovation and in turn into economic activity in these areas. For instance, in Spain the great part of expansion in R&D investment is due to the university sector, and in particular to the founding of universities and the improvement of the current ones in lagging regions. Maybe the main reason is the weak economic structure of these regions. Rodriguez-Pose (2001) concludes that investment in R&D in lagging regions may become in the long run a more effective and less costly alternative to social transfers and to the investments related to the traditional development programs.

In his earlier study, Rodriguez-Pose (1999) finds statistically a significant positive, but weak correlation between R&D effort and growth in GDP across the EU regions on average, with some outliers. He argues that the capability of any location and region to generate new technological knowledge inside and to implement or imitate those from outside is not uniquely tied to the magnitude of local resources invested in R&D. As a result, the transition from R&D investments to innovations or technologic knowledge and in turn eventually to output or productivity growth is not a smooth process. It substantially differs by localities and regions. As a matter of fact, many factors beside economic condition determine the innovative capability of a location or region. He finds that localities with unfavorable social conditions to innovate cannot succeed in transforming resources invested in R&D into economic activity while localities with favorable social conditions are in general successful.

Fagerberg et al. (1997) empirically investigate the dynamic interrelations of some key determinants in growth disparities across the EU regions. They find that R&D effort and R&D capability are both important factors in growth process. However, even though some catching-up is realized, the poor regions do not benefit enough from the spillovers of R&D activities in rich regions because they do not have an adequate infrastructure, i.e., educated and skilled labor force and supporting institutions such as universities. Moreover, the share of agriculture in GDP, the level of unemployment and country-specific factors (as measured by country dummies) significantly influence growth process.

Furthermore, Cheshire and Carbonaro (1996) specify a spatial process of regional economic growth for the EU. They emphasize spatial factors which are observed to have

plausible influence on the disparate per capita income growth in reality across the EU regions during the period between 1979 and 1990. Instead of a long-run balanced growth model, a spatial model, which reflects observed reality in explaining the differential growth of per capita income across the EU regions in medium-term, is specified. Under this specification, beside the other spatial factors, Romer's argument of increasing returns to technological knowledge is modified and tested in a spatial context. Spatial units, functional urban regions (FURs) across the EU are defined and employed rather than administrative ones in this research.

They find evidence that purely spatial variables and conditions dominate the differential growth process across the EU regions. The coefficient of Romer variable in spatial form is also consistent with the increasing returns. However, they find no evidence for either convergence or divergence on the basis of initial income level alone. Thus, Cheshire and Carbonaro (1996) conclude that

“since the determination of net changes in GDP per capita is a multivariate process, this does not necessarily imply that observed per capita incomes would diverge in any given time period. ... So there are some forces producing convergence and others producing divergence and the actual outcome over time is determined by the net effect of those forces” (p. 1125-27).

Cheshire and Magrini (1999) in a following empirical study, which is in a similar context to that of Cheshire and Carbonaro (1996) above, examine the factors that contribute to the regional growth and the extent to which certain factors create either divergence or convergence in per capita incomes. Almost the same variables but observed proxies for some dummies are replaced, and the cross section of spatial units (FURs) and the period of time are somewhat expanded in this work. The empirical model is a spatially specified version (Magrini 1997) of endogenous growth theory (Romer

1990; and Rivera-Batiz and Romer 1991) for EU regional growth. They find variables contributing to convergence and others to divergence. In this econometric specification for the EU regional growth, the knowledge spillovers due to R&D activity (as measured by staff in universities and R&D laboratories of Fortune top 500 companies) play an important role. The knowledge spillovers are divided into tacit and abstract knowledge. Interregional income disparities are attributed to the existence of a regional specialization process between knowledge creating and knowledge applying regions. The tacit type of knowledge spillovers is geographically bounded within certain clusters, while the abstract knowledge spillovers are open to the use of public everywhere. The advantageous regions in R&D activity can benefit relatively more from the both sorts of knowledge spillovers. Thus, they can offer higher wages relatively to the human capital engaged in working in R&D sector. Consequently, the human capital working already with relatively high wages will move in these regions. EU integration by reducing the transaction costs to the distance between nations can improve the influence of R&D efforts on the overall EU productivity, but differentially by regions (see the theoretical content in Magrini 1997). In conclusion, the empirical evidence suggests that the differences in technological competence in R&D substantially contribute to regional disparities and to their dynamics (i.e., in income levels and divergence). The spatial interaction across regions (measured by the sum of the differences in growth rates) can contribute to convergence in per capita income levels when the level of the interaction is considerably strong. The impact of the EU integration (measured by the change in economic potential variable) suggests that if all regions benefit evenly, divergence forces are not diminished significantly. The

employment share of agriculture sector in the total contributes to the divergence process, but simply between the poor regions.

Alternatively, Caniels (2000) develops a technology gap model in which the specific characteristics of a region are assumed to determine how knowledge spillovers take place. Among others, she finds geographic location and its technological distance from other regions are important factors for diffusion of knowledge. Based on this model she observes that the distribution of GDP per capita across the EU regions can be explained by knowledge spillovers, knowledge generation and learning capability.

In a recent empirical study Paci and Pigliaru (2001) specified an empirical model, which incorporates technological catch up as well as convergence in per capita capital. The technologic progress of the leading region is a consequence of its own innovativeness and R&D effort (number of patents) while the technological advance of the lagging regions are determined by both their own R&D efforts and the technology diffusion from the technology leader due to the technology gap potential to be realized by them. Thus the lagging regions have a potential to grow faster than the leader region, which is conditional on particular factors. By using a panel data approach on the EU regional data for the period of 1978-97, they observe that both capital deepening and the technological catch up are important determinants of the convergence process in total factor productivity across regions. The study exploits spatial econometric technique and finds that the performance of each region depends on that of surrounding regions, and diminishes by distance. The neighboring effects for a region reach until the third order contiguous neighbors of regions. The test results support the spatial lag model versus the

error model. After the spatial econometric technique is employed for correcting of spatial dependencies, the performance of the model improves significantly.

4.4 The importance of public sector R&D in the regional development

In addition, an important and relevant subject with the above discussions is the role of public sector R&D in determining the EU regional economic performance. A great fraction of R&D activities have been funded by government or/and done in research labs of government and universities. For instance, the share of total R&D expenditure funded by government is 32 % in the UK, 37 % in Germany, and about 45 % in both France and Italy (Feldman and Lichtenberg 1997). Those numbers are much more diverse across regions within countries.

“Public R&D –R&D directly related to government expenditure and to research in universities- has traditionally been less applied and considered more prone to generate spillovers than private R&D. Local returns of public investment in R&D are thus not expected to be as direct and as immediate as those of private R&D. However, ... public R&D plays a decisive role as the engine of innovative activity for small and medium sized enterprises in dynamic environments. From this perspective, public investment in R&D may influence productivity growth indirectly by means of stimulating private research investment. But even more important than this indirect effect on private R&D is the impact of public R&D on the output of local companies. This is achieved via the collaboration between local enterprises and local universities or research programs, or via public assistance to achieve greater competitiveness of local companies in a series of ways...”(Rodriguez-Pose 1999, p. 80).

On the basis of the US data, Bozeman (2000) has found statistical evidence that

“... 70 % of university laboratories view basic research as a major mission, 42 % of government laboratories do (and only 11 % of industry labs). ... 40 % of university laboratories were involved in technology transfer and 52 % of government laboratories. ... University laboratories devoted 44 % of their activity to publishing scientific research, compared to 36 % in government labs ...” (p. 634).

Once the great size and the different nature of public sector R&D is the case, the impact of public sector R&D and of the knowledge spillovers due to that on the regional

development is important to know because they have different implications than that of private ones. As the evidence has frequently supported, public rather than private sector R&D is exogenous, and it can be taken as a policy tool for regional development. However, there is also not an adequate empirical work on this dimension of the problem with respect to the EU regional development within our discussed context above, beyond the empirical studies in the type of knowledge production function. Few empirical studies, which are not worth to mention in much detail, have just touched the issue such as a side problem when testing the influence of private sector R&D effort on the levels or growth of total factor productivity and labor productivity in output production. They have simply concluded that public sector R&D efforts do not have a significant impact on the economic productivity and performance, but they have not considered the role of public sector R&D on the EU regional economic performance exclusively.

In conclusion, we have surveyed a large literature about European disparate regional development process based on the recent various popular approaches and along with the implications of the European integration process. Various approaches take different perspectives of the problem and suggest different results, so that the problem appears to be controversial and it seems there is not exist one-way solution or answer to that. However, alternative approaches emphasize some common factors to be crucial for the differential European regional economic performance. In this regard, technological knowledge generation within the region, knowledge spillovers across regions, in addition to other factors such as socio-economic infrastructure, industrial structure and traditional input factors, are recently emphasized as significant factors for the EU diverse regional performance. Moreover, the further European integration process is expected to influence

the regions diversely because of the heterogeneity of regions in those factors, if appropriate steps are not taken. So it is relevant to test whether these factors have a significant influence on the EU regional performance within the context of a spatial specification.

CHAPTER III

TECHNOLOGICAL KNOWLEDGE FOR ECONOMIC DEVELOPMENT: THEORETICAL CONSIDERATION

This chapter gives a descriptive review of mainstream economic growth theory with regard to the role of the technological knowledge in economic growth. The mainstream tradition with its simple assumptions provides a sound theoretical basis for learning or predicting stylized facts, for easily communicating and understanding different aspects of the subject, and for modifying the model for different situations. It starts in section one with Schumpeter's insight regarding capitalism. After examining the seminal contribution of Robert Solow (1956) and neoclassical economic growth theory in an evolutionary perspective in section two, the recent contributions to the regional convergence literature and the technology gap approach are surveyed in sections three and four. Much of the convergence literature is recent and has crucial implications for regional economic growth. Consequently, the new endogenous growth theory, basically in the Romer version, is reviewed in section five, relating it to the Schumpeterian notions presented in section one. The recent R&D- or innovation-based endogenous growth models rely upon this argument. The technological catch-up approach described in section four provides a source to appropriately specify the formal models, which are mathematically conceptualized in the mainstream tradition, in accordance with the

observed phenomenon in the reality. Its relevance is emphasized particularly in the recent regional econometric studies on cross-section or panel data. These considerations influence the regional specification of the R&D-based endogenous growth model developed in Chapter IV.

1. The Schumpeterian Patterns of Innovation Process

Since the ancient communities to recent modern societies, people have perceived the huge influence of development of products and ideas on their wealth and welfare. Economics has long recognized knowledge as a key ingredient in generating economic growth. Only during the last few decades, however, has it formally emphasized the importance of knowledge and innovations. This fact can be attributed mainly to the emergence and extensive use of information and telecommunication technologies and their impact on our way of life in recent decades (Caniels 2000, p. 1).

The modern theories of economic growth considering innovation start with Schumpeter's contributions. Schumpeter argued that economic agents have incentives to innovate new products and technologies in competitive economies. The economic incentives to invest in innovations arise because innovations provide monopoly rents albeit temporarily, because new-comers will imitate and improve the relevant products and processes. This competition among firms for monopoly rents from innovation generates technological progress and improvement in the productive capacity of the economy (Caniels 2000, p. 1-2).

Schumpeterian patterns of innovative activities are placed in two categories: *widening* and *deepening*. Between these two extreme patterns many intermediate cases

exist. The widening pattern of innovative activity is typified by European industrial development in the late 19th century, and it is characterized by industries in which there are great numbers of small and medium sized firms that compete to enter the market. It is technologically easy to enter and new firms with innovative activities play a major role. New ideas, products, and processes are brought in an industry by new entrepreneurs. They initiate new enterprises and challenge the established firms by forcing them to change existing ways of life and to abolish the rents from previous innovations.

The *deepening* pattern of innovative activity is typified by development of US industry in the first half of the 20th century. It is characterized by industries in which there are a few large-scale firms with industrial R&D laboratories for technological innovation. Large firms have advantages in the market because of their accumulated stock of knowledge in specific technological areas and their high competence in large-scale R&D projects. The prevalence of such large established firms creates barriers to entry in an industry for new entrepreneurs and firms. As a result, their monopoly rents provide a tremendous opportunity for people to develop new products and processes so as to capture some of these rents.

Low appropriability implies easy and permanent entry of new innovators in the industry, and low cumulativeness conditions do not permit the persistence of monopoly rents to the existing innovator in the industry. So they describe *widening* patterns. High opportunity for potential innovators to enter in an industry, appropriability, and cumulativeness conditions encourage existing entrepreneurs to accumulate technological knowledge and capabilities consistently and to build up innovative advantages against potential entrants leading to *deepening* patterns (Malerba and Orsenigo 1995, p. 47-49).

Economists have attempted to model these Schumpeterian ideas in various studies of economic growth. The initial attempts within the mainstream tradition following the Solow's (1956) seminal contribution have not succeeded in incorporating the Schumpeterian insight regarding innovation into economic growth theory. The main reasons for the failure are the assumptions of neoclassical growth theory. Under perfect competition all markets are cleared by price taking behavior of economic agents who have observed the relative prices. As a result of this overall optimization behavior of individuals and firms, a competitive general equilibrium exist in relative prices and quantities of inputs and outputs in all markets. However, as suggested by the Schumpeterian argument, innovations are different goods than ordinary ones. Entrepreneurs have taken an extra risk because of the uncertainty in the innovative process. So they have to be compensated for those extra costs; otherwise they cannot survive. This outcome requires dropping the price taking assumption and adopting price-searching models. However, monopoly pricing of innovations in competitive market with many firms open to the entry (monopolistic competition) contradicts the traditional neoclassical approach. There is no place for such uncertainty in the traditional neoclassical economics since all economic agents have perfect knowledge and foresight in all markets. Mainstream economists in the traditional neoclassical stream, therefore, did not formalize this Schumpeterian behavior of innovation markets in their growth framework.

On the other hand, because of the cumulateness of technological innovation, entrepreneurs migrate the two extreme choices above. Either R&D stocks are built up in a few big firms, or a large number of small firms can geographically concentrate their

investments in R&D activities. Either way, they reduce the uncertainty or the risk and minimize or perhaps reduce some fixed costs. Moreover, concentration of innovative activity in a few firms or regions increases its productivity by benefiting from the previous stock of knowledge, the common basic research, and the R&D activities of one another without cost. The knowledge spillovers and externalities that arise from the innovation and R&D activities in this cumulative way lead to increasing returns to scale in the production of knowledge. These kinds of external economies and increasing returns are in conflict with the traditional neoclassical framework. That is, there is no room for such distortions in the perfectly competitive general equilibrium model. Thereby mainstream economists in the traditional neoclassical stream again could not formalize this different insight, the so-called Marshallian externalities, of innovation activity in their equilibrium growth framework.

Some neoclassical economists during the 1960s attempted to formalize an endogenous growth model by incorporating innovations as endogenously determined in the neoclassical model. However, those models did not capture the Schumpeterian basic insight that economic agents invest in R&D activities in order to take rents on their innovations. On the basis of these earlier attempts, however, Romer (1990) formulated the R&D-based endogenous growth model within a complete general equilibrium framework. This endogenous growth model has properly incorporated the Schumpeterian insight of R&D process into the model alongside the Marshallian externalities. Then a number of extensions to the Romer's model of endogenous growth has been added by Grossman and Helpman (1991), Aghion and Howitt (1992), and others in this mainstream tradition. This issue is explained in more detail below.

Rodriguez-Pose (2001) explains the theory with regard to the role of R&D investments in the regional development process on the basis of three alternative approaches. First is the Schumpeterian stream of the endogenous growth approach, which suggests that the concentration of R&D efforts in a few regions rather than their dispersion across locations will generate greater innovation rates because knowledge spillovers and external economies are maximized. Then the knowledge spillovers may spread out to the neighboring regions from those innovative regions. For the knowledge to spillover, however, the technologically backward economy must have a minimum threshold of technological capacity to innovate or of R&D effort to absorb the technology from the technologically advanced locations. Thus lagging regions with limited technological capacity cannot generate a satisfactory rate of return from R&D investment. These characteristics make the relationship between R&D and economic growth nonlinear.

The second approach, the neoclassical one, treats investment in R&D as the same as investment in physical capital. Because of decreasing returns to accumulation of R&D capital, marginal returns to investment in R&D would be higher in lagging regions with less R&D effort relative to that in technologically advanced regions with more R&D effort. That is, R&D investment in technologically less developed regions will be more effective than that of developed regions. As a consequence, an even distribution of R&D efforts across regions will maximize the possible outcome. However, as long as knowledge flows are strong, particularly from the technologically developed regions to the lagging regions, with a cost smaller than the cost of innovation, free riding on the

knowledge spillovers leads to a substantial under-investment, especially in the less developed regions.

Finally, the regional policy approach suggests public investment in R&D in less developed regions. Public investment in R&D encourages the private investment in R&D because it creates spillovers and externalities within those lagging regions by establishing R&D infrastructure, basic science, etc. It is unlikely to expect most technologically lagging regions to invest in R&D activities at a satisfactory level. Public R&D investment in lagging regions starts economic convergence because it reduces congestion in the developed core regions, and encourages talent to stay and creates spin-offs in the less developed localities. Moreover, it improves the lagging regions' capacity to free ride on the technologically advanced regions.

2. Technological Progress in the Neoclassical Theory of Economic Growth

According to the traditional neo-classic models of economic growth (Solow 1956), during the short run transition process toward the steady state, the growth rate of per capita output is determined by per capita capital accumulation. Because of decreasing returns to per capita capital accumulation, at the steady state net investment is zero, with the new investment just replacing capital depreciation. Net addition to the capital stock stops. Long run per capita output growth is attributed to exogenously determined technological progress. But the neoclassical model does not consider how the technological change occurs in the model. Moreover, because it is assumed that any economic unit can instantly access technological knowledge without cost, growth rate differentials in per capita output across economic units cannot be attributed to technology

differences. So, in the long run, each economic unit grows at the same rate, which is determined by a constant technological growth, even though they can grow differentially during the transition path to the steady state. Therefore, the growth rates of economic units converge to a steady state of growth rate, which is determined by the growth rate of technology over time. Furthermore, less developed economic units will grow relatively faster than the others in the transition process under the relevant assumptions. This theory indeed rests on the basic assumption that all spatial units have similar characteristics and foundations, and all production factors are completely mobile and freely shift across regions to eliminate the differentials in marginal products. Because per capita capital is relatively less and hence its marginal product is relatively higher, the less developed economies grow faster during the transition.

By technical change Solow (1957) means any type of shift in the production function, which may stem from the developments in education, performance of labor force, manufacturing technology, and all such things. However, he claims that major portion of innovations is embodied in new plant and equipments. Solow assumes a neutral technical change (which implies pure scale effects) in the aggregate production function of $Q = A(t) f(K, L) = A(t) K^\alpha L^{1-\alpha}$, where Q stands for aggregate output, K capital stock and L employment level under constant returns to scale in K and L . The multiplicative shift factor $A(t) = A(0) e^{gt} = A(0) (1 + g)^t$, where g implies annual growth rate, measures the cumulated effects of shifts within the relevant period of time t . The evolution of technical progress does not associate with that of capital stock, and principally exhibits roughly random fluctuations around a fixed mean over time.

Solow (1957) applied a simple growth accounting equation derived from the above basic model to the US time series data for the period between 1909 and 1949. He observed that output per man-hour about doubled, and the production function cumulatively shifted upward by around 80 % in this period. Hence, about 12.5 % of the total increase in output per man-hour is attributable to raise in capital per man-hour, and the rest 87.5 % of that to technical change. Solow's results, confirmed by others, are that only a small portion of the US productivity growth could be explained by growth in traditional production factors. The major portion was due to the growth in total factor productivity.

Later empirical studies in this growth accounting tradition have applied two different approaches to reduce the large unidentified part of the output growth. One of which has embodied technological progress into the factors themselves, adjusting as much as possible, for improvements in their quality, composition and so on. Others have added other plausible explanatory variables such as structural change, economies of scale, etc. into the equations. However, many of the factors employed in these studies are interdependent and contradict the assumptions of neoclassical growth theory. Later, a separate catch up term is added into these equations, but it has been difficult to distinguish the impacts from growth in capital from those of technological progress. These limitations are in fact related to the weaknesses of the neoclassical theory of economic growth. So, the weak explanatory power of this neoclassical tradition comes mainly from the interconnectedness of the factors included in the equations and the possible missing factors (Fagerberg 1994).

The neoclassical growth model has been used as the basic means of explaining the process and determinants of economic growth in developed nations. Later on, the traditional neoclassical model was modified for analysis of regional economic growth. However, the assumptions of the earlier regional versions of neoclassical growth model were not realistic. In particular, the most commonly criticized assumption under the regional context is that the diffusion of technical knowledge is instantaneous and complete. This omission of knowledge in the earlier forms was the essential limitation. In other words, the early regional specification of the neoclassical growth model assumed that each region had the same production function and was operating on its frontier under constant returns to scale. So, the early regional specifications of neoclassical growth model did not include the concepts of distance and space, which may be crucial in understanding the dynamics of persistent interregional growth differentials. Assuming the same technology level across regions, these early neoclassical specifications automatically predict convergence in output growth across regions. This convergence occurs through mobility of traditional production factors, labor and, particularly capital, across regions under competition (Caniels 2000, p. 10-12).

Some later approaches have modified this basic growth process by accounting for particular characteristics of economic units, such as human capital and unobservable fixed characteristics of economies. Mankiw et al. (1992) added human capital as an input in production for the basic Solow growth model. Their findings on this specification supported the neoclassical growth model. Islam (1995) criticized this specification because it does not allow cross-section differences in the technology, which, Islam thinks, are obvious. Moreover, Islam does not think human capital input separate from

the physical one is appropriate in this kind of specification, because individuals do not make investment decisions separately either on physical capital or on human capital. Instead, they are made jointly. So, after accounting for country-specific factors as an omitted variable by exploiting the panel data approach on the basic growth model of Solow, Islam has estimated a convergence rate of between 4 % and 9 % rather than the earlier estimates of about 2 %. Furthermore, Islam's estimate is more reflective of the share of physical capital in aggregate income. These specifications of neoclassical growth model within the cross-section context have also suggested that the convergence in per capita output across economies is conditional rather than absolute as in the traditional model. Thus, the recent empirical contributions have attempted to fix the shortcomings of the neoclassical growth theory. They have showed that the neoclassical framework can be used to study the determinants of economic growth across economies (Mankiw et al. 1992; and Islam 1995).

In a most recent empirical study, Paci and Pigliaru (2001) specified an empirical model that incorporates technological catch up as well as convergence in per capita capital. Hence, the model assumes that the differentials in technology across economies are not stationary as in the case of Islam (1995); instead they are a dynamic source of income convergence due to the gradual technology diffusion across economies over time. The technological progress of the leading region is a consequence of its own innovativeness and R&D effort, while the technological advance of the lagging regions is determined by both their own R&D efforts and the technology diffusion from the technology leader. Thus the lagging regions have a potential to grow faster than the leader region, which is conditional on particular factors. By using a panel data approach

with EU regional data, they find that both capital deepening and the technological catch up are important determinants of the convergence process in total factor productivity across regions.

However, the empirical findings for the cross section data is not quite consistent with the predictions of the neoclassical growth theory, even when cross regional data for more integrated units are tested. Nonetheless, some argue that the neoclassical growth theory is not tested quite properly and quite enough yet with cross section data. Moreover, it is not possible to test the predictions of neoclassical model properly due to the lack of reasonably well-defined regional data, especially regarding capital stock and the returns. The empirical studies that test whether convergence in regional per capita income levels occurs only indirectly test the hypotheses of the neoclassical model (Caniels 2000, p.10-12; Moomaw et al. 2002).

To adapt the model for regional analysis, the neoclassical assumptions have been altered in many regional studies. It is possible to achieve different implications, especially to predict divergence rather than convergence, by adjusting some assumptions of the neoclassical model. Thus, many models have been specified in this tradition that deal with market imperfections in a complex way. In the same way, adjustments were made to incorporate space and distance in a neoclassical growth model. This kind of manipulations on the neoclassical model in order to eliminate its spatial limitations and hence to approximate the regional growth process better may lead to a model that contradicts the essential methodology. However, there exist some alternative models, which predict divergence without causing such consequence (Caniels 2000, p.12-13).

In short, many economists have found the traditional neoclassical theory of economic growth to be unsatisfactory in explaining regional phenomenon, particularly with its assumption of exogenous technological progress. It attributes much of the observed growth to a black box (technological change). Although growth accounting studies in this tradition have attempted to reduce the unexplained part of the growth, they have not been completely successful. On the other hand, the results from the observations on cross-country data have been found inconsistent with the predictions of the traditional neoclassical theory. Many empirical studies suggest that conditional convergence across heterogeneous group of countries and absolute convergence across regions within different countries is much smaller than the traditional theory suggests.

3. Regional Economic Convergence

A large number of empirical studies on growth and convergence in per capita income across countries and regions have been added into the relevant literature since the beginning of the last decade. Barro's (1991) seminal study empirically examines whether and to what extent particular factors have a significant effect on growth and tests the neoclassical hypothesis of convergence in per capita income across countries. He finds some evidence of a weak conditional convergence with an annual speed of less than 1 %. Because countries differ so dramatically, many economists would agree that conditional convergence is consistent with a modified neoclassical model. On the other hand, smaller dissimilarities across regions within national borders and easier flows of factors suggest to many economists that the convergence rate will be absolute and faster across regions

within countries than those across countries. In the light of these views, researchers have recently paid much more attention to cross-regional data within countries.

Barro and Sala-i-Martin (1995) state that:

“Although differences in technology, preferences, and institutions do exist across regions, these differences are likely to be smaller than those across countries. Firms and households of different regions within a single country tend to have access to similar technologies and have roughly similar tastes and cultures. Furthermore, the regions share a common central government and therefore have similar institutional setups and legal systems. This relative homogeneity means that absolute convergence is more likely to apply across regions within countries than across countries. ... inputs tend to be more mobile across regions than across countries. Legal, cultural, linguistic, and institutional barriers to factor movements tend to be smaller across regions within a country than across countries. Hence, the assumption of a closed economy –a standard condition of the neoclassical growth model –is likely to be violated for regional data sets” (p. 382-383).

Accordingly, another study by Barro and Sala-i-Martin (1991) tests convergence in per capita income across the US states and European regions and finds some evidence of absolute convergence rate of about 2 % in per capita income across states and across regions within the European nations. Hence, they have suggested that if fundamentals or structural characteristics of countries' growth paths were properly controlled, a log linear approximation of the neoclassical growth model would predict about a 2 % annual convergence rate across countries. In this regard, the following empirical studies (see, in particular, Barro and Sala-i-Martin 1995, chap. 11; Barro 1997, chap. 1; Barro and Sala-i-Martin 1992; Mankiw et al. 1992; Sala-i-Martin 1996a, 1996b) report convergence in per capita income across countries and across regions at about 2 %, in most cases. However, the estimated same speed of annual convergence in per capita income across heterogeneous group of countries is conditional while it is absolute across homogenous group of OECD countries and across the states and regions within nations.

On the other hand, the convergence rate found is much smaller than theory predicts. Especially across European regions it is not stable over time, and there are some periods of divergence. Across the states it is stable only when conditioning variables, particularly sectoral composition, are accounted for. To observe a stable rate of convergence in per capita income over time across European regions, Barro and Sala-i-Martin (1991) suggest that a proper sectoral composition variable should be included as a proxy to control the structural change dynamics of those regional economies, rather than simply by employing shares of main sectors, agriculture and industry in the equation. Because industrial compositions of the EU regions are diverse, they have been differentially affected by global shocks, particularly the two oil shocks during the 1970s.

A log linear approximation around the steady state of the neoclassical growth model is adopted to estimate the transitional dynamics of growth process initially for a closed economy and then for an extended-open economy version in these specifications. A conditional convergence specification of the neoclassical growth theory predicts that each country or region converges towards its own steady state rather than a common one across units, so that holding constant the factors that significantly affect steady states of output per worker and growth rate is crucial to predict convergence in this model. So, we need an economic theory that guides us to find such variables that proxy for the steady state. There exist various growth models that suggest different variables. The strict version of the Solow-Swan model, for instance, suggests that the steady state hinges on the level of technology A , the saving rate, and the parameters of exogenous growth in population and technology, and the depreciation rate of capital. Following Barro (1991), a large literature has estimated such equations, in which more than 50 variables have

been found to be significant in at least one regression. The finding of a significant conditional β -convergence is robust to the exact choice of conditioning variables, as predicted by the neoclassical theory (Sala-i-Martin 1996b, p. 1028).

“The steady-state value of output per effective worker depends on the parameters of technology and preferences. We can extend the notion of technology to include natural resources, such as geography, fertile land, and the availability of minerals, as well as government policies (considered exogenous) that affect property rights, the provision of infrastructure services, tax rates, and so on” (Barro and Sala-i-Martin 1991, p. 109).

Thus they adopt a broad interpretation of technology, which is captured in parameter A of the production function.

Moreover, the neoclassical growth model does not predict the same rate of convergence in all times and spaces. It is determined by the underlying parameters of technology and preferences, but not by differences in technologies or government policies, because they may have simply a proportional impact on the production function, implying a marked impact on steady state output per worker, but not on the speed of convergence. Therefore, a similar rate of convergence across economies can be observed even though they greatly differ in per capita output because of disparities in some other respects, particularly in the parameters of technology across them (Barro and Sala-i-Martin 1991, 1992).

In addition, the theory predicts that the greater the degree of labor and capital mobility across spatial units, the higher is the convergence rate. However, the estimates across regions within countries do not display significantly faster convergence rates than across countries. If technologies in broad term differ across economies, then both physical and human capital may flow from poor to rich economies and thereby cause divergence in per capita output across them. Thus, it is unclear whether greater physical

and human capital mobility across regions within a nation than across nations would result in faster rates of convergence across regions than across nations (Barro and Sala-i-Martin 1991, 1992). Nevertheless, production factors are not perfectly mobile even across regions and some portion of physical and human capital is indigenous. Also, in reality, capital markets are not functioning perfectly. Thereby, the instantaneous equalization of relative volumes or rates of returns of production factors across regions within a nation is not a necessary assumption.

“The main point, therefore, is that although regions within a country are relatively open to flows of capital and persons, the neoclassical growth model still provides a useful framework for the empirical analysis” (Barro and Sala-i-Martin 1995, p. 383).

In other words, an open economy version of the neoclassical model does not necessarily lead to significantly different estimates of the convergence rate, and does not necessarily differ from the closed economy version, once both financial and real capital markets with regard to investment in human and physical capital are assumed to operate imperfectly. Further, Barro and Sala-i-Martin (1992, p. 240-241) propose that

“once we allow for differences in technologies, we also have to consider the diffusion of technology across economies, ... The potential to imitate is another reason for poor, follower economies to grow at relatively high rates ... a resolution of this puzzle will involve the construction of an open economy growth model that satisfactorily incorporates credit markets, factor mobility, and technological diffusion”.

Thus, once partial capital mobility is adopted, the neoclassical growth model along with technological diffusion will be the likely approach in explaining the convergence hypothesis (Sala-i-Martin 1996a).

According to Barro and Sala-i-Martin (1995), the findings of around 2 % convergence are consistent with the neoclassical growth model (i.e., with its basic

assumption of diminishing returns to capital) if regions within a nation have about the same preferences, technologies and institutions, which represent relatively homogenous steady state conditions. The observed convergence rate is also consistent with models of technological diffusion. Barro and Sala-i-Martin (1991, p.111) argue that

“the rate of convergence also tends to be higher if we allow for the flow of technological advances from rich to poor economies. However, differences in levels of technology can alter the implications of capital mobility. Human and physical capital may move from poor to rich economies and thereby create a force toward divergence”.

Whereas, this slow rate of convergence implies that it takes almost 35 years to eliminate one half of the initial gaps in steady state per capita incomes. It is not consistent with the empirics of the neoclassical growth model as the reasonable size of capital share in income is assumed to be one-third of that. Whereas, it is consistent with the prediction of the theory once broader capital (including human capital, and may be knowledge capital as well as physical capital) concept is considered with its share of three-quarters of income. Otherwise, with this size of one-third capital share in output the neoclassical growth model predicts a speed of convergence between 6-7 % (Barro and Sala-i-Martin 1992; Sala-i-Martin 1996a, p. 1349).

Consequently, as some elements of an open economy tend to reduce the predicted rate of convergence in labor productivity, if the level of technology is different across regions, other elements of an open economy tend to increase it in a neoclassical context.

Then,

“in open-economy versions of the neoclassical growth model, it is possible to find convergence effects associated with technological diffusion even if the returns to capital are constant ($\alpha = 1$). ... Thus we would like to break down the observed convergence into various components: first, effects related to diminishing returns to capital and to imbalances among types of capital in the context of a closed economy; second, effects involving the mobility of capital and labor across

economies; and third, effects that involve the gradual spread of technology” (Barro and Sala-i-Martin 1992, p. 247).

Therefore, the recent empirical research on cross-country growth has relied mostly on the extended versions of the traditional neoclassical model by including government policies, human capital, and the diffusion of technology. But one shortcoming of these theories is that they do not determine variation in relative long-run growth rates across economies (Barro 1997, p. 7-8). On the other hand, there may exist other models that are consistent with the existence of convergence. Endogenous growth theories that include the discovery of new ideas and methods of production are important for providing possible explanations for long-term growth disparities across economies. But one shortcoming of the early versions of these theories is that they do not predict conditional convergence. The later ones (Grossman and Helpman 1991, chap. 9 and 11; Rivera-Batiz and Romer 1991) however analyze the knowledge flows across economies and the impact of them on economies at the steady state rather than during the transitional process of conditional convergence. Because there exists a strong empirical consistency of such behavior in the data for countries and regions it is important to incorporate this behavior into the innovation- or R&D-based endogenous growth theory. Thus a model combining endogenous growth and technological diffusion (with their two distinct effects of growth and convergence) can predict an equation exactly like a conditional convergence specification of the neoclassical growth theory (Sala-i-Martin 1996a, b; Barro 1997, p. 7-8).

In this context, Barro and Sala-i-Martin (1995, chap. 8) present an initial attempt to construct such a model and in a following work Barro and Sala-i-Martin (1997) improve that model. According to the endogenous growth theory, the long run growth

rates of economies are determined by their innovation rates. The rate of innovation depends on the cost of innovation in an economy. Because the performance of R&D and innovation activities is the outcome of a cumulative process and they are concentrated in a few economies due to the knowledge spillovers arising from the large knowledge stocks within their economies, the cost of innovation is lower in those economies. Consequently, just the few economies with large knowledge stocks invest in R&D to innovate. On the other hand, many other economies invested in R&D to copy innovations from these technology leaders because the cost of imitation is cheaper than the cost of innovation. Thereby, these follower economies could grow faster than the rich technology leaders. But this convergence process which stems from the gap between technology levels of poor and rich economies is conditional in that the convergence in per capita product asymptotically disappears as the technology gap between poor and rich declines because the followers will face increasing cost of finding innovations to copy. Thus, the imitation cost will increase. Growth rates of followers during the transitional process toward the steady state are determined by their characteristics relative to the leader economies. Therefore, it is also likely that the growth rates of some followers can be lower than that of the leaders, if their characteristics are worse relative to that of the leaders. Further, Barro and Sala-i-Martin (1997) suggest that such measures as physical distance or the degrees of similarities in language or culture between followers and leaders can be used as proxies for the followers' cost of adopting technology.

On the other hand, some researchers, notably Quah (1993a, b; 1996a, b, c), criticize the methodology used in recent cross-section empirical studies to test the convergence hypothesis based on the neoclassical growth model and hence the finding of

roughly 2 % rate of convergence in almost all cases. These models regress average growth rates in per capita incomes on initial levels of them for absolute convergence, and on conditioning variables for the conditional convergence. Thus, this approach predicts simply the transition path of a representative economy toward the average steady state. There is no such smooth process of transition in the cross-section data. The relative economic performance of each economy, rich and poor, to each other is important for convergence, rather than the economic performance of a single economy relative to its own history. Indeed, diversity in steady state conditions and initial per capita income levels across different groups of economies and over time characterize the real world. So, each group of economy has different distributional dynamics relative to that of the entire cross-section distribution, so that a global convergence across all economies is unlikely. The distribution dynamics of each economy relative to all economies should be considered in a model. This type of strong convergence has been observed simply across the US states (Quah 1996a), but a uniform 2 % annual speed of cross-section convergence in per capita income could arise for reasons rather than the dynamics of economic growth.

Thus different convergence patterns and rates are likely for diverse economies. According to Quah, the following cross-sectional distribution dynamics for each economy are likely to be observed: (i) Initially any rich economy relative to the average can be eventually poor relative to the average, or vice versa. (ii) Whether an economy will be eventually rich or poor relative to the average is independent of its initial position. (iii) Income disparities between economies can persist over time. (iv) Dispersion of per capita income across economies can diminish over time.

If, by the concept of cross-sectional convergence in per capita income, we mean whether poor economies are catching up with rich ones, we must consider the conditions above. The neoclassical approach to the convergence does not provide any information about those distributional dynamics of the entire cross section, and therefore the findings from neoclassical approach are misleading. If the neoclassical approach points to the outcome (iv) with cross-sectional convergence, σ -convergence, this does not provide any information about the other three plausible distributional dynamics. Moreover, it does not say whether poor economies are catching up with rich ones, or anything about persistent disparities in per capita income between economies. Furthermore, β -convergence does not shed any light on σ -convergence.

Consequently, according to Quah, models for studying transitional characteristics and cross-section convergence in per capita incomes, such as the Markov chain rule, are appropriate to uncover such effects. This alternative approach does not impose restrictive assumptions on the nature of long run growth. So, this approach allows multi-peaked distributions and convergence clubs of per capita income, as observed across countries and regions within nations.

Furthermore, convergence clubs are endogenously formed. Various convergence dynamics are generated based on the initial distribution of characteristics across economies. The number of convergence clubs and their composition are determined by their initial distribution of incomes relative to that of the entire cross-section. If initial distributions of incomes are relatively close to each other across economies, then a global distribution and convergence of incomes form across economies. In contrast, if initial distributions of incomes are relatively disparate across economies, then multiple

convergence clubs are most likely to be formed. As a result, conditioning variables in the conventional approach to the conditional convergence are endogenously homogenized around the values determined by each member's convergence club. Those conditioning variables do not determine an economy's position; in contrast, the factors in deciding club membership determine everything. So, since the traditional approach attributes both growth and convergence to those conditioning variables, it leads to the misleading results (Galor 1996, p.1066-1068).

In addition, Cheshire and Magrini (1999) argue that the actual growth performance and convergence or divergence is a consequence of a multivariate process. Some variables are likely to contribute significantly to convergence in regional incomes (such as technological diffusion), whereas others are likely to contribute significantly to divergence (such as agglomeration economies). Moreover, the same variables can contribute significantly to either convergence or divergence within different contexts. Therefore, in order to provide credible estimates of the impact of a certain variable, it is vital to properly specify a model and to pay attention to the data, and to the model's performance. In the tests of conditional convergence, the estimated value for β hinges on the choice of the conditioning variables. When some variables are proxies for the forces of divergence, it is most likely to estimate a significant β -convergence. An adequately specified econometric model, which contains proxies for all the economic forces influencing the growth process, may not predict a β -convergence, as in the estimates of Cheshire and Carbonara (1996). However, even if a significant β -convergence is estimated, the method would still represent a weak test of the neoclassical growth theory because it would simply be consistent with such a theory. It would also be relevant to a

number of alternative reasons such as the influences of implementation of the EU regional development policy.

Barro and Sala-i-Martin (1991) and Sala-i-Martin (1991) respond to such critics by arguing that the both approaches have dealt with very different aspects of the same problem. That is, both the empirical studies based on β -convergence and σ -convergence, and those based on the cross-section distributional dynamics have provided interesting and different knowledge about cross-sectional economic growth and convergence in per capita incomes.

Furthermore, Oded Galor (1996, p.1056-1061) argues that the neoclassical growth model may predict a conditional club convergence when the empirically significant variables such as human capital, income distribution, and fertility are incorporated into the basic model along with capital market imperfections, externalities and non-convexities. So if multiple steady state equilibriums are formed by the dynamic system across economies, a conditional club convergence rather than a global conditional convergence is most likely to be observed. In other words, economies that have similar structural characteristics converge to the same steady state equilibrium if their initial per capita incomes are also similar. Further, club convergence, as a competing hypothesis with conditional convergence, is perfectly consistent with constant returns to scale and diminishing marginal productivity of capital. Nonetheless, this theoretical approach of Galor (1996) obviously dismisses some integral assumptions of the neoclassical economic theory in order to be consistent with the cross-sectional data.

Since the steady state equilibrium of an economy is determined by its structural characteristics, absolute convergence requires convergence in structural characteristics

across economies. But because the fundamentals of countries (and hence their dynamical systems) are very disparate, the recent empirical studies with regard to cross-country regressions and the evolution in cross-country income distribution have rejected the absolute convergence hypothesis. Although the neoclassical growth theory is consistent with conditional convergence and the absence of absolute convergence, the empirical rejection of absolute convergence has been one of the principle reasons that has led the pioneers of the endogenous growth literature to reject the neoclassical growth model as a framework to explain cross-sectional economic growth (Galor 1996, p.1056-1061).

4. The Technology Gap Approach

The technology gap approach, in contrast to neoclassical growth theory, has facilitated more extensive and mostly descriptive analyses of the determinants of cross-section disparities in per capita output (Fagerberg 1994). The technology gap approach is conceptualized based on the implicit basic assumption that technological knowledge is to some extent a public good. It is not, however, a pure public good as assumed in the neoclassical growth theory, so that it can diffuse across economies only gradually and with a cost rather than instantly without cost. The main assumption of this approach is that the differentials in technology levels across economies are the primary reason for the differentials in productivity levels. Closing the technology gap is a way for the technologically backward economies to grow faster than the technologically developed economies. Because of technology diffusion, the less developed economies have an opportunity to close the technology gap and hence catch up with productivity levels of developed economies. The earlier econometric studies have exploited per capita income

variables as a proxy for the catch up, at the beginning in absolute form and later in the form of conditional on the other variables, as in the case of convergence analysis.

However, the empirical analyses of the findings in this way could not differentiate between the neoclassical theory of growth and the technology gap approach. That is, they could not determine whether or to what extent the observed catch up in per capita output is due to the catch up in per capita capital stocks and/or to closing technology gaps.

Recently, the studies following the technology gap approach have employed R&D and patent statistics as proxy for technology activities in economies.

Technological catch up however is not an easy task for the backward economies. Realizing the potential by closing technology gap primarily depends on the social capability of lagging economies and their technological competence to absorb and exploit the advanced technologies of the leader economies. Social competence and technological congruence cannot be formed in a short term by such activities as education, it requires establishing an institutional structure and specific characteristics for them in societies (Abramovitz 1986, p. 600). This aspect of the technology gap approach is developed in growing literature in the beginning of 1980s. It is based on an evolutionary view of institutions originated by Nelson and Winters, which is labeled appreciative theory (Caniels 2000, p. 30-43; Fagerberg 1994, p. 1155-1156). Technological catch up depends also on such factors as facilitating the diffusion of knowledge, structural change in the composition of economy, macroeconomic and financial conditions that facilitates the accumulation of capital and expansion of demand. Abramovitz (1986) notes that in the early decades after World War II, Western European countries were unsuccessful in closing the large technology gap with the US. The catch up in productivity of those

countries with the US had to wait until the 1960s for the conditions to mature. Then, during the 1960s and 1970s the European countries experienced a rapid catch up with the US in technology levels and hence in productivity levels.

On the other hand, technology spillovers are not restricted to going from the leader to the followers. As the technology level of a follower economy approaches that of the leader, it becomes harder to exploit spillovers from the leader's R&D activity. Furthermore, the follower economy can become a source of knowledge spillovers in certain industries for the leader. Hence, both the followers and the leader can benefit mutually from each other's knowledge spillovers in sectors of the economy as the technology gap has all but vanished. For economies at this stage, R&D investments to innovate rather than knowledge spillovers will become the major source of growth disparities in productivity levels. Nonetheless, the productivity level of the leader economy will be greater than that of the followers as long as it has greater knowledge stock relative to the followers (Abramovitz 1986).

This argument suggests that a threshold level of R&D effort is required to imitate successfully. Cross-country convergence patterns in productivity levels have followed similar cross-country patterns in levels of R&D and patenting activity. One limitation of most studies in this approach is that the influence of the R&D activities in the knowledge diffusion process in any economy other than the leader economy is ignored. In follower economies imitation and innovation activities are probably complements. Even though some studies using the technology gap approach have dealt with some of these limitations, other limitations have been ignored. As a result, findings are not robust, and the forecasts for certain economies based on them are not reliable (Fagerberg 1994).

Verspagen (1991) observes that particular countries have been successful in the catching up process, while many other less-developed countries have lagged farther behind the developed countries. He argues that the capabilities of these lagging economies to learn, assimilate, and apply the existing knowledge of advanced economies is weak. Following Cohen and Levinthal (1989), he suggests that the capability of the lagging regions to imitate and implement the knowledge spillovers from the leader economies hinges first of all on the R&D efforts of these lagging regions themselves. According to Verspagen's model, the learning capability of a country is assumed to rely on both intrinsic characteristics (such as education, infrastructure and other measures which require mostly public investment) and on its technological distance from the leading country. But the relationship between the technology gap and catch up is not a monotonic linear process. If the gap is too large or too close, the possibility of catch up between these economies is weak, other factors held constant. Between these two extremes, as the gap closes, the possibility of catch up increases until an optimum and then decreases.

5. The New Endogenous Growth Theory

In order to respond to the theoretical and empirical shortcomings of the neoclassical growth models, the new endogenous growth theory originated in the mid-1980s. The endogenous growth models can be classified into two broad categories: broad capital models and innovation-based models. Broad capital models may be divided once more into physical capital and human capital based ones (Martin and Sunley 1998). Since

our case is particularly related to the innovation- or R&D-based endogenous growth theory, our emphasis is on that.

Paul Romer (1993b) stresses the importance of understanding the difference between the economics of ideas and the economics of objects in order to understand the growth and development issue.

“... ideas are extremely important economic goods, far more important than the objects. ... In a world with physical limits, it is discoveries of big ideas together with the discovery of millions of little ideas ..., that make persistent economic growth possible. Ideas are the instructions that let us combine limited physical resources in arrangements that are even more valuable” (p. 64). “Once we have the idea, the process of mixing will require its own ... specialized capital and labor ... Important as these tangible inputs are, it is still the idea itself that permits the resulting increase in value” (p. 68). In contrast to the conventional wisdom, “there will always be at least as much scope for improvement through large numbers of small changes in the way things are done in a manufacturing process as through laboratory research ...” (p. 69). This is why, “to understand growth, we need to understand not only how big ideas, ..., are discovered and put to use but also how millions of little ideas, ..., are discovered and put to use. To understand development, we need to understand how both kinds of ideas, but especially the millions of small ones, can be used and produced in a developing country” (p. 69-70).

Economic goods can be classified on the basis of two basic features: (i)

Excludability of a good or service from other users, and (ii) rivalry in use of those goods, that is, whether they can or cannot be used at the same time by many people without diminishing the benefits obtained. A private good (excludable and rival) can be produced and sold for a price that compensates the cost of its production because the persons who do not pay price cannot use it. A public good (non-excludable and non-rival) cannot be priced because there is no way to keep people who do not pay from benefiting from it. Everybody benefits from a public good once produced, without causing any decline each other's benefit within an economy. Consequently, an excellent example of a public good is basic scientific research. It should not be priced. A public good might be bounded by

the local community (police protection), the nation (national defense), or the globe (science). Between the extremes of private and public, there are some goods that have mixed-characteristics. For example, the provision of education is excludable but non-rival, at least until capacity is reached. The returns to investment in human capital are partly private and partly external. The private returns are excludable and rival. The external returns are non-rival because they are derived from the impacts on economic growth provided by the accumulation of human capital. External returns in developed countries, may, at the margin be zero. If so, investment in human capital can be left to the private sector without an efficiency cost. Furthermore, human capital (skills or ability) is embodied in human beings and once the person dies it vanishes with him. To maintain the stock of human capital, someone else must invest. The returns to ideas, like the return to human capital are only partially excludable (Romer 1993b).

In this regard, to understand growth and development, the distinction between objects (rival goods) and ideas (non-rival goods) is much more important than the concepts of excludability (appropriability) or related concepts. Once an idea is produced with a fixed cost, it can be used over and over again with a trivial cost. Consequently, the value of non-rival goods relies on the size of market.

“Ideas are therefore the critical input in the production of more valuable human and nonhuman capital. But human capital is also the most important input in the production of new ideas. ... human capital and ideas are so closely related as inputs and outputs, ... nevertheless, ... ideas and human capital ... have different fundamental attributes as economic goods, with different implications for economic theory” (Romer 1993b, p. 71).

To establish a complete R&D-based endogenous growth model within general equilibrium framework, the following (Romer 1994) must be considered: (i) A market economy with many firms exists in production of new products. (ii) Ideas or innovations

as non-rival goods that differ from other inputs. (iii) The production function should exhibit increasing returns to scale by considering the R&D efforts to innovate new ideas⁴. (iv) Technological progress arises as a consequence of intentional decisions of economic agents who tend to maximize their utility and profits. (v) Monopolistic competition exists in the market for production of new products.

The importance of knowledge in growth was reemphasized in the mid-1980s with the emergence of new (endogenous) growth theory. Romer's (1986) pioneer contribution showed that increasing returns to investment in R&D activities can lead to a sustainable or increasing growth rate in per capita income over time in an economy, or across economies. He adopted a simple production function for the firm f , $Q_f = A L_f^\beta K_f^\alpha R_f^{1-\beta-\alpha}$

and for the aggregate economy of consisting of F numbers of firms, $Q = \sum_{f=1}^F Q_f = \sum_{f=1}^F$

$A L_f^\beta K_f^\alpha R_f^{1-\beta-\alpha} = A L^\beta K^\alpha R^{1-\beta-\alpha+\phi}$, because of $\sum_{f=1}^F R_f^{1-\beta-\alpha} = R^{1-\beta-\alpha} R^\phi$, where Q is

output, A a constant, L labor, K capital stock and R R&D in aggregate levels. Each firm invests in R&D beside other inputs and works under constant returns to scale in those three production factors, given R&D investments of all other firms. Moreover, each firm benefits from the aggregate R&D invested by all firms in the aggregate economy without any cost. Thus, when we sum R&D capital over firms, the coefficient picks up the spillover effects of R&D capital. Then, under competitive equilibrium, the aggregate economy exhibits increasing returns to scale in all inputs with overall externalities stemming from aggregate R&D investment. The basic implication of this model is that

⁴ If the aggregate production function is characterized with homogeneity of one in all traditional (rival) inputs and firms are price takers in the market, then Euler's theorem says that the compensation paid to the rival inputs will just equal to the value of output produced. However, there is nothing to compensate the inputs used to produce innovations and hence to accumulate knowledge.

the more the economy invested in R&D, the higher the output level and growth rate of output will be. Then rather than convergence in per capita income over time and across economies, divergence should be the most likely case observed.

As an alternative to the technological change in the neoclassical theory, Robert E. Lucas (1988) emphasized human capital accumulation as the engine of growth in explaining disparities in growth rate across economies. The level of or change in technology does not differ much across economies with similar levels of human capital and investment in human capital. The level and accumulation of human capital that exploits the technological knowledge in useful way differ sharply across economies. In this sense, disembodied technology does not matter in explaining differential knowledge accumulation across economies as in the neoclassical theory. However, the technological knowledge that is embodied in human beings matters in explaining differential knowledge accumulation because human capital stock and accumulation of that and hence the useful knowledge is essentially disparate across economies.

According to this theory, individuals invest in human capital (i.e. demand education) based on the rate of return to an additional period of education in order to maximize the present value of lifetime income streams, as in the human capital theory. At the same time human capital has externalities. Overall, an individual's investment in human capital may contribute to aggregate human capital stock at the margin more than simply individual's private return because of knowledge spillovers across individuals, depending on average level of human capital in a society. So, the higher the average human capital level and the more people living in a society, the greater will be the additional to knowledge from a unit increase in education or private human capital.

Moreover, the more people producing a certain product and the more of that product produced, the greater will be the accumulation of human capital, because people learn by doing. Knowledge spillovers across individuals in a society lead to increasing returns to the human capital accumulation and hence to the scale of production process.

According to Romer, technological knowledge is produced by human capital, but in major part is disembodied. As a result, where the level and accumulation of this technological knowledge is higher, the marginal contribution of human or physical capital to the economy is higher. Hence, the wage rate is higher and human capital accumulates more rapidly in those economies. However, the influence of knowledge creation with own R&D efforts inside the economy and/or the knowledge inflows from outside the economy on the growth of per capita output will get stronger with the accompanied accumulation in per capita physical and human capital stocks (Meier and Rauch 2000, p. 207-208).

These contributions have triggered many studies, but they have not formulated some key issues such as why individuals invest in R&D (i.e., rents to innovations in the market or monopolistic competition) in the model as described by the Schumpeterian argument. Romer (1990, 1993a,b, and 1994) has stated that these earlier models have dealt with technology and technological progress as a side effect of investments of economic agents in R&D, human and physical capital rather than intentional decisions of investing in R&D to innovate technology. These models have simply incorporated one aspect of endogenous growth theory (Marshallian externalities and increasing returns to scale) into the mainstream framework. However, technological knowledge or change has

still stayed simply as public good. It results as a side effect from investment decisions of economic agents for physical or human capital accumulation.

The R&D-based endogenous growth model within a complete general equilibrium framework is formulated by Paul Romer (1990) within mainstream tradition, following his own earlier study and other attempts to model endogenous growth. In this endogenous growth model, Romer incorporated the Schumpeterian insight of the R&D process. A number of extensions to the Romer's model were quickly added by Grossman and Helpman (1991), Aghion and Howitt (1992), and others in the mainstream tradition. As an alternative to the Romer's assumption that increase in variety in capital goods (horizontal innovation) causes output growth in an economy, they assume that it is the rise in quality of capital goods (vertical innovation) that causes output growth, given that variety is fixed. The two types of endogenous growth models have many similar implications with regard to the long run growth within a reduced form context. However, normative analyses of both approaches are quite different.

In the Grossman and Helpman (1991) version, entrepreneurs improve the quality of their own product to capture rents until someone else improves further the quality of that good. The success of each R&D effort for each product is uncertain and is modeled by a probability distribution. When aggregate R&D activities for all firms on all products are accounted for, a smooth or deterministic functional relationship between R&D efforts and horizontal innovations (overall quality improvement in particular number of capital goods) and hence growth occurs.

On the other hand, in the Aghion and Howitt (1992) version, the investment in R&D in a period hinges on the expected investment in the next period, because more

research in future is basically perceived to destroy rents provided by the current R&D investment. Thus both the average growth rate and its variation are increasing function of the magnitudes of innovations, R&D efforts and productivity of these activities, and decreasing function of the rate of time preference for the average person. Moreover, better products make the previous products obsolete. In this process, R&D efforts can create losses as well as gains. Consequently, the average growth rate in stationary equilibrium may be higher or lower than socially optimal since the conflicting distortions exist in the economy.

The common point of the endogenous growth models is that the diverging growth process over time or across economies arises from the increasing returns to production of technological knowledge because of the existence of externalities to knowledge accumulation. Indeed, open economy extensions of endogenous growth models have adopted and empirically assessed the influence of technology diffusion across economies. This kind of assumption with regard to the technology transfer can alleviate divergence across spatial units. It can even lead to convergence instead of divergence across regions depending on how much the followers benefit from catch up relative to the innovation of leaders. In this regard, the endogenous growth models have taken the formal theory closer to the appreciative theory (Fagerberg 1994; Martin and Sunley 1998). The formal incorporation of the technological knowledge spillover across economies into the endogenous growth model at steady state conditions by Rivera-Batiz and Romer (1991) and Grossman and Helpman (1991, chaps. 6, 9, and 11) provides insights into the regional growth process.

The new (endogenous) growth theory assumes technological knowledge as an endogenous factor in the production process. It considers externalities from knowledge spillovers and hence increasing returns associated with knowledge accumulation as the engine of economic growth. This prospect is consistent with the argument that generated knowledge is partly public in nature because it adds to the general knowledge level in society. One implication of endogenous growth theories is that knowledge spillovers and hence increasing returns to knowledge are spatially bounded. This prospect would explain the divergence of growth rates and their uneven distribution across regions (Caniels 2000, p.2).

In fact, both endogenous and neoclassical growth theories assume that long run growth of output is determined by technological change. However, the essential difference arises from the assumption that treats the technology or knowledge in corresponding models. Solow type growth models assume that technological progress is a constant exogenous factor to the model. It is not determined in the model. Technological knowledge grows exogenously at a constant rate. Because it is assumed that any economic unit can access it instantly without any cost, output growth rate differentials across economic units cannot be attributed to the technology levels across economic units. Consequently, in the long run equilibrium, all economic units will grow at the same constant rate of technological change. Only in the short run during the transition process toward the steady state will the growth rates of various spatial economic units differ. Because of decreasing returns to capital accumulation, poor spatial economic units will grow faster than the rich ones, because their capital stock is assumed to be relatively scarce, and hence its marginal product relatively higher.

Alternatively, the endogenous growth theory assumes that technological progress is a variable systematically changing over time and across economies. It is the engine of growth, which is an endogenous input in production process determined by the intentional profit and utility maximizing behavior of economic agents. The differentials in growth rates across economic units in the long run as well as in the short run arise in major part from the technology differentials across economic units because it is not possible to access technological knowledge across economies, at least instantaneously and without compensation. So the diverse individual efforts of economic units to accumulate knowledge contribute to the disparate growth rates across them, given that other factors are constant. Because technological knowledge accumulation is not bounded over time, the marginal product of capital never goes to zero, implying non-decreasing returns to capital. So capital accumulation does not stop even in the long run. Hence, according to this theory, developed and technologically superior economic units can grow faster than the rest: divergence rather than convergence across economic units is likely. Further, capital accumulation follows the knowledge accumulation, not the other way around, because it causes the marginal product of capital to rise. Thus, knowledge and knowledge accumulation lead to the growth of output in two ways. One is indirect in its role as an input in production of producer durables together with capital. It causes the marginal product of capital to rise and lead in turn to permanent capital accumulation. Hence knowledge and capital indirectly through producer durables contributes to economic growth. The other is its direct effect on productivity of production factors through knowledge spillovers (see Romer 1990).

Both object gaps and idea gaps are important factors in disparities of the level and growth rates in per capita income across economies. However, the latter is more crucial than the former. Romer (1993a) argues that the concept of an idea gap is broader than that suggested by the technology gap approach.

“The world technology invokes images of manufacturing, but most economic activity takes place outside of factories. Ideas include the innumerable insights about packaging, marketing, distribution, inventory control, payments systems, information systems, transactions processing, quality control, and worker motivation that are all used in the creation of economic value in a modern economy” (p. 544).

It is not easy to close the object gaps for less developed economies because closing the object gap has substantial opportunity costs. Because idea gaps might be closed without significant opportunity costs, it might be easier to eliminate these gaps. A substantial portion of low incomes in less developed nations is attributable to the idea gaps, which can be reduced at a relatively low cost. On the other hand, a number of economies have experienced rapid growth particularly due to the international flows of ideas. International flows of ideas can be partially realized through unimpeded flows of capital goods, which embody new ideas. Development relies more on the flows of disembodied ideas, which are used in production process. It is difficult, however, to find statistical evidence on the economic role of ideas. Therefore, there is very little evidence regarding this economic role. The evidence does not inform us about the relative importance of ideas versus objects, so we do not know whether the observed catch up of poor economies with rich ones is due to closing idea gaps, object gaps, or both. Hence, to grasp a reasonable conclusion from all available evidence we need additional evidence from the technology gap approach based on historical observations or current events (Romer 1993a).

Romer (1993b) has given the successful Mauritius experience of public policy reforms to attract entrepreneurs from Hong Kong in 1970s and 1980s as an example of economic development strategy by bringing and using the ideas from a technologically developed economy. He has presented the experience of government intervention in Taiwan (China) to encourage the domestic production and exploitation of ideas, as an example of economic development strategy not simply by bringing and using the ideas inside from a technologically developed economy, but also by marketing them in the world market.

On the other hand, the fact that

“... external economies, skilled labor, and technological innovation all seem to be spatially clustered within nations indicates that geography is fundamental to the growth process. ... the forces of growth and accumulation develop unevenly across the regions of a national economy and this geographic unevenness in turn has a major influence on national growth, trade, and competitiveness ...” (Martin and Sunley 1998).

The observed data have suggested that R&D activity, economic activity (capital stock and labor), and population cluster spatially in certain locations within states because spillovers and externalities due to technological knowledge and perhaps due to other factors and hence increasing returns to scale are most likely to be geographically bounded within those clusters. They have also developed unevenly over the geography. Further, many empirical studies have given a consistent evidence of slow regional convergence in per capita income and spatial clusters of high- and low-growth regions. These observations shed some light on the fact that spillovers due to technological knowledge, labor, human or physical capital, and other factors have influenced economic growth within a certain cluster of regions. The endogenous growth models are familiar with such concepts as human capital, knowledge spillovers, increasing returns to

production of knowledge and hence to the scale of aggregate production. However, the major challenge for the endogenous growth theory is to spatially specify the interregional knowledge flows and the other regional concepts.

Even though the endogenous growth models have contributed to understanding some dynamics of differential regional growth process, they have some crucial limitations, most of which come out from their reliance simply on formal mathematical modeling strategy. That is to say, the regional features cannot be clearly incorporated into formal growth process. A great number of studies with regard to endogenous growth literature have constructed such formal models. This approach does not lead to an understanding and empirical measurement of the relationships of regional growth. So, it is more promising to use the potentials of endogenous growth models to guide more informal and empirical inquiry for regional analysis. In other words, because region intrinsic characteristics and geographic dependencies clearly cannot be readily incorporated into formal growth models, these models can be exploited to provide a series of propositions as starting point for empirical specification of the real phenomena. However, there are few empirical studies (in terms of our case, specifically Caniels 2000; Cheshire and Carbonaro 1996; Cheshire and Magrini 1999; and Paci and Pigliuri 2001) which benefit from the endogenous growth theory and account for the regional characteristics, such as distance, geography and location of spatial units properly in their analysis (Martin and Sunley 1998).

In conclusion, we have a sound formal theoretical model in the mainstream tradition. We have also the technology gap approach and convergence approaches that provide a source to appropriately specify the formal model, which is mathematically

conceptualized in the mainstream tradition, in accordance with the observed phenomenon in the EU regional development process. The theories that conceptually surveyed come eventually to the common main conclusion that there are tremendous differences in technological knowledge levels across the regions so that technological knowledge spillovers are plausible source of closing the technological gaps and hence economic gaps. Thus, the technologically less developed regions have opportunity to grow faster than the technologically developed ones, but it is conditional to many economic, social and infrastructure of the regions. Our empirical specification follows this prospect.

CHAPTER IV

THE THEORETICAL MODEL AND ECONOMETRIC SPECIFICATION FOR THE EUROPEAN REGIONAL DEVELOPMENT

1. Derivation of the Theoretical Framework

Romer's (1990) theoretical growth model takes technological progress as an endogenously determined input in the production process based on intentional investment decisions of rationally-behaved economic agents in market. It is the engine of growth. Technology is treated as neither a pure private good nor a pure public good; instead, it is considered as a 'non-rival' and at least 'partially excludable' good. Therefore, the equilibrium condition is derived from monopolistic competition. In monopolistically competitive markets with positive externalities to the economy from technological knowledge, firms will devote less than the optimal level of resources to technology production relative to the other products. Hence, effective interventions in the market that increase the resources devoted to technology producing sector will increase the growth rate.

The model rests on the three main arguments. The first one suggests that technological progress provides the incentive for permanent capital accumulation. Thereby capital accumulation and technological progress together explain a major portion of growth in labor productivity. The second implies that technological progress is a

consequence of rational economic decisions of economic agents, responding to market incentives. In this sense, technological progress is endogenous rather than exogenous. The fact that some individuals are not motivated by market incentives, for instance, academic scientists who are supported by government grants, does not change the underlying consequence. The third and most crucial argument claims that knowledge is different from conventional economic goods. Once new knowledge is created with a fixed cost, it can be used over and over again with no marginal cost; its use does not have opportunity cost. These arguments imply that a price taking equilibrium cannot be sustained. A model of monopolist competition with external effects arising from knowledge spillovers can capture these conditions. This specification suggests that larger markets induce greater research and higher growth. However, the right measure of market size is human capital stock rather than the size of labor force or population.

The production process in this model proceeds through the dynamic interconnected activities of three different sectors. The knowledge-producing sector employs the traditional inputs and benefits from the knowledge spillovers from the existing knowledge stock in the knowledge production process. This sector compensates only the employed rival inputs --not the cost of non-rival ones-- and hence it generates increasing returns to scale in the competitive market. Once a new idea is created, it is added to the existing stock of knowledge. As the existing knowledge stock grows, the potential for knowledge spillovers grows, making it easier to find new ideas. This sector sells new ideas to the producers of intermediate capital goods. The capital goods sector then employs ideas along with traditional inputs to produce intermediate capital goods. So new ideas facilitate the production of new capital goods and the intermediate sector

charges a price that covers the cost of ideas as well as of the traditional inputs. That is, it can sell the intermediate capital goods to the final goods production sector at a price higher than its marginal cost in the market. In the intermediate sector, the sector of producer durables, the producers can survive only under monopolistic competition and it performs under increasing returns to scale in traditional inputs and ideas in the market. The final goods producing sector is willing to pay the higher price because the marginal product of the new intermediate capital goods is greater than the old ones, at least for a period of time. The new and old capital goods are not perfect substitutes for each other, and added variety of producer durables increases the productivity of the final goods sector. This sector also performs under constant returns to scale in the traditional inputs and a certain number of various producer durables at a point of time in the competitive market. This dynamic process provides the framework of economic growth.

We, following Romer (1990), first present the model and then note its testable implications. Suppose we take an extended version of the Cobb-Douglas production function in which output Q is determined by human capital employed in final goods production H_q , labor quantity employed L , and capital stock K , which is embodied in infinitely different types of producer durables, represented with an infinite, continuous variable x_i . Let

$$Q = H_q^\alpha L^\beta \int_{i=0}^{\infty} x_i^{1-\alpha-\beta} di \quad (1)$$

where i represents an index of knowledge level A in terms of number of ideas and x -goods' variety --i.e, $i=A$, $i \in (0, \infty)$ and $A = \in (0, \infty)$, $i=\forall$. The continuous variable x ranges between 0 and ∞ , which implies a potentially infinite number of diversified

producer durables derived from the unbounded knowledge production process. There is no bound to knowledge accumulation and hence to the development of new intermediate goods over time. Thereby, the relevant technology variable is found by taking the integral between zero and infinity.

Next define an accounting measure of aggregate capital stock K as cumulative forgone consumption. Output, investment, and capital stock are measured in terms of consumer goods. Then, capital accumulation is determined via forgone consumption $C(t)$ from produced output $Q(t)$ over time t . The capital stock accumulated starting from the initial year t_0 at the end of the period t_1 is

$$K(t_1) = \int_{t_0}^{t_1} [Q(t) - C(t)] dt = \int_{t_0}^{t_1} (1 - \lambda) I(t) dt \quad (2)$$

where $I(t)$ is the gross investment and λ is a constant depreciation rate of capital through time. The depreciation is perceived as consumption and contained in that. The net addition to the capital stock at time t is

$$dK(t)/dt = K'(t) = Q(t) - C(t) = s Q(t) = I(t) - \lambda K(t) \quad (3)$$

where s is a constant rate of saving through time.

Still following Romer, we next explain individual consumption and saving behavior. We assume that a representative individual maximizes permanent utility by making an inter-temporal decision between present future consumption over an infinite time span using a Ramsey style utility function.

$$\int_{t=0}^{\infty} U [C(t)] e^{-\rho t} dt, \text{ and } U [C(t)] = [C^{1-\sigma} - 1] / [1 - \sigma] \quad (4)$$

where U is the utility of individual, ρ the inter-temporal rate of discount, and σ ($0 < \sigma \leq \infty$) the constant elasticity of substitution. An individual is willing to forego a unit of present consumption for future consumption only if compensated by an interest rate r , which is above the difference of the present and future value of a unit of consumption (the ρ). Saving also depends on how hard it is to substitute present consumption for future; that is, the greater the rate of saving the harder it is to forgo present consumption (the σ). As the function above implies, the marginal utility of a unit of consumption diminishes the further it is postponed. That is, at the same rate of consumption, the marginal utility of a unit of present consumption good is always greater than that of tomorrow's. Then, given that ρ and σ are constant, the relationship between the growth rate of consumption and interest rate is given as $C'/C = (r - \rho) / \sigma$.

The demand for additional capital continuously increases because knowledge accumulation, *ceteris paribus*, causes the marginal product of capital to rise continuously. So capital accumulation is also unbounded over time, following the boundless knowledge accumulation process. As a result, both knowledge accumulation and capital accumulation together determine producer durables. Then at a point of time we can write a long-term fixed relationship between capital stock and the producer durables as follows. To produce one unit of durable good requires a constant η unit of forgone consumption,

$$K = \eta \int_{i=0}^{\infty} x_i \, di \quad (5)$$

We cannot, however, define the levels of the relevant variables from this relationship (potential variety). At any point of time, a given variety (from the infinite) of durable

goods (constrained by the index i which equals to existing level of knowledge stock A , i.e., $i=A$) is produced and employed in the economy.

$$K = \eta \int_{i=0}^A x_i di \quad (6)$$

The accumulation (growth) of aggregate knowledge stock A' is determined by human capital employed in research H_A , the level of total knowledge stock A , and a productivity parameter δ in knowledge sector of an economy.

$$A' = \delta H_A A. \quad (7)$$

Total fixed human capital consists of that employed in the final goods sector and in the R&D sector, respectively, $H = H_q + H_A$.

Suppose now that at any point of time an economy has a certain level of technology given by the of technology index, i.e., $i = A$. This implies a constant amount of durables in use. Moreover, an equal amount of each durable good x will exist. Otherwise, their marginal products would differ and resources would be reallocated. The relationship between total capital stock and durables therefore is

$$K = \eta A x \quad \text{or} \quad x = K / \eta A \quad \text{or} \quad A = K / \eta x \quad (8)$$

where x implies an equal amount of each producer durable. Under this assumption, producer durables can be fragmented into two pieces, physical capital stock K and knowledge stock A . As a consequence of this assumption concerning the stationary state, the production function takes the form

$$Q = H_q^\alpha L^\beta \int_{i=0}^A x_i^{1-\alpha-\beta} di = H_q^\alpha L^\beta A x^{1-\alpha-\beta}. \quad (9)$$

Next, by plugging equation (8) into the equation (9) the function becomes

$$Q = H_q^\alpha L^\beta A (K / \eta A)^{1-\alpha-\beta} = (H_q A)^\alpha (L A)^\beta (K)^{1-\alpha-\beta} \eta^{\alpha+\beta-1}, \quad (10)$$

which can be rewritten as

$$Q = H_q^\alpha L^\beta K^{1-\alpha-\beta} A^{\alpha+\beta} \eta^{\alpha+\beta-1}. \quad (11)$$

This production function does not differ from the neoclassical model with technological change. It is a neoclassical function with human capital and labor augmented technological change. The essential difference arises from the assumption about technology or knowledge in the corresponding models. In a Solow type growth model, technological progress is assumed constant, while the endogenous growth models assume that it is a variable over time and across economic units.

According to the theory, which is summarized in equations (9)-(11), constant returns to scale in L , H_q and x holds, given that A is a constant number of diversified capital goods at any point of time (equation (9)). After adjustment is completed, equal amount x of each variety x_i from A number of capital goods are employed in the production process in the steady state. What aggregate amount of producer durables Ax contributes into a unit of change in aggregate output receives that much share $(1-\alpha-\beta)$ from a unit of value added to aggregate output in a competitive market in the long run equilibrium. Further, since the producer durables are produced by combining ideas and raw capital units in the intermediate sector, the cost of knowledge production as well as raw capital is compensated by the relevant share received by Ax in aggregate from a unit of output production.

However, if A is considered as a variable rather than a constant and if it doubles, output also doubles, when the production factors L , H_q and x are fixed. Ax in aggregate is fixed, so that if variety of intermediate goods $i = A$ doubles, then, given that aggregate

amount of x (or aggregate capital stock K) is constant, the half of the combined capital unit in every intermediate good is transferred into producing of new varieties of intermediate goods. This is so because marginal product of capital in producing new intermediates is higher until the capital is again allocated equally to all varieties of intermediates. At the same time, marginal productivity of capital in use of the earlier capital goods and marginal product of the other factors (L and H_q) doubles, provided that their magnitudes are also fixed. Thus the amount of each intermediate good x_i declines proportionately and equalizes in the long run equilibrium condition along with a proportionate increase in marginal product of the same amount of aggregate capital stock. So, as long as new ideas are found a proportional long run growth in output occurs. Moreover, during the adjustment period, new ideas increase the marginal product of capital and hence combined by finer divided units of (more specialized) physical capital, given that aggregate capital stock is fixed, they take place in producing new intermediate goods. So the marginal product of capital does not decline as long as new ideas are found even in the long run. Then, the new varieties of capital goods take place in and increase the final goods production. Thus an increase in knowledge stock creates a proportionate increase in the value of capital stock and the other factors and through that a proportionate increase in the final goods in the long run equilibrium condition.

On the other hand, the production process is constant returns to scale in L , H_q and K in equation (11) in a competitive market economy if growth in knowledge stock A is taken as a constant, as in the assumption of Solow type neoclassical model, where η is a constant. However, A is a variable in this model and increasing returns to scale in L , H_q , K and A is current with scale economies of $1+(\alpha+\beta)$. So, doubling all factors including A

leads to a more than proportional change in output Q . Increasing returns to scale is simply attributed to spillovers arising from knowledge stock A in the model. In short, it increases productivity of the production factors without any cost and compensation. In other words, a $(1-\alpha-\beta)$ portion of one unit change in output in final goods production processes due to the change in knowledge level A compensates the cost of knowledge in knowledge production sector. The rest of one unit of contribution to output due to the change in A is $(\alpha+\beta)$, knowledge spillovers (or positive externalities), which is benefited without any compensation in an economy. It increases the productivity of L and H_q proportionally.

As a result, the knowledge stock variable A has two effects on growth in output. One is indirect through a finer division of physical capital in the production of new intermediate goods. This increases the value of aggregate fixed capital in the closed economy context or causes aggregate capital accumulation in an open economy context, by increasing the marginal product of capital. In turn the new intermediate goods are inputs in final goods production. The other is directly through spillovers arising from knowledge stock A , which increases productivity of the traditional production factors without any cost and compensation.

Furthermore, as in the Solow model, in the long run stationary case, output Q and knowledge stock A grow at the same rate, given that total labor L , human capital employed in production of final goods H_q , and producer durables x are fixed. If x is fixed, K and A grow at the same rate since aggregate demand for capital is $K = \eta Ax$. Also, because the K/Q ratio converges to a constant in the long run, the consumption share converges to a constant,

$$C/Q = 1 - K'/Q = 1 - (K'/K)(K/Q) \quad (12)$$

because K'/K is a constant as well. Then growth rates of both consumption and output will be equal, $(C'/C) / (Q'/Q) = 1$. That is, we know that $K(t)'/K(t) = 0$ if $A'/A = 0$ in the steady state condition. Therefore, if only $A'/A > 0$, $K'/K > 0$ and $A'/A = K'/K = Q'/Q > 0$, and hence the common growth rate in the long run equilibrium is

$$g = C'/C = Q'/Q = K'/K = A'/A = \delta H_A \quad (13)$$

Romer (1989) has specified an econometric model to test some implications of this theoretical model with cross-country data. Following him, we present the same regression equation.

Let the derivative of natural logarithm of any variable (VAR) with respect to time be $VAR'' = d(\ln VAR)/dt$ and the elasticity of output with respect to that variable be $\varepsilon_{VAR} = \partial(\ln Q)/\partial(\ln VAR)$, where $\varepsilon_H = \alpha$; $\varepsilon_L = \beta$; $\varepsilon_K = 1 - \alpha - \beta$; $\varepsilon_A = \alpha + \beta$. Then, the conventional growth accounting equation can be written as

$$Q'' = \varepsilon_H H_q'' + \varepsilon_L L'' + \varepsilon_K K'' + \varepsilon_A A'' \quad (14)$$

Because cross-section capital data are not available, following Romer we redefine the equation in terms of investment share (I/Q) of output. Capital growth is replaced by $(\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda$ ⁵.

$$\begin{aligned} Q'' &= \varepsilon_H H_q'' + \varepsilon_L L'' + (\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda + \varepsilon_A A'' \\ &= \varepsilon_H H_q'' + \varepsilon_L L'' + \kappa(I/Q) - \varepsilon_K \lambda + \varepsilon_A A'' \end{aligned} \quad (15)$$

where $\kappa = \partial Q/\partial K$ is the marginal product of capital.

⁵ The derivation is

$$\varepsilon_K K'' = (\partial \ln Q / \partial \ln K)(d \ln K / dt) = [(\partial Q / \partial K)(K / Q)][(I / K) - \lambda] = (\partial Q / \partial K)(I / Q) - \varepsilon_K \lambda$$

from equation (3), $dK(t)/dt = K' = [(I/K) - \lambda] K = I - \lambda K$

by definition, $d \ln K(t) / dt = K' / K = (dK / dt) / K = (I - \lambda K) / K = (I / K) - \lambda$

With output per capita $q = Q/L$ and constant returns to scale in H_q , L and K (i.e., $\varepsilon_H + \varepsilon_L + \varepsilon_K = 1$) the accounting equation for growth in per capita output is⁶

$$q'' = -\varepsilon_K L'' + \varepsilon_H (H_q/L)'' + \kappa(I/Q) - \varepsilon_K \lambda + \varepsilon_A A'' \quad (16)$$

Because we cannot directly observe knowledge level A or its change, we can measure its impacts indirectly through its influence both on the marginal product of capital κ and on the investment rate I/Q . Suppose now that saving behavior adjusts in each country to a permanent progress in A , so that marginal product of capital is equalized across countries. Thereby, the opportunities for investment, i.e. knowledge stock A , and capital stock K , grow at the same rate. Also, assume that marginal product of capital κ is proportional to the Q/K ratio, which is a constant in the long run. Then, we can show that⁷

$$A'' = K'' = (I/K) - \lambda = (I/Q)(Q/K) - \lambda. \quad (17)$$

Hence, variation in A'' will not associate with variation in I/Q and in $\kappa = \partial Q/\partial K$ in equation (16). That is, in a regression equation over cross country data in a long enough duration, the I/Q variable would collect all of the impacts of the variation in A'' .

⁶ The derivation of the relevant growth accounting equation is

$$\begin{aligned} Q'' &= (1 - \varepsilon_H - \varepsilon_K) L'' + \varepsilon_H H_q'' + (\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda + \varepsilon_A A'' \\ &= L'' - \varepsilon_H L'' - \varepsilon_K L'' + \varepsilon_H H_q'' + (\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda + \varepsilon_A A'' \\ (Q'' - L'') &= q'' = -\varepsilon_K L'' + \varepsilon_H (H_q'' - L'') + [(\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda] + \varepsilon_A A'' \end{aligned}$$

⁷ This concept, which follows from the footnote 5 above, is derived such that

$$\begin{aligned} \varepsilon_K K'' &= [(\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda] \\ A'' = K'' &= [(\partial Q/\partial K)(I/Q) - \varepsilon_K \lambda] / \varepsilon_K = [(\partial Q/\partial K)(I/Q)] / [(\partial Q/\partial K)(K/Q)] - \lambda \\ &= [(I/Q) / (K/Q)] - \lambda = (I/K) - \lambda \end{aligned}$$

Let us consider a P proxy vector for the variables representing variation in growth of aggregate knowledge stock A'', which is not correlated with variation in I/Q. Then the basic equation (16) in which λ is a constant takes the following form

$$q'' = \alpha_0 - \varepsilon_K L'' + \varepsilon_H h'' + \kappa (I/Q) + \alpha_A P \quad (18)$$

where α_0 is a constant, α_A represents the coefficient of per capita output growth elasticity with respect to the proxy vector for variables representing for the variation in knowledge stock A'' in P vector and $h'' = (H_q/L)''$ is percentage growth rate in human capital per employee.

On the other hand, variation in A'' may not lead to completely offsetting variation in I/Q within a short time period. This is actually not an unreasonable case to expect over cross-country data with an ordinary time span such as 20-30 years. Then variation in A'' is correlated with variation in growth of per capita output q'' even after accounting for the impact of I/Q. It is also possible that the rise of the A/K ratio is correlated with a rise in the marginal product of capital $\kappa = \partial Q/\partial K$. Then, the P proxy vector for the same variables representing variation in growth of aggregate knowledge stock A'' is not perfectly correlated with variation in I/Q. So, the basic equation takes the following form

$$q'' = \alpha_0 - \varepsilon_K L'' + \varepsilon_H h'' + [\kappa + \alpha_B P] (I/Q) + \alpha_A P \quad (19)$$

where α_A is the coefficient of proxy vector for variables representing the variation in knowledge stock A'' in P vector, and α_B is the parameter of the interaction of (I/Q) with variables in P.

Moreover, the causality does not run from the change in I/Q to the growth in A. Exogenous change in I/Q has the same impacts here as in the neoclassical model, which causes offsetting changes in $\kappa = \partial Q/\partial K$. In the long run, the Q/K ratio converges to its

steady state value. Once the adjustment is completed, variation in I/Q , without any variation in A , does not correlate with any variation in growth of per labor output q ". Then, if variation in P results in change in I/Q without causing any change in A , it is expected to have a negative α_B coefficient in equation (19).

Table I. The definition of variables and notations in the theoretical model

<p>Q = the level of aggregate output</p> <p>H = aggregate human capital</p> <p>H_q = human capital employed in production of final goods</p> <p>H_A = human capital employed in production of technological knowledge</p> <p>L = total labor employed</p> <p>K = aggregate level of capital stock</p> <p>x_i = the amount of variety i from producer durables</p> <p>i = an index which implies the number of ideas or differentiated producer durables and hence the level of technological knowledge stock</p> <p>x = an equal amount of each producer durable</p> <p>A = the number of ideas or differentiated producer durables, and hence the level of technological knowledge stock</p> <p>C = aggregate consumption level</p> <p>η = a constant productivity parameter in transforming foregone consumption into producer durables</p> <p>δ = a constant productivity parameter in transforming human capital employed in research sector into new technological knowledge</p>

g = common growth rate of the relevant variables

λ = a constant depreciation rate of capital over time

(I/Q) = investment share in output

P = a vector of proxy variables for knowledge accumulation

$VAR(t)$ = one of the variables in the context as a function of the time

$VAR(t)' = dVAR(t)/dt$ (taking the differential of any variable by time gives total change in that variable over time)

$VAR(t)'' = VAR(t)' / VAR(t) = [dVAR(t)/dt] / VAR(t) = d\ln VAR(t)/dt$ (taking the differential of natural log of any variable by time gives percentage change in that variable)

$\epsilon_{VAR} = \partial(\ln Q) / \partial(\ln VAR)$ (the elasticity of any variable with respect to output)

$\epsilon_H = \alpha$; $\epsilon_L = \beta$; $\epsilon_K = 1 - \alpha - \beta$; $\epsilon_A = \alpha + \beta$ (the elasticity of output with respect to human capital, labor, capital and knowledge, respectively)

$\kappa = \partial Q / \partial K$ (the marginal product of capital)

$q = Q/L$ (output per labor)

q'' = growth rate of labor productivity

L'' = growth rate of employment

h'' = growth rate of per labor human capital

A'' = growth rate of technological knowledge

2. Econometric Specification for the European Regional Development

There are a number of alternative specifications of the economic growth process for the cross-section data. Among outstanding ones, in a pioneer work Rivera-Batiz and Romer (1991) present a long-term specification of the theoretical model within a decentralized two-economy context. Caniels (2000) exploits a technology gap approach for cross regional data in this regard. Magrini (1997) spatially specifies the Romer-type growth model for the disparate EU regional development process. He also exploits certain concepts from the evolutionary theory. These types of theoretical models consider the growth of income or productivity simply as a linear function of growth in technology or knowledge stocks.

Griliches (1998) surveys the earlier micro level empirical studies and specifications that analyse the influences of R&D and R&D spillovers on productivity performance in producing knowledge or income with data across-firms or across-industries. These studies were the basis for the many following studies, for instance, by Romer (1986), and of knowledge production function-type.

On the other hand, short- or mid-term empirical specifications of the Romer-type growth model take the growth process as a consequence of multivariate-effects rather than that of simply variation of growth in technology or knowledge stocks across economies. Specifically, Magrini (1999), Cheshire and Magrini (1999), and in an earlier empirical study Cheshire and Carbonaro (1996) exploit the EU regional data to estimate its regional growth process in this framework.

Rivera-Batiz and Romer (1991) have defined the open economy implications of the R&D-driven endogenous growth model. Integration of two economies, as long as it enables the flow of ideas or the trade-of different variety of capital goods between them,

encourages the increasing returns to scale in R&D sector and raises the global growth of output. If the economies are similar in terms of production processes of output, capital goods and knowledge, output growth increases in both economies.

Assume that both economies have the same number of present ideas or present intermediate goods A , the same R&D effort H_A , and the same degree of R&D productivity δ . After complete integration, the R&D sector of one economy will perform using a larger global basis of knowledge stock than its own, depending on the extent that the existing ideas in the other economy differ from its own. Provided that the number of duplicates of ideas, if any, are the same for both economies, then the potential basis of knowledge stock that both economies can access in order to produce new ideas is the same $(A_1 + \theta A_2) = (A_2 + \theta A_1)$. Where θ ($0 < \theta \leq 1$) implies a fraction of the ideas in the second economy A_2 that are not duplicates for the first economy. By symmetry, it is true for the second economy A_1 as well.

$$A' = A'_1 = A'_2 = \delta H_A (1 + \theta) A \quad (20)$$

However, if the existing ideas in both economies are completely different of each other's, that is, $\theta = 1$, then the existing knowledge stock doubles for knowledge producing sector of both economies.

$$A' = A'_1 = A'_2 = \delta H_A 2 A \quad (21)$$

Furthermore, if the flows of ideas or intermediate goods between two economies, as a consequence of integration, increase the productiveness of knowledge production, the same results hold. A unique fixed cost for each production of an idea leads to a lower unit cost than duplication of fixed costs for the production of the same ideas. These

effects are the similar to resulting from an increase of R&D efforts H_A , provided that other factors are constant.

Alternatively, Caniels (2000) specifies the knowledge accumulation in a location as a consequence of regional dynamics over the geography and region fixed factors as well as its own R&D effort. That is, suppose that regional growth rate of output is a linear function of regional growth rate of knowledge stock or technology, $Q'_r/Q_r = \beta (A'_r/A_r)$, where β is a constant. And let region's growth rate of knowledge stock be a function of the growth rate of its own output, knowledge spillovers absorbed from other regions (S_r), and resources it devotes to R&D (R_r), $A'_r/A_r = \phi (\gamma Q'_r/Q_r + S_r + R_r)$, where ϕ and γ are constants. The extent that a region benefits from interregional knowledge spillovers, S_r , depends upon its absorption capability (implementation and imitation), which may be represented by the infrastructure of a region's human capital, basic science and research (E_r), technology gap (G_{rs}) and spatial distance (d_{rs}) of the region relative to other regions: $S_r = f(E_r, G_{rs}, d_{rs})$.

Cheshire and Carbonaro (1996), on the other hand, specify a cross regional development process in which growth is assumed to be a multivariable process determined by spatial factors as well as knowledge accumulation. They spatially modify Romer's knowledge accumulation equation (7), by making regional growth rate of knowledge by adding spillovers within the region and between regions in it. Within region knowledge spillovers differ by concentration of the knowledge stock and human capital employed in research in a region, and interregional knowledge spillovers decay by distance. So, the equation can be considered in a regional sense as

$$A'_r = \delta H_{Ar} A \phi$$

$$A'_t/A = \delta H_{At}^{1+\nu} \quad (22)$$

where $\varphi = H_A^\nu$ represents knowledge spillovers both within the region and between regions, and ν is the parameter implying the influence of both spillovers on knowledge production. This equation implies dynamic increasing returns to the spatial concentration of human capital through increasing knowledge accumulation when $\nu > 0$.

Moreover, in a more complete framework, Magrini (1997, p. 3-4, 10-11) assumes that the regional knowledge production and hence output growth structure is significantly influenced by a combination of both types of knowledge spillovers within a location and across locations. The knowledge production structure is taken into account in two different forms, disembodied abstract knowledge A and location-sticky tacit knowledge, which is embodied in a location's people, firms, and institutions. The first type of knowledge is produced by outcomes of R&D activity. The ideas produced in this Romer-type of model are non-rival and partially excludable in their nature. So, once a new idea is produced, it does not have an opportunity cost in producing intermediate goods and its cost is compensated in the market. This new idea contributes to the existing knowledge stock, which is open to the public use as well, and everybody can access that without any compensation.

Tacit knowledge is spatially localized, and its interregional knowledge spillovers hinge on the interactions among human beings, so that those are bounded by location and decay by the cost of physical distance. Thus integration and growth in output will raise the global knowledge production by decreasing the distance cost, but at the expense of relatively poor regions with less advanced knowledge production structure.

Consequently, the region that is relatively more specialized in R&D activity will absorb

more knowledge spillovers from outside as well as within the region and hence will produce more ideas; thereby, it will grow relatively faster. In this perception, a regional knowledge production process for two-region case, provided that region 1 is technologically lagging and region 2 is technology leader, can be specified such that

$$A'_1 = \delta_1 H_{A1} H_{A1}^\pi (H_{A2} d_{1,2}^{-1/\beta_{1,2}}) A = \delta_1 H_{A1}^{1+\pi} (H_{A2} d_{1,2}^{-1/\beta_{1,2}}) A \quad (23)$$

where δ_1 implies the capability extent of first region's R&D sector, H_{A1} and H_{A2} stand for human capital employed in first and second region's R&D sectors, respectively. The coefficient π represents the impact of within location tacit knowledge spillovers due to the region's concentration or specialization in R&D. $H_{A2} d_{1,2}^{-1/\beta_{1,2}}$ indicates that the first region can exploit potential tacit knowledge spillovers from the second region's R&D activity H_{A2} . But it decays by the cost of physical distance between the two regions $d_{1,2}$ and relies on a $\beta_{1,2}$ parameter which measures the first region's potential benefit from the second region's knowledge spillovers due to the interaction of human capital employed in R&D sectors. So, the extent of realizing the potential knowledge spillovers from the second region by the first region through interacting of both regions' researchers is an increasing function of the first region's technological competence relative to that of the second region. That is, if $\delta_1 > \delta_2$ then $\beta_{1,2} = 1$, and if $\delta_1 < \delta_2$ then $\beta_{1,2} > 1$. By symmetry, the same is true for the second region.

Consequently, both models of Magrini (1997) and Caniels (2000) assume that knowledge gradually spills over spatial economic units. The extent of the spillovers' potential influence on the economy is conditional on particular factors and it decays by the cost of physical distance. In a full specification of Romer's theoretical model, Magrini (1997) divides the knowledge into two categories, abstract and tacit in character,

and gives a particular role for growth disparities to the tacit knowledge with regard to within- and between-regions knowledge spillovers. However, the approach of Caniels (2000) assumes that the cross-regional disparities in long run total factor productivities exist because of the technology gaps across them, and that the technologically lagging regions that have technological competence can realize this potential by closing that gap and thus growing faster. But he does not classify the knowledge into the different characters. Accordingly, the variables contained within the regional proxies vector P_{it} are theoretically supposed to imply regional variation in regional knowledge accumulation A . However, in reality there are also other essential regional factors that are likely to have significant affect on the regional productivity performance, especially when studied with short term data.

Furthermore, the economic growth theory of Romer (1990) only approximates real phenomena by employing simple key assumptions to make it easier to understand. It focuses on knowledge accumulation due to R&D efforts and knowledge spillovers across firms within a closed economy. It does not consider knowledge spillovers across spatial economic units and other factors that may have significant influence on regional economic performance. Rivera-Batiz and Romer (1991) show how the integration of economies enables them to exploit the existing knowledge stock in their R&D process at the steady state condition, but it does not define how the differential production structures in R&D sectors or output sectors across economies affect the process outside the steady state. So, we assume a relatively larger and more realistic concept than Romer's for the regional growth process by considering particular proxies for those essential factors in our empirical specification.

In order to empirically test the role of the own-region R&D efforts and knowledge spillovers across regions due to the outside-region R&D efforts, we spatially specify a regional growth process based on the intuition of Romer model and in the light of the regional specifications of it mentioned above. We assume that the disparate regional growth is a consequence of multivariate process as specified in such empirical studies as Magrini (1999), Cheshire and Magrini (1999), and Cheshire and Carbonaro (1996) along with the regional adaptation of Romer-type theoretical model by Magrini (1997). However, for simplicity we assume that knowledge is one kind and locally accumulates as in the specification of Caniels (2000). That is to say, own R&D efforts together with particular local fixed characteristics and spatial connections of local economic units to each other over the geography allow regional knowledge accumulation. In addition to the generation of knowledge within locations, knowledge accumulation of spatial economic units results from knowledge spillovers across regions.

Specifically, we empirically test the influences of local employment in R&D activities implemented or funded by private (R_{rp}) or government (R_{rg}) sectors, respectively, on growth in labor productivity. Beside own sources devoted to R&D activity by these sectors, growth in labor productivity is determined by knowledge spillovers across regions due to the R&D efforts of the other regions. We assume that the potential extent of knowledge spillovers likely to be exploited by a region hinges positively on its technological gap relative to other regions. However, the realization of that potential force decays by physical distance within country and additionally by cultural, linguistic, institutional, and etc. obstacles across country borders. Therefore, the cross regional R&D efforts in relative and absolute forms, respectively, for the private

and government sectors above are separately weighted because of the assumed transaction costs across regions r and s , in general forms $([R_s - R_r]/d_{rs})$ and R_s/d_{rs} .

Moreover, certain other factors are likely to have significant influence on the disparate EU regional economic performance. As mentioned in the literature review, industrial mix and its transformation (M_r) is one. Another plausible crucial factor is industrial specialization or diversification of a region, as measured by the Herfindahl index (HI_r). Further, to control the economic (hence physical capital intensity) and technological extent of a region we use the usual variable, initial year per labor income ($\ln q_0$). Finally, the neighbor regions' economic performance is likely to influence positively that of a region through spillovers other than knowledge spillovers, it is measured by labor productivity growth in neighbor regions (q_{rN}). Also, a number of recent regional empirical studies on the EU data have used spatial econometric techniques and found significant spatial dependencies in many economic variables. This variable also corrects the plausible bias in the parameter estimates due to the spatial autocorrelation by accounting for the first and second degrees of lags in the dependent variable in the model.

The spatial autocorrelation problem:

As Anselin et al. (1998, p. 9-12) express, when the observations are contiguous cross-sectional units, a spatial autocorrelation may exist and present a spurious sign of structural effects if it is not appropriately accounted for. There are two types of spatial autocorrelation problem in specification of regression models. One of which is misspecification in the form of a spatial lag model (with regard to the dependent variable, Y), which causes the OLS estimator to be biased and inconsistent (as a special case of an

omitted endogenous variable). The other is misspecification in the form of a spatial error (with regard to the error term, ϵ), which affects the precision of the OLS estimator, although remains unbiased (as a special case of non-spherical error variance-covariance matrix). Hence, the interpretation of these two types of alternatives differs substantially.

A spatial error model can be presented as

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

$$\boldsymbol{\epsilon} = \theta\mathbf{W}\boldsymbol{\epsilon} + \boldsymbol{\eta}$$

$$\boldsymbol{\eta} = (\mathbf{I} - \theta\mathbf{W}) \boldsymbol{\epsilon}$$

$$\boldsymbol{\epsilon} = (\mathbf{I} - \theta\mathbf{W})^{-1} \boldsymbol{\eta}$$

$$\mathbf{Y} = \mathbf{X}\boldsymbol{\beta} + (\mathbf{I} - \theta\mathbf{W})^{-1} \boldsymbol{\eta}$$

$$\mathbf{E} [\mathbf{Y}|\mathbf{X}] = \mathbf{X}\boldsymbol{\beta} \text{ since } \mathbf{E} [\boldsymbol{\eta}|\mathbf{X}] = \mathbf{0} \quad (24)$$

where spatial dependence is embodied in the error term $\boldsymbol{\epsilon}$, which is the vector of error terms of the model in order of n by 1 . $\boldsymbol{\eta}$ is the vector of random components of the error terms of the model in order of n by 1 . \mathbf{Y} is the vector in order of n by 1 with n observations (which equals number of regions) of dependent variable. \mathbf{X} is a matrix in order of n by k with k -independent variables and n observations on each independent variable. $\boldsymbol{\beta}$ is a vector of k -parameters to be estimated in k by 1 order. \mathbf{W} is the spatial interactions matrix in an n by n order in which w_{ij} elements represent the weights of relative spatial distances across regions. θ is the spatial autocorrelation coefficient. \mathbf{I} is the identity matrix in order of n by n with diagonal elements equal 1 and off diagonal elements equal 0 . So, if the regional interdependencies are in error components form, then after specification in the form of spatial lagged errors, it is possible to reach more

efficient unbiased-estimates. If it is known that error terms are spatially correlated and not corrected for, then the parameter estimates are still consistent but not efficient.

On the contrary, when the spatial dependence is in a lag form, the model can be written as

$$\mathbf{Y} = \mathbf{X}\beta + \varepsilon$$

$$\varepsilon = \rho\mathbf{W}\mathbf{Y} + \eta$$

$$\mathbf{Y} = \mathbf{X}\beta + \rho\mathbf{W}\mathbf{Y} + \eta$$

$$(\mathbf{I} - \rho\mathbf{W}) \mathbf{Y} = \mathbf{X}\beta + \eta$$

$$\mathbf{Y} = (\mathbf{I} - \rho\mathbf{W})^{-1} \mathbf{X}\beta + (\mathbf{I} - \rho\mathbf{W})^{-1} \eta$$

$$\mathbf{E} [\mathbf{Y}|\mathbf{X}] = (\mathbf{I} - \rho\mathbf{W})^{-1} \mathbf{X}\beta \text{ given that } \mathbf{E} [\eta|\mathbf{X}] = \mathbf{0}$$

$$\mathbf{E} [\mathbf{Y}|\mathbf{X}] = \mathbf{X}\beta + \rho\mathbf{W} \mathbf{X}\beta + \rho^2\mathbf{W}^2 \mathbf{X}\beta + \dots, \text{ as } \sum_j w_{ij} = 1 \text{ in } \mathbf{W} \text{ matrix} \quad (25)$$

where, ρ is the autoregressive parameter. The remaining definitions are the same as above. This implies a serial increasing order in the values of the local explanatory variables \mathbf{X} (powers of the spatial weight matrix \mathbf{W}) through contiguity. Thus, the dependent variable is not only explained by local variables but also by those of all other regions in the system, decaying by any type of distance cost. If spatial dependency is in the lag form of dependent variable and it is not corrected for, then the parameter estimates are not consistent as well as being inefficient.

In the context of a regression equation, spatial lag dependence can arise from various regional economic forces in \mathbf{X} that affect \mathbf{Y} and transcend the regional borders. Specifically, variables that characterize production functions should be taken into account both within the region (\mathbf{X}), as well as in all other locations in the system ($\mathbf{W}\mathbf{X}$, $\mathbf{W}^2 \mathbf{X}$, ...). That is, any change in \mathbf{X} in any of the interconnected regions affects all other regions

in the system (the spatial multiplier effect). In contrast, spatial error dependence suggests that the un-specified (error) terms in neighboring locations (such as the magnitude of production and innovation in other sectors) are pertinent, but they only affect the estimator's precision. This form of spatial interdependence does not result in a spatial multiplier effect. In this regard, misspecification in the form of a spatial lag model (with regard to the dependent variable, \mathbf{Y}) leads to a much more serious problem.

Nonetheless, determining a relevant \mathbf{W} matrix for the underlying subject is essential. It can be constructed based on the right knowledge or observations about the form, its extent, the reasons, and etc. of spatial dependencies in the system. So it can take various forms depending on different spatial patterns in the system. A simple widely used form is the binomial distinction of locations in a contiguous system of spatial units, by assigning one to a region for neighbors and zero for the rest (see Anselin 1988, chap. 3).

The variables contained within the regional proxies vector \mathbf{P}_{rt} are assumed to imply regional variation in regional productive efficiency rather than simply in the technological frontier A_{rt} at time t . Then, it can be written as

$$\mathbf{P}_{rt} = [R_{rp}, R_{rg}, (R_s - R_r)/d_{rs} \text{ or } R_s/d_{rs}, M_r, HI_r, q_{s,N}, \ln q_0]_t \quad (26)$$

As a result, our specification considers particular forces that most likely have significant influence on convergence and divergence across regions. Thus, the deterministic relationship in equations (18 and 19) can be specified in the following stochastic general forms for our panel data on the NUTS 2-regions of the three EU nations (France, Italy and Spain) for the period of 1985-1995,

$$q_{rt}'' = \mu_r - \varepsilon_K L_{rt}'' + \varepsilon_H h_{rt}'' + \kappa (I/Q)_{rt} + \alpha_A P_{rt} + \tau_t + v_{rt} \quad (27)$$

$$q_{rt}'' = \mu_r - \varepsilon_K L_{rt}'' + \varepsilon_H h_{rt}'' + [\kappa + \alpha_B P_{rt}] (I/Q)_{rt} + \alpha_A P_{rt} + \tau_t + v_{rt} \quad (28)$$

where α_A implies the parameters of proxy variables in \mathbf{P}_{rt} , α_B is the parameters of interaction (between investment share and proxies for A), variables, μ_r and τ_t are assumed to represent respectively cross regional and time effects. Whether they have significant systematic, fixed or random effects in the model is tested through the panel data procedure. v_{rt} stands for an error term randomly distributed across regional units and over time. The two econometric specifications have different implications as mentioned above. In particular, the second specification is more relevant with the non-long term data and reality. However, the first one is specified based on the assumption of the steady state condition, so that a change in the \mathbf{P}_{rt} vector is assumed to have a proportionate change in growth of per labor output. Such a constraint is not needed for this parameter of the second equation. Specifically, for instance, if government sector R&D significantly affects both $(I/Q)_{rt}$, and marginal product of capital κ (beyond directly affecting growth in labor productivity), and if it is excluded from the estimation, then we expect that the coefficient κ would be overestimated capturing the effect of government sector R&D variable, so that the coefficient α_B is expected to be positive. The same interpretation follows also for other variables, but we may not be able to capture separate impacts at the same time if all variables are estimated together because most of the relevant variables are likely to embody similar systematic information (co-linearity problem). We therefore estimate various combinations of these general forms of empirical specifications, separately. The general purpose here is to test whether the underlying variables have significant separate influence on the regional growth in per labor income.

Furthermore, in order to test whether the relevant variables in the \mathbf{P}_{rt} vector have significant separate impact on cross-regional disparities in productive-efficiencies, we

exploit the panel data method with one type of stochastic frontier approach (see Mullen, et al. 1996, for a similar approach to the cross-states data). First, we estimate the parameters of cross-regional effects with fixed effects dummy variable technique by simply employing the input variables in the model. Next, we run the estimated parameters on the average values of the proxy variables in the $\mathbf{P}_{r,t}$ vector for the relevant period, $\mathbf{P}_{r,av}$.

$$\mu_r = \alpha_0 + \epsilon_A \mathbf{P}_{r,av} + e_{r,av} \quad (29)$$

where α_{av} is intercept, and $e_{r,av}$ cross-regional random error term with mean zero, regarding the average values of the variables. All variables are explained in the following section.

3. The Variables, Hypotheses and Data

Under this section the variables employed in the model, the hypotheses, and the data are described.

3. 1. The variables

The following variables are constructed, in order to estimate the coefficients of them and to test the hypotheses for the model specified above.

1. *labor productivity growth:*

$$q_{rt} = \text{GPLGVA}_{rt} = \text{Ln} (\text{PLGVA}_t / \text{PLGVA}_{t-1})_r$$

where $\text{PLGVA}_{rt} = (\text{GVA} / \text{EMP})_{rt}$

The annual growth rate in per labor gross value added for a region and year (GPLGVA_{rt}) is approximated as natural logarithmic differential of per labor

gross value added of that year ($PLGVA_{rt}$) from its one earlier year value ($PLGVA_{r,t-1}$). Per labor gross value added for a considered region and year ($PLGVA_{rt}$) is measured by dividing total gross value added GVA_{rt} by total employment EMP_{rt} in all sectors.

2. *employment growth:*

$$L_{rt}'' = GEMP_{rt} = \text{Ln} (EMP_t / EMP_{t-1})_r$$

The annual growth rate of total employment in all sectors for a region and year ($GEMP_{rt}$) is approximated as natural logarithmic differential of total employment in all sectors of that year (EMP_{rt}) from its one earlier year value ($EMP_{r,t-1}$).

3. *human capital growth:*

$$h_{rt}'' = GPLHED_{rt} = \text{Ln} (PLHED_t / PLHED_{t-1})_r$$

where $PLHED_{rt} = (HED / EMP)_{rt}$

and $HED_{rt} = (GVA_r / GVA_N)_t * HED_{Nt}$

Annual growth rate of per labor aggregate enrollment in higher education for a region and year ($GPLHED_{rt}$) is approximated as the natural logarithm differential of per labor population enrolled in higher education of that year ($PLHED_t$) from its one earlier year value ($PLHED_{t-1}$). Per labor aggregate enrollment rate in higher education ($PLHED_{rt}$) is simply a division of total number of persons enrolled in higher education (HED_{rt}) to total employment (EMP_{rt}) for a considered region and year. Regional aggregate enrollments in higher education (HED_{rt}) are estimated simply by breaking the national higher education enrolments (HED_{Nt}) into regional ones based on their aggregate gross value added proportions $(GVA_r / GVA_N)_t$ because neither regional higher education enrollment (or any other regional educational) data are available for the required time series length.

4. *investment share:*

$$(I/Q)_{rt} = INVESTSH_{rt} = (INVEST / GVA)_{rt}$$

Investment share for a region and year ($INVESTSH_{rt}$) is calculated as its investment ($INVEST_{rt}$) share in gross value added (GVA_{rt}) in the same year.

5. *economic spillovers from first (and both first and second) order neighbors:*

$$q_{rN}'' = GPLGVAW1_{rt} = \sum_{r=1}^N \text{Ln} (PLGVAW1_t / GPLGVAW1_{t-1})_{rt} / N_{S1}$$

The annual-average growth rate of per labor gross value added in first order neighboring regions for a region and year ($GPLGVAW1_{r,t}$) is measured by division of aggregated growth rates in per labor gross value added in these first order neighbors by the number of those regions N_{S1} . First order neighbors are regions that border the considered regions. Second order neighbors border first order neighbors. Annual average percentage growth rate of per labor gross value added in a first order neighboring region is approximated as the natural logarithmic differential of per labor gross value added in considered year ($PLGVAW1_t$) from its earlier year value ($PLGVAW1_{t-1}$). The same computation by exact analogy is true for both surrounding border neighbors and second order regions jointly ($GPLGVAW12_{r,t}$). A similar variable is defined by Pons-Novell, and Viladecans-Marsal (1999).

6. *initial-year labor productivity:*

$$\ln q_0 = LPLGVA_{r,t_0} = \ln (PLGVA_{r,t_0})$$

The logarithm of per labor gross value added of region r at the initial year t_0 ($LPLGVA_{r,t_0}$) is calculated by taking the natural logarithm of its per labor gross value added for each corresponding initial year t_0 . Hence, these annual levels of log-per labor gross value added variable correspond to the initial year terms of annual growth rates in per labor gross value added within the relevant period since this year's annual growth rate in per labor gross value added is measured as this year's log-per labor gross value added relative to one earlier year's log-per labor gross value added.

7. *growth of industrial specialization:*

$$GHERFINDX_{r,t} = \ln (HERFINDX_t / HERFINDX_{t-1})_r$$

$$\text{where } HI_{r,t} = HERFINDX_{r,t} = \sum_{j=1}^9 (S_{r,tj})^2, \quad S_{r,tj} = (GVA_{rj} / GVA_r)_t$$

$$\text{and } GVA_r = \sum_{j=1}^9 S_{rj}$$

The annual-growth rate in Herfindahl Index of a region ($GHERFINDX_{r,t}$) is approximated by taking the natural logarithmic differential of the Herfindahl Index in a considered year from that of its earlier year value. The Herfindahl Index for region r and year t ($HERFINDX_{r,t}$) is measured by aggregating the squares of gross value added shares (S_{rj}) of all j sectors (our sample is restricted to 9 sectors due to the sectoral data constraint) in total regional gross value added. It is used here so as to compare the degree of sectoral concentration or diversity of regions relative to each other and over time.

8. *growth of industrial mix:*

$$GSECMIX_{rt} = \text{Ln} (\text{SECMIX}_t / \text{SECMIX}_{t-1})_r$$

$$\text{where } M_{rt} = \text{SECMIX}_{rt} = \left\{ \sum_{j=1}^9 (\text{GVA}_{rj} / \text{GVA}_r) * (\text{GVA}_{\text{EU}j} / \text{EMP}_{\text{EU}j}) \right\} \\ / \left\{ \sum_{j=1}^9 (\text{GVA}_{\text{EU}j} / \text{GVA}_{\text{EU}}) * (\text{GVA}_{\text{EU}j} / \text{EMP}_{\text{EU}j}) \right\}$$

The annual-growth rate of the sectoral mix variable for region r and year t ($GSECMIX_{rt}$) relative to that of European average (57 regions in the sample) is approximated by taking the natural logarithmic differential of sectoral mix in the considered year (SECMIX_t) from its prior year value (SECMIX_{t-1}). The sectoral mix variable is calculated by aggregating the products of gross value added shares of the relevant 9 sectors in total regional gross value added and average European per labor gross value added in those 9 sectors, and then it is divided by the aggregation of products of gross value added shares of the relevant 9 sectors in total European gross value added and average European per labor gross value added in those 9 sectors. Sectoral mix index (SECMIX_{rt}) here represents the extent to which a region has per labor gross value added over or below the European average due to its industrial composition. In other words, it controls the size of higher or lower per labor gross value added sectors in a region relative to that of European average. The definition of this variable comes from Partridge and Rickman (1999).

9. *private sector R&D:*

$$R_{rp} = \text{LPLRDBP}_{rt} = \text{Ln} (\text{RDBPER} / \text{EMP})_{rt}$$

The logarithm of per labor personnel employed in business sector research and development activities (R&D) for region r and year t (LPLRDBP_{rt}) is simply the natural logarithm of the ratio of total personnel employed in business sector R&D activities to total employment in the same year.

10. *government sector R&D:*

$$R_{rg} = \text{LPLRDGP}_{rt} = \text{Ln} (\text{RDGPER} / \text{EMP})_{rt}$$

The logarithm of per labor personnel employed in government sector research and development activities (R&D) for region r and year t (LPLRDGP_{rt}) is simply the natural logarithm of the ratio of total personnel employed in government sector R&D activities to total employment in the same year.

11. *private sector R&D gap that diminishes with distance:*

$$(R_s - R_r) / d_{rs} = \text{RLRDBPDW}_{rt} = \left\{ \sum_{s=1}^S \text{Ln} (\text{PLRDBP}_s / \text{PLRDBP}_r)_t * \text{Ln} (\text{DISTANCE}_{r,s})^{-1} \right\}$$

where $\text{Ln} (\text{PLRDBP}_{s,r})_t > 0$, $r \neq s$, $S * 56$, and $\sum_{s=1}^{57} \text{Ln} (\text{DISTANCE}_{r,s})^{-1} = 1$

The distance adjusted-relative log of per labor R&D personnel in the business sector for each region and year (RLRDBPDW_{rt}) is approximated as a distance weighted (DW_{rs}) aggregation (over the corresponding regions) of the natural logarithmic differentials of per labor personnel employed in business sector R&D activities in all regions (PLRDBP_s) from that of the considered region (PLRDBP_r). It collects the regions where PLRDBP_s is greater than PLRDBP_r . More clearly, the natural log of per labor R&D personnel in business sector of an region r in year t is subtracted from that of all other 56 regions in the sample one by one. Negative values are assigned the value zero. This provides a column vector, which represents the relative PLRDBP_s of all other regions s to PLRDBP_r of the considered region r . This procedure is repeated for each region of all 57 regions and hence a collection of 57 column vectors provides an R&D gap matrix of 57 by 57, which takes diagonal elements with zero. In the same way, for each of the considered 10 years this matrix is calculated. Correspondingly, a geographical distance matrix of 57 by 57 is constructed. The geographical distance of each region to all other 56 regions gives a column vector. This method is repeated for each region of all 57 regions and hence a collection of 57 column vectors provides a distance matrix of 57 by 57, which also takes diagonal elements with zero. The over all aggregation of the distance weights is equalized to one, so that the interaction of distance weight elements with observations of any variable in this research simply affects the variation of the relevant variable rather than its mean value. Hence, the possible spatial interdependence issue with regard to the relevant variables is assumed being dealt with via a simple procedure. The geographic distance between regions is measured as a straight line on the map, which defines the centers of European regions (NUTS2), as follows. The distance between urban centers of regions within a national border is measured directly in the centimeter value. However, the portion of the distance crossing national border is doubled. The portion of the distance crossing the second national border is tripled. It assumes that the national borders represents cultural, linguistic, ethnic, institutional, social, national etc. disparities which are much more diverse across nations than across regions within a nation. So they can be significant obstacles to formal or informal human interactions. Moreover, considering the regions made up an island or a group of islands the portion of the distance corresponding to over sea is doubled. This implies that formal or informal communication with this type of isolated regions is more costly and harder relative to others. Furthermore, the measurement of the physical distance between regions in any measurement term such as in inches, centimeter, miles or kilometer does not change the result in our case. The important thing is that it is supposed to reflect the relativity concept. Moreover, the measurement errors

arising from the same measurement procedure attributed to the random error term so that they do not change the results as well. Consequently, the division of the first 57 by 57 cross regional R&D deviations matrix by the second 57 by 57 cross regional distance matrix provides a 57 by 57 cross regional spillover gap matrix. The aggregations of positive values of each column vector in this matrix give us an observation of corresponding region. This variable is inspired from Caniels (2000, chap. 4).

12. *private sector R&D gap with first (or second or both) order neighbors:*

$$RLRDBPDW_{1rt} = \left\{ \sum_{s=1}^{S1} \text{Ln} (\text{PLRDBP}_{S1} / \text{PLRDBP}_r)_t / S1 \right.$$

The relative log of per labor R&D personnel in business sector (if and only if $\text{PLRDBP}_{S1} \exists \text{PLRDBP}_r$) with regard to the bordering neighbors for each region r and year t ($RLRDBPDW_{1rt}$) is approximated by dividing the aggregates of natural logarithm differentials of per labor personnel employed in business sector R&D activities in first order bordering regions (PLRDBP_{S1}) from that of the considered region (PLRDBP_r) into the number of those regions $S1$. The same analogy is valid for computation of per labor R&D personnel in business sector of the second order neighbors ($RLRDBPDW_{2rt}$) and of both first and second order regions jointly ($RLRDBPDW_{12rt}$).

13. *government sector R&D gap that diminishes with distance:*

$$(\text{R}_s - \text{R}_r) / d_{rs} = \text{RLRDGP}DW_{rt} = \left\{ \sum_{s=1}^S \text{Ln} (\text{PLRDGP}_s / \text{PLRDGP}_r)_t \right. \\ \left. * \text{Ln} (\text{DISTANCE}_{r,s})^{-1} \right\}$$

where $\text{Ln} (\text{PLRDGP}_s / \text{PLRDGP}_r)_t > 0$, $r \neq s$, $S * 56$, and $\sum_{s=1}^{57} \text{Ln} (\text{DISTANCE}_{r,s})^{-1} = 1$

The distance adjusted-relative log of per labor R&D personnel in government sector for each region and year ($RLRDGP}DW_{rt}$) is approximated as a distance weighted ($_{DW}_{rs}$) aggregation (over the corresponding regions) of natural logarithm differentials of per labor personnel employed in government sector R&D activities in all regions (PLRDGP_s) from that of the considered region (PLRDGP_r). The same procedure, as in the case of $RLRDBPDW_{rt}$ above, applies here.

14. *private sector R&D that diminishes with distance:*

$$R_s/d_{rs} = LRDBPDW_{rt} = \left\{ \sum_{s=1}^{56} \text{Ln} (\text{PLRDBP}_{s,t}) * \text{Ln} (\text{DISTANCE}_{r,s})^{-1} \right\}$$

where $r \neq s$, and $\sum_{s=1}^{57} \text{Ln} (\text{DISTANCE}_{r,s})^{-1} = 1$

The distance adjusted-logarithm of per labor R&D personnel in business sector for each region and year ($LRDBPDW_{rt}$) is approximated as a distance weighted ($_{DW}_{rs}$) aggregation (over the corresponding regions) of natural logarithm of per labor personnel employed in business sector R&D activities in all regions ($PLRDBP_s$). The same procedure as in the case of $RLRDBPDW_{rt}$ above applies here as well, with the only difference being that per labor personnel working in business sector R&D activities in all 56 other regions is considered rather than relative term of that.

15. *private sector R&D of first (or second or both) order neighbors:*

$$LRDBPDW_{1rt} = \sum_{s=1}^{S1} \text{Ln} (\text{PLRDBP}_{S1,t}) / S1$$

The log of per labor R&D personnel in business sector with regard to the bordering neighbors for each region and year ($LRDBPDW_{1rt}$) is approximated by dividing the aggregates of natural logarithm of per labor personnel employed in business sector R&D activities in the first order bordering regions ($PLRDBP_{S1}$) into the number of those regions $S1$. The same computation by the analogy works for the second order neighbors ($LRDBPDW_{2rt}$) and for both first and second order neighbors jointly ($LRDBPDW_{12rt}$).

16. *government sector R&D that diminishes with distance:*

$$R_s/d_{rs} = LRDGPDW_{rt} = \left\{ \sum_{s=1}^{57} \text{Ln} (\text{PLRDGP}_{s,t}) * \text{Ln} (\text{DISTANCE}_{r,s})^{-1} \right\}$$

where $r \neq s$, and $\sum_{s=1}^{57} \text{Ln} (\text{DISTANCE}_{r,s})^{-1} = 1$

The distance adjusted-log of per labor R&D personnel in government sector for each region and year ($LRDGPDW_{rt}$) is approximated as a distance weighted ($_{DW}_{rs}$) aggregation (over the corresponding regions) of natural logarithm of per labor personnel employed in government sector R&D activities in all regions ($PLRDGP_s$). The same procedure as in the case of $LRDBPDW_{rt}$ above applies here.

Table II. The definition of variables employed in the regional specifications

Symbols	Name of Variable	Definition
	<i>1. Growth and input variables:</i>	
$q_{rt}'' = \text{GPLGVA}_{rt}$	<i>labor productivity growth</i>	growth rate of labor productivity
$L_{rt}'' = \text{GEMP}_{rt}$	<i>employment growth</i>	growth rate of total employment
$h_{rt}'' = \text{GHED}_{rt}$	<i>human capital growth</i>	growth rate of per labor enrolment in higher education
$(I/Q)_{rt} = \text{INVESTSH}_{rt}$	<i>investment share</i>	investment share in aggregate output
$P_{rt} :$	<u>Proxies Vector:</u>	Vector of proxy variables for productive-efficiency:
	<i>2. R&D and knowledge spillover variables:</i>	
$R_{rp} = \text{LPLRDBP}_{rt}$	<i>private sector R&D</i>	natural log of per labor personnel employed in private sector R&D
$R_{rg} = \text{LPLRDGP}_{rt}$	<i>government sector R&D</i>	natural log of per labor personnel employed in government sector R&D
$(R_s - R_r)/d_{rs} :$	<i>regional spillovers of private or government sector due to R&D gaps that diminish with distance:</i>	the R&D gap of the considered region r from the other regions s is weighted with spatial distance from them:
RLRDBPDW_{rt}	<i>private sector R&D gap that diminishes with distance</i>	
RLRDGPDW_{rt}	<i>government sector R&D gap that diminishes with distance</i>	

$RLRDBPDW_{1,t}$	<i>private sector R&D gap with first order neighbors</i>	
$RLRDBPDW_{12,t}$	<i>private sector R&D gap with first and second order neighbors</i>	
R_s/d_{rs} :	<i>regional spillovers of private or government sector R&D that diminish with distance:</i>	R&D of all of the other regions is weighted with spatial distance to them:
$LRDBPDW_t$	<i>private sector R&D that diminishes with distance</i>	
$LRDGPDW_t$	<i>government sector R&D that diminishes with distance</i>	
$LRDBPDW_{1,t}$	<i>private sector R&D of first order neighbors</i>	
$LRDBPDW_{2,t}$	<i>private sector R&D of second order neighbors</i>	
$LRDBPDW_{12,t}$	<i>private sector R&D of first and second order neighbors</i>	
	3. Economic structure:	
$M_t = SECMIX_t$	<i>industrial mix</i>	the concentration rate of the region in high per capita income industries
$GSECMIX_t$	<i>growth of industrial mix</i>	
$HI_t = HERFINDX_t$	<i>industrial specialization</i>	Herfindahl Index
$GHERFINDX_t$	<i>growth of industrial specialization</i>	Growth rate of Herfindahl Index
q_{rN} :	<i>economic spillovers from</i>	growth in per labor income of

	neighbors:	neighbor regions:
GPLGVAW1 _{rt}	<i>economic spillovers from first order neighbors</i>	
GPLGVAW12 _{rt}	<i>economic spillovers from first and second order neighbors</i>	
$\ln q_0 = \text{LPLGVA}_{rt0}$	<i>initial-year labor productivity</i>	natural log of labor productivity at the initial year
	4. Interaction variables:	
$(I/Q)^* q_{rN}'' =$	<i>investment share* economic spillovers from first order neighbors</i>	interaction between region's investment share and labor productivity growth of first order neighbors
$(I/Q)^* R_{rp} =$	<i>investment share*private sector R&D</i>	interaction between region's investment share and its private sector R&D effort
$(I/Q)^* R_s/d_{rs} =$	<i>investment share* private sector R&D that diminishes with distance</i>	interaction between region's investment share and private sector R&D efforts of the other regions that weighted with distance
$(I/Q)^* (R_s - R_r)/d_{rs} =$	<i>investment share* private sector R&D gap that diminishes with distance</i>	interaction between region's investment share and private sector R&D gap of the region from other regions that weighted with distance
P_{ra}v :	<u>Average Proxies Vector:</u>	Vector of average proxy variables for productive-efficiency:
LINPUTSwLq ₀	<i>Log of cross region effects</i>	natural log of cross region effects from inputs model with initial year labor productivity
	5. Socio-demographic variables:	

POPRT2544 _{r av}	<i>population rate25-44</i>	average population rate between 25-44 years of age
LTUNRT _{r av}	<i>long term unemployment rate</i>	average long term unemployment rate
FEMACTRT _{r av}	<i>female activity rate</i>	average female activity rate

Notes: Of the lower case letters, r is considered region while s stands for regions other than r, and t is the relevant year. The computation of these variables is explained above. The average values of the other proxy variables defined in the table above, under the vector $\mathbf{P}_{r,av}$ at the bottom of table, regarding the relevant period, are employed in the regressions of cross-region effects.

3. 2. The hypotheses

We expect the estimates of the elasticities of the standard input variables (growth in employment, physical and human capital) employed in a growth model that stems from a Cobb Douglas-type production function to take reasonable signs and sizes. That is, the elasticity coefficients should represent their shares in production in a market economy in the long run. However, many empirical studies have not found these results. Moreover, it is not so clear what the shares of those inputs are in economy. Some economists argue that it is shared having about equal weights in production (for instance, Solow 1957, Mankiw et al. 1992, and Islam 1995). Although we have no specific prediction for sizes of these coefficients, we expect them to be reasonable correct signs.

Since we specify and estimate a restricted form of the model, a negative sign of the elasticity coefficient of *labor productivity growth* corresponding to *employment growth* variable represents a positive elasticity coefficient of *labor productivity growth* with respect to capital stock. The elasticity of *labor productivity growth* with respect to *human capital growth* is expected to have a positive sign. Some economists expect it to be about 0.33, accounting for about one third of the aggregate contribution. Because we

do not have capital stock data, we show that investment share can replace it in the specification. Its elasticity is expected to be positive and equal to the annual real interest rate. The output shares, elasticity of each one of the three standard inputs, represent their contribution to output.

We expect *economic spillovers from first order neighbors* to measure the influence of the growth of the first order contiguous neighbor regions on growth of the considered region, for which we expect a significant positive coefficient. This variable represents economic interactions through changes in demand for and supply of various products and services. It may also capture knowledge spillovers. Likewise *economic spillovers from first and second order neighbors* measure the influence of both the first and second degree of contiguous neighbors on the region's labor productivity growth and are expected to be smaller than the first order because of a distance decaying effect.

Initial-year labor productivity, measured by natural logarithm of per labor gross value added at the initial year, is expected to have a significant negative elasticity coefficient, reflecting conditional convergence. Poor regions relative to rich ones have potential to catch up the income level of rich regions, given that other factors are constant, depending on their capability of closing the gap in per labor capital stock or/and in the technology level. This view is based either on the standard neoclassical assumption of decreasing returns to capital accumulation or on the assumption that the rich regions produce close to the technology frontier relative to others. Technological knowledge spillovers from them to poorer regions may permit rapid movement to the frontier. We do not intend to interpret whether a finding of convergence supports the neoclassical

hypothesis or the technological catch up because it may capture the net result of the both effects.

The elasticity of *labor productivity growth* with respect to *growth of industrial specialization* can take either positive or negative sign. According to Romer's growth theory for a closed economy, specialization of an economy within particular sectors and monopolist shape of the market is the source of the knowledge spillovers and hence productivity growth. Because within the same sector it is easier to communicate and because of monopolist structure of the market each firm can impose its price on own product, the specialization of firms in different products will be easier. In contrast, some other approaches argue that diversity of sectors rather than specialization in particular sectors is the source of knowledge spillovers. Some empirical tests have also supported this idea that knowledge spillovers are greater across different sectors rather than within sector (for instance, Glaeser et al. 1992; and Feldman and Audretsch 1999).

The elasticity of *growth of industrial mix* is expected to be significant and positive because the EU regions have recently experienced a relatively faster industrial transformation in a positive way. *Industrial mix* index here represents the extent to which per labor income of a region deviates from the European average due to the industry mix. So there is a positive correlation between growth of this index and growth of per labor income. In other words, the more a region has higher per labor income sectors relative to the European average over time, the higher the growth rate of per labor income is in this region relative to the European average over time.

The main hypothesis:

More specifically, regarding the primary hypothesis and objective of this dissertation, we expect the elasticity of *private* and *government sector R&D* to be significant and positive. We assume that most regions invest in R&D activities to benefit from knowledge spillovers within and between regions as well as relying on their own R&D investments to innovate. So, the cross-regional knowledge spillovers due to the *private* or *government sector R&D* efforts of other regions need to be properly specified in the model.

We have constructed different spatial variables to account for cross-regional knowledge spillovers by considering the interactions of human beings across spatial-units. One variable, *regional spillovers of private or government sector R&D gap that diminishes with distance*, represents the distance weighted-per employee personnel working in private or government R&D of the regions other than itself relative to the relevant region. The closer a region is to regions with greater technology levels, greater R&D intensity, the greater is the possibility of technology catch up.

Another variable is *regional spillovers of private or government sector R&D that diminishes with distance*. This variable, per employee personnel working in private or government R&D of regions other than itself is adjusted for distance, but it does not constrain spillovers to be from regions with greater R&D efforts than its own. We expect the cross-regional knowledge spillovers to have a significant positive impact on *labor productivity growth* through improving directly productive efficiency and indirectly the productivity and magnitude of R&D. In this sense, *government sector R&D* efforts are expected to influence significantly the growth through more indirectly relative to that of the *private sector R&D*.

The first and second order contiguous forms of these variables are established and employed in various specifications. We expect that physical distance to have a significant impact on the strength of knowledge spillovers on growth in per labor income.

3.3. The data

The regions considered in this research are the Nomenclature of Territorial Units for Statistics at level 2 (NUTS2). The EU15 geography is broken down into 211 such regions by the present version (NUTS 99). The NUTS classification has been used since 1988 in Community legislation. The regions are in some respects fairly heterogeneous. For instance, there exist large variation across regions with respect to their sizes of population, area, population intensity, economic weight or administrative powers. On the other hand, because some nations have relatively a small area or population they do not have all the three regional levels. However, to make the data available and to help the implementation of regional policies, the NUTS is determined based on the criteria of institutional division (see, for more information, EUROSTAT (1999). *Regio Database – User's Guide*. 1999 Edition, Luxemburg: Office for official publications of the European Communities; and EUROSTAT (2000). *Regions: Statistical yearbook 2000*, Luxemburg: Office for official publications of the European Communities).

Moreover, Casellas and Galley (1999) argue that the current regional classification influences considerably the size of regional discrepancies in the EU. Actually, if more comparable regions in the EU corresponding to those in the US are classified based on a more functional definition of regions, the regional disparities in the EU as compared to that in the US are not as large as has been asserted. So, the region

concept is not so clear in the EU. Present administrative regions are created in order to implement certain regional policies in line with planning and programming. Historical, cultural, administrative, political, economic, metropolitan and geographic regions form very diverse regional structure in the EU. But the regional borders are determined mostly based on historical or cultural features. Because at the beginning of the 1970s the EC initiated to implement regional development policies, it was required to get a classification of regions in the member nations to compare their economic standing on a common basis. Three different levels of regional division are formed to have a uniform hierarchy across states by adopting the different administrative borders that have already existed in each member nation. Consequently, we have faced a relatively heterogeneous group of regions for statistical aims in the EU. The current classification of regions at the NUTS 2 level, which is the official level to measure regional discrepancies by the EC, consists of cities and metropolitan areas, countries, collections of small islands, remote areas, and large rural areas.

Furthermore, the European Commission has observed the indicators of the NUTS2 regions and implemented the regional policies through the NUTS2 regions. In this regard, studying the NUTS2 regions is much more relevant.

This research focuses on 57 NUTS 2 regions, which consist of 17 regions from Spain, 21 from France and 19 from Italy. Unavailable data, particularly R&D data, constrain the size of sample. One NUTS 2 region from Spain, one from Italy and five from France have been excluded, again because of unavailable data (see the names of regions in Table AXII). The time series length is again constrained by R&D data. The time series segment of the data is taken at two different lengths. One is taken annually at

a 10-year time span between 1985-95. The other is taken annually at a 7-year time span between 1988-95 because government sector R&D data is not available before 1988. These three countries are contiguous over the EU territory, with France bridging Italy and Spain. They have some geographical parts with the same climate and similar geographical sizes of NUTS 2. They come after Germany and the UK in many economic magnitudes --physical geographic area-size, population size and others-- in the EU. In short, even though these three countries are not the greater fraction of the EU, they represent important ingredients.

The required regional data for this project have been obtained from the REGIO database of the EUROSTAT office under the European Commission and from the European Regional Prospects, Analysis and Forecasts to 2004, Cambridge Econometrics, May 2000. The education data at the national level have been taken from the OECD Education Database. The national GDP deflators and exchange rates are provided in OECD Economic Outlook, various years' editions. All data in monetary terms are fixed to their 1990 values. The regional data considering total gross value added, total employment, investment expenditures, sectoral gross value added by 9 sectors, sectoral employment by 9 sectors (see the names of sectors in Table AXIII) are collected from the European Regional Prospects, Analysis and Forecasts to 2004, Cambridge Econometrics, May 2000. The data for all relevant R&D personnel by private and government sectors, and patents are collected from the REGIO database of EUROSTAT.

In conclusion, in the following chapter we first estimate the empirical models in equations (27) and (28), which correspond to the theoretical model in equations (18) and (19), respectively, based on the data, variables and hypotheses described above. The

purpose is to test whether R&D efforts and associated knowledge spillovers have a significant impact on European regional labor productivity growth, and on the marginal product of capital. Next, we estimate the empirical equation (29) for testing whether R&D and associated knowledge spillovers have a significant influence on the disparate EU regional economic performance.

CHAPTER V

ANALYSIS OF THE EMPIRICAL RESULTS

This chapter starts with a preliminary evaluation of the regional distribution characteristics of primary indicators based on the simple moment statistics. Next, the empirical results are taken on the two broad bases. First, the parameters of the concerned variables are directly estimated and tested through the specified growth accounting equations (27) and (28) in Chapter IV. Second, those are indirectly estimated and tested through a two-stage specification method. By exploiting the panel data approach with the least squares dummy variables (LSDV) estimator, initially the regional fixed effects (i.e., the parameters of the regional dummy variables) are estimated from the growth accounting specification that simply contains the inputs in the production function. These estimated observations are taken as a proxy variable for the variation in cross-regional productivity performance. Then, this estimated variable is run on the relevant variables, which are assumed to have a significant impact in equation (29) in Chapter IV.

Two different panels are in the data base corresponding to two different time periods, 1985-95 and 1988-95. Data availability for government sector R&D requires use of the shorter time period. To compare the findings with regard to government sector R&D to those with regard to the private sector R&D on the basis of the same time period,

we estimate the business sector R&D equations with both panels. The summary statistics of various data sets and primary data are provided separately in the Appendix.

Furthermore, the knowledge spillovers due to R&D efforts are approximated with two different variables. One of which is the distance-adjusted per employee-personnel working in business or government sector R&D of all regions other than the region itself. The other is the distance-adjusted per employee-personnel working in business or government sector R&D of all other regions relative to that of the region itself --R&D gap. Moreover, the spillover effects of the first and second order contiguous regions on the regional productivity performance are examined in order to test the neighborhood effects.

1. Preliminary Evaluation of the Regional Distribution of the Primary Indicators

The regional distribution characteristics of primary indicators are substantially different (see Table 1) and have in general rather similar properties observed by other studies over the larger regional samples of the EU countries. The 57 regions of the three EU countries (Spain, France and Italy) in the sample have displayed an average annual growth rate of 1.73 % in per employee gross value added between 1988 and 1995. However, the distribution of this *labor productivity growth* is diverse across the regions. The coefficient of variation is about 0.38, which is twice the 0.17 of average *labor productivity* between 1989 and 1995. Twenty-six regions grew faster than the sample-average, and the 31 regions grew below the average (see Table AIX). The regions in the upper quartile have grown faster than 2.18 % a year, while those in the bottom quartile have grown slower than 1.35 %. Since the weight of the regional performance of those

regions that grow above the average is a little heavier than that of those regions that perform below the average, the mean of this variable (0.0173) is slightly greater than its median (0.0168). Because the relative frequency of *labor productivity growth* peaks a little more than the mean value relative to that of the normal distribution, its kurtosis is 1.32. The regional distribution of *labor productivity growth* is slightly biased toward the tail at the left hand of the distribution compared to that of the other primary indicators, with its skewness equals to about -0.06. Thereby, it has a smaller deviation from the normal distribution with the mean equal zero and variance equal one relative to that of the other primary indicators other than *labor productivity*. Three of the lowest 5 growth regions are from Spain and 2 are from Italy, but 4 of the highest 5 growth regions are from Spain and 1 from Italy. This result also points to the country effect in both growth rates and cross-regional variation of that within country.

The distribution of *labor productivity* is relatively less disparate across the regions. Of the 57 regions in the sample, 29 have *labor productivity* below the sample average. The major part of that is made up of all regions of Spain, which became a member of the community in 1986, and the southern regions of Italy. So the variation in this variable appears country-specific as well. Contrary to that of other indicators, the mean of this variable is slightly smaller than its median, and the relative frequency is slightly less peaked at the mean compared to that of the normal distribution, so that it takes a negative but relatively small value of kurtosis of roughly -0.07. Again, the skewness of *labor productivity* toward the right tail is relatively small with a value of around 0.03. Hence it is likely that its regional distribution does not deviate much from the normal distribution. In other words, the regional distribution of per labor income does

Table III. Descriptive statistics on the averages of primary indicators in the period between 1988 and 1995

Variables:	<i>labor productivity growth</i>	<i>labor productivity</i>	<i>per labor R&D personnel in business</i>	<i>per labor R&D personnel in government</i>	<i>per labor number of patents</i>	<i>patents per R&D personnel in business</i>	<i>patents per R&D personne in government</i>
Mean	0.0173	34475	3272.40	1325.83	9.49	3.64	19.53
Std. Dev.	0.0066	5893	3183	1601	9.80	4.86	40.42
Min.	0.0028	20492	12.57	88.73	0.20	0.45	0.17
Max.	0.0342	50141	17279	8988	45.38	36.22	221.49
Median	0.0168	34618	2536.80	860.00	7.53	2.57	5.96
Range	0.0370	29649	17267	8900	45.18	35.77	221.32
Interq. Range	0.0082	7171	3781	983.57	13.63	3.08	13.33
Skewness	-0.06	0.03	1.86	3.23	1.64	5.60	3.58
Kurtosis	1.32	-0.07	5.39	12.19	3.37	37.26	13.72
Coeff. Var.	0.38	0.17	0.97	1.21	1.03	1.34	2.07
<u>Quantiles:</u>							
99-100% Max.	0.0342	50141	17279.38	8988.41	45.38	36.22	221.49
95%	0.0316	44044	8671.95	4133.83	32.77	7.86	130.60
90%	0.0244	41887	7674.54	2923.69	19.72	6.95	58.50
75%	0.0218	38568	4604.42	1466.03	15.00	4.47	14.91
50%	0.0168	34618	2536.80	860.00	7.53	2.57	5.96
25%	0.0135	31398	822.95	482.46	1.37	1.40	1.59
10%	0.0106	26855	346.33	184.42	0.51	0.83	0.62
5%	0.0054	25237	121.98	113.75	0.41	0.57	0.31
0-1% Min.	0.0028	20492	12.57	88.73	0.20	0.45	0.17
<u>Lowest 5 Obs:</u>							
1	0.0028	20492	12.57	88.73	0.20	0.45	0.17
	(17)	(1)	(51)	(28)	(11)	(4)	(11)
2	0.0044	23506	117.38	94.18	0.31	0.48	0.29
	(14)	(11)	(14)	(19)	(1)	(1)	(54)
3	0.0054	25237	121.98	113.75	0.41	0.57	0.31
	(53)	(9)	(17)	(20)	(55)	(9)	(1)
4	0.0060	25407	168.67	125.12	0.43	0.66	0.43
	(42)	(2)	(55)	(34)	(54)	(8)	(17)
5	0.0088	26356	260.61	159.44	0.47	0.75	0.60
	(8)	(55)	(11)	(51)	(51)	(11)	(16)
<u>Highest 5 Obs:</u>							
1	0.0256	42523	8078.08	3108.95	20.07	7.36	58.96
	(11)	(44)	(28)	(33)	(28)	(43)	(34)
2	0.0257	43640	8512.86	3582.13	21.84	7.64	79.64
	(10)	(49)	(35)	(37)	(41)	(42)	(21)
3	0.0316	44044	8671.95	4133.83	32.77	7.86	130.60
	(1)	(40)	(33)	(18)	(27)	(27)	(19)
4	0.0317	44156	9388.47	7542.42	40.15	8.63	163.58
	(50)	(41)	(39)	(8)	(35)	(48)	(20)
5	0.0342	50141	17279.38	8988.41	45.38	36.22	221.49
	(6)	(18)	(18)	(49)	(18)	(51)	(28)

Notes: Total number of observations consists of 57 cross-section units over the average of 7 years of time-series observations between 1988-95. Within parentheses are the corresponding numbers of the relevant regions.

not concentrate at the one extreme-tail with a relatively very high income cluster of few regions beside others or vice versa.

On the other hand, the cross-regional distribution of personnel working in R&D activity in private sector and in government sector per 979,008 employee (the average total of all employees in the region). Patents per total employment and patents per R&D personnel are distributed similarly. R&D is disparate and concentrated in few regions. Both *per labor R&D personnel in business* and *in government* sectors have large regional variation and are concentrated in few regions. *Per labor R&D personnel in the government* sector has greater skewness and kurtosis of 3.23 and 12.19 compared to 1.86 and 5.39 of *per labor R&D personnel in business*. That is, *per labor R&D personnel in government* has a higher regional distribution and is more severely concentrated in fewer regions than *per labor R&D personnel in business*. The cross-regional distribution of average *per labor number of patents* slightly differs from that of *per labor R&D personnel in business* with its coefficient of variation equals around 1.03. But this variable's regional concentration with its skewness value of 1.64 and kurtosis value of 3.37 is somewhat less relative to that of *per labor R&D personnel in business*. The regional distribution of number of *patents per R&D personnel in business* sector and especially that of *patents per R&D personnel in government* sector is much more disparate compared to the all other variables. Their coefficients of variation statistics are respectively 1.34 and 2.07. The regional concentration of *patents per R&D personnel in business* is greater with its skewness and kurtosis equal respectively to 5.60 and 37.26. In other words, few regions appear extremely productive in patenting per personnel-

employed, particularly in business sector R&D compared to the rest of regions in the sample. However, this result is particularly attributable to one extreme observation.

Furthermore, none of the regions either in the quantile of the lowest 5 observations or in the quantile of the highest 5 observations of *labor productivity growth* is the same one in corresponding quantiles of average per labor productivity. However, the two poorest Spanish regions (1 and 11) have the highest in *labor productivity growth*. These two poorest regions have the lowest *per labor number of patents*, the lowest *per labor R&D personnel in business* and *in government* sectors, and the lowest per R&D personnel patenting productivity in both private and public sectors. So their high growth performance looks related to the factors beyond R&D and patenting activity, such as industrial transformation or tourism. Once more, the lowest growth 2 regions (17 and 14) are from Spain, and they have the lowest *per labor R&D personnel in business*. Of the two rich regions, the richest French region (18) has the highest *per labor R&D personnel in business*, *per labor number of patents* and third highest *per labor R&D personnel in government*, and the Italian region (49) has the highest *per labor R&D personnel in government*. However, their performances are not at the extreme quantiles.

In addition to studying the extreme observations, we examine the Pearson correlation coefficients across the relevant indicators (Table IV). There is no statistically significant linear association between growth in per employee productivity and all the other variables. Nevertheless, the linear associations of *labor productivity* with *per labor R&D personnel in business*, with *per labor R&D personnel in government*, and particularly with *per labor number of patents* are significant and positive with their respective coefficients of 0.63, 0.31, and 0.75. This may imply that relatively rich regions

Table IV. Pearson correlation coefficients across the averages of primary indicators in the period between 1988 and 1995

Variables:	<i>labor productivity growth</i>	<i>labor productivity</i>	<i>per labor R&D personnel in business</i>	<i>per labor R&D personnel in government</i>	<i>per labor number of patents</i>	<i>patents per R&D personnel in business</i>	<i>patents per R&D personnel in government</i>
<i>Labor productivity growth</i>	1.0000						
<i>Labor productivity</i>	0.1532 (0.2553)	1.0000					
<i>per labor R&D personnel in business</i>	0.0051 (0.9698)	0.6286 (<.0001)	1.0000				
<i>per labor R&D personnel in government</i>	0.0633 (0.6398)	0.3097 (0.0191)	0.3530 (0.0071)	1.0000			
<i>per labor number of patents</i>	0.0291 (0.8300)	0.7491 (<.0001)	0.7944 (<.0001)	0.1692 (0.2082)	1.0000		
<i>patents per R&D personnel in business</i>	0.0756 (0.5764)	0.0656 (0.6278)	0.1718 (0.2013)	0.1643 (0.2221)	0.0368 (0.7860)	1.0000	
<i>patents per R&D personnel in government</i>	0.0846 (0.5314)	0.2586 (0.0522)	0.2666 (0.0450)	0.2612 (0.0497)	0.3520 (0.0072)	0.0200 (0.8826)	1.0000

Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob > |r| under H0: Rho=0. Total number of observations consists of 57 cross-section units over the averages of 7 years of time-series observations between 1988-95.

invest especially in business sector R&D and produce more patents. Moreover, the linear association between *per labor number of patents* and *per labor R&D personnel in business* is very strong positive and significant with a coefficient of roughly 0.79, whereas the linear association between *per labor number of patents* and *per labor R&D*

personnel in government is relatively a weak coefficient of around 0.17 and insignificant at 10 % significance level.

On the other hand, the linear association between *per labor R&D personnel in business* and *per labor R&D personnel in government* is statistically significant at the 1 % level with a coefficient of about 0.35. The overall results may imply that relatively rich regions invest in business sector R&D in great part so as to innovate new ideas.

2. Important Econometric Issues on the Estimation Method

The two-way fixed effects estimation method is used on the panel data sets to estimate and test the significance and extent of the impact of knowledge spillovers due to R&D efforts on regional labor productivity performance. Both regional effects and time effects are heterogeneous across regions and over time, even after all the variables that are assumed to have major impact are included in the specifications.

First, the null hypothesis that regional effects are not significantly different from each other is tested with the joint F-test statistic. All estimated models reject this null hypothesis in favor of the alternative that the regional effects are significantly different. Thus, the ordinary least squares (OLS) estimator on pooled cross-section and time series data set with simply a common intercept term for all regions is not consistent and not efficient. We also test whether regional effects are random components of cross-section error terms or fixed components of the regional observations in the function using Hausman's m-test statistic, which is distributed asymptotically as chi-square under the null hypothesis. The test statistic rejects the null hypothesis that the regional effects are

not correlated with the regressors --the random effects hypothesis-- in favor of regional fixed effects in all of the specifications.

In other words, it suggests that the random effects specification, using either the generalized least squares (GLS) estimator or the feasible generalized least squares (FGLS) estimator, with a single intercept, would be inconsistent. So, the LSDV estimator with a different intercept (parameter) estimated for each regional observation is consistent and for non-small samples asymptotically efficient. Even if the null hypothesis is true, the LSDV is a consistent, albeit, inefficient estimator.

A crucial advantage of the LSDV estimator versus the random effects estimators is that it is consistent regardless of whether the individual effects are correlated with the regressors. A major disadvantage is that inferences are conditional on those fixed effects. Hence, the inferences are restricted to the sample in contrast to random effects estimators for which inferences with respect to the population are valid. Another disadvantage of the LSDV estimator is that it diminishes the degrees of freedom by imposing as many intercept dummy parameters as there are cross-section units (see Judge et al. 1988, p. 489-491; and Green 1997, p. 613-634).

Regardless of these considerations, the Hausman m-test statistic rejects the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Therefore, we use the two-way fixed effects estimator on our panel data in all of the growth accounting specifications.

3. Empirical Results from the 1985-95 Data Set

Under this section, various forms of the empirical specification in equation (28), which corresponds to the theoretical specification in equation (19), are first estimated to test the impact of the R&D and spillover variables on the marginal product of capital as well as their direct effects on labor productivity performance using the 1985-95 data (Tables V and VI). Second, various forms of the empirical specification in equation (27), which corresponds to the theoretical specification in equation (18), are estimated in order to test the direct impact of private sector R&D efforts, of their associated knowledge spillovers and of other factors assumed to be crucial for *labor productivity growth* for EU regional development (Tables VII and VIII).

We first follow these four different tables and present approximate elasticity estimates of the common variables. The elasticity of *labor productivity growth* with respect to the accumulation of capital stock, which is defined in the specification as negative sign of the corresponding variable of *employment growth*, is estimated with an average value of 0.28. The estimates are statistically highly significant (i.e., at the levels of significance lower than 1 %) in all of the specifications. Moreover, the elasticity size is reasonable, giving capital close to its conventional one-third share.

The elasticity of *human capital growth* is estimated as a larger value --about 0.60-- which leaves only about 12 % share for raw labor. The estimated values of this elasticity are also highly significant in all of the specifications. A value of 0.60 for human capital's share is larger than expected. The combined human capital and raw labor share of 0.72, however, is quite reasonable. Because raw labor is essentially not observed in a modern economy, it may be expecting too much to separate the human capital and labor

shares. This is particularly so because the regional data for education is allocated from the national data based on the regions' gross value added weights.

The implied elasticity of *labor productivity growth* with respect to *investment share* is on average between 0.06 and 0.07. This estimated elasticity with respect to the *investment share* implies an annual average rate of return slightly above the annual rate of interest paid during the period of 10 years between 1985 and 1995. This annual rate of return (about 6-7 %) was paid on average for the *investment share* of about 0.23 from output to the investors during the relevant period. However, it requires between 27-30 % of additional output to encourage entrepreneurs at the margin to postpone today's consumption and to invest 1 % more of their income (an *investment share* of about 0.24 instead of about 0.23).

Because this variable is not in the log form as the dependent variable is, the elasticity is calculated as follows: given the equation is that $\ln(q_{\pi} / q_{\pi,t-1}) = q_{\pi}'' = \mu_{\pi} + \dots + \kappa (I/Q)_{\pi} + \dots$, where κ is parameter of *investment share* $(I/Q)_{\pi}$ being estimated in the specification. Then, the elasticity of *labor productivity growth* q_{π}'' with respect to $(I/Q)_{\pi}$ is found by taking the derivative of the equation with respect to $(I/Q)_{\pi}$, $d q_{\pi}'' / d (I/Q)_{\pi} = \kappa \Rightarrow \{ d q_{\pi}'' \} / \{ d (I/Q)_{\pi} / (I/Q)_{\pi} \} = \kappa * (I/Q)_{\pi}$.

Next, we test whether variation in R&D and spillover variables in the proxy vector in equation (26), have an effect on the marginal product of capital. To do so, we interact each variable in the proxy vector with *investment share*. The specifications in general correspond to the first model in Tables V and VI. Because the other specifications yielded similar results, they are not reported. While the variable interacted with *investment share* is not contained separately in the specifications in Table V, it is in

Table VI. The interaction variables are tested one by one in Models 1, 2 and 3, and all together in Model 4 in both tables.

Regarding first three models in Table V, the interaction variable *economic spillovers from first order neighbors*investment share* has a highly significant positive coefficient. The contribution of *economic spillovers from first order neighbors* on the marginal product of physical capital is about 0.01. However, both *investment share*private sector R&D* and *investment share* private sector R&D that diminishes with distance* take positive parameter estimates of around 0.053 and 0.081, but they are not significant at 10 % level. In Model 4, while the interaction variable *investment share*economic spillovers from first order neighbors* has significant positive coefficient at about the same size, *investment share*private sector R&D* and *investment share* private sector R&D that diminishes with distance* have around 0.09 and 0.04, but again not significant. The parameter estimate of *investment share* is not significant even at 10 % level.

On the other hand, all three interaction variables have negative signs in all four models in Table VI. The *economic spillovers from first order neighbors* has a negative impact on marginal product of capital by about -0.05 and significant at 5 % level in both Models 1 and 4. The negative contributions of the other two interaction variables on the marginal product of capital are higher but only that of *private sector R&D that diminishes with distance* is significant at 10 % level with a value of around -0.27 in Model 3.

Table V. Estimates for testing the impact of the variables interacted with *investment share* in the proxy vector on the marginal product of capital from the 1985-95 data

Dependent Variable = <i>labor productivity growth</i>	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2915*** (-10.34)	-0.2914*** (-10.34)	-0.2974*** (-10.40)	-0.3028*** (-10.54)
<i>human capital growth</i>	0.5964*** (27.22)	0.6003*** (27.34)	0.5938*** (26.54)	0.5910*** (26.32)
<i>investment share</i>	0.2696** (9.12)	0.2440*** (3.65)	0.2276* (1.76)	0.1753 (1.29)
<i>investment share* economic spillovers from first order neighbors</i>	0.6392** (4.87)			0.7535*** (5.75)
<i>investment share* private sector R&D</i>		0.0072 (0.88)		0.0117 (1.40)
<i>investment share* private sector R&D that diminishes with distance</i>			0.0109 (0.65)	0.0048 (0.28)
<i>economic spillovers from first order neighbors</i>		0.1575*** (5.39)	0.1735*** (5.93)	
<i>initial-year labor productivity</i>	-0.1596*** (-9.44)	-0.1564*** (-9.26)	-0.1568*** (-9.13)	-0.1570*** (-9.11)
<i>growth of industrial specialization</i>	-0.1117*** (-4.92)	-0.1059*** (-4.68)	-0.1197*** (-5.23)	-0.1179*** (-5.14)
<i>growth of industrial mix</i>	0.0249 (1.56)	0.0234 (1.47)	0.0268* (1.66)	0.0265 (1.63)
<i>private sector R&D</i>	0.0042** (2.01)		0.0044** (2.07)	
<i>private sector R&D that diminishes with distance</i>	0.0534*** (4.08)	0.0512*** (3.87)		
m-Value (Pr > m)	223.22*** (<.0001)	215.08*** (<.0001)	184.37*** (<.0001)	178.95*** (<.0001)
F-Value (Pr > F)	19.75*** (<.0001)	19.71*** (<.0001)	19.02*** (<.0001)	18.71*** (<.0001)
R-Square	0.9076	0.9077	0.9053	0.9041
SSE	0.0518	0.0518	0.0531	0.0538
DFE	495	495	495	495

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0647, 0.0685, 0.0710 and 0.0547 in models 1, 2, 3, and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 570, which consists of 57 cross-section units over 10 years time series observations between 1985-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

Table VI. Estimates for testing the impact of the variables interacted with *investment share* in the proxy vector on the marginal product of capital by including the interacted variable separately from the 1985-95 data

Dependent Variable = <i>labor productivity growth</i>				
Independent Variables	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2822 ^{***} (-10.03)	-0.2870 ^{***} (-10.20)	-0.2821 ^{***} (-9.96)	-0.2766 ^{***} (-9.77)
<i>human capital growth</i>	0.6117 ^{***} (27.40)	0.6004 ^{***} (27.46)	0.6071 ^{***} (27.35)	0.6171 ^{***} (27.22)
<i>investment share</i>	0.3598 ^{**} (8.58)	0.4438 ^{**} (4.01)	0.5512 ^{***} (3.74)	0.6376 ^{***} (4.01)
<i>investment share* economic spillovers from first order neighbors</i>	-2.7329 ^{**} (-2.42)			-2.5604 ^{**} (-2.25)
<i>investment share*private sector R&D</i>		-0.0229 (-1.46)		-0.0094 (0.56)
<i>investment share* private sector R&D that diminishes with distance</i>			-0.0362 [*] (-1.82)	-0.0300 (-1.42)
<i>economic spillovers from first order neighbors</i>	0.7600 ^{***} (3.01)	0.1475 ^{***} (5.01)	0.1491 ^{***} (5.09)	0.7171 ^{***} (2.81)
<i>initial-year labor productivity</i>	-0.1518 ^{***} (-8.95)	-0.1586 ^{***} (-9.41)	-0.1557 ^{***} (-9.23)	-0.1506 ^{***} (-8.84)
<i>growth of industrial specialization</i>	-0.1062 ^{***} (-4.69)	-0.1107 ^{***} (-4.89)	-0.1097 ^{***} (-4.85)	-0.1060 ^{***} (-4.69)
<i>growth of industrial mix</i>	0.0223 (1.41)	0.0258 (1.62)	0.0261 [*] (1.65)	0.0243 (1.54)
<i>private sector R&D</i>	0.0036 [*] (1.76)	0.0089 ^{**} (2.26)	0.0036 [*] (1.75)	0.0054 (1.26)
<i>private sector R&D that diminishes with distance</i>	0.0506 ^{***} (3.89)	0.0566 ^{***} (4.23)	0.0677 ^{***} (4.35)	0.0654 ^{***} (4.21)
m-Value	277.19 ^{***}	210.69 ^{***}	361.00 ^{***}	299.17 ^{***}
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	20.16 ^{***}	19.46 ^{***}	19.87 ^{***}	19.76 ^{***}
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9093	0.9086	0.9088	0.9099
SSE	0.0509	0.0513	0.0511	0.0505
DFE	494	494	494	492

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0715, 0.0631, 0.0659 and 0.0772, and that of *economic spillovers from first order neighbors*, *private sector R&D* and *private sector R&D that diminishes with distance* are 0.1306, 0.0036 and 0.0594 in models 1, 2 and 3, and 0.1300, 0.0034, 0.0585 in model 4, respectively. The negative sign of estimated parameter corresponding to the employment growth variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 570, which consists of 57 cross-section units over 10 years time series observations between 1985-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

The effect of these variables interacted with *investment share* on the marginal product of capital and their elasticity are approximated as follows: provided that the equation is $\ln(q_{rt}/q_{r,t-1}) = q_{rt}'' = \mu_r + \dots + [\kappa + \alpha_B P_{rt}] (I/Q)_{rt} + \alpha_A P_{rt} + \dots = \mu_r + \dots + \kappa (I/Q)_{rt} + \alpha_B [P_{rt} * (I/Q)_{rt}] + \alpha_A P_{rt} + \dots$, where α_A and α_B are parameters of the proxy variable P_{rt} and of the interaction of *investment share* with the proxy $[P_{rt} * (I/Q)_{rt}]$ being estimated in specifications. The impact of the proxy variable on the marginal product of capital is estimated simply by $\alpha_B * P_{rt}$. The elasticity of *labor productivity growth* q_{rt}'' with respect to *investment share* is found by taking the derivative of the equation with respect to $(I/Q)_{rt}$, $d q_{rt}'' / d (I/Q)_{rt} = [\kappa + \alpha_B P_{rt}] \Rightarrow (d q_{rt}'') / \{ d (I/Q)_{rt} / (I/Q)_{rt} \} = [\kappa + \alpha_B P_{rt}] * (I/Q)_{rt}$, gives the measure where *investment share* is about 0.23. The elasticity of *labor productivity growth* q_{rt}'' with respect to the proxy variable P_{rt} is found by taking the derivative of the equation with respect to P_{rt} , $d q_{rt}'' / d P_{rt} = [\alpha_B * (I/Q)_{rt} + \alpha_A] \Rightarrow (d q_{rt}'') / (d P_{rt} / P_{rt}) \cong [\alpha_B * (I/Q)_{rt} + \alpha_A] * P_{rt}$.

In conclusion, the labor productivity growth of neighbor regions has a positive significant impact on the marginal product of physical capital of about 0.01 in Table V. However, when the average marginal product of capital (which is about 0.29) is considered, this magnitude is a small one. In contrast to expectations, the negative contributions of the economic and knowledge spillover variables in Table VI are statistically significant and large. Thus, the influence of the relevant factors on the growth process indirectly through its effect on the marginal product of physical capital and hence on the investment is controversial. Regarding Table V, this test may imply the fact that the relevant factors could influence the marginal product of capital, but the adjustment of physical capital in responding to the relative differentials in returns across regions and

over time might be faster than expected from this data. The significant findings in Table VI may suggest that variation in regional investment rates and/or the marginal product of capital can be attributed to factors other than R&D and spillovers (technological knowledge) following Romer's interpretation. On the other hand, the relevant variables have direct observable significant impacts on the regional performance in labor productivity. Therefore, we will continue by assuming that the marginal product of capital is not affected by variables in the proxy vector.

The elasticity estimates of growth in per labor income with respect to the *economic spillovers from first order neighbors* and of the *economic spillovers from first and second order neighbors* are on average 0.16 and 0.32, and are highly significant in all the specifications (Tables VII and VIII). The first elasticity implies that a percentage increase in the growth of labor productivity of the first order contiguous regions will increase the growth in per labor productivity of the considered regions by an average of 0.16 %. However, the second one implies that a percentage increase in growth of labor productivity of the first and second orders of contagious regions jointly will increase the growth in per labor productivity of the considered regions on average by 0.32 %. These variables control for various sorts of interconnections between neighbor regions relying on demand and supply relations beside the knowledge spillovers among them. These variables are entered to correct the variables with the separate effect of economic interregional interactions, controlling spatial autocorrelation in its lag form of the dependent variable across the regions.

Table VII. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on *labor productivity growth* from the 1985-95 data

Dependent Variable = <i>labor productivity growth</i>	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2886*** (-10.25)	-0.2723*** (-9.77)	-0.2753*** (-9.71)	-0.2822*** (-9.98)
<i>human capital growth</i>	0.5999*** (27.41)	0.6124*** (28.29)	0.6046*** (27.66)	0.6021*** (27.49)
<i>investment share</i>	0.2880*** (9.66)	0.3033*** (10.29)	0.2733*** (8.98)	0.2861*** (9.58)
<i>economic spillovers from first order neighbors</i>	0.1523*** (5.20)		0.1462*** (4.99)	0.1509*** (5.15)
<i>economic spillovers from first and second order neighbors</i>		0.3033*** (6.87)		
<i>initial-year labor productivity</i>	-0.1579*** (-9.36)	-0.1560*** (-9.42)	-0.1616*** (-9.58)	-0.1590*** (-9.43)
<i>growth of industrial specialization</i>	-0.1104*** (-4.87)	-0.1009*** (-4.52)	-0.1107*** (-4.91)	-0.1110*** (-4.91)
<i>growth of industrial mix</i>	0.0245 (1.54)	0.0218 (1.40)	0.0255 (1.61)	0.0242 (1.53)
<i>private sector R&D</i>	0.0040* (1.93)	0.0037* (1.81)	0.0037* (1.74)	0.0032 (1.54)
<i>private sector R&D that diminishes with distance</i>	0.0522*** (3.99)	0.0447*** (3.46)		
<i>private sector R&D of first order neighbors</i>			0.0075*** (2.68)	
<i>private sector R&D of second order neighbors</i>			0.0164*** (3.53)	
<i>private sector R&D of first and second order neighbors</i>				0.0175*** (4.11)
m-Value	222.29***	236.08***	229.03***	224.19***
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	19.88***	19.89***	20.13***	19.96***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9082	0.9116	0.9092	0.9084
SSE	0.0515	0.0496	0.0509	0.0514
DFE	495	495	494	495

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0663, 0.0698, 0.0629 and 0.0659 in models 1, 2, 3 and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 570, which consists of 57 cross-section units over 10 years time series observations between 1985-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

Table VIII. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on *labor productivity growth* from the 1985-95 data

Dependent Variable = <i>labor productivity growth</i>	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2934 ^{***} (-10.24)	-0.2742 ^{***} (-9.69)	-0.2882 ^{***} (-10.07)	-0.2879 ^{***} (-10.07)
<i>human capital growth</i>	0.5998 ^{***} (26.51)	0.6144 ^{***} (27.56)	0.6017 ^{***} (27.02)	0.6020 ^{***} (27.05)
<i>investment share</i>	0.3119 ^{***} (10.41)	0.3256 ^{***} (11.07)	0.3154 ^{***} (10.58)	0.3158 ^{***} (10.60)
<i>economic spillovers from first order neighbors</i>	0.1742 ^{***} (5.97)		0.1741 ^{***} (5.99)	0.1738 ^{***} (5.98)
<i>economic spillovers from first and second order neighbors</i>		0.3366 ^{***} (7.78)		
<i>initial-year labor productivity</i>	-0.1539 ^{***} (-8.92)	-0.1520 ^{***} (-9.01)	-0.1574 ^{***} (-9.23)	-0.1573 ^{***} (-9.23)
<i>growth of industrial specialization</i>	-0.1223 ^{***} (-5.33)	-0.1102 ^{***} (-4.89)	-0.1171 ^{***} (-5.13)	-0.1168 ^{***} (-5.12)
<i>growth of industrial mix</i>	0.0283 [*] (1.76)	0.0249 (1.58)	0.0265 [*] (1.66)	0.0263 (1.64)
<i>private sector R&D</i>	0.0085 [*] (1.74)	0.0082 [*] (1.72)	0.0194 ^{***} (2.72)	0.0208 ^{***} (2.82)
<i>private sector R&D gap that diminishes with distance</i>	0.0059 (0.95)	0.0061 (1.00)		
<i>private sector R&D gap with first order neighbors</i>			0.0208 ^{**} (2.22)	
<i>private sector R&D gap with first and second order neighbors</i>				0.0231 ^{**} (2.34)
m-Value	188.08 ^{***}	208.26 ^{***}	194.04 ^{***}	195.21 ^{***}
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	18.92 ^{***}	19.15 ^{***}	19.30 ^{***}	19.33 ^{***}
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9054	0.9097	0.9062	0.9063
SSE	0.0530	0.0507	0.0526	0.0526
DFE	495	495	495	495

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0718, 0.0750, 0.0727 and 0.0727 in models 1, 2, 3 and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 570, which consists of 57 cross-section units over 10 years time series observations between 1985-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

The elasticity of annual growth in per labor gross value added with respect to *initial-year labor productivity* (per labor gross value added at the beginning of the each corresponding year) is estimated an average of -0.16. It is highly significant in all the specifications. This variable controls for the development levels of the regions. The empirical studies regarding the test of the traditional neoclassical economic growth theory assume that it represents per labor capital stock. Since poor economies have less per capita capital stock relative to rich economies, the rate of return to capital accumulation will be greater in poor economies relative to rich ones. Hence, in poor economies per capita capital stock accumulates rapidly and they grow faster than rich economies during the adjustment process toward the steady state equilibrium. That is, it is an evidence of decreasing returns to physical capital accumulation. On the other hand, earlier empirical studies based on the technology gap approach exploit this variable as a proxy for the technology levels of economies. So the size of the existing gap is a measure of the potential opportunity. The economies that have social capability and competence with the advanced technologies can exploit technological knowledge spillovers and hence can catch up the technologies and per capita income levels of advanced economies by relatively faster growth of their technology and per capita income. Regardless of interpretation, the coefficient shows conditional convergence among the regions.

The elasticity of annual growth in per labor gross value added with respect to *growth of industrial specialization* averages about -0.11. This finding implies that 1 % more specialization of the region than the annual specialization rate (0.0029) (see Table AII) in a particular sector among the considered 9 sectors (see Table AXIII) on average decreases the growth rate in per labor income by 0.11 %. This parameter estimate is also

highly significant in all the estimated specifications. There are theoretical arguments and empirical studies both supporting and refuting the proposition that specialization of an economy in certain industries will increase productivity and economic performance.

Similarly, the elasticity of annual growth in per labor gross value added with respect to the *growth of industrial mix* averages about 0.03. However, it is significant at only 10 % level and in only some estimates. This finding implies that 1 % more concentration of the region in the relatively higher per labor income sectors than the annual average rate (-0.0007) (see Table AII) among the relevant 9 sectors on average will increase the growth rate in per labor income by 0.03 %, if it is significant.

Finally, the two Tables VII and VIII differ from each other simply by considering the knowledge spillover variables. Table VIII takes regional R&D gaps as a potential force to realize knowledge spillovers, while Table VII takes simply regional R&D efforts for that. The two models in both tables take the distance-weighted forms of these variables. The difference between the two models is that Model 1 includes the variable *economic spillovers from first order neighbors* and Model 2 includes *economic spillovers from first and second order neighbors*. The other models (3 and 4) test the knowledge spillover effects from first order and from both first and second order neighbors unadjusted for distance in. The elasticity of *private sector R&D* averages 0.004 in the models that include the variable *private sector R&D that diminishes with distance* or neighbor spillover effects due to simply neighbor R&D efforts rather than R&D gaps to them. It is significant at 10 % level in most of the estimated models. The elasticity of the spillover variable *private sector R&D that diminishes with distance* averages 0.05 and is highly significant in the same models (see Tables V, VI and VII).

When the *private sector R&D of first order neighbors* and *private sector R&D of second order neighbors*, or *private sector R&D of first and second order neighbors* are in the specifications, the elasticity estimates with respect to these neighbor spillover variables are on average 0.0075 and 0.0164 or 0.0175, respectively. These estimates are statistically highly significant (see Table VII).

On the other hand, the elasticity of *private sector R&D* averages 0.008 and only is significant at 10 % level in the specifications that include the variable *private sector R&D gap that diminishes with distance* in Models 1 and 2, in Table VIII. However, the elasticity estimate regarding the spillover variable *private sector R&D gap that diminishes with distance* is not significant at any ordinary level in these estimated specifications, taking a value of about 0.006.

In contrast to the estimates above, when the *private sector R&D gap with first order neighbors*, or *private sector R&D gap with first and second order neighbors* is considered in the specifications, the elasticity estimates of these neighbor spillover variables are on average 0.0208 and 0.0231, respectively. They are significant at 5 % level. At the same time, the growth elasticity of *private sector R&D* is on average 0.02 and highly significant in both models 3 and 4 in Table VIII.

The correlations among the various spillover variables may help in interpreting these results. Per labor R&D personnel, R&D intensity, is significantly (above 0.90) and negatively correlated with the various measures of the R&D gap. Higher R&D intensity regions do not, in general, experience an R&D gap. The distance weighted spillovers of R&D, however, is positively correlated with R&D intensity (0.49), as are the various measures of neighboring R&D intensity (0.35 to 0.37). In the specification with the R&D

gap with neighbors, the spillin of knowledge is clearly differentiated from the local R&D intensity. The local R&D intensity, being positively correlated with distance weighted spillovers, is not so clearly differentiated from the spillovers. On the basis of the analysis thus far, models 3 and 4 in Table VIII are preferred. The spillin variable is conceptually distinct from the spillover variables and from the local R&D intensity variable. We have strong evidence of a spillin effect. With the specification in model 4 we have evidence that own region R&D intensity and spillin from regions with greater R&D intensity have about equal elasticity.

Hence, cross-regional knowledge spillovers over the sample geography in the EU due to personnel working in business sector R&D are significantly transmitted mutually across all regions rather than simply from the regions with higher R&D intensity to those with lower R&D intensity. However, the knowledge spillovers due to business sector R&D in the neighbor regions are significantly transmitted from the R&D intensive neighbor regions to those with lower R&D intensity.

4. Empirical Results from the 1988-95 Data Set

The average elasticity estimates of common variables from Tables IX-XII are presented. The tables differ first by considering private sector R&D and government sector R&D, and then by considering knowledge spillovers due to R&D gaps and to R&D spillovers. The first two models use the distance-adjusted forms, and the other two models use neighbor spillover effects due to R&D efforts. The elasticity of *labor productivity growth* with respect to the accumulation of capital stock, which is specified as a negative sign of the coefficient of *employment growth*, has average value of 0.27.

The estimated values of this elasticity are highly significant in all the specifications. So, it is around 0.03 of lower than the estimate on the basis of the 1985-95 data set. Offsetting this smaller capital share estimate is the *human capital growth* that is estimated with an average value of 0.64. This is almost 0.05 greater than that estimated with the 1985-95 data set. The marginal product of capital stock is also statistically significant with an average value of 0.21. The elasticity of *labor productivity growth* with respect to *investment share* is on average 0.05. In brief, estimates are similar to those from the larger data set for the output elasticity and the marginal product of capital. So, the same general inferences with regard to these input variables hold here.

However, the elasticity estimates of *labor productivity growth* with respect to the *economic spillovers from first order neighbors* and of *economic spillovers from first and second order neighbors* are, respectively, on average 0.09 and 0.16, which are almost half the sizes of the earlier estimates above on the basis of the 1985-95 data. They are still statistically significant at 1 % level in all estimates. These findings may suggest that the neighboring spillover effects due to various interactions among the neighbor regions that are materialized in the market conditions (pecuniary externalities) have been diminished in most recent years. Instead, pure knowledge spillovers may become more effective across them. The growth elasticity of *initial-year labor productivity* is estimated on average by -0.15, which is slightly smaller than the earlier estimate of around -0.16 in absolute value. It is also highly significant in all of the estimated specifications regarding the 1988-95 data set.

Table IX. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on *labor productivity growth* from the 1988-95 data

Dependent Variable = <i>labor productivity growth</i>	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2691*** (-8.35)	-0.2625*** (-8.16)	-0.2705*** (-8.34)	-0.2701*** (-8.34)
<i>human capital growth</i>	0.6454*** (24.35)	0.6486*** (24.63)	0.6428*** (24.15)	0.6433*** (24.20)
<i>investment share</i>	0.1866*** (5.45)	0.2071*** (5.84)	0.1878*** (5.41)	0.1882*** (5.47)
<i>economic spillovers from first order neighbors</i>	0.0831*** (2.99)		0.0847*** (3.03)	0.0854*** (3.06)
<i>economic spillovers from first and second order neighbors</i>		0.1555*** (3.57)		
<i>initial-year labor productivity</i>	-0.1441*** (-7.54)	-0.1433*** (-7.54)	-0.1459*** (-7.60)	-0.1462*** (-7.64)
<i>growth of industrial specialization</i>	-0.0908*** (-3.79)	-0.0873*** (-3.66)	-0.0926*** (-3.84)	-0.0920*** (-3.83)
<i>growth of industrial mix</i>	0.0654*** (3.48)	0.0623*** (3.34)	0.0632*** (3.36)	0.0626*** (3.33)
<i>private sector R&D</i>	0.0013 (0.53)	0.0010 (0.39)	0.0009 (0.37)	0.0009 (0.36)
<i>private sector R&D that diminishes with distance</i>	0.0542*** (2.73)	0.0483** (2.42)		
<i>private sector R&D of first order neighbors</i>			0.0079* (1.84)	
<i>private sector R&D of second order neighbors</i>			0.0076 (1.18)	
<i>private sector R&D of first and second order neighbors</i>				0.0142** (2.18)
m-Value	82.35***	85.09***	76.71***	78.21***
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	18.57***	17.89***	18.23***	18.37***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9425	0.9432	0.9421	0.9421
SSE	0.0205	0.0202	0.0206	0.0206
DFE	327	327	326	327

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0440, 0.0488, 0.0442 and 0.0443 in models 1, 2, 3 and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 399, which consists of 57 cross-section units over 7 years time series observations between 1988-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

Table X. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on *labor productivity growth* from the 1988-95 data

Dependent Variable = <i>labor productivity growth</i>	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2847*** (-8.87)	-0.2761*** (-8.62)	-0.2689*** (-8.31)	-0.2690*** (-8.32)
<i>human capital growth</i>	0.6348*** (24.12)	0.6390*** (24.50)	0.6419*** (24.25)	0.6418*** (24.25)
<i>investment share</i>	0.1862*** (5.45)	0.2102*** (5.96)	0.1902*** (5.53)	0.1906*** (5.55)
<i>economic spillovers from first order neighbors</i>	0.0887*** (3.21)		0.0915*** (3.30)	0.0915*** (3.30)
<i>economic spillovers from first and second order neighbors</i>		0.1715*** (4.01)		
<i>initial-year labor productivity</i>	-0.1435*** (-7.52)	-0.1419*** (-7.49)	-0.1548*** (-8.06)	-0.1549*** (-8.07)
<i>growth of industrial specialization</i>	-0.0981*** (-4.09)	-0.0941*** (-3.95)	-0.0889*** (-3.70)	-0.0889*** (-3.70)
<i>growth of industrial mix</i>	0.0493*** (2.67)	0.0472** (2.58)	0.0501*** (2.70)	0.0497*** (2.68)
<i>private sector R&D</i>	0.0153*** (2.89)	0.0150*** (2.86)	0.0205** (2.49)	0.0213** (2.52)
<i>private sector R&D gap that diminishes with distance</i>	0.0211*** (2.94)	0.0213*** (2.99)		
<i>private sector R&D gap with first order neighbors</i>			0.0266** (2.41)	
<i>private sector R&D gap with first and second order neighbors</i>				0.0282** (2.44)
m-Value	84.30***	89.25***	80.54***	80.68***
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	18.61***	18.06***	18.46***	18.47***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9428	0.9437	0.9423	0.9423
SSE	0.0204	0.0201	0.0206	0.0206
DFE	327	327	327	327

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share* which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0439, 0.0495, 0.0448 and 0.0449 in models 1, 2, 3 and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 399, which consists of 57 cross-section units over 7 years time series observations between 1988-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

The elasticity with respect to *growth of industrial specialization* is estimated on average as -0.09, which is a little smaller than the earlier estimate in absolute value, and highly significant in all the estimated specifications. Similarly, the elasticity of *growth of industrial mix* is estimated as on average 0.06, which is as the twice size of the earlier one. Moreover, it is significant in almost all of the estimated models at 1 % level. In short, these findings may suggest that the influence of higher specialization rate in certain sectors of the regions have become a little bit less negative on the regional labor productivity performance in most recent years. On the contrary, the impact of the change in sectoral transformation rate of economic activity from the relatively low per labor income sectors to high per labor income sectors of the regions have become larger in the most recent years. These results may also emphasize the influence of the recent deeper EU integration on the regional dynamics.

Finally, the estimated elasticity of *private sector R&D* is not statistically significant at any ordinary significance level in the models that include distance weighted variables of the *private sector R&D* of other regions, or *private sector R&D* of first and/or second order neighbors (see Table IX). The elasticity of *private sector R&D that diminishes with distance* averages 0.05 and is statistically significant in Models 1 and 2. Only the estimated elasticity of *private sector R&D of first order neighbors* is significant (at 10 % level), when *private sector R&D* of first and second order neighbors is included, with an estimated value of less than 0.01 in Model 3. The estimated elasticity of *private sector R&D of first and second order neighbors* is significant at 5 % level in Model 4, with a value of 0.014.

The average growth elasticity of own-region *private sector R&D* is 0.015 in models 1 and 2 which include the variable of the *private sector R&D gap that diminishes with distance*. It is estimated as about 0.021 in the models 3 and 4 that include, respectively, the variable of the *private sector R&D gap with first order neighbors*, and *private sector R&D gap with first and second order neighbors* (see Table X). The elasticity estimates of this variable *private sector R&D* are statistically significant at 1 % level in the first two models and at 5 % level in the other two. Moreover, the elasticity regarding the spillover variable *private sector R&D gap that diminishes with distance* is estimated as on average 0.021 and also significant at 1 % level. The elasticity estimates regarding the neighbor spillover variables *private sector R&D of first order neighbors* and *private sector R&D of first and second order neighbors* are, respectively, on average 0.027 and 0.028, and both are significant at 5 % level.

These findings are consistent with the earlier ones. As with the earlier data set, they may suggest that the spillover variables *private sector R&D gap that diminishes with distance*, *private sector R&D gap with first order neighbors* and *private sector R&D gap with first and second order neighbors* are more relevant than the distance weighted R&D intensity and give consistent results. In short, the distance-weighted positive differences of business sector R&D efforts by other regions relative to that of the region have significantly influenced the region's performance in labor productivity. The data sets together suggest that the influence is significantly greater using the contiguous neighbor gap variables rather than the distances weighted gap variable. Further, when the models include the gap variables, the influence of the region's own business sector R&D on the labor productivity performance is greater and statistically significant.

Evidence from government sector R&D and knowledge spillovers:

In addition to private sector R&D by region, we have information in this data on government R&D. The models in Table XI consider only government sector R&D and its regional spillovers. The models in Table XII consider both government and private sector R&D and their cross-regional knowledge spillovers. Preliminary investigation revealed that government sector R&D gap measured on the basis of contiguous neighbors was not as useful a variable as the gap with respect to all regions weighted by distance. In general, with government sector R&D, regardless of whether private sector R&D is included, the gap variables dominated the R&D intensity variables.

In Table XI and XII, the control variables (variables other than the R&D variables) take coefficients similar to those in earlier models. Consequently, we confine our discussion of these results to the R&D variables.

The elasticity of *labor productivity growth* with regard to the *government sector R&D* averages 0.015 in the models 1 and 2, which include the variable *government sector R&D gap that diminishes with distance*. It is statistically significant at 1 % level in both models in Table XI. The elasticity of the spillover variable *government sector R&D gap that diminishes with distance* is about 0.018 and highly significant in the same two models. However, the elasticity of the variable *government sector R&D* is smaller, about 0.0035 and less precisely estimated in models 3 and 4 that include the spillover variable *government sector R&D that diminishes with distance* rather than the gap variable. It is statistically significant at 5 % level in model 3 and 10 % level in model 4. The elasticity of the spillover variable *government sector R&D that diminishes with distance* is

estimated on average 0.023 and statistically significant at 5 % level in models 3 and 4 in Table XI.

Next, in order to compare the results obtained from government sector R&D efforts and knowledge spillovers due to government sector R&D efforts to the results obtained from business sector R&D efforts and knowledge spillovers due to business sector R&D efforts, both types of variables are contained in the specifications in Table XII. The regional R&D gap definitions of both business and government sector spillover variables are included in the models. All of the parameter estimates are statistically significant at 1 % level in the models presented. The elasticities of *private sector R&D* in models 1 and 2 average 0.016 as do the elasticities of *government sector R&D*. The elasticities of *private sector R&D gap that diminishes with distance* and *government sector R&D gap that diminishes with distance* average, respectively, on average 0.023 and 0.019 in models 1 and 2. The elasticities of the variables that are proxies for government sector R&D effort *government sector R&D* and cross-regional knowledge spillovers due to that *government sector R&D gap that diminishes with distance* take about the same value in Table XII as in Table XI, which omits *private sector R&D*. However, the elasticities of business sector R&D efforts, *private sector R&D* and *private sector R&D gap that diminishes with distance*, are somewhat greater in Table XII than the corresponding elasticities in Table X.

Table XI. Estimates for testing the impacts of one-way and two-way knowledge spillovers associated with government sector R&D efforts and gaps across regions on *labor productivity growth* from the 1988-95 data

Dependent Variable = <i>labor productivity growth</i>				
Independent Variables	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2650*** (-8.28)	-0.2583*** (-8.09)	-0.2709*** (-8.49)	-0.2642*** (-8.28)
<i>human capital growth</i>	0.6420*** (24.68)	0.6455*** (24.97)	0.6482*** (24.62)	0.6511*** (24.87)
<i>investment share</i>	0.2133*** (6.08)	0.2311*** (6.43)	0.2402*** (6.38)	0.2540*** (6.65)
<i>economic spillovers from first order neighbors</i>	0.0852*** (3.09)		0.0949*** (3.45)	
<i>economic spillovers from first and second order neighbors</i>		0.1568*** (3.67)		0.1664*** (3.90)
<i>initial-year labor productivity</i>	-0.1542*** (-8.18)	-0.1528*** (-8.15)	-0.1464*** (-7.73)	-0.1457*** (-7.73)
<i>growth of industrial specialization</i>	-0.0968*** (-4.10)	-0.0932*** (-3.96)	-0.0936*** (-3.96)	-0.0899*** (-3.82)
<i>growth of industrial mix</i>	0.0573*** (3.15)	0.0553*** (3.06)	0.0593*** (3.24)	0.0567*** (3.12)
<i>government sector R&D</i>	0.0154*** (3.49)	0.0145*** (3.27)	0.0037** (1.99)	0.0033* (1.79)
<i>government sector R&D gap that diminishes with distance</i>	0.0186*** (2.77)	0.0177*** (2.64)		
<i>government sector R&D that diminishes with distance</i>			0.0249** (2.34)	0.0217** (2.05)
m-Value	87.04***	90.13***	84.81***	87.27***
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	18.90***	18.27***	18.75***	18.08***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9434	0.9441	0.9431	0.9436
SSE	0.0202	0.0199	0.0203	0.0201
DFE	327	327	327	327

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0502, 0.0544, 0.0566 and 0.0598 in models 1, 2, 3 and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 399, which consists of 57 cross-section units over 7 years time series observations between 1988-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

Table XII. Estimates for testing the impacts of one-way knowledge spillovers associated with private and government sector R&D gaps across regions on *labor productivity growth* from the 1988-95 data

Dependent Variable = <i>labor productivity growth</i>				
Independent Variables	Model 1	Model 2	Model 3	Model 4
<i>employment growth</i>	-0.2734*** (-8.62)	-0.2665*** (-8.42)	-0.2555*** (-7.98)	-0.2557*** (-7.99)
<i>human capital growth</i>	0.6378*** (24.71)	0.6415*** (25.01)	0.6458*** (24.85)	0.6456*** (24.85)
<i>investment share</i>	0.2143*** (6.17)	0.2323*** (6.52)	0.2179*** (6.24)	0.2183*** (6.25)
<i>economic spillovers from first order neighbors</i>	0.0819*** (3.00)		0.0849*** (3.10)	0.0848*** (3.10)
<i>economic spillovers from first and second order neighbors</i>		0.1525*** (3.60)		
<i>initial-year labor productivity</i>	-0.1493*** (-7.96)	-0.1476*** (-7.91)	-0.1620*** (-8.56)	-0.1620*** (-8.56)
<i>growth of industrial specialization</i>	-0.1056*** (-4.47)	-0.1017*** (-4.32)	-0.0953*** (-4.03)	-0.0953*** (-4.03)
<i>growth of industrial mix</i>	0.0521*** (2.88)	0.0499*** (2.77)	0.0527*** (2.90)	0.0523*** (2.87)
<i>private sector R&D</i>	0.0164*** (3.16)	0.0161*** (3.12)	0.0227*** (2.80)	0.0234*** (2.81)
<i>private sector R&D gap that diminishes with distance</i>	0.0233*** (3.30)	0.0234*** (3.33)		
<i>private sector R&D gap with first order neighbors</i>			0.0301*** (2.77)	
<i>private sector R&D gap with first and second order neighbors</i>				0.0317*** (2.78)
<i>government sector R&D</i>	0.0164*** (3.75)	0.0155*** (3.54)	0.0164*** (3.72)	0.0163*** (3.71)
<i>government sector R&D gap that diminishes with distance</i>	0.0195*** (2.95)	0.0186*** (2.82)	0.0198*** (2.97)	0.0197*** (2.96)
m-Value	100.58***	104.55***	97.04***	97.08***
(Pr > m)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
F-Value	19.41***	18.76***	19.24***	19.24***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
R-Square	0.9453	0.9460	0.9448	0.9448
SSE	0.0195	0.0193	0.0197	0.0197
DFE	325	325	325	325

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. All the coefficients estimated above represent elasticity of corresponding variables beyond that of *investment share*, which stands for the marginal product of capital stock. The implied elasticity estimates of *investment share* variable which is in non logarithm form are 0.0505, 0.0547, 0.0513 and 0.0514 in models 1, 2, 3 and 4, respectively. The negative sign of estimated parameter corresponding to the *employment growth* variable is the elasticity coefficient of capital stock. Hausman m-test statistic values above reject the null hypothesis of random effects in favor of fixed effects at any ordinary significance level. Further, F-statistic values above reject the null hypothesis of no fixed effects and no intercept at any ordinary significance level. The sample size is 399, which consists of 57 cross-section units over 7 years time series observations between 1988-95. SSE and DFE imply respectively sum of squared errors and degrees of freedom of model error term.

The elasticities of *private sector R&D*, *private sector R&D gap with first order neighbors*, *government sector R&D* and *government sector R&D gap that diminishes with distance* are 0.023, 0.03, 0.016, and 0.02 in model 3. However, although the elasticities for the government sector variables are little changed, the elasticities of *private sector R&D* and *private sector R&D gap with first order neighbors* are somewhat greater in Table XII than the corresponding elasticities in Tables X.

In model 4 the elasticities of *private sector R&D*, *government sector R&D* and *government sector R&D gap that diminishes with distance* are changed but little when the *private sector R&D gap with first order neighbors* is replaced with the *private sector R&D gap with first and second order neighbors*. The corresponding elasticities are 0.023, 0.032, 0.016 and 0.02 in model 4. However, the elasticities of *private sector R&D* and *private sector R&D gap with first and second order neighbors* are somewhat greater in Model 4 of Table XII than those in the corresponding elasticities in model 4 in Table X with a 2.5 percent.

The preferred specification includes private sector R&D intensity with spillins from any R&D gap with contiguous neighbors (first or second order) In the tables (VIII, X, and XII) regional R&D intensity and spillins from neighbors with greater R&D intensity both have significant effects on growth. A 10 percent increase in private R&D intensity leads to a 0.2 percent increase in the growth rate. Alternatively, a 100 increase in private R&D intensity leads to a 2 percent increase in the growth rate. In other words, a doubling of private R&D intensity in a region with a 2.5 percent growth would increase the growth rate to 2.55 percent. At the average level of spillins, the elasticity of labor productivity growth with respect to spillins is 2.8 percent. Therefore a doubling of the

R&D gap would increase the growth rate by 2.8 percent. Comparing the elasticity of government R&D with private sector R&D in models 3 and 4 where the growth enhancing effect of private sector R&D is about one-third greater than that of government sector R&D. Examining model 1 in Table XII, we see that the elasticity of R&D gap variable is almost 50 percent greater than that of the corresponding government R&D gap variable.

5. Empirical Results from the Region Specific Effects

By implementing the panel data approach with the LSDV estimator, various forms of regional fixed effects (i.e., the parameters of the regional dummy variables) are estimated from various growth accounting specifications on both the 1985-95 data set (Table XIII) and the 1988-95 data set (Table XIV), respectively. These estimated variables are normalized by adjusting their means to 100 for easy comparison.

The standard deviation of *estimates from Model with input variables without initial-year labor productivity* is 14.80 regarding the 1985-95 data set, which is lower than 21.04 of the corresponding 1988-95 data set. After the three input variables of production are accounted for, the cross-regional variation in performance of productive efficiency has increased substantially during the most recent years. In contrast, when the development levels of the regions are also controlled in the specification, the standard deviation of *estimates from Model with input variables and initial-year labor productivity* is 2.01 regarding the 1985-95 data set, which is larger than the 1.73 of the corresponding 1988-95 data set.

Likewise, the variables regarding *estimates from Full Model with initial-year labor productivity* and *estimates from Full Model without initial-year labor productivity* have standard deviations of 7.05 and 1.97 from the 1985-95 data set, both of which are larger than 5.51 and 1.84 from the corresponding 1988-95 data set. Hence, when the three production inputs the factors that are assumed to influence the labor productivity performance of the regions are included in the models, the cross-regional variation in productive-efficiency performance appears to decrease during the most recent years.

As a result, the development levels of the regions determine the major part of the cross-regional variation in the productive-efficiency performance. The estimated Pearson correlation coefficients also support this result. The linear association between the estimated variables from the specifications that include the log of per labor income at the initial year as well is relatively much greater than that between the others. The linear association between *estimates from Full Model with initial-year labor productivity* and *estimates from Model with input variables and initial-year labor productivity* is about 0.97 from the 1985-95 data and about 0.95 from the 1988-95 data (see Tables XV and XVI).

Table XIII. Basic statistics on the estimates of cross-region fixed-effects from various specifications of LSDV estimator and on particular demographic variables for the period between 1985 and 1995

Estimated Model	Mean	Std. Dev.	Min.	Max.
<i>estimates from Full Model with initial-year labor productivity</i>	100.00	1.97	94.28	103.53
<i>estimates from Full Model without initial-year labor productivity</i>	100.00	7.05	88.72	121.96
<i>estimates from Model with input variables and initial-year labor productivity</i>	100.00	2.01	94.23	103.61
<i>estimates from Model with input variables without initial-year labor productivity</i>	100.00	14.80	77.97	147.76
<i>log of estimates from Model with input variables and initial-year labor productivity</i>	0.5212	0.0203	0.4619	0.5569
<i>average labor productivity growth</i>	0.0180	0.0050	0	0.0251
<i>average industrial specialization</i>	0.9690	0.0658	0.863	1.2012
<i>average industrial concentration</i>	0.4464	0.0746	0.3471	0.7654
<i>population rate₂₅₋₄₄</i>	0.2746	0.0179	0.2332	0.3271
<i>long term unemployment rate</i>	0.0685	0.0375	0.0129	0.1651
<i>female activity rate</i>	0.3757	0.0722	0.2479	0.5381

Notes: The estimated variables of cross-region fixed-effects from various specifications of LSDV estimator are standardized with the mean values equal to 100.

Table XIV. Basic statistics on the estimates of cross-region fixed-effects from various specifications of LSDV estimator and on particular demographic variables for the period between 1988 and 1995

Estimated Model	Mean	Std. Dev.	Min.	Max.
<i>estimates from Full Model with initial-year labor productivity</i>	100.00	1.84	94.80	103.37
<i>estimates from Full Model without initial-year labor productivity</i>	100.00	5.51	84.60	116.20
<i>estimates from Model with input variables and initial-year labor productivity</i>	100.00	1.73	95.00	103.61
<i>estimates from Model with input variables without initial-year labor productivity</i>	100.00	21.04	79.91	191.95
<i>log of estimates from Model with input variables and initial-year labor productivity</i>	0.5387	0.0174	0.4876	0.5743
<i>average labor productivity growth</i>	0.0173	0.0052	0	0.0253
<i>average industrial specialization</i>	0.9668	0.0623	0.8611	1.1728
<i>average industrial concentration</i>	0.4460	0.0735	0.3457	0.7509
<i>population rate₂₅₋₄₄</i>	0.2779	0.0168	0.2424	0.3299
<i>long term unemployment rate</i>	0.0660	0.0379	0.0090	0.1606
<i>female activity rate</i>	0.3808	0.0699	0.2544	0.5400

Notes: The estimated variables of cross-region fixed-effects from various specifications of LSDV estimator are standardized with the mean values equal to 100

Table XV. Pearson correlation coefficients across the estimated variables of cross-region fixed-effects for the period between 1985 and 1995

Variables	<i>estimates from Full Model with initial-year labor productivity</i>	<i>estimates from Full Model without initial-year labor productivity</i>	<i>estimates from Model with inputs and initial year labor productivity</i>	<i>estimates from Model with inputs without initial-year labor productivity</i>
<i>estimates from Full Model with initial-year labor productivity</i>	1.0000			
<i>estimates from Full Model without initial-year labor productivity</i>	0.3691 (0.0047)	1.0000		
<i>estimates from Model with inputs and initial-year labor productivity</i>	0.9731 (<.0001)	0.1755 (0.1917)	1.0000	
<i>estimates from Model with inputs without initial-year labor productivity</i>	0.7305 (<.0001)	0.7086 (<.0001)	0.6626 (<.0001)	1.0000

Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob > |r| under H0: Rho=0. Total number of observations consists of 57 cross-section units over the 1985-95 data.

Table XVI. Pearson correlation coefficients across the estimated variables of cross-region fixed-effects for the period between 1988 and 1995

Variables	<i>estimates from Full Model with initial-year labor productivity</i>	<i>estimates from Full Model without initial-year labor productivity</i>	<i>estimates from Model with inputs and initial year labor productivity</i>	<i>estimates from Model with inputs without initial-year labor productivity</i>
<i>estimates from Full Model with initial-year labor productivity</i>	1.0000			
<i>estimates from Full Model without initial-year labor productivity</i>	0.2344 (0.0792)	1.0000		
<i>estimates from Model with inputs and initial-year labor productivity</i>	0.9519 (<.0001)	-0.0632 (0.6407)	1.0000	
<i>estimates from Model with inputs without initial-year labor productivity</i>	0.3711 (0.0045)	0.5583 (<.0001)	0.2532 (0.0574)	1.0000

Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob > |r| under H0: Rho=0. Total number of observations consists of 57 cross-section units over the 1988-95 data.

The natural logarithm of the *regional specific effects*, the fixed effects from the LSDV model which uses the three input variables and log of per labor income at the initial year, is regressed on the average values of the variables to have a significant impact on the fixed effects.

By averaging the independent variables over the relevant time period we assume that they are time-invariant. Our procedure is as follows. In the first stage we regress *labor productivity growth* on *employment growth*, *human capital growth*, *investment share*, *initial-year labor productivity*, and the regional fixed effects. Thus, differences in the regional effects are differences in the growth rates of labor productivity. We then

regress the logarithm of the regional fixed effects on R&D variables, the other control variables (*economic spillovers from first order neighbors, industrial mix, and industrial specialization*), dummy variables for Spain and Italy, the *long-term unemployment rate* and the percentage of the region's population age 25-44. Following Partridge and Rickman (1999), we look at the independent variables in this second stage equation as variables whose effect take a substantial amount of time to be realized. Since they are determinants of the region's growth rate, like Partridge and Rickman, we assume that they reflect dynamic externalities. The R&D variables and the economic spillovers can be interpreted as reflecting dynamic externalities, as can the long-run unemployment rate and the percentage of the population in what is probably the most productive age group-25 to 44. The results of these regressions are presented in Tables XVII through XXI.

OLS estimation method is run on the averages of the 57 regions for both 1985-95 period and 1988-95 period. The joint F-test statistic rejects the null hypothesis that all slope parameters are not jointly significant at 1 % level. That is, all of the models are statistically valid. The intercept is estimated on average by 0.45 and statistically significant at 1 % level in all of the estimated specifications. Adjusted R-squares are found between around 0.70 and around 0.80 in various specifications, which consider R&D and spillover variables at least in addition to the country dummies (see particularly the last models of Tables XVII-XXI).

Now, regarding the 1985-95 data set, Table XVII and XVIII differ from each other by the spillover variables considered. The earlier one uses the *private sector R&D gap that diminishes with distance*, while the latter one uses *private sector R&D that diminishes with distance*. Table XVIII and XX use the same variables as Tables XVII and

XIX with a different data set. Table XXI uses government sector R&D and associated spillover variables, which are simply different from the variables corresponding in Tables XVIII and XX.

The first regression (model 0) in Table XVII and (model 0) in Table XIX (for the 11 year period and the 8 year period, respectively) establishes that holding the variables in the first stage regression constant, the growth rate of the Spanish regions is less than the growth rate of the French regions (France is the excluded country) and that the growth rate of the Italian regions does not differ significantly from that of the French.

Tables XVII - XXI show the results of adding the R&D variables (model 1), and then adding economic spillovers and industrial mix (model 2). Next industrial specialization is substituted for industrial mix (model 4), and finally model 5 results from adding the percent prime age population and the average long-term unemployment rate to model 3. The results for the control variables are robust across the several tables. Perhaps surprisingly, the economic spillover from surrounding regions has a negative coefficient. This is a type of backwash effect (which is consistent with the finding of Cheshire and Carbonaro 1996, but inconsistent with the finding of Pons-Novell and Viladecans-Marsal 1999), which may suggest that rapid growth of labor productivity in surrounding regions dampens its growth in the given region. In addition favorable industrial mix and/or industrial specialization enhance long-term growth, suggesting that they generate dynamic externalities. (Putting both variables in the same equation is generally unsuccessful; the high correlation between the two variables does not permit a separation of their effects).

The two socio-demographic variables—the age composition of the population and the long-term unemployment rate—have the expected effects on economic growth. The larger the share of the population in the prime age group, the greater is the growth rate, while the higher the long-term unemployment rate, the lower the growth rate of labor productivity.

Turning to the variables of major interest, the R&D variables, we see in Tables XVII and XVIII that a region's own R&D intensity and the associated R&D spillovers both increase the long-term growth rate of the region. Spillovers, as measured by the R&D gap—the so-called spillins—have a larger effect than the distance-weighted spillovers from all regions. Moreover, when the spillin measure is used the effect of own-region R&D intensity on productivity is twice what it is when the other measure is used. These results are consistent with the earlier findings. They also hold for Tables XIX and XX, which uses the 8 year data set. (Note, however, the precision of the R&D gap coefficient falls relative to that of the other spillover coefficient).

An examination of model 4 in each of these four tables shows the growth disadvantage of the Spanish regions relative to French regions is substantially less when the other variables are added to model 0. In contrast, adding the variables results in the Italy dummy taking a significant positive coefficient, showing that it has an inherent growth advantage relative to the French regions.

Comparing model 4 in Table XXI with model 4 in Tables XIX and XX suggests that government R&D intensity within a region may not have as strong an impact as private R&D intensity. The government R&D spillover, on the other hand, is stronger than the private spillover.

Table XVII. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on *regional effects* from the 1985-95 data

Dependent Variable = <i>log of cross region effects</i>					
Independent Variables	Model 0	Model 1	Model 2	Model 3	Model 4
<i>Intercept</i>	0.5302*** (169.70)	0.4233*** (14.00)	0.3390*** (12.97)	0.3895*** (17.61)	0.3380*** (10.49)
<i>SPAINDUMMY</i>	-0.0312*** (-6.67)	-0.0180*** (-4.05)	-0.0236*** (-6.70)	-0.0223*** (-6.54)	-0.0159*** (-3.39)
<i>ITALYDUMMY</i>	0.0009 (0.20)	0.0130** (3.08)	0.0107** (3.15)	0.0115** (3.48)	0.0120** (3.64)
<i>private sector R&D</i>		0.0125*** (3.62)	0.0154*** (5.55)	0.0149*** (5.25)	0.0119*** (3.88)
<i>private sector R&D gap that diminishes with distance</i>		0.0081 (1.61)	0.0123*** (3.23)	0.0112*** (2.89)	0.0083** (2.06)
<i>economic spillovers from first order neighbors</i>			-1.0284*** (-3.77)	-0.9290*** (3.27)	-0.8816*** (-3.28)
<i>industrial mix</i>			0.0827*** (4.15)		0.0726*** (3.68)
<i>industrial specialization</i>				0.0723*** (4.11)	
<i>population rate25-44</i>					0.1497* (1.72)
<i>long term unemployment rate</i>					-0.0903** (-2.17)
F-Value (Pr > F)	29.05*** (<.0001)	30.52*** (<.0001)	48.77*** (<.0001)	48.52*** (<.0001)	40.49*** (<.0001)
Adj. R-Square	0.5005	0.6783	0.8366	0.8358	0.8494
Coeff. Var.	0.0275	0.0220	0.0157	0.0157	0.0151

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. The sample size consists of 57 cross-section units over the average of 10 years time series observations between 1985-95. Among the variables in non log form, the implied elasticity estimate of *industrial mix* is 0.08 in Model 3 and 0.07 in Model 5. The implied elasticity estimate of *industrial specialization* is 0.033 in Model 4. The implied elasticity estimates of *population rate25-44* and *long term unemployment rate* are 0.04 and -0.006, respectively, in Model 5.

Table XVIII. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on *regional effects* from the 1985-95 data

Dependent Variable = <i>log of cross region effects</i>				
Independent Variables	Model 1	Model 2	Model 3	Model 4
<i>intercept</i>	0.4662*** (32.15)	0.3743*** (17.91)	0.4292*** (34.74)	0.3570*** (12.39)
<i>SPAINDUMMY</i>	-0.0194*** (-4.32)	-0.0256*** (-7.39)	-0.0239*** (-7.20)	-0.0166*** (-3.48)
<i>ITALYDUMMY</i>	0.0116*** (2.74)	0.0076** (2.33)	0.0089** (2.81)	0.0101*** (3.09)
<i>private sector R&D</i>	0.0073*** (4.80)	0.0062*** (5.25)	0.0064*** (5.59)	0.0056*** (4.92)
<i>private sector R&D that diminishes with distance</i>	0.0004 (0.24)	0.0036*** (2.90)	0.0034*** (2.72)	0.0024* (1.79)
<i>economic spillovers from first order neighbors</i>		-0.9836*** (-3.57)	-0.8688*** (-3.09)	-0.8408*** (-3.13)
<i>industrial mix</i>		0.1000*** (4.95)		0.0829*** (4.08)
<i>industrial specialization</i>			0.0875*** (5.05)	
<i>population rate25-44</i>				0.1719* (1.99)
<i>long term unemployment rate</i>				-0.0901** (-2.08)
F-Value	28.50***	46.89***	47.61***	39.56***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Adj. R-Square	0.6626	0.8310	0.8332	0.8464
Coeff. Var.	0.0257	0.0160	0.0159	0.0152

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. The sample size consists of 57 cross-section units over the average of 10 years time series observations between 1985-95. Among the variables in non-log form, the implied elasticity estimate of *industrial mix* is 0.10 in Model 2 and 0.08 in Model 4. The implied elasticity estimate of *industrial specialization* is 0.04 in Model 3. The implied elasticity estimates of *population rate25-44* and *long term unemployment rate* are 0.046 and -0.006, respectively, in Model 4.

Table XIX. Estimates for testing the impact of one-way knowledge spillovers associated with private sector R&D gaps across regions on *regional effects* from the 1988-95 data

Dependent Variable = <i>log of cross region effects</i>					
Independent Variables	Model 0	Model 1	Model 2	Model 3	Model 4
<i>intercept</i>	0.5466*** (185.93)	0.4366*** (14.60)	0.3559*** (13.66)	0.4033*** (17.26)	0.3564*** (11.53)
<i>SPAINDUMMY</i>	-0.0250*** (-5.68)	-0.0122 (-2.96)	-0.0130*** (3.15)	-0.0108*** (-2.72)	-0.0048 (-1.06)
<i>ITALYDUMMY</i>	-0.0013 (-0.31)	0.0105** (2.67)	0.0085** (2.28)	0.0104*** (2.88)	0.0105*** (3.01)
<i>private sector R&D</i>		0.0128*** (3.76)	0.0143*** (4.81)	0.0147*** (4.88)	0.0102*** (3.38)
<i>private sector R&D gap that diminishes with distance</i>		0.0089* (1.78)	0.0109*** (2.76)	0.0108** (2.66)	0.0064 (1.64)
<i>economic spillovers from first order neighbors</i>			-0.7579*** (-2.82)	-0.7091** (-2.49)	-0.6458** (-2.59)
<i>industrial mix</i>			0.0848*** (3.97)		0.0646*** (3.15)
<i>industrial specialization</i>				0.0658*** (3.65)	
<i>population rate25-44</i>					0.1973** (2.44)
<i>long term unemployment rate</i>					-0.1053*** (-2.83)
F-Value	19.51***	24.37***	37.03***	35.30***	34.52***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Adj. R-Square	0.3980	0.6253	0.7942	0.7861	0.8272
Coeff. Var.	0.0250	0.0197	0.0146	0.0149	0.0134

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. The sample size consists of 57 cross-section units over the average of 7 years time series observations between 1988-95. Among the variables in non-log form, the implied elasticity estimate of *industrial mix* is 0.08 in Model 3 and 0.06 in Model 5. The implied elasticity estimate of *industrial specialization* is 0.03 in Model 4. The implied elasticity estimates of *population rate25-44* and *long term unemployment rate* are 0.055 and -0.007, respectively, in Model 5.

Table XX. Estimates for testing the impact of two-way knowledge spillovers across regions associated with private sector R&D efforts on *regional effects* from the 1988-95 data

Dependent Variable = <i>log of cross region effects</i>				
Independent Variables	Model 1	Model 2	Model 3	Model 4
<i>intercept</i>	0.4810*** (35.86)	0.3875*** (20.01)	0.4410*** (38.03)	0.3674*** (14.00)
<i>SPAINDUMMY</i>	-0.0136*** (-3.29)	-0.0144*** (-3.74)	-0.0119*** (-3.23)	-0.0056 (-1.27)
<i>ITALYDUMMY</i>	0.0090** (2.30)	0.0061* (1.77)	0.0082** (2.48)	0.0090** (2.73)
<i>private sector R&D</i>	0.0068*** (4.76)	0.0060*** (5.09)	0.0065*** (5.67)	0.0053*** (4.89)
<i>private sector R&D that diminishes with distance</i>	0.0011 (0.71)	0.0036*** (3.13)	0.0037*** (3.11)	0.0025** (2.06)
<i>economic spillovers from first order neighbors</i>		-0.8034*** (-3.02)	-0.7367** (2.65)	-0.6875*** (-2.79)
<i>industrial mix</i>		0.0989*** (4.85)		0.0735*** (3.63)
<i>industrial specialization</i>			0.0787*** (4.61)	
<i>population rate25-44</i>				0.2108** (2.67)
<i>long term unemployment rate</i>				-0.0927** (-2.43)
F-Value	22.55***	38.73***	37.28***	35.77***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Adj. R-Square	0.6062	0.8017	0.7954	0.8324
Coeff. Var.	0.0202	0.0144	0.0146	0.0132

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. The sample size consists of 57 cross-section units over the average of 7 years time series observations between 1988-95. Among the variables in non-log form, the implied elasticity estimate of *industrial mix* is 0.096 in Model 2, 0.07 in Model 4 and 0.076 in Model 5. The implied elasticity estimate of *industrial specialization* is 0.035 in Model 3. The implied elasticity estimates of *population rate25-44* and *long term unemployment rate* are 0.059 and -0.006 in Model 4; they are 0.06 and -0.007, respectively, in Model 5.

Table XXI. Estimates for testing the impact of two-way knowledge spillovers across regions associated with government sector R&D efforts on *regional effects* from the 1988-95 data

Dependent Variable = <i>log of cross region effects</i>				
Independent Variables	Model 1	Model 2	Model 3	Model 4
<i>intercept</i>	0.4827*** (27.51)	0.3801*** (15.95)	0.4513*** (28.98)	0.3581*** (11.09)
<i>SPAINDUMMY</i>	-0.0231*** (-5.50)	-0.0260*** (-6.68)	-0.0235*** (-6.01)	-0.0129** (-2.55)
<i>ITALYDUMMY</i>	-0.0015 (-0.39)	-0.0057* (1.70)	-0.0038 (-1.12)	0.00003 (0.01)
<i>government sector R&D</i>	0.0048*** (2.92)	0.0016 (1.06)	0.0023 (1.48)	0.0014 (1.01)
<i>government sector R&D that diminishes with distance</i>	0.0046** (2.62)	0.0057*** (3.40)	0.0062*** (3.58)	0.0038** (2.22)
<i>economic spillovers from first order neighbors</i>		-0.3642 (-1.12)	-0.2947 (-0.84)	-0.2787 (-0.94)
<i>industrial mix</i>		0.1294*** (4.84)		0.0926*** (3.53)
<i>industrial specialization</i>			0.0973*** (4.19)	
<i>population rate25-44</i>				0.2614*** (2.73)
<i>long term unemployment rate</i>				-0.1238*** (-2.70)
F-Value	15.32***	22.32***	19.86***	22.08***
(Pr > F)	(<.0001)	(<.0001)	(<.0001)	(<.0001)
Adj. R-Square	0.5057	0.6955	0.6690	0.7507
Coeff. Var.	0.0227	0.0178	0.0185	0.0161

Notes: Within parenthesis are t-statistic values. *** implies significant at 1% level, ** at 5% level and * at 10% level, respectively. The sample size consists of 57 cross-section units over the average of 7 years time series observations between 1988-95. Among the variables in non-log form, the implied elasticity estimate of *industrial mix* is 0.13 in Model 2 and 0.09 in Model 4. The implied elasticity estimate of *industrial specialization* is 0.044 in Model 3. The implied elasticity estimates of *population rate25-44* and *long term unemployment rate* are 0.07 and -0.008, respectively, in Model 4.

In conclusion, regarding the growth accounting equations, the elasticity of *labor productivity growth* with regard to the knowledge spillover variable *private sector R&D that diminishes with distance* is estimated roughly as 0.05 from the both data sets of 1985-95 and 1988-95. However, the elasticity estimate with regard to the *private sector R&D* efforts within the region from this specification is very small with a value of about 0.004 and significant only at 10 % level for the 1985-95 data and not significant for the

1988-95 data. On the other hand, the elasticity estimate with regard to the knowledge spillover variable *government sector R&D that diminishes with distance* is roughly 0.023 from the data set of 1988-95 (see Models 3 and 4 in Table XI). The elasticity estimate with regard to the *government sector R&D* efforts within the region is about the same size as that of *private sector R&D*. Hence, the spillover variable *private sector R&D that diminishes with distance* has an influence on the regional productivity performance at a roughly twice size of that of *government sector R&D that diminishes with distance*.

Moreover, the elasticity estimate with regard to the knowledge spillover variable *private sector R&D gap that diminishes with distance* is not significant at 10 % level from the data sets of 1985-95 while it is about 0.022 and significant at 1 % level from the 1988-95 data set (see Table X and XII). Its elasticity with regard to the knowledge spillovers from neighbors variable *private sector R&D gap with first order neighbors* or *private sector R&D gap with first and second order neighbors*, however, is 0.022 and statistically significant at 5 % level from the data set of 1985-95 (see Models 3 and 4 in Table VIII), and it is about the same size elasticity of the *government sector R&D gap that diminishes with distance* from the 1988-95 data set (see Model 1 and 2 in Table X). In addition, the effect of own-region private R&D is much greater when the R&D gap variable is used.

In contrast to the earlier estimates from the growth accounting equations, the estimated elasticity of *region effects* with respect to *economic spillovers from first order neighbors* has a value of around -0.8. This implies that a percentage increase in growth rate in per labor income of neighbors has a negative effect on regional productivity growth by -0.8 %. The estimated elasticity with respect to *industrial specialization* is a

positive value of around 0.04. This implies that a unit more concentration in particular sector production has a positive impact with around 0.04 of that on cross-regional variation in productivity growth. The elasticity estimate with respect to *industrial mix* is about 0.08. This implies that a unit more concentration in production of relatively high per labor income sectors has a positive impact with about 0.08 of that on cross-regional variation in productive efficiency performance. The elasticity estimates with respect to *population rate25-44* and *long term unemployment rate* are about 0.05 and -0.007, respectively. As expected, the regions that have relatively higher rate of dynamic young population between 25-44 ages have higher growth. The long-term unemployment rates influence, however, is negative.

CHAPTER VI

CONCLUSIONS

1. Summary of the Study

The dynamic phenomena of European regional development and growth cannot be properly analyzed without accounting for the economic implications of the European integration process. After an introduction of the study in Chapter I, this dissertation therefore provides a literature review in Chapter II that starts with a basic background about the EU integration process and the evolution of its institutions with regard to the regional economic development. The EU disparate interregional development process and the influence of the integration process on it are then reviewed. In this regard, the findings of prominent empirical studies that tend to test the neoclassical hypothesis of convergence in per capita income across regions are first surveyed. Next, the findings and implications of the pertinent empirical studies on the regional income distribution dynamics are presented. Also, the results and implications of analyses based on the approach of the new economic geography are submitted. Finally, the findings, implications and methods of the empirical studies of the influences of the R&D efforts and knowledge spillovers on cross sectional economic development, specifically on EU differential regional economic performance are critically analyzed.

Not very many empirical papers have attempted to estimate knowledge and knowledge spillovers as significant factors of the disparate EU regional development. First, only a few estimate the effects of those factors on the per capita income or total factor productivity. The OECD studies at the national level show, however, that the major impact of knowledge spillovers is most likely to raise the efficiency of the production process directly. Indeed, the knowledge spillovers are most likely to matter much more across regions within countries than that simply across countries. Because most of the regions are poor and technologically backward relative to the few top developed ones, they benefit more from the knowledge spillovers than from the development of new technology. Only a few technologically developed ones could use the knowledge spillovers mostly within the region to innovate new goods. Second, few papers specify an econometric model that is consistent with the mainstream economic growth theory. So, the interpretations of the findings of such econometric studies have been inconsistent and incomparable with each other because they do not have a sound basis of theoretical framework.

Third, most do not specify and analyze the observed phenomenon within a proper spatial context. Furthermore, there are not many regional empirical studies that fit the formal endogenous growth theory properly into the spatial context by considering the regional dynamics (Martin and Sunley 1998), particularly for the EU. As we know there are a few exceptions (Caniels 2000; Cheshire and Carbonaro 1996; Cheshire and Magrini 1999; Fagerberg et. al 1997; Paci and Pigliaru 2001; and Rodriguez-Pose 1999). In other words, the EU regions are relatively economically heterogeneous, which results in significant interdependencies. For instance, Pons-Novell and Viladecans-Marsal (1999),

Paci and Pigliaru (2001) and others find strong spatial interdependencies in the growth rates and levels of many economic variables (such as aggregate output, employment, labor productivity) employed in their analyses across the EU regions. After the spatial autocorrelations are corrected, the fits of the models improve significantly. In order to consider these facts in the empirical studies on the EU regional data, either the spatial units are reconstructed on the basis of self-sufficiency and independency criteria, i.e., a city or urban center with its hinterlands accommodating to which such as FURs, which are similar to MSAs in the US, employed by Cheshire and Carbonaro (1996), or the empirical specifications have to account for such dependencies in some way. In both cases a full specification of growth process, as Cheshire and Magrini (1999) and Magrini (1997) have emphasized, is also essential along with heterogeneity and dependencies between regions.

So, we cannot learn adequately why regions grow differently from empirical studies that omit the spatial condition of regions over the geography and location-specific factors because those are essential regional parameters, which play a major role in the regional dynamics of differential growth process. This fact is much more crucial when the European case is considered because the diversity across regions and nations in the EU is much larger in many respects than in the US. That is, the role of location dynamics on disparate economic performance of the EU regions is most likely to be more dominant relative to the US case. The behavior of regional dynamics is not well shaped especially in Europe. No smooth regional growth process seems to generate a tendency towards either convergence or divergence across the EU regions in a sense that simply because of

one factor such as capital accumulation the poor regions either are growing faster relative to the rich regions or vice versa.

Nevertheless, it is most likely for the EU regions that there are both kinds of forces at work, some for divergence, others for convergence. The net impact of these opposing forces over time determines the actual outcome (Cheshire and Carbonaro 1996; Cheshire and Magrini 1999; and Martin and Sunley 1998). Therefore, in order to understand the large disparities in regional economic performance, we should determine the key region-specific parameters, which provide regional dynamics of economic performance and perhaps will permit the prediction of regional differentials in economic performance. According to Adams and Pigliaru (1999), because of the two crucial factors, industrial mix (and its structural evolution) and the technological knowledge spillovers across regions that substantially differ across the EU regions, integration has had disparate effects on the cross-regional economic growth. There are many studies with different approaches that stress the essential role of region-specific factors in determining regional differentials in economic performance. When compared to the US case (Blanchard and Katz 1992) they are much more heterogeneous and have much greater influence on regional economies of the EU in creating regional economic differentials (Decressin and Fatas 1995; Simonazzi and Villa 1999; Estaban 2000; and Forni and Reichlin 2001).

Even though the issue has recently received a great deal of attention, only a few empirical studies have carefully specified the EU regional development process. Therefore, in a different way than most of the earlier empirical work, we spatially specify Romer's (1990) growth model in the light of Caniels (2000) and Magrini (1997) for EU

regional development. Hence, we can interpret the empirical findings along with the mainstream economic growth theory, which is ignored in much of the earlier empirical literature.

Chapter III gives a descriptive review of mainstream economic growth theory with regard to the role of technological knowledge in economic growth. The mainstream tradition with its simple assumptions provides a sound theoretical basis for learning or predicting stylized facts, for easily communicating and understanding working sides on the subject, and for modifying the model for different situations. It starts with Schumpeter's insight regarding capitalism. After examining the seminal contribution of Robert Solow (1956) and neoclassical economic growth theory in an evolutionary perspective, the recent contributions to the convergence literature are surveyed. Much of the convergence literature is recent and has crucial implications for regional economic growth. Consequently, the new endogenous growth theory, basically in the Romer version, is reviewed, relating it to the Schumpeterian notions presented. The recent R&D- or innovation-based endogenous growth models rely upon this argument. The technological catch-up approach is described because it provides a source to empirically specify the formal models, which are in the mainstream tradition, and appropriately interpret the findings from the empirical specifications, in accordance with the observed phenomenon in the reality. Its relevance is emphasized particularly in the recent regional econometric studies on cross-section or panel data. In this sense, a regional specification of the R&D-based endogenous growth model is developed in Chapter IV. Consequently, based on the specified this model, the empirical results are analyzed in Chapter V.

2. Empirical Conclusions

First, regarding the growth accounting models, the elasticity estimates of *labor productivity growth* with respect to input variables on the basis of 1985-95 data set are not significantly different from that on the basis of 1988-95 data set. They are expected to represent their shares in production in a market economy in the long run equilibrium condition. However, it is not so clear what the shares of those inputs are in economy. Some economists argue that it is shared equally (for instance, Mankiw et al. 1992, and Islam 1995). The elasticity of growth in capital stock, which corresponds to the opposite sign of *employment growth*, is about 0.28 and statistically highly (at 1 % level) significant. By the analogy, it is a reasonable size. However, the elasticity of *human capital growth* is estimated with a larger value of about 0.60, which leaves only a 0.12 share for raw labor. This remaining portion for the ordinary labor working in final products sector is apparently less than the reasonable share in additional output. It might be because of the imprecision of the human capital measure. The estimated values of *human capital growth* elasticity are highly significant in all of the specifications as well. In any case, the elasticity of this variable is estimated almost as twice the size of an acceptable one. This consequence is most likely attributable to the fact that national data on education, because of lack of regional data on education, is partitioned to the regions based on their gross value added weights in aggregate of the sample. The implied elasticity of *investment share*, which in theory is the average interest rate, is around 0.06 and highly significant. It is not an unreasonable estimate because this result is close to annual interest rate for an amount of credit opened to an entrepreneur for between 7 and 10 years.

Second, among the economic structure variables, the elasticity estimates of *economic spillovers from first order neighbors* and *economic spillovers from first and second order neighbors* of 0.09 and 0.16 from the 1988-95 data are about half that of the 1985-95 data with values of 0.16 and 0.32. They are statistically significant at 1 % level in all the estimated specifications. This variable represents economic interactions through changes in demand for and supply of various products and services. It may also capture knowledge spillovers. A significant positive influence from neighbors' economic performance is consistent with what we expected from that. However, that a greater impact comes from second order neighbors rather than first ones conflicts with what we expect regarding a distance decay effect. These findings may suggest that various interactions among the neighbor regions that are materialized in the market conditions (pecuniary externalities) have been diminished in most recent years. Instead, pure knowledge spillovers may become more effective across them.

The growth elasticity of *initial-year labor productivity* is estimated on average between -0.15 and -0.16, and highly significant in all specifications. Some regional empirical studies based on panel data have also found a greater size of this parameter than that found by regional empirical studies of Barro and Sala-i-Martin (see the relevant subsection in Chapter II in the context). This variable measures the fact that poor regions relative to the rich ones have a potential force to catch up the income level of the rich regions, given that other factors are constant, depending on their capability of closing the gap in per labor capital stock or/and in the technology level in a broad term. So poor regions have a potential source of growing faster relative to the rich ones. This view is based either on the standard neoclassical assumption of decreasing returns to capital

accumulation or on the assumption that the rich regions produce close to the frontier of technology relative to others, and the technological knowledge spillovers from them to the poor ones are a potential advantage to catch up the advanced technologies of the rich regions. However, we are aware that some forces, in reality, have a convergence effect while other forces have a divergence effect over spatial economic units. Therefore, we do not interpret this to support the hypothesis of neoclassical or the technological catch up, because it may capture the net result of both effects. In brief, here it simply represents the extent of a region's development level at the beginning of each year, and it substantially influences the parameter estimates and the performance of the estimated models.

The elasticity with respect to *growth of industrial specialization* is estimated as on average -0.10 and highly significant in all specifications. We have expected that it can take either positive or negative sign. According to the Romer's growth theory for a closed economy, specialization of an economy within particular sectors and monopolist shape of the market is the source of the knowledge spillovers and hence productivity growth. Because within the same sector it is easier to communicate and because of monopolist structure of the market each firm can impose its price on own product, the specialization of firms in different products will be easier. In contrast, some other approaches argue that diversity of sectors rather than specialization in particular sectors is the source of knowledge spillovers. Some empirical tests have also supported this idea that knowledge spillovers are greater across different sectors rather than within sector (for instance, Glaeser et al. 1992; and Feldman and Audretsch 1999).

Similarly, the elasticity of *growth of industrial mix* is estimated as on average 0.06 from the 1988-95 data, which is as the twice size of 0.03 from the 1985-95 data. It is

significant in almost all of the estimated models at 1 % level from the 1988-95 data, whereas it is significant in only few models at 10 % level from the 1985-95 data. So it is consistent with the expected one because the EU regions have recently experienced a relatively faster industrial transformation in a positive way. The *Industrial mix* index here represents the extent to which per labor productivity of a region deviates from the European average due to the industry mix. So there is a positive correlation between growth of this index and growth of per labor income. In other words, the more a region has higher per labor income sectors relative to the European average over time, the higher the growth rate of per labor income is in this region relative to the European average over time.

In short, these findings may suggest that the influence of higher specialization rate in certain sectors of the regions have become a little bit less negative on the regional labor productivity performance in most recent years. In contrast, the impact of the change in sectoral transformation rate of economic activity from the relatively low per labor income sectors to high per labor income sectors of the regions have become relatively much bigger on the regional labor productivity performance in most recent years. These results may also emphasize the influence of the recent deeper EU integration on the regional dynamics.

Among the variables with regard to R&D efforts (per labor R&D-personnel working in private or government sector) and associated cross-regional knowledge spillovers, the elasticity with regard to *private sector R&D* and *government sector R&D* is estimated on average at less than 0.01. The results are stronger when spillover variable

reflects a spillover from more R&D intensive region than when they reflect a two way exchange.

Next, the elasticity with respect to *private sector R&D that diminishes with distance* is estimated on average as 0.05 and highly significant from the both data bases, whereas that of *government sector R&D that diminishes with distance* is estimated on average as 0.023. Nonetheless, the elasticity of *private sector R&D of first order neighbors, private sector R&D of second order neighbors and private sector R&D of first and second order neighbors* is estimated on average as 0.015.

The elasticity with regard to *private sector R&D gap that diminishes with distance* is estimated about 0.02 and highly significant from the 1988-95 data, while it is not significantly estimated from the 1985-95 data. The elasticity with regard to *government sector R&D gap that diminishes with distance* is estimated as about 0.018 and statistically significant at 1 % level from the 1988-95 data. Moreover, the elasticity with respect to *private sector R&D gap with first and second order neighbors* is estimated approximately as 0.23 from the 1985-95 data and as 0.028 from the 1988-95 data.

Consequently, the positive and statistically significant impacts of regional R&D efforts and cross-regional knowledge spillovers on *labor productivity growth* are as expected. However, the impact of cross-regional knowledge spillovers due to *government sector R&D* efforts on *labor productivity growth* is smaller than to *private sector R&D* efforts. This may suggest that cross-regional knowledge spillovers due to *government sector R&D* affect the productivity performance of regions indirectly through improving productivity of investment and private sector R&D efforts as well. Furthermore, there

exist differences between the estimates from the specifications that include simply one type of R&D efforts, either in business sector or in government sector, with spillover variable due to R&D efforts. In other words, the influence of business sector R&D efforts and knowledge spillovers due to business sector R&D efforts in particular from neighbor regions on the regional performance in labor productivity becomes greater on average by 10 % once government sector R&D efforts and knowledge spillovers due to government sector R&D efforts are accounted for. Hence, these findings may imply that government sector R&D investments are partially complements of that of business sector.

On the other hand, of the variables interacted with *investment share*, the impact of *economic spillovers from first order neighbors* on the marginal product of capital is estimated with a relatively small value of about 0.01 and highly significant in the model where the interacted variable is not separately included as a variable. This result implies a negligible impact. However, it is estimated as about -0.05 and significant at 5 % level in the model the interacted variable is separately included as a variable as well. Moreover, the impact of *private sector R&D that diminishes with distance* is estimated with approximately -0.27 and significant only at 10 % level. These marginal impacts of the relevant interaction factors are unavoidable sizes, but they are in contrast with the expected ones.

Finally, regarding the specifications of regional effects, the parameter estimate of *SPAINDUMMY* implies that the Spanish regions on average have a significant productivity growth rate -0.016 lower than that of the French regions, after particular R&D, knowledge spillovers, economic structure and socio-demographic factors are controlled, using the 1985-95 data. However, the growth gap of the Spanish regions

relative to the French regions is statistically eliminated in the 1988-95 data. In contrast, *ITALYDUMMY* suggests a significant growth rate about 0.010 higher than that of the French regions under the same condition from both data bases.

However, once *government sector R&D* and knowledge spillovers due to that are considered in the same model, the parameter estimate of *SPAINDUMMY* is about the same size as estimated from the 1985-95 data. It is not significant for *ITALYDUMMY*. It may imply that private sector R&D and associated spillovers rather than government sector R&D and associated spillovers are relevant for the growth of both countries' regions relative to that of the French regions.

Again, as in the case of the results from growth accounting models, the elasticity of growth with regard to *private sector R&D* is estimated as around 0.01 and significant in the model which contains *private sector R&D gap that diminishes with distance*. Its estimate is half size of that in the model which includes *private sector R&D that diminishes with distance*. However, the elasticity estimate with respect to *government sector R&D* is not statistically significant. The elasticity of *private sector R&D gap that diminishes with distance* is estimated roughly as 0.008 from the 1985-95 data, but it is not significantly estimated from 1988-95 data. The elasticity of *private sector R&D that diminishes with distance* is estimated roughly as 0.002 from both data bases. The elasticity of *government sector R&D that diminishes with distance* is estimated roughly as 0.004 from 1988-95 data. The elasticity estimate of *economic spillovers from first order neighbors* is on average -0.8, whereas it is not significant once *government sector R&D* and spillover variable due to that are replaced with private sector R&D and

spillover variable due to that. This finding is a contrast to the estimates from growth accounting models.

The influence of *industrial mix* on the regional efficiency is estimated as approximately 0.08. In contrast to the finding from growth accounting models, industrial specialization has a positive impact on regional growth of about 0.04. In addition, a young and dynamic *population rate₂₅₋₄₄* has an influence of around 0.06 on regional growth. However, *long term unemployment rate* has a slight negative significant impact of about -0.007.

3. Implications of the Findings

First of all, the elasticity of growth in capital stock is estimated with a reasonable size. Even though the elasticity with respect to human capital growth is estimated on average as greater than expected and the elasticity with respect to employment growth is estimated with a smaller size relative to a reasonable one, input variables have the right signs. They are in general consistent with the mainstream economic growth theory.

Private sector and government sector R&D efforts with regard to the various specifications have a statistically significant influence on average between 1 and 2 % on labor productivity growth of European regions in the sample. Cross-regional knowledge spillovers due to private sector R&D efforts of other regions have an influence about 0.05 on labor productivity growth of the regions. However, cross-regional knowledge spillovers due to government sector R&D efforts of foreign regions have an influence about 0.023 on labor productivity growth of the regions. Knowledge spillovers across neighbors due to private sector R&D efforts of neighbors have an influence about 0.015

on labor productivity growth of the regions. On the other hand, cross-regional knowledge spillovers from private sector R&D gaps relative to other regions have an influence about 0.02 on labor productivity growth of the regions considering the 1988-95 data, but it is not statistically significant for the 1985-95 data. Knowledge spillovers from neighbors due to private sector R&D gaps have an influence about 0.028 on labor productivity growth of the regions considering the 1988-95 data, while they have an influence about 0.23 for the 1985-95 data.

Thus, it may suggest that cross-regional knowledge spillovers over the sample geography in the EU due to personnel working in business sector R&D are significantly transmitted mutually across all regions rather than simply from the regions that have R&D intensity above the average to those below that. This result might imply that even distribution of R&D efforts across the regions generates relatively more benefit from knowledge spillovers for overall regions in the sample.

However, the knowledge spillovers due to business sector R&D in the neighbor regions are significantly transmitted from the R&D intensive regions above the sample average to those below the mean. That is, once R&D efforts of all neighbors below and above that of the region are accounted for a potential knowledge spillover factor, then the influence of that on labor productivity performance of the region is relatively weak. In contrast, this result might imply that concentration of R&D efforts in a few regions generates relatively more benefit from knowledge spillovers for the neighbor regions in the sample. In addition, the elasticity of *private sector R&D* and *government sector R&D* is estimated from the earlier specifications are twice the size of those estimated from the latter ones. Hence, if the cross-regional knowledge spillovers are properly accounted for,

the real impact of region's own R&D efforts on the performance of labor productivity is explicitly captured as well. Moreover, cross-regional knowledge spillovers due to private sector R&D efforts of all other or neighbor regions that are greater than that of the region itself have relatively greater effect on labor productivity growth in the 1988-95 period than that in the 1985-95 period. So, it may suggest that cross-regional knowledge spillovers have been more effective along with the recent dynamism due to the further EU integration.

Regions that have higher labor productivity growth neighbors grow relatively faster. The size of influence from this factor is very large between 0.18-0.32 in the 1985-95 period, but it is between 0.9-0.16 in the 1988-95 period. In contrast, the influence of growth of industrial mix has increased in most recent years from 0.03 regarding the 1985-95 period to 0.06 regarding the 1988-95 period. So, the influence of economic spillovers due to demand and supply relations in various markets across regions have declined substantially in most recent years, which may be attributed the recent tighter European integration. On the other hand, growth of industrial specialization has a significant negative impact on labor productivity growth with around -0.10.

The greatest impact of private sector R&D on the regional efficiency is about 0.01, while that of knowledge spillovers due to private or government sector R&D is less than 0.01. However, the regional productivity is affected strongly and negatively from the neighbors that have higher labor productivity growth. Next, industrial mix, industrial specialization and young dynamic population have a positive and significant influence on regional productivity growth, while long term unemployment has a negative significant influence.

4. Limitations of the Study

First, the time series segment of the data is not in a sufficient length for testing the mainstream economic growth theory. Because of unavailable long run time series component of the data set for the required variables, annual observations are assigned to the cross section panels in this study. Because annual fluctuations of variables can be diverse due to outside factors such as short run business cycles and time lags, some portion of the associations between dependent variable and independent variables cannot be captured properly. Even though fixed effect estimation method deals with some part of the problem, its consistency is related to the length of the time series component.

Second, since the cross-section component of the sample consists of the regions of three countries, cross-regional knowledge spillovers are constrained to simply across them over the geography. In particular, omitting the regions of Germany, which has the major part of R&D and innovative activity in the EU, England, the Netherlands and Switzerland may mean that we are omitting the essential part of cross regional spillovers in the EU.

Third, because of unavailable data set for the all required variables in this study, cross-section component covers only 57 regions from three countries of the 211 regions at NUTS 2 level from the 15 EU countries. We estimate the parameters with a consistent estimator (LSDV) only, but not an efficient estimator. Moreover, we cannot infer the conclusions on all the EU.

Fourth, we construct regional human capital variable from the national higher education enrolment data because of unavailable regional education data. The national

data is broken into regions based on their output shares in the sample aggregate. Maybe this is why, the elasticity of labor productivity growth with respect to this variable is estimated greater than a reasonable one.

Finally, we employ only 9 sectors for constructing the economic structure variables, industrial specialization and industrial mix. Using the industry data that is finer divided into sub-sectors represents the influence of industrial characteristics of the regions much better. Moreover, R&D data that is finer divided into sub-sectors based on their knowledge or innovation characteristics provides richer knowledge about the issue, whereas we could not use such data in this research. Transmission of knowledge among the similar bases of knowledge or innovation characteristics is expected easier and faster, so that its influence is expected more effective.

5. Suggestions for Further Research

First, regarding the limitations given above, once the data is expanded in aspects of both the time series and cross section components, the subject is worth to restudy based on the underlying model. If cross-section component of the sample is expanded toward other countries as well, cross-regional knowledge spillovers are considered over a broader geography.

Second, it is crucial to obtain an efficient estimator beside the consistent estimator even for the same data set. If we can also estimate the parameters with an efficient statistically unbiased estimation method, we can compare the results and hence make inference more confidently about the sample and the EU regional development.

Third, regional right proxy for human capital may influence the elasticity size of this variable.

Fourth, it is also worth study with patents data within the same context. As output proxy for innovations, they can provide different results. Our data suggest a strong linear association between regional per capita income and per capita number of patents, but there is not exist any significant association between patents and labor productivity growth.

Finally, studying with finer divided industry data and R&D or patents data that are finer divided into sub-sectors based on their knowledge or innovation characteristics has different implications and is desirable in many respects. Thus, studying with finer divided industrial data, we can learn what types of industrial R&D or patents and associated knowledge spillovers significantly and disparately influence the regional economic performance. We can also test whether the underlying impacts are greater within the same industries or otherwise. In addition, R&D efforts in higher education sector and associated knowledge spillovers with a richer data deserve empirically study in the same context.

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**APPENDIXES: Tables for the Summary Statistics of
the Variables and Indicators**

Table AI. Descriptive statistics of particular indicators for the period between 1985 and 1995

Variables	Mean	Std. Dev.	Min.	Max.
GSPAIN	0.0162	0.0162	-0.0901	0.0849
GFRANCE	0.0188	0.0153	-0.0799	0.1064
GITALY	0.0191	0.0194	-0.0902	0.0997
PLGVA8695	33654	5988	17484	53359
PLGVA8594	33052	5877	16751	52877
HERFINDX	1.0000	0.1690	0.7525	1.8140
SECMIX	0.9690	0.0694	0.7933	1.3620
PLRDBP	3138.12	3156.24	8.0465	18233.08
EMPTOTAL	969458	849462	94000	5035000
POPTOTAL	2666370	2105512	260000	10978000
POPDENSITY	150.6820	146.9038	21.1540	913.9190

Notes: Total number of observations, N = 570, consist of 57 cross-section units over 10 years of time-series observations between 1985-95. Definitions of the variables are given in Table II. The basic statistics with regard to annual growth rates of the relevant nations (GSPAIN, GFRANCE and GITALY) are within nation estimates since the observations are constrained with their number of regions, 17, 19 and 21, respectively, employed in the sample for the same term. Monetary terms are in 1990 values of European Currency Unit (ECU). Population density (POPDENSITY) is measured in terms of per square kilometer.

Table AII. Descriptive statistics of the variables for the period between 1985 and 1995

Variables	Mean	Std. Dev.	Min.	Max.
GPLGVA	0.0181	0.0256	-0.0902	0.1064
GEMP	0.0039	0.0245	-0.1224	0.0959
GPLHED	0.0417	0.04012	-0.0901	0.1603
INVESTSH	0.2303	0.0280	0.1471	0.2817
GHINDEX*INV	0.00054	0.0057	-0.0272	0.0157
GSECMX*INV	-0.00017	0.0069	-0.0394	0.0321
GW1*INV	0.0041	0.0039	-0.0194	0.0237
LPLRDBP*INV	1.7051	0.3637	0.3762	2.5852
LRDBDW*INV	1.7070	0.3256	0.8087	2.6866
RRDBDW*INV	0.1719	0.2057	0	1.3146
LPLGVA8594	10.3893	0.1848	9.7262	10.8757
GHERFINDX	0.0029	0.0237	-0.1029	0.0709
GSECMIX	-0.0007	0.0298	-0.1492	0.1425
LPLRDBP	7.4187	1.3769	2.0852	9.8110
RLRDBPDW	0.7362	0.8648	0	5.1591
RLRDBPDW1	0.7362	0.9050	0	5.1382
RLRDBPDW2	0.7362	0.8769	0	4.9720
RLRDBPDW12	0.7362	0.8893	0	5.0464
LRDBPDW	7.4187	1.1195	4.2145	9.6163
LRDBPDW1	7.6864	4.0324	0	17.0511
LRDBPDW2	7.7598	3.4319	0	16.0587
LRDBPDW12	7.7231	3.3428	0	14.4315
GPLGVAW1	0.0180	0.0177	-0.0902	0.1064
GPLGVAW2	0.0184	0.0145	-0.0333	0.0852
GPLGVAW12	0.0182	0.0133	-0.0387	0.0591

Notes: Total number of observations, N = 570, consist of 57 cross-section units over 10 years of time-series observations between 1985-95. Definitions of the variables are given in Table II.

Table AIII. Pearson correlation coefficients across the variables for the period between 1985 and 1995

Variables	GPLGVA	GEMP	GPLHED	INVESTSH	GHINDX*INV	GSECMX*INV
GPLGVA	1.0000					
GEMP	-0.5981 ($<.0001$)	1.0000				
GPLHED	0.5586 ($<.0001$)	-0.5844 ($<.0001$)	1.0000			
INVESTSH	-0.0963 (0.0215)	0.1630 ($<.0001$)	0.0064 (0.8783)	1.0000		
GHINDX*INV	-0.1112 (0.0079)	-0.1539 (0.0002)	-0.0594 (0.1565)	-0.1951 ($<.0001$)	1.0000	
GSECMX*INV	-0.0019 (0.9633)	0.0059 (0.8879)	-0.0326 (0.4374)	-0.0359 (0.3927)	0.3816 ($<.0001$)	1.0000
GW1*INV	0.2640 ($<.0001$)	-0.1130 (0.0069)	0.0304 (0.4688)	0.0687 (0.1012)	-0.0672 (0.1088)	-0.0460 (0.2728)
LPLRDBP*INV	-0.0026 (0.9508)	0.0098 (0.8159)	0.0529 (0.2070)	0.4767 ($<.0001$)	-0.0655 (0.1186)	0.0025 (0.9528)
LRDBDW*INV	-0.0020 (0.9616)	-0.0095 (0.8207)	0.0592 (0.1580)	0.5850 ($<.0001$)	-0.0691 (0.0993)	0.0192 (0.6482)
RRDBDW*INV	-0.0631 (0.1326)	0.0641 (0.1265)	-0.0146 (0.7278)	0.2155 ($<.0001$)	-0.0382 (0.3626)	-0.0209 (0.6185)
LPLGVA8594	-0.0855 (0.0412)	-0.0211 (0.6148)	-0.0147 (0.7271)	-0.2887 ($<.0001$)	0.1532 (0.0002)	0.0658 (0.1167)
GHETFINDX	-0.1220 (0.0035)	-0.1390 (0.0009)	-0.0749 (0.0739)	-0.1961 ($<.0001$)	0.9945 ($<.0001$)	0.3797 ($<.0001$)
GSECMIX	-0.0107 (0.7980)	0.0069 (0.8690)	-0.0390 (0.3524)	-0.0292 (0.4863)	0.3672 ($<.0001$)	0.9949 ($<.0001$)
LPLRDBP	0.0582 (0.1650)	-0.0851 (0.0422)	0.0497 (0.2365)	-0.0836 (0.0461)	0.0461 (0.2718)	0.0191 (0.6495)
RLRDBPDW	-0.0561 (0.1813)	0.0408 (0.3309)	-0.0111 (0.7921)	0.0976 (0.0197)	-0.0176 (0.6744)	-0.0139 (0.7410)
RLRDBPDW1	-0.0619 (0.1402)	0.0719 (0.0863)	-0.0335 (0.4247)	0.0828 (0.0482)	-0.0359 (0.3921)	-0.0174 (0.6784)
RLRDBPDW2	-0.0615 (0.1424)	0.0728 (0.0825)	-0.0344 (0.4128)	0.0828 (0.083)	-0.0361 (0.3902)	-0.0172 (0.6820)
RLRDBPDW12	-0.0617 (0.1413)	0.0723 (0.0846)	-0.0339 (0.4187)	0.0828 (0.0483)	-0.0360 (0.3913)	-0.0173 (0.6800)
LRDBPDW	0.0698 (0.0960)	-0.1364 (0.0011)	0.0644 (0.1248)	-0.0419 (0.3184)	0.0592 (0.1578)	0.0413 (0.3246)
LRDBPDW1	0.0615 (0.1425)	-0.0942 (0.0246)	0.0394 (0.3482)	0.0126 (0.7649)	0.0293 (0.4852)	0.0363 (0.3865)
LRDBPDW2	0.0335 (0.4251)	-0.0433 (0.3027)	0.0456 (0.2773)	0.1416 (0.0007)	-0.0404 (0.3354)	-0.0005 (0.9901)
LRDBPDW12	0.0650 (0.1213)	-0.0946 (0.0240)	0.0507 (0.2269)	0.0671 (0.1098)	0.0156 (0.7108)	0.0277 (0.5093)
GPLGVAW1	0.2779 ($<.0001$)	-0.1393 (0.0009)	0.0225 (0.5927)	-0.0805 (0.0547)	-0.0403 (0.3366)	-0.0392 (0.3504)
GPLGVAW2	0.2382 ($<.0001$)	-0.0738 (0.0784)	-0.0183 (0.6637)	-0.0812 (0.0528)	-0.0657 (0.1170)	-0.0044 (0.9169)
GPLGVAW12	0.3142 ($<.0001$)	-0.1327 (0.0015)	0.0050 (0.9056)	-0.0976 (0.0197)	-0.0626 (0.1358)	-0.0284 (0.4985)

Table AIII. Continued

Variables	GW1*INV	LPLRDBP*INV	LRDBDW*INV	RRDBDW*INV	LPLGVA8594	GHERFINDX
GW1*INV	1.0000					
LPLRDBP*INV	0.1374 (0.0010)	1.0000				
LRDBDW*INV	0.1530 (0.0002)	0.6276 (<.0001)	1.0000			
RRDBDW*INV	-0.0702 (0.0940)	-0.6918 (<.0001)	-0.0497 (0.2364)	1.0000		
LPLGVA8594	-0.0455 (0.2779)	0.3412 (<.0001)	0.1455 (0.0005)	-0.4758 (<.0001)	1.0000	
GHERFINDX	-0.0671 (0.1097)	-0.0690 (0.0997)	-0.0757 (0.0708)	-0.0389 (0.3546)	0.1356 (0.0012)	1.0000
GSECMIX	-0.0448 (0.2861)	-0.00007 (0.9986)	0.0143 (0.7327)	-0.0163 (0.6987)	0.0603 (0.1503)	0.3689 (<.0001)
LPLRDBP	0.1111 (0.0079)	0.8294 (<.0001)	0.3382 (<.0001)	-0.9112 (<.0001)	0.5793 (<.0001)	0.0424 (0.3124)
RLRDBPDW	-0.0760 (0.0700)	-0.7572 (<.0001)	-0.1173 (0.0050)	0.9852 (<.0001)	-0.4638 (<.0001)	-0.0177 (0.6733)
RLRDBPDW1	-0.1122 (0.0073)	-0.8012 (<.0001)	-0.3086 (<.0001)	0.9376 (<.0001)	-0.4969 (<.0001)	-0.0351 (0.4025)
RLRDBPDW2	-0.1124 (0.0072)	-0.8041 (<.0001)	-0.3098 (<.0001)	0.9382 (<.0001)	-0.5017 (<.0001)	-0.0352 (0.4021)
RLRDBPDW12	-0.1123 (0.0073)	-0.8028 (<.0001)	-0.3093 (<.0001)	0.9379 (<.0001)	-0.4994 (<.0001)	-0.0351 (0.4024)
LRDBPDW	0.1405 (0.0008)	0.4072 (<.0001)	0.7792 (<.0001)	-0.2238 (<.0001)	0.4076 (<.0001)	0.0516 (0.2191)
LRDBPDW1	0.1180 (0.0048)	0.3212 (<.0001)	0.7500 (<.0001)	-0.1219 (0.0036)	0.2529 (<.0001)	0.0238 (0.5710)
LRDBPDW2	0.1486 (0.0004)	0.4662 (<.0001)	0.5394 (<.0001)	-0.2728 (<.0001)	0.0754 (0.0722)	-0.0436 (0.2986)
LRDBPDW12	0.1489 (0.0004)	0.4558 (<.0001)	0.7829 (<.0001)	-0.2216 (<.0001)	0.2372 (<.0001)	0.0109 (0.7958)
GPLGVAW1	0.9822 (<.0001)	0.0570 (0.1744)	0.0607 (0.1481)	-0.0911 (0.0297)	0.0082 (0.8459)	-0.0407 (0.3321)
GPLGVAW2	0.3387 (<.0001)	0.0120 (0.7748)	0.0384 (0.3604)	-0.0533 (0.2040)	0.0596 (0.1552)	-0.0716 (0.0875)
GPLGVAW12	0.8367 (<.0001)	0.0444 (0.2903)	0.0612 (0.1447)	-0.0895 (0.0326)	0.0379 (0.3669)	-0.0660 (0.1154)

Table AIII. Continued

Variables	GSECMIX	LPLRDBP	RLRDBPDW	RLRDBPDW1	RLRDBPDW2	RLRDBPDW12
GSECMIX	1.0000					
LPLRDBP	0.0120 (0.7754)	1.0000				
RLRDBPDW	-0.0097 (0.8176)	-0.9261 (<.0001)	1.0000			
RLRDBPDW1	-0.0100 (0.8117)	-0.9666 (<.0001)	0.9536 (<.0001)	1.0000		
RLRDBPDW2	-0.0098 (0.8153)	-0.9700 (<.0001)	0.9541 (<.0001)	0.9999 (<.0001)	1.0000	
RLRDBPDW12	-0.0099 (0.8133)	-0.9684 (<.0001)	0.9539 (<.0001)	0.9999 (<.0001)	0.9999 (<.0001)	1.0000
LRDBPDW	0.0314 (0.4547)	0.4860 (<.0001)	-0.2215 (<.0001)	-0.4470 (<.0001)	-0.4485 (<.0001)	-0.4479 (<.0001)
LRDBPDW1	0.0265 (0.5278)	0.3497 (<.0001)	-0.1204 (0.0040)	-0.3174 (<.0001)	-0.3181 (<.0001)	-0.3179 (<.0001)
LRDBPDW2	-0.0045 (0.9142)	0.4511 (<.0001)	-0.3013 (<.0001)	-0.4412 (<.0001)	-0.4433 (<.0001)	-0.4423 (<.0001)
LRDBPDW12	0.0191 (0.6494)	0.4725 (<.0001)	-0.2315 (<.0001)	-0.4385 (<.0001)	-0.4398 (<.0001)	-0.4393 (<.0001)
GPLGVAW1	-0.0387 (0.3563)	0.1146 (0.0062)	-0.0804 (0.0552)	-0.1121 (0.0074)	-0.1125 (0.0072)	-0.1123 (0.0073)
GPLGVAW2	-0.0080 (0.8486)	0.0643 (0.1254)	-0.0429 (0.3063)	-0.0583 (0.1648)	-0.0586 (0.1622)	-0.0584 (0.1635)
GPLGVAW12	-0.0301 (0.4737)	0.1111 (0.0079)	-0.0767 (0.0672)	-0.1062 (0.0112)	-0.1066 (0.0108)	-0.1064 (0.0110)

Table AIII. Continued

Variables	LRDBPDW	LRDBPDW1	LRDBPDW2	LRDBPDW12	GPLGVAW1	GPLGVAW2
LRDBPDW	1.0000					
LRDBPDW1	0.9147 (<.0001)	1.0000				
LRDBPDW2	0.5738 (<.0001)	0.4878 (<.0001)	1.0000			
LRDBPDW12	0.9194 (<.0001)	0.9325 (<.0001)	0.7362 (<.0001)	1.0000		
GPLGVAW1	0.1426 (0.0006)	0.1108 (0.0081)	0.1200 (0.0041)	0.1307 (0.0018)	1.0000	
GPLGVAW2	0.1196 (0.0042)	0.1112 (0.0079)	0.0862 (0.0396)	0.1147 (0.0061)	0.3635 (<.0001)	1.0000
GPLGVAW12	0.1598 (0.0001)	0.1341 (0.0013)	0.1266 (0.0025)	0.1492 (0.0003)	0.8620 (<.0001)	0.7856 (<.0001)

Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob > |r| under H0: Rho=0. Total number of observations, N = 570, consist of 57 cross-section units over 10 years of time series observations between 1985-95. Definitions of the variables are given in Table II.

Table AIV. Descriptive statistics of particular indicators for the period between 1988 and 1995

Variables	Mean	Std. Dev.	Min.	Max.
GSPAIN	0.0179	0.0146	-0.0579	0.0733
GFRANCE	0.0160	0.0145	-0.0799	0.1064
GITALY	0.0181	0.0193	-0.0902	0.0997
PLGVA8995	34496	6011	18689	53359
PLGVA8894	33908	5905	18209	52877
HERFINDX	1.0000	0.1643	0.7525	1.7288
SECMIX	0.9667	0.0627	0.0627	1.1971
PLRDBP	3272.40	3180.55	8.1258	17722.58
PLRDGP	1325.83	1607.84	64.5851	9477.34
AVPLPAT	9.4882	9.8017	0.1990	45.3795
PATPRDBP	3.6358	4.8552	0.4493	36.2227
PATPRDGP	19.5317	40.4218	0.1721	221.4908
EMPTOTAL	979008	856937	97000	5035000
POPTOTAL	2677632	2121030	260000	10978000
POPDENSITY	151.2800	148.0905	21.1540	913.9190

Notes: Total number of observations, N = 399, consist of 57 cross-section units over 7 years of time-series observations between 1988-95. Definitions of the variables are given in Table II. The basic statistics with regard to annual growth rates of the relevant nations (GSPAIN, GFRANCE and GITALY) are within nation estimates since the observations are constrained with their number of regions, 17, 19 and 21, respectively, employed in the sample for the same term. Monetary terms are in 1990 values of European Currency Unit (ECU). Population density (POPDENSITY) is measured in terms of per square kilometer.

Table AV. Descriptive statistics of the variables for the period between 1988 and 1995

Variables	Mean	Std. Dev.	Min.	Max.
GPLGVA	0.0173	0.0244	-0.0902	0.1064
GEMP	0.0009	0.0002	-0.0928	0.0959
GPLHED	0.0524	0.0353	-0.0463	0.1603
INVESTSH	0.2356	0.0307	0.1471	0.2817
LPLGVA8894	10.4156	0.1807	9.8097	10.8757
GHERFINDX	0.0011	0.0234	-0.1029	0.6903
GSECMIX	-0.0006	0.0271	-0.1492	0.1425
LPLRDBP	7.4906	1.3436	2.0950	9.7826
RLRDBPDW	0.7193	0.8445	0	5.1118
RLRDBPDW1	0.7193	0.8901	0	5.1271
RLRDBPDW2	0.7193	0.8640	0	4.9719
RLRDBPDW12	0.7193	0.8754	0	5.0406
LRDBPDW	7.4906	1.1271	4.2920	9.6268
LRDBPDW1	7.7550	4.0820	0	17.0511
LRDBPDW2	7.8247	3.4574	0	16.0587
LRDBPDW12	7.7899	3.3737	0	14.4315
LPLRDGP	6.6859	1.0334	4.1680	9.1567
RLRDGPDW	0.5696	0.6218	0	2.7586
LRDGPDW	6.6859	0.9758	3.8639	8.6952
GPLGVAW1	0.0173	0.0182	-0.0902	0.1064
GPLGVAW2	0.0174	0.0140	-0.0333	0.0585
GPLGVAW12	0.0174	0.0139	-0.0387	0.0591

Notes: Total number of observations, N = 399, consist of 57 cross-section units over 7 years of time-series observations between 1988-95. Definitions of the variables are given in Table II.

Table AVI. Pearson correlation coefficients across variables for the period between 1988 and 1995

Variables	GPLGVA	GEMP	GPLHED	INVESTSH	LPLGVA8894
GPLGVA	1.0000				
GEMP	-0.6440 ($<.0001$)	1.0000			
GPLHED	0.6234 ($<.0001$)	-0.7013 ($<.0001$)	1.0000		
INVESTSH	-0.1157 (0.0208)	0.2397 ($<.0001$)	-0.1607 (0.0013)	1.0000	
LPLGVA8894	-0.0975 (0.0517)	0.0444 (0.3761)	-0.0400 (0.4252)	-0.4068 ($<.0001$)	1.0000
GHERFINDX	-0.1323 (0.0082)	-0.2084 ($<.0001$)	-0.0081 (0.8712)	-0.1800 (0.0003)	0.2178 ($<.0001$)
GSECMIX	0.0936 (0.0617)	-0.0432 (0.3895)	-0.0324 (0.5190)	-0.0464 (0.3555)	0.1292 (0.0098)
GPLGVAW1	0.3690 ($<.0001$)	-0.1965 ($<.0001$)	0.1223 (0.0145)	-0.1126 (0.0245)	-0.0353 (0.4821)
GPLGVAW2	0.3338 ($<.0001$)	-0.1661 (0.0009)	0.0742 (0.1389)	-0.1227 (0.0142)	0.0061 (0.9032)
GPLGVAW12	0.4112 ($<.0001$)	-0.2131 ($<.0001$)	0.1179 (0.0184)	-0.1360 (0.0065)	-0.0201 (0.6885)
LPLRDBP	0.0168 (0.7380)	0.0059 (0.9072)	0.0423 (0.3993)	-0.0473 (0.3462)	0.5970 ($<.0001$)
RLRDBPDW	0.0110 (0.8274)	-0.0477 (0.3423)	0.0147 (0.7692)	0.0521 (0.2992)	-0.4904 ($<.0001$)
RLRDBPDW1	-0.0197 (0.6951)	-0.0194 (0.6990)	-0.0395 (0.4312)	0.0326 (0.5164)	-0.5228 ($<.0001$)
RLRDBPDW2	-0.0196 (0.6968)	-0.0191 (0.7033)	-0.0383 (0.4457)	0.0333 (0.5067)	-0.5267 ($<.0001$)
RLRDBPDW12	-0.0196 (0.6964)	-0.0194 (0.6998)	-0.0389 (0.4384)	0.0329 (0.5123)	-0.5249 ($<.0001$)
LRDBPDW	0.0805 (0.1082)	-0.0688 (0.1702)	0.0836 (0.0955)	-0.0649 (0.1955)	0.4220 ($<.0001$)
LRDBPDW1	0.0812 (0.1053)	-0.0568 (0.2573)	0.0701 (0.1624)	0.0091 (0.8563)	0.2705 ($<.0001$)
LRDBPDW2	0.0317 (0.5274)	-0.0209 (0.6771)	0.0239 (0.6342)	0.2052 ($<.0001$)	0.0833 (0.0967)
LRDBPDW12	0.0810 (0.1061)	-0.0550 (0.2728)	0.0686 (0.1714)	0.0906 (0.0706)	0.2560 ($<.0001$)
LPLRDGP	0.0162 (0.7476)	0.0143 (0.7756)	-0.0174 (0.7293)	-0.0636 (0.2048)	0.1882 (0.0002)
RLRDGPDW	0.0046 (0.9279)	-0.0382 (0.4471)	0.0334 (0.5063)	0.0194 (0.6991)	-0.0279 (0.5783)
LRDGPDW	0.0890 (0.0758)	-0.0713 (0.1551)	0.0626 (0.2125)	-0.1179 (0.0185)	0.3951 ($<.0001$)

Table AVI. Continued

Variables	GHERFINDX	GSECMIX	GPLGVAW1	GPLGVAW2	GLGVAW12
GHERFINDX	1.0000				
GSECMIX	0.3948 ($<.0001$)	1.0000			
GPLGVAW1	-0.1084 (0.0304)	-0.0164 (0.7443)	1.0000		
GPLGVAW2	-0.0919 (0.0667)	0.0146 (0.7710)	0.4707 ($<.0001$)	1.0000	
GPLGVAW12	-0.1177 (0.0187)	-0.0034 (0.9461)	0.8953 ($<.0001$)	0.8144 ($<.0001$)	1.0000
LPLRDBP	0.0282 (0.5743)	0.1369 (0.0062)	0.0838 (0.0946)	0.0648 (0.1962)	0.0879 (0.0797)
RLRDBPDW	0.0076 (0.8805)	-0.0882 (0.0784)	-0.0666 (0.1845)	-0.0497 (0.3220)	-0.0689 (0.1697)
RLRDBPDW1	-0.0051 (0.9196)	-0.1334 (0.0076)	-0.0929 (0.0639)	-0.0676 (0.1781)	-0.0952 (0.0575)
RLRDBPDW2	-0.0058 (0.9079)	-0.1332 (0.0077)	-0.0931 (0.0633)	-0.0680 (0.1755)	-0.0955 (0.0566)
RLRDBPDW12	-0.0054 (0.9142)	-0.1333 (0.0077)	-0.0929 (0.06370)	-0.0677 (0.1771)	-0.0953 (0.0572)
LRDBPDW	0.0734 (0.1435)	0.2202 ($<.0001$)	0.1191 (0.0173)	0.1115 (0.0260)	0.1346 (0.0071)
LRDBPDW1	0.0401 (0.4239)	0.2221 ($<.0001$)	0.1015 (0.0428)	0.0992 (0.0477)	0.1168 (0.0196)
LRDBPDW2	-0.0349 (0.4869)	0.1390 (0.0054)	0.1076 (0.0317)	0.1079 (0.0312)	0.1252 (0.0123)
LRDBPDW12	0.0196 (0.6971)	0.2120 ($<.0001$)	0.1186 (0.0178)	0.1183 (0.0181)	0.1377 (0.0059)
LPLRDGP	-0.0245 (0.6250)	-0.1281 (0.0104)	0.0472 (0.3473)	0.0881 (0.0787)	0.0755 (0.1321)
RLRDGPDW	0.0532 (0.2896)	0.1234 (0.0136)	-0.0090 (0.8577)	-0.0582 (0.2459)	-0.0353 (0.4818)
LRDGPDW	0.0759 (0.1300)	0.2237 ($<.0001$)	0.1365 (0.0063)	0.1241 (0.0131)	0.1524 (0.0023)

Table AVI. Continued

Variables	LPLRDBP	RLRDBPDW	RLRDBPDW1	RLRDBPDW2	RLRDBPDW12
LPLRDBP	1.0000				
RLRDBPDW	-0.9328 ($<.0001$)	1.0000			
RLRDBPDW1	-0.9684 ($<.0001$)	0.9587 ($<.0001$)	1.0000		
RLRDBPDW2	-0.9715 ($<.0001$)	0.9594 ($<.0001$)	0.9999 ($<.0001$)	1.0000	
RLRDBPDW12	-0.9701 ($<.0001$)	0.9591 ($<.0001$)	0.9999 ($<.0001$)	0.9999 ($<.0001$)	1.0000
LRDBPDW	0.4921 ($<.0001$)	-0.2442 ($<.0001$)	-0.4582 ($<.0001$)	-0.4593 ($<.0001$)	-0.4588 ($<.0001$)
LRDBPDW1	0.3610 ($<.0001$)	-0.1463 (0.0034)	0.3327 ($<.0001$)	-0.3332 ($<.0001$)	-0.3331 ($<.0001$)
LRDBPDW2	0.4673 ($<.0001$)	-0.3307 ($<.0001$)	0.4638 ($<.0001$)	-0.4655 ($<.0001$)	-0.4648 ($<.0001$)
LRDBPDW12	0.4857 ($<.0001$)	-0.2607 ($<.0001$)	-0.4566 ($<.0001$)	-0.4577 ($<.0001$)	-0.4573 ($<.0001$)
LPLRDGP	0.2733 ($<.0001$)	-0.3106 ($<.0001$)	-0.2535 ($<.0001$)	-0.2548 ($<.0001$)	-0.2541 ($<.0001$)
RLRDGPDW	-0.1159 (0.0205)	0.2186 ($<.0001$)	0.1328 (0.0079)	0.1324 (0.0081)	0.1326 (0.0080)
LRDGPDW	0.4660 ($<.0001$)	-0.2398 ($<.0001$)	-0.4431 ($<.0001$)	-0.4438 ($<.0001$)	-0.4435 ($<.0001$)

Table AVI. Continued

Variables	LRDBPDW	LRDBPDW1	LRDBPDW2	LRDBPDW12
LRDBPDW	1.0000			
LRDBPDW1	0.9160 (<.0001)	1.0000		
LRDBPDW2	0.5720 (<.0001)	0.4842 (<.0001)	1.0000	
LRDBPDW12	0.9207 (<.0001)	0.9322 (<.0001)	0.7342 (<.0001)	1.0000
LPLRDGP	-0.1643 (0.0010)	-0.2041 (<.0001)	-0.0071 (0.8875)	-0.1252 (0.0123)
RLRDGPDW	0.3406 (<.0001)	0.3651 (<.0001)	0.1035 (0.0389)	0.2924 (<.0001)
LRDGPDW	0.9799 (<.0001)	0.9059 (<.0001)	0.5653 (<.0001)	0.9018 (<.0001)

Table AVI. Continued

Variables	LPLRDGP	RLRDGPDW	LRDGPDW
LPLRDGP	1.0000		
RLRDGPDW	-0.9084 (<.0001)	1.0000	
LRDGPDW	-0.1443 (<.0001)	0.3215 (<.0001)	1.0000

Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob > |r| under H0: Rho=0. Total number of observations, N = 399, consist of 57 cross-section units over 7 years of time series observations between 1988-95. Definitions of the variables are given in Table II.

Table AVII. Pearson correlation coefficients across the variables employed in OLS estimates of cross-region fixed-effects for the period between 1985 and 1995

Variables	LINPUTSwLq	SPAIND	ITALYD	LPLRDBP	LRDBPDW
LINPUTSwLq	1.0000				
SPAIND	-0.7197 ($<.0001$)	1.0000			
ITALYD	0.3487 (0.0079)	-0.4610 (0.0003)	1.0000		
LPLRDBP	0.5533 ($<.0001$)	-0.3036 (0.0217)	-0.2627 (0.0484)	1.0000	
LRDBPDW	0.3746 (0.0041)	-0.3038 (0.0216)	-0.0529 (0.6959)	0.4859 (0.0001)	1.0000
LRDBPDW1	0.2289 (0.0868)	-0.1598 (0.2352)	-0.0336 (0.8039)	0.3512 (0.0074)	0.9169 ($<.0001$)
LRDBPDW2	0.0229 (0.8657)	0.0161 (0.9051)	-0.3704 (0.0046)	0.4565 (0.0004)	0.5739 ($<.0001$)
RLRDBPDW	-0.4608 (0.0003)	0.2386 (0.0739)	0.2086 (0.1194)	-0.9294 ($<.0001$)	-0.2246 (0.0931)
RLRDBPDW1	-0.4877 (0.0001)	0.2684 (0.0435)	0.2334 (0.0806)	-0.9674 ($<.0001$)	-0.4538 (0.0004)
GPLGVAW1	0.0295 (0.8275)	-0.2126 (0.1123)	0.0643 (0.6345)	0.3410 (0.0094)	0.4758 (0.0002)
SECMIX	0.2222 (0.0967)	0.2499 (0.0608)	0.1019 (0.4508)	-0.0013 (0.9923)	-0.2423 (0.0693)
HERFINDX	0.2735 (0.0396)	0.1901 (0.1566)	0.0726 (0.5917)	0.0030 (0.9826)	-0.2218 (0.0972)
POPRT2544	0.6540 ($<.0001$)	-0.6606 ($<.0001$)	0.1914 (0.1539)	0.3399 (0.0097)	0.1828 (0.1734)
LTUNRT	-0.6279 ($<.0001$)	0.5334 ($<.0001$)	0.0106 (0.9379)	-0.5029 ($<.0001$)	-0.5633 ($<.0001$)
FEMACTRT	0.4783 (0.0002)	-0.5524 ($<.0001$)	-0.3429 (0.0090)	0.5616 ($<.0001$)	0.4272 (0.0009)

Table AVII. Continued

Variables	LRDBPDW1	LRDBPDW2	RLRDBPDW	RLRDBPDW1	GPLGVAW1
LRDBPDW1	1.0000				
LRDBPDW2	0.4877 (0.0001)	1.0000			
RLRDBPDW	-0.1208 (0.3706)	-0.3069 (0.0202)	1.0000		
RLRDBPDW1	-0.3212 (0.0149)	-0.4479 (0.0005)	0.9555 (<.0001)	1.0000	
GPLGVAW1	0.3706 (0.0045)	0.4133 (0.0014)	-0.2220 (0.0969)	-0.3545 (0.0068)	1.0000
SECMIX	-0.2831 (0.0328)	-0.2657 (0.0458)	-0.0276 (0.8384)	0.0703 (0.6036)	-0.3104 (0.0188)
HERFINDX	-0.2630 (0.0481)	-0.2858 (0.0311)	-0.0088 (0.9482)	0.0858 (0.5256)	-0.3745 (0.0041)
POPRT2544	0.0743 (0.5829)	-0.2175 (0.1041)	-0.2692 (0.0429)	-0.2722 (0.0405)	0.0339 (0.8023)
LTUNRT	-0.3889 (0.0028)	-0.3157 (0.0167)	0.3407 (0.0095)	0.4675 (0.0002)	-0.1672 (0.2138)
FEMACTRT	0.2661 (0.0454)	0.3052 (0.0210)	-0.4107 (0.0015)	-0.4630 (0.0003)	0.1578 (0.2410)

Table AVII. Continued

Variables	SECMIX	HERFINDX	POPRT2544	LTUNRT	FEMACTRT
SECMIX	1.0000				
HERFINDX	0.9771 (<.0001)	1.0000			
POPRT2544	0.0215 (0.8737)	0.0809 (0.5495)	1.0000		
LTUNRT	0.0650 (0.6309)	0.0302 (0.8233)	-0.3413 (0.0094)	1.0000	
FEMACTRT	-0.1423 (0.2910)	-0.0761 (0.5736)	0.5544 (<.0001)	-0.6835 (<.0001)	1.0000

Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob > |r| under H0: Rho=0. Total number of observations consist of N=57 cross-section units over average of 7 years of time-series observations between 1985-95. Definitions of the variables are given in Table II.

Table AVIII. Pearson correlation coefficients across the variables employed in OLS estimates of cross-region fixed-effects for the period between 1988 and 1995

Variables	LINPUTSwLq	SPAIND	ITALYD	LPLRDBP	LPLRDGP	LRDBPDW
LINPUTSwLq	1.0000					
SPAIND	-0.6469 ($<.0001$)	1.0000				
ITALYD	0.2697 (0.0425)	-0.4610 (0.0003)	1.0000			
LPLRDBP	0.5900 ($<.0001$)	-0.2928 (0.0271)	-0.2712 (0.0413)	1.0000		
LPLRDGP	0.1884 (0.1604)	0.0811 (0.5490)	0.0540 (0.6901)	0.2753 (0.0382)	1.0000	
LRDBPDW	0.4164 (0.0013)	-0.2942 (0.0263)	-0.0558 (0.6801)	0.4919 (0.0001)	-0.1675 (0.2130)	1.0000
LRDGPDW	0.3957 (0.0023)	-0.2916 (0.0277)	0.0540 (0.6899)	0.4660 (0.0003)	-0.1491 (0.2683)	0.9816 ($<.0001$)
LRDBPDW1	0.2715 (0.0411)	-0.1500 (0.2654)	-0.0355 (0.7931)	0.3601 (0.0059)	-0.2057 (0.1249)	0.9168 ($<.0001$)
LRDBPDW2	0.0587 (0.6647)	0.0243 (0.8579)	-0.3725 (0.0043)	0.4682 (0.0002)	-0.0105 (0.9382)	0.5721 ($<.0001$)
RLRDBPDW	-0.4901 (0.0001)	0.2213 (0.0981)	0.2268 (0.0898)	-0.9364 ($<.0001$)	-0.3096 (0.0191)	-0.2471 (0.0639)
RLRDGPDW	-0.0385 (0.7763)	-0.17296 (0.1982)	-0.0631 (0.6413)	-0.1218 (0.3668)	-0.9078 ($<.0001$)	0.3528 (0.0071)
RLRDBPDW1	-0.5250 ($<.0001$)	0.2487 (0.0621)	0.2496 (0.0612)	-0.9688 ($<.0001$)	0.2543 (0.0562)	-0.4623 (0.0003)
GPLGVAW1	-0.1755 (0.1915)	0.1852 (0.1678)	0.0069 (0.9592)	0.2464 (0.0646)	0.0980 (0.4682)	0.3739 (0.1142)
SECMIX	0.3400 (0.0097)	0.1711 (0.2033)	0.1820 (0.1754)	0.0317 (0.8147)	0.4674 (0.0002)	-0.1602 (0.2340)
HERFINDX	0.3591 (0.0061)	0.0932 (0.4906)	0.1446 (0.2832)	-0.0053 (0.9687)	0.4156 (0.0013)	-0.1944 (0.1474)
POPRT2544	0.6333 ($<.0001$)	-0.6121 ($<.0001$)	0.1795 (0.1815)	0.2995 (0.0236)	0.0606 (0.6541)	0.1419 (0.2923)
LTUNRT	-0.6462 ($<.0001$)	0.4917 (0.0001)	0.0409 (0.7624)	-0.5317 ($<.0001$)	-0.0150 (0.9117)	-0.5747 ($<.0001$)
FEMACTRT	0.4850 (0.0001)	-0.5031 ($<.0001$)	-0.3914 (0.0026)	0.5674 ($<.0001$)	-0.0891 (0.5100)	0.4141 (0.0014)

Table AVIII. Continued

Variables	LRDGPDW	LRDBPDW1	LRDBPDW2	RLRDBPDW	RLRDGPDW	RLRDBPDW1
LRDGPDW	1.0000					
LRDBPDW1	0.9082 ($<.0001$)	1.0000				
LRDBPDW2	0.5664 ($<.0001$)	0.4843 (0.0001)	1.0000			
RLRDBPDW	-0.2410 (0.0710)	-0.1476 (0.2732)	-0.3347 (0.0109)	1.0000		
RLRDGPDW	0.3357 (0.0107)	0.3766 (0.0039)	0.1072 (0.4275)	0.2253 (0.0919)	1.0000	
RLRDBPDW1	-0.4475 (0.0005)	-0.3353 (0.0108)	-0.4682 (0.0002)	0.9613 ($<.0001$)	0.1375 (0.3077)	1.0000
GPLGVAW1	0.4262 (0.0009)	0.3377 (0.0102)	0.3629 (0.0055)	-0.1870 (0.1636)	-0.0111 (0.9346)	-0.2978 (0.0245)
SECMIX	-0.1298 (0.3357)	-0.2058 (0.1247)	-0.2410 (0.0709)	-0.0445 (0.7425)	-0.4077 (0.0016)	0.0339 (0.8022)
HERFINDX	-0.1824 (0.1744)	-0.2435 (0.0680)	-0.3017 (0.0226)	0.0055 (0.9674)	-0.3453 (0.0085)	0.0923 (0.4949)
POPRT2544	0.0909 (0.5014)	0.0434 (0.7484)	-0.2610 (0.0499)	-0.2304 (0.0847)	-0.0267 (0.8437)	-0.2222 (0.0966)
LTUNRT	-0.5436 ($<.0001$)	-0.3943 (0.0024)	-0.3381 (0.0101)	0.3769 (0.0039)	-0.1102 (0.41460)	0.4990 ($<.0001$)
FEMACTRT	0.3301 (0.0121)	0.2524 (0.0582)	0.3092 (0.0193)	-0.4186 (0.0012)	0.1988 (0.1382)	-0.4670 (0.0002)

Table AVIII. Continued

Variables	GPLGVAW1	SECMIX	HERFINDX	POPRT2544	LTUNRT	FEMACTRT
GPLGVAW1	1.0000					
SECMIX	-0.1811 (0.1776)	1.0000				
HERFINDX	-0.3244 (0.0138)	0.9658 ($<.0001$)	1.0000			
POPRT2544	-0.2642 (0.0470)	0.1241 (0.3576)	0.1885 (0.1603)	1.0000		
LTUNRT	0.0048 (0.9717)	-0.0347 (0.7976)	-0.0320 (0.8134)	-0.3013 (0.0227)	1.0000	
FEMACTRT	-0.1618 (0.2292)	-0.0875 (0.5175)	-0.0234 (0.8628)	0.5023 ($<.0001$)	-0.6863 ($<.0001$)	1.0000

Notes: Notes: Within parenthesis are probability levels of significance for Pearson correlation coefficients, Prob $> |r|$ under $H_0: \rho=0$. Total number of observations consist of $N=57$ cross-section units over average of 7 years of time-series observations between 1988-95. Definitions of the variables are given in Table II.

Table AIX. Cross-regional averages of R&D and patent data for the period between 1988 and 1995

No.	Region	GPLGVA	AVPLGVA	PLRDBP	PLRDGP	AVPLPAT	PATPRDBP	PATPRDGP
1	ES11	0.0316	20492	623	984	0.31	0.48	0.31
2	ES12	0.0228	25407	1064	1080	1.12	1.03	1.01
3	ES13	0.0163	28447	801	781	1.27	1.55	1.59
4	ES21	0.0170	34227	6279	357	2.88	0.45	7.91
5	ES22	0.0134	30201	3380	573	4.30	1.25	7.35
6	ES23	0.0342	32631	805	839	1.38	1.68	1.61
7	ES24	0.0175	28748	1656	1658	2.06	1.22	1.22
8	ES3	0.0088	33366	7065	7542	4.78	0.66	0.62
9	ES41	0.0237	25237	1516	587	0.88	0.57	1.47
10	ES42	0.0257	27755	599	448	0.51	0.83	1.11
11	ES43	0.0256	23506	261	1132	0.20	0.75	0.17
12	ES51	0.0130	31893	4142	972	5.91	1.40	5.96
13	ES52	0.0142	27678	974	631	2.13	2.15	3.31
14	ES53	0.0044	32139	117	416	0.83	6.95	1.96
15	ES61	0.0194	27585	940	1276	0.84	0.88	0.65
16	ES62	0.0194	28530	823	1373	0.84	1.00	0.60
17	ES7	0.0028	31674	122	1259	0.56	4.47	0.43
18	FR1	0.0232	50141	17279	4134	45.38	2.57	10.75
19	FR21	0.0123	38506	2375	94	12.56	5.18	130.61
20	FR22	0.0143	37852	5558	114	19.01	3.35	163.58
21	FR23	0.0168	41887	6108	184	15.00	2.40	79.64
22	FR24	0.0137	36713	5451	1292	16.68	3.00	12.64
23	FR25	0.0202	33868	2547	228	10.99	4.22	47.12
24	FR26	0.0106	35730	4279	831	19.72	4.51	23.25
25	FR3	0.0151	39287	2537	405	9.70	3.74	23.45
26	FR41	0.0133	38120	3194	948	15.16	4.65	15.65
27	RF42	0.0148	39967	4084	548	32.77	7.86	58.50
28	FR43	0.0159	37261	8078	89	20.07	2.43	221.49
29	FR51	0.0128	35423	3200	860	9.26	2.83	10.54
30	FR52	0.0197	34734	4353	2346	11.85	2.66	4.94
31	FR53	0.0177	33545	2382	711	9.91	4.07	13.65
32	FR61	0.0135	37497	5531	757	11.54	2.04	14.91
33	FR62	0.0218	34983	8672	3109	15.84	1.79	4.99
34	FR63	0.0234	31479	2606	125	7.53	2.83	58.96
35	FR71	0.0177	39299	8513	1685	40.15	4.62	23.33
36	FR72	0.0142	33022	7675	1745	13.31	1.70	7.47
37	FR81	0.0130	36695	2645	3582	11.54	4.27	3.15
38	FR82	0.0127	40265	6181	2924	19.31	3.06	6.47
39	IT11	0.0157	40632	9388	776	17.21	1.79	21.72
40	IT13	0.0206	44044	4604	2777	10.17	2.16	3.59
41	IT2	0.0238	44156	6451	1748	21.84	3.31	12.23
42	IT31	0.0060	39463	851	888	6.65	7.64	7.33
43	IT32	0.0218	40063	1661	647	12.49	7.36	18.89
44	IT33	0.0170	42523	3069	1723	19.43	6.20	11.04
45	IT4	0.0226	40972	2971	1446	17.06	5.62	11.55
46	IT51	0.0143	38568	2056	1579	8.47	4.03	5.25
47	IT52	0.0155	34618	869	482	4.73	5.33	9.60
48	IT53	0.0244	36150	699	293	6.16	8.63	20.56
49	IT6	0.0159	43640	3517	8988	7.53	2.10	0.82
50	IT71	0.0317	34914	2530	826	3.52	1.36	4.17
51	IT72	0.0198	27957	13	159	0.47	36.22	2.86

52	IT8	0.0193	31398	1273	881	1.37	1.05	1.52
53	IT91	0.0054	31858	685	475	1.04	1.48	2.14
54	IT92	0.0220	26855	450	1466	0.43	0.94	0.29
55	IT93	0.0125	26356	169	207	0.41	2.36	1.93
56	ITA	0.0140	31778	510	563	2.38	4.58	4.15
57	ITB	0.0211	33340	346	1028	1.40	3.97	1.34

Notes: Total number of observations consists of 57 cross-section units over the average of 7 years of time-series observations between 1988-95. GPLGVA is the average percentage annual growth rate of per labor gross value added in income. AVPLGVA is the average per labor gross value added in 1990 values of European Currency Unit (ECU). PLRDBP is the per 979008 employee- (i.e., the sample average) personnel working in business sector R&D, PLRDGP is the per 979008 employee-personnel working in government sector R&D, AVPLPAT is the average per 1000000 employee-number of patents cited by the origin of region, PATPRDBP is the average number of patents per 1000 personnel working in business sector R&D cited by the origin of region, and PATPRDGP is the average number of patents per 1000 personnel working in government sector R&D cited by the origin of region.

Table AX. Cross-region fixed effects (with LSDV estimator) for the period between 1988 and 1995

No.	Region	FMwLq	FMnoLq	INPUTSwLq	INPUTSnoLq
1	ES11	94.80	100.92	95.00	90.18
2	ES12	96.96	100.07	97.07	85.69
3	ES13	97.92	97.00	98.22	88.10
4	ES21	99.41	95.09	100.07	95.40
5	ES22	98.30	96.13	98.88	94.72
6	ES23	98.39	89.31	99.67	116.80
7	ES24	98.19	99.39	98.33	89.83
8	ES3	99.13	94.85	99.87	95.35
9	ES41	96.77	99.37	97.03	89.13
10	ES42	97.79	98.17	98.04	99.50
11	ES43	96.30	99.98	96.37	92.32
12	ES51	99.14	98.65	99.46	100.90
13	ES52	98.05	100.92	98.03	94.61
14	ES53	99.98	100.93	99.46	88.68
15	ES61	98.24	103.50	98.00	97.62
16	ES62	98.53	102.47	98.33	98.46
17	ES7	100.62	108.95	99.30	83.63
18	FR1	102.61	89.61	103.61	86.34
19	FR21	100.93	96.34	101.05	80.23
20	FR22	100.65	96.37	100.98	88.63
21	FR23	101.67	96.11	101.94	89.28
22	FR24	100.25	95.89	100.59	80.39
23	FR25	99.92	99.92	99.93	94.61
24	FR26	100.1	96.68	100.34	79.91
25	FR3	101.49	99.66	101.27	83.41
26	FR41	100.97	98.07	100.96	81.37
27	FR42	101.47	98.35	101.47	86.62
28	FR43	100.24	94.77	100.83	89.63
29	FR51	100.26	98.64	100.29	84.16
30	FR52	100.06	99.43	100.11	88.19

31	FR53	99.70	98.81	99.74	84.20
32	FR61	100.64	97.32	100.85	84.91
33	FR62	99.63	95.73	100.23	93.83
34	FR63	98.86	97.67	99.11	84.69
35	FR71	100.79	94.85	101.31	88.14
36	FR72	98.92	94.54	99.58	81.37
37	FR81	100.82	100.12	100.71	90.75
38	FR82	101.26	96.20	101.51	82.42
39	IT11	101.49	97.39	101.94	127.00
40	IT13	103.37	106.40	102.92	191.95
41	IT2	102.58	99.41	102.62	113.48
42	IT31	101.92	100.90	101.62	109.89
43	IT32	102.11	103.01	101.71	116.37
44	IT33	103.15	107.59	102.47	146.56
45	IT4	102.35	103.89	101.92	116.63
46	IT51	101.89	104.80	101.40	119.15
47	IT52	100.64	102.53	100.37	121.87
48	IT53	100.90	101.03	100.63	105.47
49	IT6	103.08	104.33	102.56	114.70
50	IT71	100.65	104.22	100.29	107.67
51	IT72	96.69	84.60	98.01	86.52
52	IT8	99.97	107.48	99.29	104.10
53	IT91	100.14	106.23	99.37	88.63
54	IT92	98.70	109.93	98.02	149.57
55	IT93	98.41	107.30	97.73	115.78
56	ITA	100.66	112.02	99.51	114.29
57	ITB	101.56	116.20	100.10	146.42

Notes: Total number of observations consist of N=57 cross-section units over average of 7 years of time-series observations between 1988-95. FMwLnq is estimated from full model with log of initial year per labor income. FMnoLnq is estimated from full model without log of initial year per labor income. INPUTSwLq is estimated from the model with only input variables and log of initial year per labor income. INPUTSnoLnq is estimated from the model with only input variables and without log of initial year per labor income.

Table AXI. Cross-region fixed effects (with LSDV estimator) for the period between 1985 and 1995

No.	Region	FMwLq	FMnoLq	INPUTSwLq	INPUTSnoLq
1	ES11	94.28	97.26	94.23	82.24
2	ES12	96.25	93.48	96.36	77.97
3	ES13	97.55	94.36	97.56	81.73
4	ES21	98.88	89.21	99.52	82.49
5	ES22	98.02	92.43	98.46	86.32
6	ES23	98.64	88.72	98.84	81.80
7	ES24	97.76	95.09	97.87	84.11
8	ES3	98.79	88.93	99.59	85.87
9	ES41	96.15	92.93	96.41	80.03
10	ES42	97.54	98.60	97.40	89.53
11	ES43	96.02	98.98	95.68	83.30
12	ES51	98.65	93.05	99.11	88.00
13	ES52	97.69	96.83	97.67	85.59
14	ES53	100.23	103.23	99.29	84.73
15	ES61	97.59	97.71	97.54	85.68
16	ES62	97.92	96.22	97.85	82.65
17	ES7	100.44	108.46	99.22	85.75
18	FR1	102.86	89.47	103.61	95.98
19	FR21	101.11	97.90	101.15	96.47
20	FR22	100.68	95.69	101.05	98.33
21	FR23	101.65	94.66	102.03	96.32
22	FR24	100.39	95.53	100.74	95.89
23	FR25	99.81	100.10	99.87	101.02
24	FR26	100.27	96.50	100.54	96.34
25	FR3	101.34	98.89	101.32	95.62
26	FR41	100.96	98.12	101.06	96.92
27	FR42	101.52	97.93	101.70	99.65
28	FR43	100.37	95.05	100.89	100.89
29	FR51	100.28	98.34	100.45	98.38
30	FR52	99.98	98.75	100.19	100.33
31	FR53	99.78	98.93	99.85	97.29
32	FR61	100.63	95.60	100.97	95.91
33	FR62	99.64	94.77	100.24	101.42
34	FR63	99.00	98.49	99.13	97.71
35	FR71	100.95	94.62	101.47	100.42
36	FR72	99.06	93.88	99.68	97.83
37	FR81	101.00	101.17	100.98	103.69
38	FR82	101.29	94.81	101.71	97.30
39	IT11	102.05	101.07	102.56	132.04
40	IT13	103.53	109.65	103.51	147.76
41	IT2	102.75	100.71	103.01	116.69
42	IT31	102.40	105.20	102.04	111.44
43	IT32	102.24	105.52	102.03	114.23
44	IT33	103.17	109.73	102.97	131.36
45	IT4	102.33	105.06	102.22	114.79
46	IT51	101.88	105.15	101.72	111.69
47	IT52	100.98	107.18	100.66	115.87
48	IT53	101.03	104.31	100.65	104.36
49	IT6	103.11	104.75	103.10	118.95
50	IT71	100.33	102.89	100.26	103.92
51	IT72	99.13	102.48	98.09	97.67

52	IT8	99.76	107.13	99.46	107.38
53	IT91	100.18	108.61	99.67	105.54
54	IT92	98.96	116.00	98.33	126.43
55	IT93	98.85	112.85	98.02	108.52
56	ITA	100.68	115.14	99.91	115.23
57	ITB	101.70	121.96	100.59	124.66

Notes: Total number of observations consists of 57 cross-section units over the average of 10 years of time-series observations between 1985-95. FMwLnq is estimated from full model with log of initial year per labor income. FMnoLnq is estimated from full model without log of initial year per labor income. INPUTSwLq is estimated from the model with only input variables and log of initial year per labor income. INPUTSnoLnq is estimated from the model with only input variables and without log of initial year per labor income.

Table AXII. Names of the regions and their most populated urban centers

No.	Region Cod #	Region Name (NUTS2 Level)	The most populated urban center in 1990
	ES	SPAIN regions	
1	ES11	GALICIA	Ourence
2	ES12	PRINCIPADO DE ASTURIAS	Gijon
3	ES13	CANTABRIA	Santander
4	ES21	PAIS VASCO	Bilbao
5	ES22	COMUNIDAD FORAL DE NAVARRA	Pamplona
6	ES23	RIOJA	Logrono
7	ES24	ARAGON	Zaragoza
8	ES3	COMUNIDAD DE MADRID	Madrid
9	ES41	CASTILLA _ LEON	Valladolid
10	ES42	CASTILLA _ LA MANCHA	Albacete
11	ES43	EXTREMADURRA	Badajoz
12	ES51	CATALUNA	Barcelona
13	ES52	COMUNIDAD VALENCIANA	Valencia
14	ES53	ISLAS BALEARES	Palma de Mallorca
15	ES61	ANDALUCIA	Sevilla
16	ES62	REGION DE MURCIA	Murcia
17	ES7	CANARIAS	Las Palmas de Gran Canaria
	FR	FRANCE regions	
18	FR1	ILE DE FRANCE	Paris
19	FR21	CHAMPAGNE_ARDENNE	Reims
20	FR22	PICARDIE	Amiens
21	FR23	HAUTE_NORMANDIE	Rouen
22	FR24	CENTRE	Orleans
23	FR25	BASSE_NORMANDIE	Caen
24	FR26	BOURGOGNE	Dijon
25	FR3	NORD _ PAS_DE_CALAIS	Lille
26	FR41	LORRAINE	Metz

27	FR42	ALSACE	Strasbourg
28	FR43	FRANCHE_COMTE	Besancon
29	FR51	PAYS DE LA LOIRE	Nantes
30	FR52	BRETAGNE	Rennes
31	FR53	POITOU_CHARENTES	Poitiers
32	FR61	AQUITAINE	Bordeaux
33	FR62	MIDI_PYRENEES	Toulouse
34	FR63	LIMOUSIN	Limoges
35	FR71	RHONE_ALPES	Lyon
36	FR72	AUVERGNE	Clermont Ferrand
37	R81	LANGUEDOC_ROUSSILLON	Montpellier
38	FR82	PROVENCE_ALPES_COTE_D'AZUR	Marseille
	IT	ITALY regions	
39	IT11	PIEMONTE	Torino
40	IT13	LIGURIA	Genova
41	IT2	LOMBARDIA	Milano
42	IT31	TRENTINO_ALTO ADIGE	Trento
43	IT32	VENETO	Venezia
44	IT33	FRIULI_VENEZIA GIULIA	Udine
45	IT4	EMILIA_ROMAGNA	Bologna
46	IT51	TOSCANA	Firenze
47	IT52	UMBRIA	Perugia
48	IT53	MARCHE	Ancona
49	IT6	LAZIO	Roma
50	IT71	ABRUZZI	Chieti
51	IT72	MOLISE	Campobasso
52	IT8	CAMPANIA	Napoli
53	IT91	PUGLIA	Bari
54	IT92	BASILICATA	Potenza
55	IT93	CALABRIA	Cosenza
56	ITA	SICILIA	Palermo
57	ITB	SARDEGNA	Cagliari

Source: Cambridge Econometrics (2000). *European Regional Prospects, Analysis and Forecasts to 2004*, May; EUROSTAT (2000). *Regions: Statistical yearbook 2000*, Luxembourg: Office for official publications of the European Communities; and EUROSTAT (1993). *Portrait of the regions*, vol. 2 and 3, Luxembourg: Office for official publications of the European Communities.

Table AXIII. Names of Sectors

Sectors

1. AGRICULTURE
2. ENERGY AND MANUFACTURING
3. CONSTRUCTION
4. MARKET SERVICES
5. DISTRIBUTION
6. TRANSPORT & COMMUNICATIONS
7. BANKING & FINANCE
8. OTHER MARKET SERVICES
9. NON MARKET SERVICES

Source: Cambridge Econometrics (2000). *European Regional Prospects, Analysis and Forecasts to 2004*, May.



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Experience: Raised in a village near Adapazari, Turkey, during summers worked on family farm throughout the years of childhood, high school and undergraduate education. Worked as a graduate assistant, 1988-1993 years, Department of Public Finance, Hacettepe University, Ankara, Turkey. Upon succeeded a nation-wide exam of selection in field, granted a scholarship to pursue higher education towards master and doctoral degrees by Higher Education Council (HEC) of Turkey in June 1993. Hired by Abant Izzet Baysal University, Bolu, Turkey as a research assistant in August 1993. Granted a research assistantship, 2000-2002 academic years, Department of Economics, Oklahoma State University.